# pandas: powerful Python data analysis toolkit

***Release 0.11.0.dev-9988e5f***

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**Binary Installers:** http://pypi.python.org/pypi/pandas

**Source Repository:** http://github.com/pydata/pandas

**Issues & Ideas:** https://github.com/pydata/pandas/issues

**Q&A Support:** http://stackoverflow.com/questions/tagged/pandas

**Developer Mailing List:** http://groups.google.com/group/pystatsmodels

**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 actually 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, moving window linear regressions, date shifting and lagging, etc.

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.

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**Note:** This documentation assumes general familiarity with NumPy. If you haven't used NumPy much or at all, do invest some time in learning about NumPy first.

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See the package overview for more detail about what's in the library.

CHAPTER

ONE

# WHAT'S NEW

These are new features and improvements of note in each release.

## 1.1 v0.10.1 (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.

### 1.1.1 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)

### 1.1.2 New features

- MySQL support for database (contribution from Dan Allan)

### 1.1.3 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 [1530]: store = HDFStore('store.h5')

In [1531]: df = DataFrame(randn(8, 3), index=date_range('1/1/2000', periods=8),
   ......:                columns=['A', 'B', 'C'])
   ......:

In [1532]: df['string'] = 'foo'

In [1533]: df.ix[4:6,'string'] = np.nan

In [1534]: df.ix[7:9,'string'] = 'bar'

In [1535]: df['string2'] = 'cool'

In [1536]: df
Out[1536]:
                   A         B         C string string2
2000-01-01  0.741687  0.035967 -2.700230    foo    cool
2000-01-02  0.777316  1.201654  0.775594    foo    cool
2000-01-03  0.916695 -0.511978  0.805595    foo    cool
2000-01-04 -0.517789 -0.980332 -1.325032    foo    cool
2000-01-05  0.015397  1.063654 -0.297355    NaN    cool
2000-01-06  1.118334 -1.750153  0.507924    NaN    cool
2000-01-07 -0.163195  0.285564 -0.332279    foo    cool
2000-01-08 -0.516040 -0.531297 -0.409554    bar    cool

# on-disk operations
In [1537]: store.append('df', df, data_columns = ['B','C','string','string2'])

In [1538]: store.select('df',[ 'B > 0', 'string == foo' ])
Out[1538]:
                   A         B         C string string2
2000-01-01  0.741687  0.035967 -2.700230    foo    cool
2000-01-02  0.777316  1.201654  0.775594    foo    cool
2000-01-07 -0.163195  0.285564 -0.332279    foo    cool

# this is in-memory version of this type of selection
In [1539]: df[(df.B > 0) & (df.string == 'foo')]
Out[1539]:
                   A         B         C string string2
2000-01-01  0.741687  0.035967 -2.700230    foo    cool
2000-01-02  0.777316  1.201654  0.775594    foo    cool
2000-01-07 -0.163195  0.285564 -0.332279    foo    cool
```

Retrieving unique values in an indexable or data column.

```
In [1540]: store.unique('df','index')
Out[1540]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2000-01-01 00:00:00, ..., 2000-01-08 00:00:00]
Length: 8, Freq: None, Timezone: None

In [1541]: store.unique('df','string')
Out[1541]: Index([bar, foo], dtype=object)
```

You can now store `datetime64` in data columns

```
In [1542]: df_mixed               = df.copy()
```

```
In [1543]: df_mixed['datetime64'] = Timestamp('20010102')

In [1544]: df_mixed.ix[3:4,['A','B']] = np.nan

In [1545]: store.append('df_mixed', df_mixed)

In [1546]: df_mixed1 = store.select('df_mixed')

In [1547]: df_mixed1
Out[1547]:
                   A         B         C string string2          datetime64
2000-01-01  0.741687  0.035967 -2.700230    foo    cool 2001-01-02 00:00:00
2000-01-02  0.777316  1.201654  0.775594    foo    cool 2001-01-02 00:00:00
2000-01-03  0.916695 -0.511978  0.805595    foo    cool 2001-01-02 00:00:00
2000-01-04       NaN       NaN -1.325032    foo    cool 2001-01-02 00:00:00
2000-01-05  0.015397  1.063654 -0.297355    NaN    cool 2001-01-02 00:00:00
2000-01-06  1.118334 -1.750153  0.507924    NaN    cool 2001-01-02 00:00:00
2000-01-07 -0.163195  0.285564 -0.332279    foo    cool 2001-01-02 00:00:00
2000-01-08 -0.516040 -0.531297 -0.409554    bar    cool 2001-01-02 00:00:00

In [1548]: df_mixed1.get_dtype_counts()
Out[1548]:
datetime64[ns]    1
float64           3
object            2
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 [1549]: store.select('df',columns = ['A','B'])
Out[1549]:
                   A         B
2000-01-01  0.741687  0.035967
2000-01-02  0.777316  1.201654
2000-01-03  0.916695 -0.511978
2000-01-04 -0.517789 -0.980332
2000-01-05  0.015397  1.063654
2000-01-06  1.118334 -1.750153
2000-01-07 -0.163195  0.285564
2000-01-08 -0.516040 -0.531297
```

`HDFStore` now serializes multi-index dataframes when appending tables.

```
In [1550]: index = 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 [1551]: df = DataFrame(np.random.randn(10, 3), index=index,
   ......:                columns=['A', 'B', 'C'])
   ......:

In [1552]: df
Out[1552]:
                  A         B         C
foo bar
```

```
foo one    0.055458 -0.000871 -0.156757
    two   -1.193604  0.768787 -0.228047
    three  0.054979 -0.423256  0.175289
bar one   -0.961203 -0.302857  0.047525
    two   -0.987381 -0.082381  1.122844
baz two    0.357760 -1.287685 -0.555503
    three -1.721204 -0.040879 -1.742960
qux one   -1.263551 -0.952076  1.253998
    two   -0.994435 -1.857899 -1.409501
    three  2.056446  0.686683  0.295824

In [1553]: store.append('mi',df)

In [1554]: store.select('mi')
Out[1554]:
                  A         B         C
foo bar
foo one    0.055458 -0.000871 -0.156757
    two   -1.193604  0.768787 -0.228047
    three  0.054979 -0.423256  0.175289
bar one   -0.961203 -0.302857  0.047525
    two   -0.987381 -0.082381  1.122844
baz two    0.357760 -1.287685 -0.555503
    three -1.721204 -0.040879 -1.742960
qux one   -1.263551 -0.952076  1.253998
    two   -0.994435 -1.857899 -1.409501
    three  2.056446  0.686683  0.295824

# the levels are automatically included as data columns
In [1555]: store.select('mi', Term('foo=bar'))
Out[1555]:
                A         B         C
foo bar
bar one -0.961203 -0.302857  0.047525
    two -0.987381 -0.082381  1.122844
```

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 [1556]: df_mt = DataFrame(randn(8, 6), index=date_range('1/1/2000', periods=8),
   ......:                                columns=['A', 'B', 'C', 'D', 'E', 'F'])
   ......:

In [1557]: df_mt['foo'] = 'bar'

# you can also create the tables individually
In [1558]: store.append_to_multiple({ 'df1_mt' : ['A','B'], 'df2_mt' : None }, df_mt, selector = 'df1

In [1559]: store
Out[1559]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/df                    frame_table  (typ->appendable,nrows->8,ncols->5,indexers->[index],dc->[B,C,strin
/df1_mt                frame_table  (typ->appendable,nrows->8,ncols->2,indexers->[index],dc->[A,B])
/df2_mt                frame_table  (typ->appendable,nrows->8,ncols->5,indexers->[index])
/df_mixed              frame_table  (typ->appendable,nrows->8,ncols->6,indexers->[index])
/mi                    frame_table  (typ->appendable_multi,nrows->10,ncols->5,indexers->[index],dc->[ba
```

```
# indiviual tables were created
In [1560]: store.select('df1_mt')
Out[1560]:
                   A         B
2000-01-01  0.452273  0.853944
2000-01-02 -0.388093  0.086667
2000-01-03 -0.727640 -0.341083
2000-01-04  1.973282 -0.336809
2000-01-05  0.436261 -0.543731
2000-01-06 -0.068377 -0.215977
2000-01-07  1.203168  0.564612
2000-01-08 -0.414547  2.005601

In [1561]: store.select('df2_mt')
Out[1561]:
                   C         D         E         F  foo
2000-01-01  0.585509  0.483793  1.387714 -0.261908  bar
2000-01-02  0.269055  0.011450 -0.104465 -0.406944  bar
2000-01-03  0.478604  0.463990  1.237388  0.628084  bar
2000-01-04  0.963953  0.053805  1.182483  0.566182  bar
2000-01-05 -0.320155  2.545145  0.301306  1.967739  bar
2000-01-06 -1.038566 -0.911641 -1.172296  1.539279  bar
2000-01-07 -0.836731  0.283662 -0.357312  1.295667  bar
2000-01-08 -0.601194 -0.134764  0.280262 -0.627031  bar

# as a multiple
In [1562]: store.select_as_multiple(['df1_mt','df2_mt'], where = [ 'A>0','B>0' ], selector = 'df1_mt'
Out[1562]:
                   A         B         C         D         E         F  foo
2000-01-01  0.452273  0.853944  0.585509  0.483793  1.387714 -0.261908  bar
2000-01-07  1.203168  0.564612 -0.836731  0.283662 -0.357312  1.295667  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 indicies 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 signficantly lower your memory usage on writing.
- You can pass `expectedrows=an integer` to the first `append`, to set the TOTAL number of expectedrows 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 businessday 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.

## 1.2 v0.10.0 (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.

### 1.2.1 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

### 1.2.2 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 [1563]: import pandas as pd

In [1564]: df = pd.DataFrame(np.random.randn(6, 4),
   ......:                   index=pd.date_range('1/1/2000', periods=6))
   ......:

In [1565]: df
Out[1565]:
                   0         1         2         3
2000-01-01  1.197755  0.443238 -0.793423  0.450845
2000-01-02 -0.833944  1.497871 -0.062647  0.156242
2000-01-03  0.752988  1.193476 -1.622707  0.924629
2000-01-04  0.865121 -0.192174 -0.924645  1.035467
2000-01-05 -0.237298 -0.193078 -0.113703 -1.510585
2000-01-06  0.426243 -0.863411  0.386999  1.318817

# deprecated now
In [1566]: df - df[0]
Out[1566]:
            0         1         2         3
2000-01-01  0 -0.754517 -1.991178 -0.746911
2000-01-02  0  2.331815  0.771297  0.990186
2000-01-03  0  0.440488 -2.375695  0.171640
2000-01-04  0 -1.057295 -1.789767  0.170346
2000-01-05  0  0.044219  0.123595 -1.273288
2000-01-06  0 -1.289654 -0.039243  0.892574

# Change your code to
In [1567]: df.sub(df[0], axis=0) # align on axis 0 (rows)
Out[1567]:
            0         1         2         3
2000-01-01  0 -0.754517 -1.991178 -0.746911
2000-01-02  0  2.331815  0.771297  0.990186
2000-01-03  0  0.440488 -2.375695  0.171640
2000-01-04  0 -1.057295 -1.789767  0.170346
2000-01-05  0  0.044219  0.123595 -1.273288
2000-01-06  0 -1.289654 -0.039243  0.892574
```

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).

Note:

```
In [1568]: dates = pd.date_range('1/1/2000', '1/5/2000', freq='4h')

In [1569]: series = Series(np.arange(len(dates)), index=dates)

In [1570]: series
Out[1570]:
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 [1571]: series.resample('D', how='sum')
Out[1571]:
2000-01-01     15
2000-01-02     51
2000-01-03     87
2000-01-04    123
2000-01-05     24
Freq: D, dtype: float64

# old behavior
In [1572]: series.resample('D', how='sum', closed='right', label='right')
Out[1572]:
2000-01-01      0
2000-01-02     21
2000-01-03     57
2000-01-04     93
2000-01-05    129
Freq: D, dtype: float64
```

- Infinity and negative infinity are no longer treated as NA by `isnull` and `notnull`. That they every were was a relic of early pandas. This behavior can be re-enabled globally by the `mode.use_inf_as_null` option:

```
In [1573]: s = pd.Series([1.5, np.inf, 3.4, -np.inf])

In [1574]: pd.isnull(s)
```

```
Out[1574]:
0    False
1    False
2    False
3    False
dtype: bool

In [1575]: s.fillna(0)
Out[1575]:
0    1.500000
1         inf
2    3.400000
3        -inf
dtype: float64

In [1576]: pd.set_option('use_inf_as_null', True)

In [1577]: pd.isnull(s)
Out[1577]:
0    False
1     True
2    False
3     True
dtype: bool

In [1578]: s.fillna(0)
Out[1578]:
0    1.5
1    0.0
2    3.4
3    0.0
dtype: float64

In [1579]: 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 [1580]: data= 'a,b,c\n1,Yes,2\n3,No,4'

In [1581]: print data
a,b,c
1,Yes,2
3,No,4

In [1582]: pd.read_csv(StringIO(data), header=None)
Out[1582]:
   0    1  2
0  a    b  c
1  1  Yes  2
```

```
2  3   No  4

In [1583]: pd.read_csv(StringIO(data), header=None, prefix='X')
Out[1583]:
  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 [1584]: print data
a,b,c
1,Yes,2
3,No,4

In [1585]: pd.read_csv(StringIO(data))
Out[1585]:
   a    b  c
0  1  Yes  2
1  3   No  4

In [1586]: pd.read_csv(StringIO(data), true_values=['Yes'], false_values=['No'])
Out[1586]:
   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 [1587]: s = Series([np.nan, 1., 2., np.nan, 4])

In [1588]: s
Out[1588]:
0   NaN
1     1
2     2
3   NaN
4     4
dtype: float64

In [1589]: s.fillna(0)
Out[1589]:
0    0
1    1
2    2
3    0
4    4
dtype: float64

In [1590]: s.fillna(method='pad')
Out[1590]:
0   NaN
1     1
```

```
2      2
3      2
4      4
dtype: float64
```

Convenience methods `ffill` and `bfill` have been added:

```
In [1591]: s.ffill()
Out[1591]:
0    NaN
1      1
2      2
3      2
4      4
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 [1592]: def f(x):
     ......:     return Series([ x, x**2 ], index = ['x', 'x^2'])
     ......:

  In [1593]: s = Series(np.random.rand(5))

  In [1594]: s
  Out[1594]:
  0    0.713026
  1    0.539601
  2    0.046682
  3    0.536308
  4    0.373040
  dtype: float64

  In [1595]: s.apply(f)
  Out[1595]:
            x       x^2
  0  0.713026  0.508406
  1  0.539601  0.291170
  2  0.046682  0.002179
  3  0.536308  0.287626
  4  0.373040  0.139159
  ```

- 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 [1596]: get_option("display.max_rows")
  Out[1596]: 100
  ```

- to_string() methods now always return unicode strings (GH2224).

### 1.2.3 New features

### 1.2.4 Wide DataFrame Printing

Instead of printing the summary information, pandas now splits the string representation across multiple rows by default:

```
In [1597]: wide_frame = DataFrame(randn(5, 16))

In [1598]: wide_frame
Out[1598]:
         0         1         2         3         4         5         6         7   \
0  0.091848 -0.318810  0.950676 -1.016290 -0.267508  0.115960 -0.615949 -0.373060
1 -0.234083 -0.254881 -0.142302  1.291962  0.876700  1.704647  0.046376  0.158167
2  0.191589 -0.243287  1.684079 -0.637764 -0.323699 -1.378458 -0.868599  1.916736
3  1.247851  0.246737  1.454094 -1.166264 -0.560671  1.027488  0.252915 -0.154549
4 -0.417236  1.721160 -0.058702 -1.297767  0.871349 -0.177241  0.207366  2.592691
         8         9         10        11        12        13        14        15
0  0.276398 -1.947432 -1.183044 -3.030491 -1.055515 -0.177967  1.269136  0.668999
1  1.503229 -0.335678  0.157359  0.828373  0.860863  0.618679 -0.507624 -1.174443
2  1.562215  0.133322  0.345906 -1.778234 -1.223208 -0.480258 -0.285245  0.775414
3  0.181686 -0.268458 -0.124345  0.443256 -0.778424  2.147255 -0.731309  0.281577
4  0.423204 -0.006209  0.314186  0.363193  0.196151 -1.598514 -0.843566 -0.353828
```

The old behavior of printing out summary information can be achieved via the 'expand_frame_repr' print option:

```
In [1599]: pd.set_option('expand_frame_repr', False)

In [1600]: wide_frame
Out[1600]:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5 entries, 0 to 4
Data columns:
0     5  non-null values
1     5  non-null values
2     5  non-null values
3     5  non-null values
4     5  non-null values
5     5  non-null values
6     5  non-null values
7     5  non-null values
8     5  non-null values
9     5  non-null values
10    5  non-null values
11    5  non-null values
12    5  non-null values
13    5  non-null values
14    5  non-null values
15    5  non-null values
dtypes: float64(16)
```

The width of each line can be changed via 'line_width' (80 by default):

```
In [1601]: pd.set_option('line_width', 40)

In [1602]: wide_frame
Out[1602]:
         0         1         2         3   \
0  0.091848 -0.318810  0.950676 -1.016290
```

```
1 -0.234083 -0.254881 -0.142302  1.291962
2  0.191589 -0.243287  1.684079 -0.637764
3  1.247851  0.246737  1.454094 -1.166264
4 -0.417236  1.721160 -0.058702 -1.297767
         4         5         6         7  \
0 -0.267508  0.115960 -0.615949 -0.373060
1  0.876700  1.704647  0.046376  0.158167
2 -0.323699 -1.378458 -0.868599  1.916736
3 -0.560671  1.027488  0.252915 -0.154549
4  0.871349 -0.177241  0.207366  2.592691
         8         9        10        11  \
0  0.276398 -1.947432 -1.183044 -3.030491
1  1.503229 -0.335678  0.157359  0.828373
2  1.562215  0.133322  0.345906 -1.778234
3  0.181686 -0.268458 -0.124345  0.443256
4  0.423204 -0.006209  0.314186  0.363193
        12        13        14        15
0 -1.055515 -0.177967  1.269136  0.668999
1  0.860863  0.618679 -0.507624 -1.174443
2 -1.223208 -0.480258 -0.285245  0.775414
3 -0.778424  2.147255 -0.731309  0.281577
4  0.196151 -1.598514 -0.843566 -0.353828
```

### 1.2.5 Updated PyTables Support

*Docs* for PyTables `Table` format & several enhancements to the api. Here is a taste of what to expect.

```
In [1603]: store = HDFStore('store.h5')

In [1604]: df = DataFrame(randn(8, 3), index=date_range('1/1/2000', periods=8),
   ......:                columns=['A', 'B', 'C'])
   ......:

In [1605]: df
Out[1605]:
                   A         B         C
2000-01-01  0.516740 -2.335539 -0.715006
2000-01-02 -0.399224  0.798589  2.101702
2000-01-03 -0.190649  0.595370 -1.672567
2000-01-04  0.786765  0.133175 -1.077265
2000-01-05  0.861068  1.982854 -1.059177
2000-01-06  2.050701 -0.615165 -0.601019
2000-01-07 -1.062777 -1.577586 -0.585584
2000-01-08  1.833699 -0.483165  0.652315

# appending data frames
In [1606]: df1 = df[0:4]

In [1607]: df2 = df[4:]

In [1608]: store.append('df', df1)

In [1609]: store.append('df', df2)

In [1610]: store
Out[1610]:
<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 [1611]: store.select('df')
Out[1611]:
                   A         B         C
2000-01-01  0.516740 -2.335539 -0.715006
2000-01-02 -0.399224  0.798589  2.101702
2000-01-03 -0.190649  0.595370 -1.672567
2000-01-04  0.786765  0.133175 -1.077265
2000-01-05  0.861068  1.982854 -1.059177
2000-01-06  2.050701 -0.615165 -0.601019
2000-01-07 -1.062777 -1.577586 -0.585584
2000-01-08  1.833699 -0.483165  0.652315

In [1612]: wp = Panel(randn(2, 5, 4), items=['Item1', 'Item2'],
   ......:        major_axis=date_range('1/1/2000', periods=5),
   ......:        minor_axis=['A', 'B', 'C', 'D'])
   ......:

In [1613]: wp
Out[1613]:
<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 [1614]: store.append('wp',wp)

# selecting via A QUERY
In [1615]: store.select('wp',
   ......:    [ Term('major_axis>20000102'), Term('minor_axis', '=', ['A','B']) ])
   ......:
Out[1615]:
<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 [1616]: store.remove('wp', [ 'major_axis', '>', wp.major_axis[3] ])
Out[1616]: 4

In [1617]: store.select('wp')
Out[1617]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 4 (major_axis) x 4 (minor_axis)
Items axis: Item1 to Item2
Major_axis axis: 2000-01-01 00:00:00 to 2000-01-04 00:00:00
Minor_axis axis: A to D

# deleting a store
In [1618]: del store['df']
```

```
In [1619]: store
Out[1619]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/wp            wide_table    (typ->appendable,nrows->16,ncols->2,indexers->[major_axis,minor_axis])
```

#### Enhancements

- added ability to hierarchical keys

```
In [1620]: store.put('foo/bar/bah', df)

In [1621]: store.append('food/orange', df)

In [1622]: store.append('food/apple',  df)

In [1623]: store
Out[1623]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/wp                     wide_table    (typ->appendable,nrows->16,ncols->2,indexers->[major_ax
/food/apple             frame_table   (typ->appendable,nrows->8,ncols->3,indexers->[index])
/food/orange            frame_table   (typ->appendable,nrows->8,ncols->3,indexers->[index])
/foo/bar/bah            frame         (shape->[8,3])

# remove all nodes under this level
In [1624]: store.remove('food')

In [1625]: store
Out[1625]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/wp                     wide_table    (typ->appendable,nrows->16,ncols->2,indexers->[major_ax
/foo/bar/bah            frame         (shape->[8,3])
```

- added mixed-dtype support!

```
In [1626]: df['string'] = 'string'

In [1627]: df['int']    = 1

In [1628]: store.append('df',df)

In [1629]: df1 = store.select('df')

In [1630]: df1
Out[1630]:
                   A         B         C  string  int
2000-01-01  0.516740 -2.335539 -0.715006  string    1
2000-01-02 -0.399224  0.798589  2.101702  string    1
2000-01-03 -0.190649  0.595370 -1.672567  string    1
2000-01-04  0.786765  0.133175 -1.077265  string    1
2000-01-05  0.861068  1.982854 -1.059177  string    1
2000-01-06  2.050701 -0.615165 -0.601019  string    1
2000-01-07 -1.062777 -1.577586 -0.585584  string    1
2000-01-08  1.833699 -0.483165  0.652315  string    1

In [1631]: df1.get_dtype_counts()
Out[1631]:
```

```
float64    3
int64      1
object     1
dtype: int64
```

- performance improvments 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.

### 1.2.6 N Dimensional Panels (Experimental)

Adding experimental support for Panel4D and factory functions to create n-dimensional named panels. *Docs* for NDim. Here is a taste of what to expect.

```
In [1632]: p4d = Panel4D(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 [1633]: p4d
Out[1633]:
<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.

## 1.3 v0.9.1 (November 14, 2012)

This is a bugfix 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.

### 1.3.1 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 [1634]: df = DataFrame(np.random.randint(0, 2, (6, 3)), columns=['A', 'B', 'C'])

In [1635]: df.sort(['A', 'B'], ascending=[1, 0])
Out[1635]:
   A  B  C
1  0  1  0
2  1  1  0
3  1  1  1
4  1  1  0
0  1  0  1
5  1  0  1
```

- *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 [1636]: df = DataFrame(np.random.randn(6, 3), columns=['A', 'B', 'C'])

In [1637]: df.ix[2:4] = np.nan

In [1638]: df.rank()
Out[1638]:
     A    B    C
0    1    3    2
1    2    1    1
2  NaN  NaN  NaN
3  NaN  NaN  NaN
4  NaN  NaN  NaN
5    3    2    3

In [1639]: df.rank(na_option='top')
Out[1639]:
   A  B  C
0  4  6  5
1  5  4  4
2  2  2  2
3  2  2  2
4  2  2  2
5  6  5  6

In [1640]: df.rank(na_option='bottom')
Out[1640]:
   A  B  C
```

```
0  1  3  2
1  2  1  1
2  5  5  5
3  5  5  5
4  5  5  5
5  3  2  3
```

- 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 [1641]: df = DataFrame(np.random.randn(5, 3), columns = ['A','B','C'])

In [1642]: df
Out[1642]:
          A         B         C
0 -1.381185  0.365239 -1.810632
1 -0.673382 -1.967580 -0.401183
2 -0.583047 -0.998625 -0.629277
3 -0.548001 -0.852612 -0.126250
4  1.765997 -1.593297 -0.966162

In [1643]: df[df['A'] > 0]
Out[1643]:
          A         B         C
4  1.765997 -1.593297 -0.966162
```

  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 [1644]: df[df>0]
Out[1644]:
          A         B   C
0       NaN  0.365239 NaN
1       NaN       NaN NaN
2       NaN       NaN NaN
3       NaN       NaN NaN
4  1.765997       NaN NaN

In [1645]: df.where(df>0)
Out[1645]:
          A         B   C
0       NaN  0.365239 NaN
1       NaN       NaN NaN
2       NaN       NaN NaN
3       NaN       NaN NaN
4  1.765997       NaN NaN

In [1646]: df.where(df>0,-df)
Out[1646]:
          A         B         C
0  1.381185  0.365239  1.810632
1  0.673382  1.967580  0.401183
2  0.583047  0.998625  0.629277
```

```
3  0.548001  0.852612  0.126250
4  1.765997  1.593297  0.966162
```

Furthermore, *where* now aligns the input boolean condition (ndarray or DataFrame), such that partial selection with setting is possible. This is analagous to partial setting via *.ix* (but on the contents rather than the axis labels)

```
In [1647]: df2 = df.copy()

In [1648]: df2[ df2[1:4] > 0 ] = 3

In [1649]: df2
Out[1649]:
          A         B         C
0 -1.381185  0.365239 -1.810632
1 -0.673382 -1.967580 -0.401183
2 -0.583047 -0.998625 -0.629277
3 -0.548001 -0.852612 -0.126250
4  1.765997 -1.593297 -0.966162
```

*DataFrame.mask* is the inverse boolean operation of *where*.

```
In [1650]: df.mask(df<=0)
Out[1650]:
          A         B   C
0       NaN  0.365239 NaN
1       NaN       NaN NaN
2       NaN       NaN NaN
3       NaN       NaN NaN
4  1.765997       NaN NaN
```

- Enable referencing of Excel columns by their column names (GH1936)

```
In [1651]: xl = ExcelFile('data/test.xls')

In [1652]: xl.parse('Sheet1', index_col=0, parse_dates=True,
   ......:          parse_cols='A:D')
   ......:
Out[1652]:
                   A         B         C
2000-01-03  0.980269  3.685731 -0.364217
2000-01-04  1.047916 -0.041232 -0.161812
2000-01-05  0.498581  0.731168 -0.537677
2000-01-06  1.120202  1.567621  0.003641
2000-01-07 -0.487094  0.571455 -1.611639
2000-01-10  0.836649  0.246462  0.588543
2000-01-11 -0.157161  1.340307  1.195778
```

- 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)

### 1.3.2 API changes

- Upsampling data with a PeriodIndex will result in a higher frequency TimeSeries that spans the original time window

```
In [1653]: prng = period_range('2012Q1', periods=2, freq='Q')

In [1654]: s = Series(np.random.randn(len(prng)), prng)

In [1655]: s.resample('M')
Out[1655]:
2012-01   -0.332601
2012-02         NaN
2012-03         NaN
2012-04   -1.327330
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 [1656]: p = Period('2012')

In [1657]: p.end_time
Out[1657]: <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 [1658]: data = 'A,B,C\n00001,001,5\n00002,002,6'

In [1659]: from cStringIO import StringIO

In [1660]: read_csv(StringIO(data), converters={'A' : lambda x: x.strip()})
Out[1660]:
       A  B  C
0  00001  1  5
1  00002  2  6
```

See the full release notes or issue tracker on GitHub for a complete list.

## 1.4 v0.9.0 (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.

### 1.4.1 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)

### 1.4.2 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 [1661]: from StringIO import StringIO

In [1662]: data = '0,0,1\n1,1,0\n0,1,0'

In [1663]: df = read_csv(StringIO(data), header=None)

In [1664]: df
Out[1664]:
   0  1  2
0  0  0  1
1  1  1  0
2  0  1  0
```

- 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 [1665]: s1 = Series([1, 2, 3])

In [1666]: s1
Out[1666]:
0    1
1    2
2    3
dtype: int64

In [1667]: s2 = Series(s1, index=['foo', 'bar', 'baz'])

In [1668]: s2
Out[1668]:
foo    NaN
bar    NaN
baz    NaN
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.

## 1.5 v0.8.1 (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.

### 1.5.1 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)

### 1.5.2 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 improvments

## 1.6 v0.8.0 (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.

### 1.6.1 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)

### 1.6.2 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 codebases 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.

### 1.6.3 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 codebase. 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_lcoalize` methods to TimeSeries and DataFrame. All timestamps are stored as UTC; Timestamps from DatetimeIndex objects with time zone set will be localized to localtime. Time zone conversions are therefore essentially free. User needs to know very little about pytz library now; only time zone names as 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

### 1.6.4 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 :ref'dayfirst <io.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

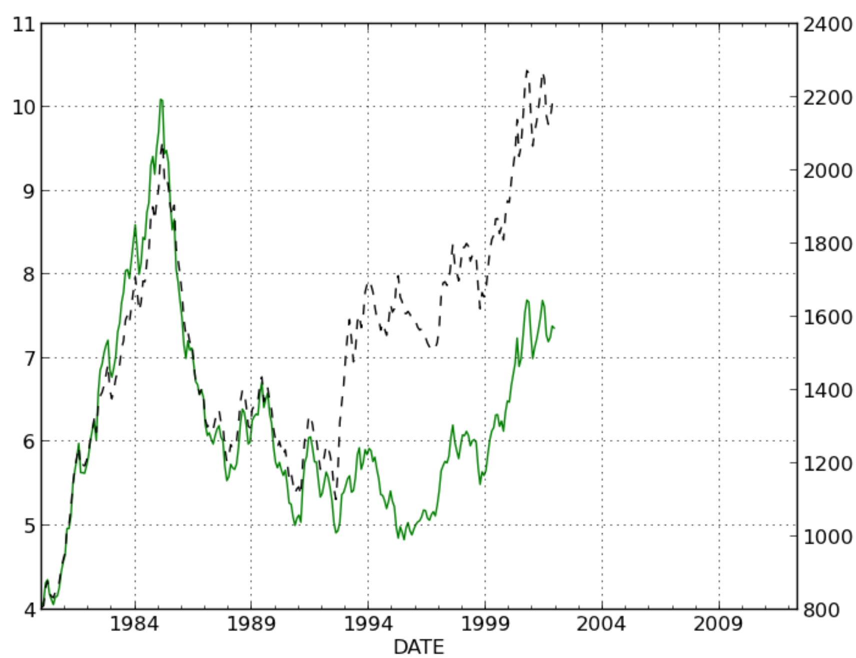
### 1.6.5 New plotting methods

`Series.plot` now supports a `secondary_y` option:

```
In [1669]: plt.figure()
Out[1669]: <matplotlib.figure.Figure at 0x1de229d0>

In [1670]: fx['FR'].plot(style='g')
Out[1670]: <matplotlib.axes.AxesSubplot at 0x1de22f50>

In [1671]: fx['IT'].plot(style='k--', secondary_y=True)
Out[1671]: <matplotlib.axes.AxesSubplot at 0x1de22f50>
```



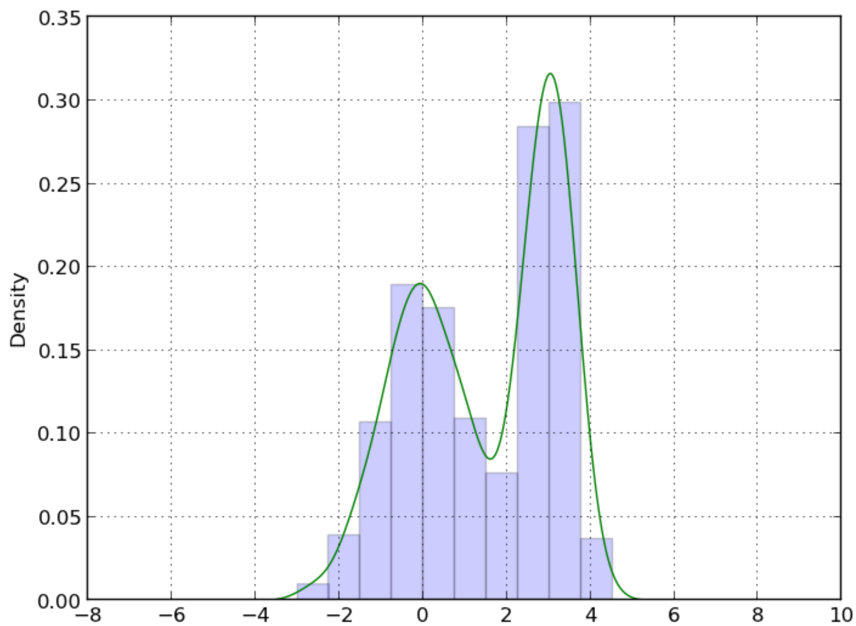
Vytautas Jancauskas, the 2012 GSOC participant, has added many new plot types. For example, 'kde' is a new option:

```
In [1672]: s = Series(np.concatenate((np.random.randn(1000),
   ......:                            np.random.randn(1000) * 0.5 + 3)))
   ......:

In [1673]: plt.figure()
Out[1673]: <matplotlib.figure.Figure at 0x1de22750>

In [1674]: s.hist(normed=True, alpha=0.2)
Out[1674]: <matplotlib.axes.AxesSubplot at 0x1e7e7ad0>

In [1675]: s.plot(kind='kde')
Out[1675]: <matplotlib.axes.AxesSubplot at 0x1e7e7ad0>
```




See *the plotting page* for much more.

### 1.6.6 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.

### 1.6.7 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 [1676]: import datetime

In [1677]: rng = date_range('1/1/2000', periods=10)
```

```
In [1678]: rng[5]
Out[1678]: <Timestamp: 2000-01-06 00:00:00>

In [1679]: isinstance(rng[5], datetime.datetime)
Out[1679]: True

In [1680]: rng_asarray = np.asarray(rng)

In [1681]: scalar_val = rng_asarray[5]

In [1682]: type(scalar_val)
Out[1682]: 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 `asobject` property of `DatetimeIndex` produces an array of `Timestamp` objects:

```
In [1683]: stamp_array = rng.asobject

In [1684]: stamp_array
Out[1684]: Index([2000-01-01, 2000-01-02, 2000-01-03, 2000-01-04, 2000-01-05, 2000-01-06, 2000-01-07,

In [1685]: stamp_array[5]
Out[1685]: <Timestamp: 2000-01-06 00:00:00>
```

To get an array of proper `datetime.datetime` objects, use the `to_pydatetime` method:

```
In [1686]: dt_array = rng.to_pydatetime()

In [1687]: dt_array
Out[1687]:
array([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 [1688]: dt_array[5]
Out[1688]: 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 [1689]: rng = date_range('1/1/2000', periods=10)

In [1690]: rng
Out[1690]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2000-01-01 00:00:00, ..., 2000-01-10 00:00:00]
Length: 10, Freq: D, Timezone: None

In [1691]: np.asarray(rng)
Out[1691]:
array([1970-01-11 184:00:00, 1970-01-11 208:00:00, 1970-01-11 232:00:00,
       1970-01-11 00:00:00, 1970-01-11 24:00:00, 1970-01-11 48:00:00,
       1970-01-11 72:00:00, 1970-01-11 96:00:00, 1970-01-11 120:00:00,
       1970-01-11 144:00:00], dtype=datetime64[ns])

In [1692]: converted = np.asarray(rng, dtype=object)

In [1693]: converted[5]
Out[1693]: datetime.datetime(1970, 1, 11, 48, 0)
```

**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.

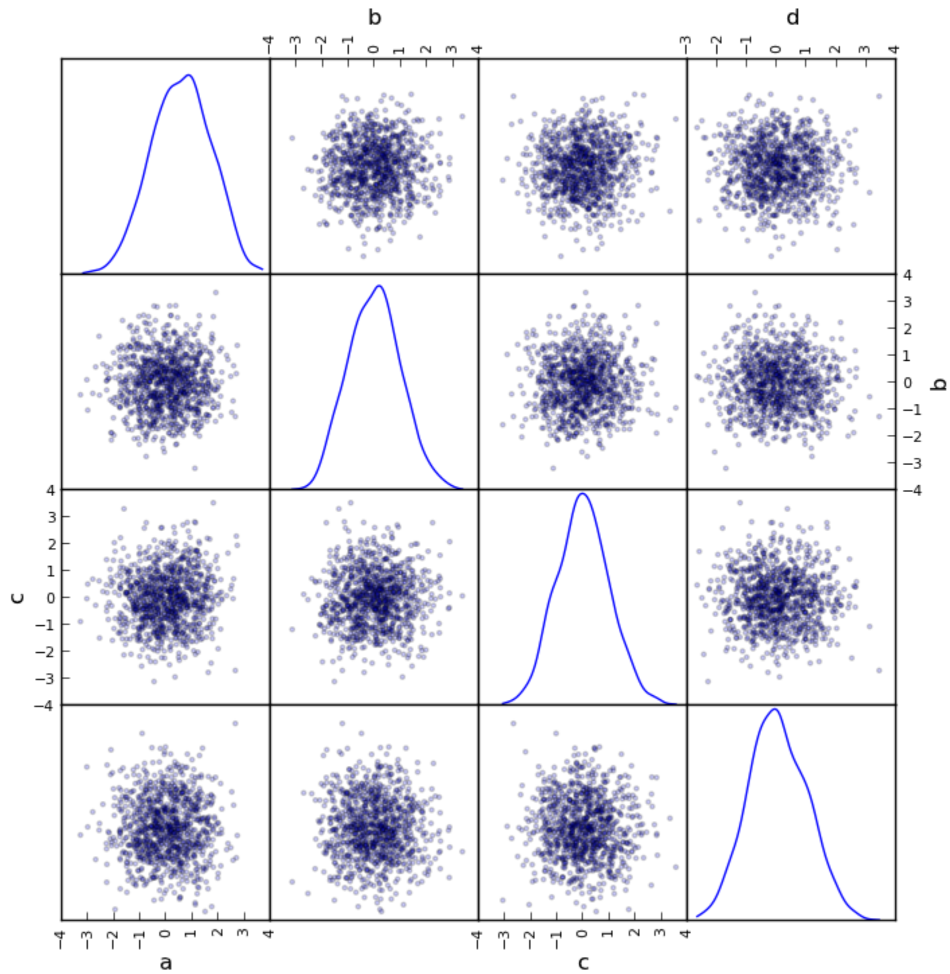
## 1.7 v.0.7.3 (April 12, 2012)

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.

### 1.7.1 New features

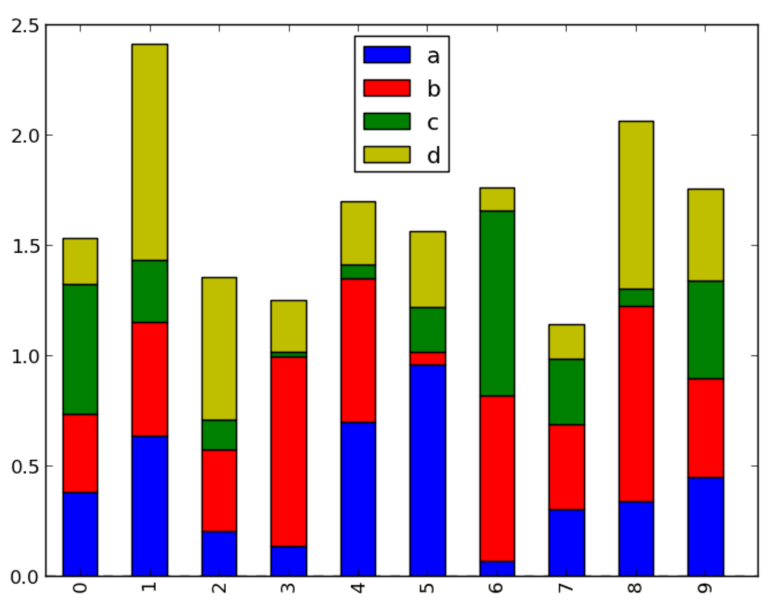
- New *fixed width file reader*, `read_fwf`
- New *scatter_matrix* function for making a scatter plot matrix

```
from pandas.tools.plotting import scatter_matrix
scatter_matrix(df, alpha=0.2)
```

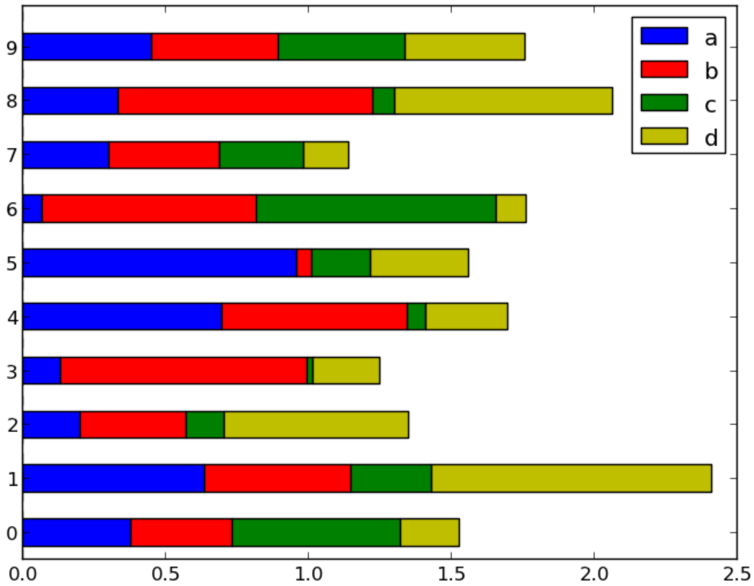



- Add `stacked` argument to Series and DataFrame's `plot` method for *stacked bar plots*.

```
df.plot(kind='bar', stacked=True)
```



```
df.plot(kind='barh', stacked=True)
```




- Add log x and y *scaling options* to `DataFrame.plot` and `Series.plot`
- Add `kurt` methods to Series and DataFrame for computing kurtosis

### 1.7.2 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 [1694]: series = Series(['Steve', np.nan, 'Joe'])

In [1695]: series == 'Steve'
Out[1695]:
0     True
1    False
2    False
dtype: bool

In [1696]: series != 'Steve'
Out[1696]:
0    False
1     True
2     True
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 [1697]: mask = series == 'Steve'

In [1698]: series[mask & series.notnull()]
Out[1698]:
0    Steve
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.

### 1.7.3 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 [1699]: df = 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 [1700]: df
Out[1700]:
     A      B         C         D
0  foo    one  0.255678 -0.295328
1  bar    one  0.055213 -2.208596
2  foo    two -0.190798 -0.097122
3  bar  three  0.247394  0.289633
4  foo    two  0.453403  0.160891
5  bar    two  1.925709 -1.902936
6  foo    one  0.714705 -0.348722
7  foo  three  1.781358  0.352378

In [1701]: grouped = df.groupby('A')['C']

In [1702]: grouped.describe()
Out[1702]:
A
bar  count    3.000000
     mean     0.742772
     std      1.028950
     min      0.055213
     25%      0.151304
     50%      0.247394
     75%      1.086551
     max      1.925709
foo  count    5.000000
     mean     0.602869
     std      0.737247
     min     -0.190798
     25%      0.255678
     50%      0.453403
     75%      0.714705
     max      1.781358
dtype: float64

In [1703]: grouped.apply(lambda x: x.order()[-2:]) # top 2 values
Out[1703]:
A
bar  3    0.247394
     5    1.925709
```

```
foo   6    0.714705
      7    1.781358
dtype: float64
```

## 1.8 v.0.7.2 (March 16, 2012)

This release targets bugs in 0.7.1, and adds a few minor features.

### 1.8.1 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)

### 1.8.2 Performance improvements

- Use khash for Series.value_counts, add raw function to algorithms.py (GH861)
- Intercept __builtin__.sum in groupby (GH885)

## 1.9 v.0.7.1 (February 29, 2012)

This release includes a few new features and addresses over a dozen bugs in 0.7.0.

### 1.9.1 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

### 1.9.2 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)

## 1.10 v.0.7.0 (February 9, 2012)

### 1.10.1 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 [1704]: df = DataFrame(randn(10, 4))

In [1705]: df.apply(lambda x: x.describe())
Out[1705]:
               0          1          2          3
count  10.000000  10.000000  10.000000  10.000000
mean    0.467956  -0.271208   0.320479   0.255854
std     1.371729   0.759631   0.962485   0.661379
min    -2.055090  -1.349964  -0.905821  -0.904464
25%    -0.357215  -0.622232  -0.529872  -0.186021
50%     0.576651  -0.298812   0.317472   0.345715
75%     1.710590  -0.184047   1.031023   0.830109
max     2.061568   1.147814   1.641604   1.034401
```

- *Add* `reorder_levels` method to Series and DataFrame (PR534)
- *Add* dict-like `get` function to DataFrame and Panel (PR521)
- *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, PR552, others)
- *Add* attribute-based item access to `Panel` and add IPython completion (PR563)
- *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 (PR563)
- *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.

### 1.10.2 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 [1706]: s = Series(randn(10), index=range(0, 20, 2))

In [1707]: s
Out[1707]:
0     0.910822
2     0.695714
4    -0.955386
6     0.359339
8    -0.189177
10   -1.168504
12   -1.381056
14    0.786651
16    0.288704
18    0.148544
dtype: float64

In [1708]: s[0]
Out[1708]: 0.910822002253868

In [1709]: s[2]
Out[1709]: 0.69571446395605785
```

```
In [1710]: s[4]
Out[1710]: -0.95538648457113173
```

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 = DataFrame(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` |

### 1.10.3 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 [1711]: s = Series(randn(6), index=list('gmkaec'))

In [1712]: s
Out[1712]:
g    0.842702
m   -1.876494
k   -0.365497
a   -2.231289
e    0.716546
c   -0.069151
dtype: float64
```

Then this is OK:

```
In [1713]: s.ix['k':'e']
Out[1713]:
k   -0.365497
```

```
a   -2.231289
e    0.716546
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 [1714]: s2 = s.sort_index()

In [1715]: s2
Out[1715]:
a   -2.231289
c   -0.069151
e    0.716546
g    0.842702
k   -0.365497
m   -1.876494
dtype: float64

In [1716]: s2.ix['b':'h']
Out[1716]:
c   -0.069151
e    0.716546
g    0.842702
dtype: float64
```

### 1.10.4 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 [1717]: s = Series(randn(6), index=list('acegkm'))

In [1718]: s
Out[1718]:
a   -0.651033
c   -1.163455
e    1.627107
g    2.008883
k   -0.431064
m   -1.687776
dtype: float64

In [1719]: s[['m', 'a', 'c', 'e']]
Out[1719]:
m   -1.687776
a   -0.651033
c   -1.163455
e    1.627107
dtype: float64

In [1720]: s['b':'l']
```

```
Out[1720]:
c   -1.163455
e    1.627107
g    2.008883
k   -0.431064
dtype: float64

In [1721]: s['c':'k']
Out[1721]:
c   -1.163455
e    1.627107
g    2.008883
k   -0.431064
dtype: float64
```

In the case of integer indexes, the behavior will be exactly as before (shadowing `ndarray`):

```
In [1722]: s = Series(randn(6), index=range(0, 12, 2))

In [1723]: s[[4, 0, 2]]
Out[1723]:
4   -0.593879
0   -0.271860
2    1.101084
dtype: float64

In [1724]: s[1:5]
Out[1724]:
2    1.101084
4   -0.593879
6    0.873445
8    2.880726
dtype: float64
```

If you wish to do indexing with sequences and slicing on an integer index with label semantics, use `ix`.

### 1.10.5 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)

### 1.10.6 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)

## 1.11 v.0.6.1 (December 13, 2011)

### 1.11.1 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 (PR435)
- 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* (PR453)
- 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 (PR482)
- *Can pass* DataFrame/DataFrame and DataFrame/Series to rolling_corr/rolling_cov (GH #462)
- MultiIndex.get_level_values can *accept the level name*

### 1.11.2 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)

## 1.12 v.0.6.0 (November 25, 2011)

### 1.12.1 New Features

- *Added* `melt` function to `pandas.core.reshape`
- *Added* `level` parameter to group by level in Series and DataFrame descriptive statistics (PR313)
- *Added* `head` and `tail` methods to Series, analogous to to DataFrame (PR296)
- *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 (PR321)
- *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, PR362)
- *Added* fast `get_value` and `put_value` methods to DataFrame (GH360)
- *Added* `cov` instance methods to Series and DataFrame (GH194, PR362)
- *Added* `kind='bar'` option to `DataFrame.plot` (PR348)
- *Added* `idxmin` and `idxmax` to Series and DataFrame (PR286)
- *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 (PR387)
- *Added* support for MaskedArray data in DataFrame, masked values converted to NaN (PR396)

- *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)

### 1.12.2 Performance Enhancements

- VBENCH Cythonized `cache_readonly`, resulting in substantial micro-performance enhancements throughout the codebase (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 (PR355)
- 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)

## 1.13 v.0.5.0 (October 24, 2011)

### 1.13.1 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. (PR233, GH230)
- *Implemented* `Series.describe` for Series containing objects (PR241)
- *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 (PR334)
- *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` (PR244)
- TODO: DOCS ABOUT TAKE METHODS

### 1.13.2 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

## 1.14 v.0.4.3 through v0.4.1 (September 25 - October 9, 2011)

### 1.14.1 New Features

- Added Python 3 support using 2to3 (PR200)
- *Added* `name` attribute to `Series`, now prints as part of `Series.__repr__`
- *Added* instance methods `isnull` and `notnull` to Series (PR209, GH203)
- *Added* `Series.align` method for aligning two series with choice of join method (ENH56)
- *Added* method `get_level_values` to `MultiIndex` (IS188)
- *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 (PR146)
- read_csv can *read* multiple columns into a MultiIndex; DataFrame's to_csv method writes out a corresponding MultiIndex (PR151)
- DataFrame.rename has a new copy parameter to *rename* a DataFrame in place (ENHed)
- *Enable* unstacking by name (PR142)
- *Enable* sortlevel to work by level (PR141)

### 1.14.2 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

CHAPTER

TWO

# INSTALLATION

You have the option to install an official release or to build the development version. If you choose to install from source and are running Windows, you will have to ensure that you have a compatible C compiler (MinGW or Visual Studio) installed. How-to install MinGW on Windows

## 2.1 Python version support

Officially Python 2.5 to 2.7 and Python 3.1+, although Python 3 support is less well tested. Python 2.4 support is being phased out since the userbase has shrunk significantly. Continuing Python 2.4 support will require either monetary development support or someone contributing to the project to maintain compatibility.

## 2.2 Binary installers

### 2.2.1 All platforms

Stable installers available on PyPI

Preliminary builds and installers on the Pandas download page .

### 2.2.2 Overview

| Platform | Distribution | Status | Download / Repository Link | Install method |
|---|---|---|---|---|
| Windows | all | stable | *All platforms* | `pip install pandas` |
| Mac | all | stable | *All platforms* | `pip install pandas` |
| Linux | Debian | stable | official Debian repository | `sudo apt-get install python-pandas` |
| Linux | Debian & Ubuntu | unstable (latest packages) | NeuroDebian | `sudo apt-get install python-pandas` |
| Linux | Ubuntu | stable | official Ubuntu repository | `sudo apt-get install python-pandas` |
| Linux | Ubuntu | unstable (daily builds) | PythonXY PPA; activate by: `sudo add-apt-repository ppa:pythonxy/pythonxy-devel && sudo apt-get update` | `sudo apt-get install python-pandas` |
| Linux | OpenSuse & Fedora | stable | OpenSuse Repository | `zypper in python-pandas` |

## 2.3 Dependencies

- NumPy: 1.6.1 or higher
- python-dateutil 1.5
- **pytz**
  - Needed for time zone support

## 2.4 Optional dependencies

- Cython: Only necessary to build development version. Version 0.17.1 or higher.
- SciPy: miscellaneous statistical functions
- PyTables: necessary for HDF5-based storage
- matplotlib: for plotting
- **statsmodels**
  - Needed for parts of `pandas.stats`
- **openpyxl**, **xlrd/xlwt**
  - openpyxl version 1.6.1 or higher
  - Needed for Excel I/O

**Note:** Without the optional dependencies, many useful features will not work. Hence, it is highly recommended that you install these. A packaged distribution like the Enthought Python Distribution may be worth considering.

## 2.5 Installing from source

**Note:** Installing from the git repository requires a recent installation of Cython as the cythonized C sources are no longer checked into source control. Released source distributions will contain the built C files. I recommend installing the latest Cython via `easy_install -U Cython`

The source code is hosted at http://github.com/pydata/pandas, it can be checked out using git and compiled / installed like so:

```
git clone git://github.com/pydata/pandas.git
cd pandas
python setup.py install
```

Make sure you have Cython installed when installing from the repository, rather then a tarball or pypi.

On Windows, I suggest installing the MinGW compiler suite following the directions linked to above. Once configured property, run the following on the command line:

```
python setup.py build --compiler=mingw32
python setup.py install
```

Note that you will not be able to import pandas if you open an interpreter in the source directory unless you build the C extensions in place:

```
python setup.py build_ext --inplace
```

The most recent version of MinGW (any installer dated after 2011-08-03) has removed the '-mno-cygwin' option but Distutils has not yet been updated to reflect that. Thus, you may run into an error like "unrecognized command line option '-mno-cygwin"'. Until the bug is fixed in Distutils, you may need to install a slightly older version of MinGW (2011-08-02 installer).

## 2.6 Running the test suite

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

```
$ nosetests pandas
..........................................................................
.......................S..................................................
..........................................................................
..........................................................................
..........................................................................
..........................................................................
..........................................................................
..........................................................................
..........................................................................
..........................................................................
```

```
.................S........................................................
....
----------------------------------------------------------------------
Ran 818 tests in 21.631s

OK (SKIP=2)
```

CHAPTER

THREE

# FREQUENTLY ASKED QUESTIONS (FAQ)

Pandas is a powerful tool and already has a plethora of data manipulation operations implemented, most of them are very fast as well. It's very possible however that certain functionality that would make your life easier is missing. In that case you have several options:

1. Open an issue on Github , explain your need and the sort of functionality you would like to see implemented.
2. Fork the repo, Implement the functionality yourself and open a PR on Github.
3. Write a method that performs the operation you are interested in and Monkey-patch the pandas class as part of your IPython profile startup or PYTHONSTARTUP file.

   For example, here is an example of adding an `just_foo_cols()` method to the dataframe class:

```
In [452]: import pandas as pd

In [453]: def just_foo_cols(self):
   .....:     """Get a list of column names containing the string 'foo'
   .....:     """
   .....:     return [x for x in self.columns if 'foo' in x]
   .....:

In [454]: pd.DataFrame.just_foo_cols = just_foo_cols # monkey-patch the DataFrame class

In [455]: df = pd.DataFrame([range(4)],columns= ["A","foo","foozball","bar"])

In [456]: df.just_foo_cols()
Out[456]: ['foo', 'foozball']

In [457]: del pd.DataFrame.just_foo_cols # you can also remove the new method
```

Monkey-patching is usually frowned upon because it makes your code less portable and can cause subtle bugs in some circumstances. Monkey-patching existing methods is usually a bad idea in that respect. When used with proper care, however, it's a very useful tool to have.

## 3.1 Migrating from scikits.timeseries to pandas >= 0.8.0

Starting with pandas 0.8.0, users of scikits.timeseries should have all of the features that they need to migrate their code to use pandas. Portions of the scikits.timeseries codebase for implementing calendar logic and timespan frequency conversions (but **not** resampling, that has all been implemented from scratch from the ground up) have been ported to the pandas codebase.

The scikits.timeseries notions of `Date` and `DateArray` are responsible for implementing calendar logic:

```
In [16]: dt = ts.Date('Q', '1984Q3')

# sic
In [17]: dt
Out[17]: <Q-DEC : 1984Q1>

In [18]: dt.asfreq('D', 'start')
Out[18]: <D : 01-Jan-1984>

In [19]: dt.asfreq('D', 'end')
Out[19]: <D : 31-Mar-1984>

In [20]: dt + 3
Out[20]: <Q-DEC : 1984Q4>
```

`Date` and `DateArray` from scikits.timeseries have been reincarnated in pandas `Period` and `PeriodIndex`:

```
In [458]: pnow('D')  # scikits.timeseries.now()
Out[458]: Period('2013-04-23', 'D')

In [459]: Period(year=2007, month=3, day=15, freq='D')
Out[459]: Period('2007-03-15', 'D')

In [460]: p = Period('1984Q3')

In [461]: p
Out[461]: Period('1984Q3', 'Q-DEC')

In [462]: p.asfreq('D', 'start')
Out[462]: Period('1984-07-01', 'D')

In [463]: p.asfreq('D', 'end')
Out[463]: Period('1984-09-30', 'D')

In [464]: (p + 3).asfreq('T') + 6 * 60 + 30
Out[464]: Period('1985-07-01 06:29', 'T')

In [465]: rng = period_range('1990', '2010', freq='A')

In [466]: rng
Out[466]:
<class 'pandas.tseries.period.PeriodIndex'>
freq: A-DEC
[1990, ..., 2010]
length: 21

In [467]: rng.asfreq('B', 'end') - 3
Out[467]:
<class 'pandas.tseries.period.PeriodIndex'>
freq: B
[1990-12-26, ..., 2010-12-28]
length: 21
```

| scikits.timeseries | pandas | Notes |
|---|---|---|
| Date | Period | A span of time, from yearly through to secondly |
| DateArray | PeriodIndex | An array of timespans |
| convert | resample | Frequency conversion in scikits.timeseries |
| convert_to_annual | pivot_annual | currently supports up to daily frequency, see issue 736 |

### 3.1.1 PeriodIndex / DateArray properties and functions

The scikits.timeseries `DateArray` had a number of information properties. Here are the pandas equivalents:

| scikits.timeseries | pandas | Notes |
|---|---|---|
| get_steps | `np.diff(idx.values)` | |
| has_missing_dates | `not idx.is_full` | |
| is_full | `idx.is_full` | |
| is_valid | `idx.is_monotonic and idx.is_unique` | |
| is_chronological | `is_monotonic` | |
| `arr.sort_chronologically()` | `idx.order()` | |

### 3.1.2 Frequency conversion

Frequency conversion is implemented using the `resample` method on TimeSeries and DataFrame objects (multiple time series). `resample` also works on panels (3D). Here is some code that resamples daily data to montly with scikits.timeseries:

```
In [468]: import scikits.timeseries as ts

In [469]: data = ts.time_series(np.random.randn(50), start_date='Jan-2000', freq='M')

In [470]: data
Out[470]:
timeseries([ 0.4691 -0.2829 -1.5091 -1.1356  1.2121 -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 -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],
   dates = [Jan-2013 ... Feb-2017],
   freq  = M)

In [471]: data.convert('A', func=np.mean)
Out[471]:
timeseries([-0.394509620575 -0.24462765889 -0.221632512996 -0.453772693384
 0.8504806638],
   dates = [2013 ... 2017],
   freq  = A-DEC)
```

Here is the equivalent pandas code:

```
In [472]: rng = period_range('Jan-2000', periods=50, freq='M')

In [473]: data = Series(np.random.randn(50), index=rng)

In [474]: data
Out[474]:
2000-01   -1.206412
```

```
2000-02    2.565646
2000-03    1.431256
2000-04    1.340309
2000-05   -1.170299
2000-06   -0.226169
2000-07    0.410835
2000-08    0.813850
2000-09    0.132003
2000-10   -0.827317
2000-11   -0.076467
2000-12   -1.187678
2001-01    1.130127
2001-02   -1.436737
2001-03   -1.413681
2001-04    1.607920
2001-05    1.024180
2001-06    0.569605
2001-07    0.875906
2001-08   -2.211372
2001-09    0.974466
2001-10   -2.006747
2001-11   -0.410001
2001-12   -0.078638
2002-01    0.545952
2002-02   -1.219217
2002-03   -1.226825
2002-04    0.769804
2002-05   -1.281247
2002-06   -0.727707
2002-07   -0.121306
2002-08   -0.097883
2002-09    0.695775
2002-10    0.341734
2002-11    0.959726
2002-12   -1.110336
2003-01   -0.619976
2003-02    0.149748
2003-03   -0.732339
2003-04    0.687738
2003-05    0.176444
2003-06    0.403310
2003-07   -0.154951
2003-08    0.301624
2003-09   -2.179861
2003-10   -1.369849
2003-11   -0.954208
2003-12    1.462696
2004-01   -1.743161
2004-02   -0.826591
Freq: M, dtype: float64

In [475]: data.resample('A', how=np.mean)
Out[475]:
2000    0.166630
2001   -0.114581
2002   -0.205961
2003   -0.235802
2004   -1.284876
```

```
Freq: A-DEC, dtype: float64
```

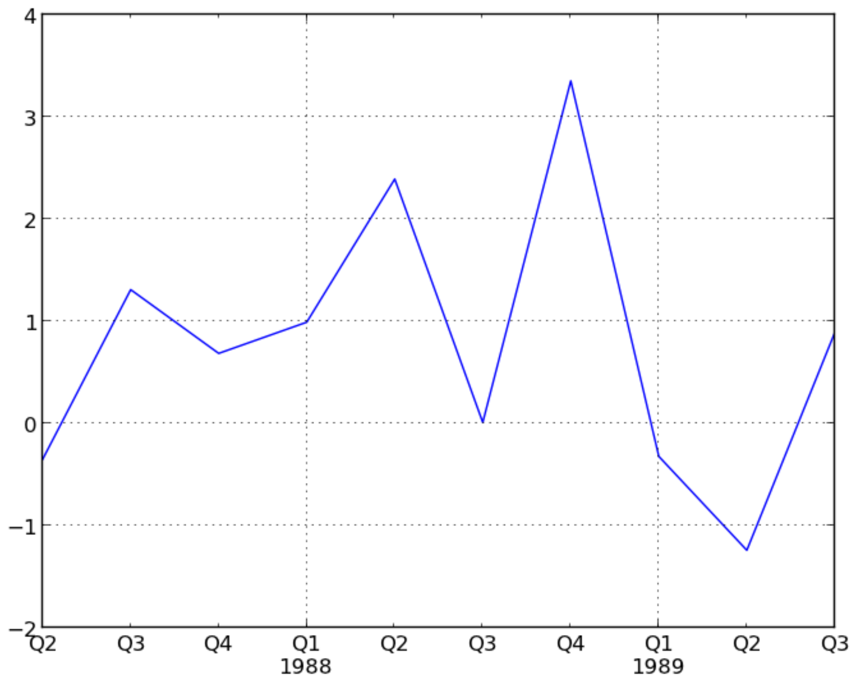
### 3.1.3 Plotting

Much of the plotting functionality of scikits.timeseries has been ported and adopted to pandas's data structures. For example:

```
In [476]: rng = period_range('1987Q2', periods=10, freq='Q-DEC')

In [477]: data = Series(np.random.randn(10), index=rng)

In [478]: plt.figure(); data.plot()
Out[478]: <matplotlib.axes.AxesSubplot at 0x9bce750>
```




### 3.1.4 Converting to and from period format

Use the `to_timestamp` and `to_period` instance methods.

### 3.1.5 Treatment of missing data

Unlike scikits.timeseries, pandas data structures are not based on NumPy's `MaskedArray` object. Missing data is represented as `NaN` in numerical arrays and either as `None` or `NaN` in non-numerical arrays. Implementing a version of pandas's data structures that use MaskedArray is possible but would require the involvement of a dedicated maintainer. Active pandas developers are not interested in this.

### 3.1.6 Resampling with timestamps and periods

`resample` has a `kind` argument which allows you to resample time series with a DatetimeIndex to PeriodIndex:

```
In [479]: rng = date_range('1/1/2000', periods=200, freq='D')

In [480]: data = Series(np.random.randn(200), index=rng)

In [481]: data[:10]
Out[481]:
2000-01-01   -0.487602
2000-01-02   -0.082240
2000-01-03   -2.182937
2000-01-04    0.380396
2000-01-05    0.084844
2000-01-06    0.432390
2000-01-07    1.519970
2000-01-08   -0.493662
2000-01-09    0.600178
2000-01-10    0.274230
Freq: D, dtype: float64

In [482]: data.index
Out[482]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2000-01-01 00:00:00, ..., 2000-07-18 00:00:00]
Length: 200, Freq: D, Timezone: None

In [483]: data.resample('M', kind='period')
Out[483]:
2000-01    0.163775
2000-02    0.026549
2000-03   -0.089563
2000-04   -0.079405
2000-05    0.160348
2000-06    0.101725
2000-07   -0.708770
Freq: M, dtype: float64
```

Similarly, resampling from periods to timestamps is possible with an optional interval (`'start'` or `'end'`) convention:

```
In [484]: rng = period_range('Jan-2000', periods=50, freq='M')

In [485]: data = Series(np.random.randn(50), index=rng)

In [486]: resampled = data.resample('A', kind='timestamp', convention='end')

In [487]: resampled.index
Out[487]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2000-12-31 00:00:00, ..., 2004-12-31 00:00:00]
Length: 5, Freq: A-DEC, Timezone: None
```

CHAPTER

FOUR

# PACKAGE OVERVIEW

`pandas` consists of the following things

- A set of labeled array data structures, the primary of which are Series/TimeSeries and DataFrame
- Index objects enabling both simple axis indexing and multi-level / hierarchical axis indexing
- An integrated group by engine for aggregating and transforming data sets
- Date range generation (date_range) and custom date offsets enabling the implementation of customized frequencies
- Input/Output tools: loading tabular data from flat files (CSV, delimited, Excel 2003), and saving and loading pandas objects from the fast and efficient PyTables/HDF5 format.
- Memory-efficent "sparse" versions of the standard data structures for storing data that is mostly missing or mostly constant (some fixed value)
- Moving window statistics (rolling mean, rolling standard deviation, etc.)
- Static and moving window linear and panel regression

## 4.1 Data structures at a glance

| Dimensions | Name | Description |
|---|---|---|
| 1 | Series | 1D labeled homogeneously-typed array |
| 1 | TimeSeries | Series with index containing datetimes |
| 2 | DataFrame | General 2D labeled, size-mutable tabular structure with potentially heterogeneously-typed columns |
| 3 | Panel | General 3D labeled, also size-mutable array |

### 4.1.1 Why more than 1 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 Panel is a container for DataFrame objects. 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 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. And 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
```

## 4.2 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, though, we like to **favor immutability** where sensible.

## 4.3 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.

Longer discussions occur on the developer mailing list, and commercial support inquiries for Lambda Foundry should be sent to: support@lambdafoundry.com

## 4.4 Credits

pandas development began at AQR Capital Management in April 2008. It was open-sourced at the end of 2009. AQR continued to provide resources for development through the end of 2011, and continues to contribute bug reports today.

Since January 2012, Lambda Foundry, has been providing development resources, as well as commercial support, training, and consulting for pandas.

pandas is only made possible by a group of people around the world like you who have contributed new code, bug reports, fixes, comments and ideas. A complete list can be found on Github.

## 4.5 Development Team

pandas is a part of the PyData project. The PyData Development Team is a collection of developers focused on the improvement of Python's data libraries. The core team that coordinates development can be found on Github. If you're interested in contributing, please visit the project website.

## 4.6 License

```
=======
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=======

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Wes is now an employee of Lambda Foundry, and remains the pandas project
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```
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CHAPTER

FIVE

# 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 [305]: import numpy as np

# will use a lot in examples
In [306]: randn = np.random.randn

In [307]: from pandas import *
```

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.

When using pandas, we recommend the following import convention:

```
import pandas as pd
```

## 5.1 Series

`Series` is a one-dimensional labeled array (technically a subclass of ndarray) 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 = 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 [308]: s = Series(randn(5), index=['a', 'b', 'c', 'd', 'e'])

In [309]: s
Out[309]:
a    0.314
b   -0.002
c    0.072
d    0.893
e    0.681
dtype: float64

In [310]: s.index
Out[310]: Index([a, b, c, d, e], dtype=object)

In [311]: Series(randn(5))
Out[311]:
0   -0.340
1    0.215
2   -0.078
3   -0.178
4    0.491
dtype: float64
```

---

**Note:** Starting in v0.8.0, pandas supports non-unique index values. In previous version, if the index values are not unique an exception will **not** be raised immediately, but attempting any operation involving the index will later result in an exception. In other words, the Index object containing the labels "lazily" checks whether the values are unique. 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**

If `data` is a dict, if **index** is passed the values in data corresponding to the labels in the index will be pulled out. Otherwise, an index will be constructed from the sorted keys of the dict, if possible.

```
In [312]: d = {'a' : 0., 'b' : 1., 'c' : 2.}

In [313]: Series(d)
Out[313]:
a    0
b    1
c    2
dtype: float64

In [314]: Series(d, index=['b', 'c', 'd', 'a'])
Out[314]:
b      1
c      2
d    NaN
a      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 [315]: Series(5., index=['a', 'b', 'c', 'd', 'e'])
Out[315]:
a    5
b    5
c    5
d    5
e    5
dtype: float64
```

### 5.1.1 Series is ndarray-like

As a subclass of ndarray, Series is a valid argument to most NumPy functions and behaves similarly to a NumPy array. However, things like slicing also slice the index.

```
In [316]: s[0]
Out[316]: 0.31422552353417077

In [317]: s[:3]
Out[317]:
a    0.314
b   -0.002
c    0.072
dtype: float64

In [318]: s[s > s.median()]
Out[318]:
d    0.893
e    0.681
dtype: float64

In [319]: s[[4, 3, 1]]
Out[319]:
e    0.681
d    0.893
b   -0.002
dtype: float64

In [320]: np.exp(s)
Out[320]:
a    1.369
b    0.998
c    1.074
d    2.441
e    1.975
dtype: float64
```

We will address array-based indexing in a separate *section*.

### 5.1.2 Series is dict-like

A Series is like a fixed-size dict in that you can get and set values by index label:

```
In [321]: s['a']
Out[321]: 0.31422552353417077

In [322]: s['e'] = 12.
```

```
In [323]: s
Out[323]:
a     0.314
b    -0.002
c     0.072
d     0.893
e    12.000
dtype: float64

In [324]: 'e' in s
Out[324]: True

In [325]: 'f' in s
Out[325]: 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 [326]: s.get('f')

In [327]: s.get('f', np.nan)
Out[327]: nan
```

### 5.1.3 Vectorized operations and label alignment with Series

When doing data analysis, as with raw NumPy arrays looping through Series value-by-value is usually not necessary. Series can be also be passed into most NumPy methods expecting an ndarray.

```
In [328]: s + s
Out[328]:
a     0.628
b    -0.003
c     0.144
d     1.785
e    24.000
dtype: float64

In [329]: s * 2
Out[329]:
a     0.628
b    -0.003
c     0.144
d     1.785
e    24.000
dtype: float64

In [330]: np.exp(s)
Out[330]:
a         1.369
b         0.998
c         1.074
d         2.441
```

```
e    162754.791
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 [331]: s[1:] + s[:-1]
Out[331]:
a      NaN
b   -0.003
c    0.144
d    1.785
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.

### 5.1.4 Name attribute

Series can also have a `name` attribute:

```
In [332]: s = Series(np.random.randn(5), name='something')

In [333]: s
Out[333]:
0   -1.360
1    1.592
2    1.007
3    0.698
4   -1.891
Name: something, dtype: float64

In [334]: s.name
Out[334]: 'something'
```

The Series `name` will be assigned automatically in many cases, in particular when taking 1D slices of DataFrame as you will see below.

## 5.2 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.

### 5.2.1 From dict of Series or dicts

The result **index** will be the **union** of the indexes of the various Series. If there are any nested dicts, these will be first converted to Series. If no columns are passed, the columns will be the sorted list of dict keys.

```
In [335]: d = {'one' : Series([1., 2., 3.], index=['a', 'b', 'c']),
   .....:      'two' : Series([1., 2., 3., 4.], index=['a', 'b', 'c', 'd'])}
   .....:

In [336]: df = DataFrame(d)

In [337]: df
Out[337]:
   one  two
a    1    1
b    2    2
c    3    3
d  NaN    4

In [338]: DataFrame(d, index=['d', 'b', 'a'])
Out[338]:
   one  two
d  NaN    4
b    2    2
a    1    1

In [339]: DataFrame(d, index=['d', 'b', 'a'], columns=['two', 'three'])
Out[339]:
   two three
d    4   NaN
b    2   NaN
a    1   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 [340]: df.index
Out[340]: Index([a, b, c, d], dtype=object)
```

```
In [341]: df.columns
Out[341]: Index([one, two], dtype=object)
```

### 5.2.2 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 [342]: d = {'one' : [1., 2., 3., 4.],
   .....:      'two' : [4., 3., 2., 1.]}
   .....:

In [343]: DataFrame(d)
Out[343]:
   one  two
0    1    4
1    2    3
2    3    2
3    4    1

In [344]: DataFrame(d, index=['a', 'b', 'c', 'd'])
Out[344]:
   one  two
a    1    4
b    2    3
c    3    2
d    4    1
```

### 5.2.3 From structured or record array

This case is handled identically to a dict of arrays.

```
In [345]: data = np.zeros((2,),dtype=[('A', 'i4'),('B', 'f4'),('C', 'a10')])

In [346]: data[:] = [(1,2.,'Hello'),(2,3.,"World")]

In [347]: DataFrame(data)
Out[347]:
   A  B      C
0  1  2  Hello
1  2  3  World

In [348]: DataFrame(data, index=['first', 'second'])
Out[348]:
        A  B      C
first   1  2  Hello
second  2  3  World

In [349]: DataFrame(data, columns=['C', 'A', 'B'])
Out[349]:
       C  A  B
0  Hello  1  2
1  World  2  3
```

**Note:** DataFrame is not intended to work exactly like a 2-dimensional NumPy ndarray.

### 5.2.4 From a list of dicts

```
In [350]: data2 = [{'a': 1, 'b': 2}, {'a': 5, 'b': 10, 'c': 20}]

In [351]: DataFrame(data2)
Out[351]:
   a   b   c
0  1   2 NaN
1  5  10  20

In [352]: DataFrame(data2, index=['first', 'second'])
Out[352]:
        a   b   c
first   1   2 NaN
second  5  10  20

In [353]: DataFrame(data2, columns=['a', 'b'])
Out[353]:
   a   b
0  1   2
1  5  10
```

### 5.2.5 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).

**Missing Data**

Much more will be said on this topic in the *Missing data* section. To construct a DataFrame with missing data, use `np.nan` for those values which are missing. Alternatively, you may pass a `numpy.MaskedArray` as the data argument to the DataFrame constructor, and its masked entries will be considered missing.

### 5.2.6 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. **DataFrame.from_records**

`DataFrame.from_records` takes a list of tuples or an ndarray with structured dtype. Works analogously to the normal `DataFrame` constructor, except that index maybe be a specific field of the structured dtype to use as the index. For example:

```
In [354]: data
Out[354]:
array([(1, 2.0, 'Hello'), (2, 3.0, 'World')],
      dtype=[('A', '<i4'), ('B', '<f4'), ('C', '|S10')])

In [355]: DataFrame.from_records(data, index='C')
Out[355]:
       A  B
C
```

```
Hello  1  2
World  2  3
```

**DataFrame.from_items**

`DataFrame.from_items` works analogously to the form of the `dict` constructor that takes a sequence of `(key, value)` pairs, where the keys are column (or row, in the case of `orient='index'`) names, and the value are the column values (or row values). This can be useful for constructing a DataFrame with the columns in a particular order without having to pass an explicit list of columns:

```
In [356]: DataFrame.from_items([('A', [1, 2, 3]), ('B', [4, 5, 6])])
Out[356]:
   A  B
0  1  4
1  2  5
2  3  6
```

If you pass `orient='index'`, the keys will be the row labels. But in this case you must also pass the desired column names:

```
In [357]: DataFrame.from_items([('A', [1, 2, 3]), ('B', [4, 5, 6])],
   .....:                      orient='index', columns=['one', 'two', 'three'])
   .....:
Out[357]:
   one  two  three
A    1    2      3
B    4    5      6
```

### 5.2.7 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 [358]: df['one']
Out[358]:
a      1
b      2
c      3
d    NaN
Name: one, dtype: float64

In [359]: df['three'] = df['one'] * df['two']

In [360]: df['flag'] = df['one'] > 2

In [361]: df
Out[361]:
   one  two  three   flag
a    1    1      1  False
b    2    2      4  False
c    3    3      9   True
d  NaN    4    NaN  False
```

Columns can be deleted or popped like with a dict:

```
In [362]: del df['two']

In [363]: three = df.pop('three')
```

```
In [364]: df
Out[364]:
   one   flag
a    1  False
b    2  False
c    3   True
d  NaN  False
```

When inserting a scalar value, it will naturally be propagated to fill the column:

```
In [365]: df['foo'] = 'bar'

In [366]: df
Out[366]:
   one   flag  foo
a    1  False  bar
b    2  False  bar
c    3   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 [367]: df['one_trunc'] = df['one'][:2]

In [368]: df
Out[368]:
   one   flag  foo  one_trunc
a    1  False  bar          1
b    2  False  bar          2
c    3   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 [369]: df.insert(1, 'bar', df['one'])

In [370]: df
Out[370]:
   one  bar   flag  foo  one_trunc
a    1    1  False  bar          1
b    2    2  False  bar          2
c    3    3   True  bar        NaN
d  NaN  NaN  False  bar        NaN
```

### 5.2.8 Indexing / Selection

The basics of indexing are as follows:

| Operation | Syntax | Result |
|---|---|---|
| Select column | `df[col]` | Series |
| Select row by label | `df.xs(label)` or `df.ix[label]` | Series |
| Select row by location (int) | `df.ix[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 [371]: df.xs('b')
Out[371]:
one              2
bar              2
flag         False
foo            bar
one_trunc        2
Name: b, dtype: object

In [372]: df.ix[2]
Out[372]:
one             3
bar             3
flag         True
foo           bar
one_trunc     NaN
Name: c, dtype: object
```

Note if a DataFrame contains columns of multiple dtypes, the dtype of the row will be chosen to accommodate all of the data types (dtype=object is the most general).

For a more exhaustive treatment of more sophisticated label-based indexing and slicing, see the *section on indexing*. We will address the fundamentals of reindexing / conforming to new sets of lables in the *section on reindexing*.

### 5.2.9 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 [373]: df = DataFrame(randn(10, 4), columns=['A', 'B', 'C', 'D'])

In [374]: df2 = DataFrame(randn(7, 3), columns=['A', 'B', 'C'])

In [375]: df + df2
Out[375]:
       A      B      C   D
0  0.229  1.547 -1.499 NaN
1  0.121 -0.234 -0.705 NaN
2 -0.561 -1.550  0.643 NaN
3 -0.263  1.071 -0.060 NaN
4 -2.588 -0.752 -1.227 NaN
5  0.628 -0.095 -3.236 NaN
6  0.983 -0.823 -0.720 NaN
7    NaN    NaN    NaN NaN
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 [376]: df - df.ix[0]
Out[376]:
       A      B      C      D
0  0.000  0.000  0.000  0.000
1  0.879 -2.485  0.133 -0.958
2  0.246 -1.482  0.106  0.685
```

```
3  0.482 -1.571  0.099 -0.054
4 -0.511 -1.333 -0.217  0.772
5  0.114 -1.401 -1.682  0.386
6  1.131 -1.280  0.060 -0.113
7 -0.313 -3.004  1.531  0.829
8 -0.232 -1.702 -0.982 -0.460
9  0.113 -1.353 -0.456  0.598
```

In the special case of working with time series data, if the Series is a TimeSeries (which it will be automatically if the index contains datetime objects), and the DataFrame index also contains dates, the broadcasting will be column-wise:

```
In [377]: index = date_range('1/1/2000', periods=8)

In [378]: df = DataFrame(randn(8, 3), index=index,
   .....:                columns=['A', 'B', 'C'])
   .....:

In [379]: df
Out[379]:
                A      B      C
2000-01-01  0.302  1.113 -0.543
2000-01-02 -2.696  0.431 -0.431
2000-01-03  1.667  0.717 -0.920
2000-01-04 -0.025  0.069  0.602
2000-01-05  0.867  0.093 -2.607
2000-01-06  0.309 -0.548 -2.045
2000-01-07 -1.666 -1.440  1.326
2000-01-08  0.222  1.841  1.165

In [380]: type(df['A'])
Out[380]: pandas.core.series.TimeSeries

In [381]: df - df['A']
Out[381]:
            A      B      C
2000-01-01  0  0.811 -0.845
2000-01-02  0  3.127  2.264
2000-01-03  0 -0.950 -2.586
2000-01-04  0  0.094  0.626
2000-01-05  0 -0.774 -3.474
2000-01-06  0 -0.858 -2.354
2000-01-07  0  0.226  2.993
2000-01-08  0  1.619  0.943
```

Technical purity aside, this case is so common in practice that supporting the special case is preferable to the alternative of forcing the user to transpose and do column-based alignment like so:

```
In [382]: (df.T - df['A']).T
Out[382]:
            A      B      C
2000-01-01  0  0.811 -0.845
2000-01-02  0  3.127  2.264
2000-01-03  0 -0.950 -2.586
2000-01-04  0  0.094  0.626
2000-01-05  0 -0.774 -3.474
2000-01-06  0 -0.858 -2.354
2000-01-07  0  0.226  2.993
2000-01-08  0  1.619  0.943
```

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 [383]: df * 5 + 2
Out[383]:
                  A       B       C
2000-01-01   3.510   7.563  -0.714
2000-01-02 -11.478   4.156  -0.155
2000-01-03  10.333   5.583  -2.599
2000-01-04   1.877   2.345   5.009
2000-01-05   6.333   2.465 -11.034
2000-01-06   3.547  -0.742  -8.224
2000-01-07  -6.331  -5.199   8.632
2000-01-08   3.108  11.205   7.826

In [384]: 1 / df
Out[384]:
                  A       B      C
2000-01-01   3.312   0.899 -1.842
2000-01-02  -0.371   2.319 -2.320
2000-01-03   0.600   1.395 -1.087
2000-01-04 -40.659  14.493  1.662
2000-01-05   1.154  10.763 -0.384
2000-01-06   3.233  -1.823 -0.489
2000-01-07  -0.600  -0.695  0.754
2000-01-08   4.511   0.543  0.858

In [385]: df ** 4
Out[385]:
                    A          B       C
2000-01-01  8.312e-03  1.532e+00   0.087
2000-01-02  5.279e+01  3.460e-02   0.035
2000-01-03  7.715e+00  2.638e-01   0.716
2000-01-04  3.659e-07  2.266e-05   0.131
2000-01-05  5.640e-01  7.452e-05  46.184
2000-01-06  9.152e-03  9.045e-02  17.482
2000-01-07  7.709e+00  4.297e+00   3.095
2000-01-08  2.415e-03  1.149e+01   1.843
```

Boolean operators work as well:

```
In [386]: df1 = DataFrame({'a' : [1, 0, 1], 'b' : [0, 1, 1] }, dtype=bool)

In [387]: df2 = DataFrame({'a' : [0, 1, 1], 'b' : [1, 1, 0] }, dtype=bool)

In [388]: df1 & df2
Out[388]:
       a      b
0  False  False
1  False   True
2   True  False

In [389]: df1 | df2
Out[389]:
      a     b
0  True  True
1  True  True
2  True  True
```

```
In [390]: df1 ^ df2
Out[390]:
       a      b
0   True   True
1   True  False
2  False   True

In [391]: -df1
Out[391]:
       a      b
0  False   True
1   True  False
2  False  False
```

### 5.2.10 Transposing

To transpose, access the `T` attribute (also the `transpose` function), similar to an ndarray:

```
# only show the first 5 rows
In [392]: df[:5].T
Out[392]:
   2000-01-01  2000-01-02  2000-01-03  2000-01-04  2000-01-05
A       0.302      -2.696       1.667      -0.025       0.867
B       1.113       0.431       0.717       0.069       0.093
C      -0.543      -0.431      -0.920       0.602      -2.607
```

### 5.2.11 DataFrame interoperability with NumPy functions

Elementwise NumPy ufuncs (log, exp, sqrt, ...) and various other NumPy functions can be used with no issues on DataFrame, assuming the data within are numeric:

```
In [393]: np.exp(df)
Out[393]:
                A      B      C
2000-01-01  1.352  3.042  0.581
2000-01-02  0.068  1.539  0.650
2000-01-03  5.294  2.048  0.399
2000-01-04  0.976  1.071  1.825
2000-01-05  2.379  1.097  0.074
2000-01-06  1.362  0.578  0.129
2000-01-07  0.189  0.237  3.767
2000-01-08  1.248  6.303  3.206

In [394]: np.asarray(df)
Out[394]:
array([[ 0.3019,  1.1125, -0.5428],
       [-2.6955,  0.4313, -0.4311],
       [ 1.6666,  0.7167, -0.9197],
       [-0.0246,  0.069 ,  0.6018],
       [ 0.8666,  0.0929, -2.6069],
       [ 0.3093, -0.5484, -2.0448],
       [-1.6663, -1.4398,  1.3264],
       [ 0.2217,  1.841 ,  1.1651]])
```

The dot method on DataFrame implements matrix multiplication:

```
In [395]: df.T.dot(df)
Out[395]:
        A      B       C
A  13.808  3.084  -5.393
B   3.084  7.714  -0.293
C  -5.393 -0.293  15.782
```

Similarly, the dot method on Series implements dot product:

```
In [396]: s1 = Series(np.arange(5,10))

In [397]: s1.dot(s1)
Out[397]: 255
```

DataFrame is not intended to be a drop-in replacement for ndarray as its indexing semantics are quite different in places from a matrix.

### 5.2.12 Console display

For very large DataFrame objects, only a summary will be printed to the console (here I am reading a CSV version of the **baseball** dataset from the **plyr** R package):

```
In [398]: baseball = read_csv('data/baseball.csv')

In [399]: print baseball
<class 'pandas.core.frame.DataFrame'>
Int64Index: 100 entries, 88641 to 89534
Data columns:
id        100  non-null values
year      100  non-null values
stint     100  non-null values
team      100  non-null values
lg        100  non-null values
g         100  non-null values
ab        100  non-null values
r         100  non-null values
h         100  non-null values
X2b       100  non-null values
X3b       100  non-null values
hr        100  non-null values
rbi       100  non-null values
sb        100  non-null values
cs        100  non-null values
bb        100  non-null values
so        100  non-null values
ibb       100  non-null values
hbp       100  non-null values
sh        100  non-null values
sf        100  non-null values
gidp      100  non-null values
dtypes: float64(9), int64(10), object(3)
```

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 [400]: print baseball.ix[-20:, :12].to_string()
              id  year  stint team  lg    g   ab    r    h  X2b  X3b  hr
88641  womacto01  2006      2  CHN  NL   19   50    6   14    1    0   1
```

```
88643  schilcu01  2006      1  BOS  AL   31    2    0    1    0    0   0
88645  myersmi01  2006      1  NYA  AL   62    0    0    0    0    0   0
88649  helliri01  2006      1  MIL  NL   20    3    0    0    0    0   0
88650  johnsra05  2006      1  NYA  AL   33    6    0    1    0    0   0
88652  finlest01  2006      1  SFN  NL  139  426   66  105   21   12   6
88653  gonzalu01  2006      1  ARI  NL  153  586   93  159   52    2  15
88662   seleaa01  2006      1  LAN  NL   28   26    2    5    1    0   0
89177  francju01  2007      2  ATL  NL   15   40    1   10    3    0   0
89178  francju01  2007      1  NYN  NL   40   50    7   10    0    0   1
89330   zaungr01  2007      1  TOR  AL  110  331   43   80   24    1  10
89333  witasja01  2007      1  TBA  AL    3    0    0    0    0    0   0
89334  williwo02  2007      1  HOU  NL   33   59    3    6    0    0   1
89335  wickmbo01  2007      2  ARI  NL    8    0    0    0    0    0   0
89336  wickmbo01  2007      1  ATL  NL   47    0    0    0    0    0   0
89337  whitero02  2007      1  MIN  AL   38  109    8   19    4    0   4
89338  whiteri01  2007      1  HOU  NL   20    1    0    0    0    0   0
89339  wellsda01  2007      2  LAN  NL    7   15    2    4    1    0   0
89340  wellsda01  2007      1  SDN  NL   22   38    1    4    0    0   0
89341  weathda01  2007      1  CIN  NL   67    0    0    0    0    0   0
89343  walketo04  2007      1  OAK  AL   18   48    5   13    1    0   0
89345  wakefti01  2007      1  BOS  AL    1    2    0    0    0    0   0
89347  vizquom01  2007      1  SFN  NL  145  513   54  126   18    3   4
89348  villoro01  2007      1  NYA  AL    6    0    0    0    0    0   0
89352  valenjo03  2007      1  NYN  NL   51  166   18   40   11    1   3
89354  trachst01  2007      2  CHN  NL    4    7    0    1    0    0   0
89355  trachst01  2007      1  BAL  AL    3    5    0    0    0    0   0
89359  timlimi01  2007      1  BOS  AL    4    0    0    0    0    0   0
89360  thomeji01  2007      1  CHA  AL  130  432   79  119   19    0  35
89361  thomafr04  2007      1  TOR  AL  155  531   63  147   30    0  26
89363  tavarju01  2007      1  BOS  AL    2    4    0    1    0    0   0
89365  sweenma01  2007      2  LAN  NL   30   33    2    9    1    0   0
89366  sweenma01  2007      1  SFN  NL   76   90   18   23    8    0   2
89367  suppaje01  2007      1  MIL  NL   33   61    4    8    0    0   0
89368  stinnke01  2007      1  SLN  NL   26   82    7   13    3    0   1
89370  stantmi02  2007      1  CIN  NL   67    2    0    0    0    0   0
89371  stairma01  2007      1  TOR  AL  125  357   58  103   28    1  21
89372  sprinru01  2007      1  SLN  NL   72    1    0    0    0    0   0
89374   sosasa01  2007      1  TEX  AL  114  412   53  104   24    1  21
89375  smoltjo01  2007      1  ATL  NL   30   54    1    5    1    0   0
89378  sheffga01  2007      1  DET  AL  133  494  107  131   20    1  25
89381   seleaa01  2007      1  NYN  NL   31    4    0    0    0    0   0
89382  seaneru01  2007      1  LAN  NL   68    1    0    0    0    0   0
89383  schmija01  2007      1  LAN  NL    6    7    1    1    0    0   1
89384  schilcu01  2007      1  BOS  AL    1    2    0    1    0    0   0
89385  sandere02  2007      1  KCA  AL   24   73   12   23    7    0   2
89388  rogerke01  2007      1  DET  AL    1    2    0    0    0    0   0
89389  rodriiv01  2007      1  DET  AL  129  502   50  141   31    3  11
89396  ramirma02  2007      1  BOS  AL  133  483   84  143   33    1  20
89398  piazzmi01  2007      1  OAK  AL   83  309   33   85   17    1   8
89400  perezne01  2007      1  DET  AL   33   64    5   11    3    0   1
89402   parkch01  2007      1  NYN  NL    1    1    0    0    0    0   0
89406  oliveda02  2007      1  LAA  AL    5    0    0    0    0    0   0
89410  myersmi01  2007      1  NYA  AL    6    1    0    0    0    0   0
89411  mussimi01  2007      1  NYA  AL    2    2    0    0    0    0   0
89412  moyerja01  2007      1  PHI  NL   33   73    4    9    2    0   0
89420   mesajo01  2007      1  PHI  NL   38    0    0    0    0    0   0
89421  martipe02  2007      1  NYN  NL    5    9    1    1    1    0   0
89425  maddugr01  2007      1  SDN  NL   33   62    2    9    2    0   0
```

```
89426  mabryjo01  2007       1  COL  NL   28   34    4    4    1    0   1
89429  loftoke01  2007       2  CLE  AL   52  173   24   49    9    3   0
89430  loftoke01  2007       1  TEX  AL   84  317   62   96   16    3   7
89431  loaizes01  2007       1  LAN  NL    5    7    0    1    0    0   0
89438  kleskry01  2007       1  SFN  NL  116  362   51   94   27    3   6
89439   kentje01  2007       1  LAN  NL  136  494   78  149   36    1  20
89442  jonesto02  2007       1  DET  AL    5    0    0    0    0    0   0
89445  johnsra05  2007       1  ARI  NL   10   15    0    1    0    0   0
89450  hoffmtr01  2007       1  SDN  NL   60    0    0    0    0    0   0
89451  hernaro01  2007       2  LAN  NL   22    0    0    0    0    0   0
89452  hernaro01  2007       1  CLE  AL    2    0    0    0    0    0   0
89460  guarded01  2007       1  CIN  NL   15    0    0    0    0    0   0
89462  griffke02  2007       1  CIN  NL  144  528   78  146   24    1  30
89463  greensh01  2007       1  NYN  NL  130  446   62  130   30    1  10
89464  graffto01  2007       1  MIL  NL   86  231   34   55    8    0   9
89465  gordoto01  2007       1  PHI  NL   44    0    0    0    0    0   0
89466  gonzalu01  2007       1  LAN  NL  139  464   70  129   23    2  15
89467  gomezch02  2007       2  CLE  AL   19   53    4   15    2    0   0
89468  gomezch02  2007       1  BAL  AL   73  169   17   51   10    1   1
89469  glavito02  2007       1  NYN  NL   33   56    3   12    1    0   0
89473  floydcl01  2007       1  CHN  NL  108  282   40   80   10    1   9
89474  finlest01  2007       1  COL  NL   43   94    9   17    3    0   1
89480  embreal01  2007       1  OAK  AL    4    0    0    0    0    0   0
89481  edmonji01  2007       1  SLN  NL  117  365   39   92   15    2  12
89482  easleda01  2007       1  NYN  NL   76  193   24   54    6    0  10
89489  delgaca01  2007       1  NYN  NL  139  538   71  139   30    0  24
89493  cormirh01  2007       1  CIN  NL    6    0    0    0    0    0   0
89494  coninje01  2007       2  NYN  NL   21   41    2    8    2    0   0
89495  coninje01  2007       1  CIN  NL   80  215   23   57   11    1   6
89497  clemero02  2007       1  NYA  AL    2    2    0    1    0    0   0
89498  claytro01  2007       2  BOS  AL    8    6    1    0    0    0   0
89499  claytro01  2007       1  TOR  AL   69  189   23   48   14    0   1
89501  cirilje01  2007       2  ARI  NL   28   40    6    8    4    0   0
89502  cirilje01  2007       1  MIN  AL   50  153   18   40    9    2   2
89521  bondsba01  2007       1  SFN  NL  126  340   75   94   14    0  28
89523  biggicr01  2007       1  HOU  NL  141  517   68  130   31    3  10
89525  benitar01  2007       2  FLO  NL   34    0    0    0    0    0   0
89526  benitar01  2007       1  SFN  NL   19    0    0    0    0    0   0
89530  ausmubr01  2007       1  HOU  NL  117  349   38   82   16    3   3
89533   aloumo01  2007       1  NYN  NL   87  328   51  112   19    1  13
89534  alomasa02  2007       1  NYN  NL    8   22    1    3    1    0   0
```

New since 0.10.0, wide DataFrames will now be printed across multiple rows by default:

```
In [401]: DataFrame(randn(3, 12))
Out[401]:
         0         1         2         3         4         5         6         7   \
0 -1.420521  1.616679 -1.030912  0.628297 -0.103189 -0.365475 -1.783911 -0.052526
1  0.652300 -0.840516 -1.405878  0.966204  0.351162  0.048154  0.485560 -1.291041
2  1.075002  0.526206  1.001947 -0.742489  0.767153  1.275288 -1.187808 -0.545179
         8         9         10        11
0 -1.408368  1.242233  0.952053 -0.172624
1  0.122389  1.652711 -0.381662 -1.328093
2  0.918173 -1.199261  0.371268  0.225621
```

You can change how much to print on a single row by setting the `line_width` option:

```
In [402]: set_option('line_width', 40) # default is 80
```

```
In [403]: DataFrame(randn(3, 12))
Out[403]:
         0         1         2         3   \
0 -0.970022 -1.127997 -0.384526 -0.492429
1  1.295440  0.027006  0.863536  0.189023
2 -0.822538 -1.590312 -0.061405  0.400325
         4         5         6         7   \
0 -1.779882 -0.391166  0.575903 -1.343193
1 -0.912154  0.946960 -0.257288  0.695208
2  1.511027  0.289143  0.349037  1.998562
         8         9         10        11
0  1.646841  0.462269  1.078574  0.883532
1  0.915200 -1.052414 -0.910945 -0.174453
2  1.056844 -0.077851 -0.057005  0.626302
```

You can also disable this feature via the `expand_frame_repr` option:

```
In [404]: set_option('expand_frame_repr', False)

In [405]: DataFrame(randn(3, 12))
Out[405]:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3 entries, 0 to 2
Data columns:
0     3  non-null values
1     3  non-null values
2     3  non-null values
3     3  non-null values
4     3  non-null values
5     3  non-null values
6     3  non-null values
7     3  non-null values
8     3  non-null values
9     3  non-null values
10    3  non-null values
11    3  non-null values
dtypes: float64(12)
```

### 5.2.13 DataFrame column types

The four main types stored in pandas objects are float, int, boolean, and object. A convenient `dtypes` attribute return a Series with the data type of each column:

```
In [406]: baseball.dtypes
Out[406]:
id         object
year        int64
stint       int64
team       object
lg         object
g           int64
ab          int64
r           int64
h           int64
X2b         int64
X3b         int64
hr          int64
```

```
rbi      float64
sb       float64
cs       float64
bb         int64
so       float64
ibb      float64
hbp      float64
sh       float64
sf       float64
gidp     float64
dtype: object
```

The related method `get_dtype_counts` will return the number of columns of each type:

```
In [407]: baseball.get_dtype_counts()
Out[407]:
float64     9
int64      10
object      3
dtype: int64
```

### 5.2.14 DataFrame column attribute access and IPython completion

If a DataFrame column label is a valid Python variable name, the column can be accessed like attributes:

```
In [408]: df = DataFrame({'foo1' : np.random.randn(5),
   .....:                 'foo2' : np.random.randn(5)})
   .....:

In [409]: df
Out[409]:
       foo1      foo2
0 -0.868315 -0.502919
1 -2.677551 -0.825049
2 -1.403487  0.518248
3 -0.561381 -0.438716
4  1.002897 -0.452045

In [410]: df.foo1
Out[410]:
0   -0.868315
1   -2.677551
2   -1.403487
3   -0.561381
4    1.002897
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>
df.foo1  df.foo2
```

## 5.3 Panel

Panel is a somewhat less-used, but still important container for 3-dimensional data. The term panel data is derived from econometrics and is partially responsible for the name pandas: pan(el)-da(ta)-s. The names for the 3 axes are intended to give some semantic meaning to describing operations involving panel data and, in particular, econometric analysis of panel data. However, for the strict purposes of slicing and dicing a collection of DataFrame objects, you may find the axis names slightly arbitrary:

- **items**: axis 0, each item corresponds to a DataFrame contained inside
- **major_axis**: axis 1, it is the **index** (rows) of each of the DataFrames
- **minor_axis**: axis 2, it is the **columns** of each of the DataFrames

Construction of Panels works about like you would expect:

### 5.3.1 From 3D ndarray with optional axis labels

```
In [411]: wp = Panel(randn(2, 5, 4), items=['Item1', 'Item2'],
   .....:            major_axis=date_range('1/1/2000', periods=5),
   .....:            minor_axis=['A', 'B', 'C', 'D'])
   .....:

In [412]: wp
Out[412]:
<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
```

### 5.3.2 From dict of DataFrame objects

```
In [413]: data = {'Item1' : DataFrame(randn(4, 3)),
   .....:         'Item2' : DataFrame(randn(4, 2))}
   .....:

In [414]: Panel(data)
Out[414]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 4 (major_axis) x 3 (minor_axis)
Items axis: Item1 to Item2
Major_axis axis: 0 to 3
Minor_axis axis: 0 to 2
```

Note that the values in the dict need only be **convertible to DataFrame**. Thus, they can be any of the other valid inputs to DataFrame as per above.

One helpful factory method is `Panel.from_dict`, which takes a dictionary of DataFrames as above, and the following named parameters:

| Parameter | Default | Description |
|---|---|---|
| intersect | False | drops elements whose indices do not align |
| orient | items | use minor to use DataFrames' columns as panel items |

For example, compare to the construction above:

```
In [415]: Panel.from_dict(data, orient='minor')
Out[415]:
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 4 (major_axis) x 2 (minor_axis)
Items axis: 0 to 2
Major_axis axis: 0 to 3
Minor_axis axis: Item1 to Item2
```

Orient is especially useful for mixed-type DataFrames. If you pass a dict of DataFrame objects with mixed-type columns, all of the data will get upcasted to `dtype=object` unless you pass `orient='minor'`:

```
In [416]: df = DataFrame({'a': ['foo', 'bar', 'baz'],
   .....:                 'b': np.random.randn(3)})
   .....:

In [417]: df
Out[417]:
     a         b
0  foo  1.448717
1  bar  0.608653
2  baz -1.409338

In [418]: data = {'item1': df, 'item2': df}

In [419]: panel = Panel.from_dict(data, orient='minor')

In [420]: panel['a']
Out[420]:
  item1 item2
0   foo   foo
1   bar   bar
2   baz   baz

In [421]: panel['b']
Out[421]:
      item1     item2
0  1.448717  1.448717
1  0.608653  0.608653
2 -1.409338 -1.409338

In [422]: panel['b'].dtypes
Out[422]:
item1    float64
item2    float64
dtype: object
```

**Note:** Unfortunately Panel, being less commonly used than Series and DataFrame, has been slightly neglected feature-wise. A number of methods and options available in DataFrame are not available in Panel. This will get worked on, of course, in future releases. And faster if you join me in working on the codebase.

### 5.3.3 From DataFrame using `to_panel` method

This method was introduced in v0.7 to replace `LongPanel.to_long`, and converts a DataFrame with a two-level index to a Panel.

```
In [423]: midx = MultiIndex(levels=[['one', 'two'], ['x','y']], labels=[[1,1,0,0],[1,0,1,0]])

In [424]: df = DataFrame({'A' : [1, 2, 3, 4], 'B': [5, 6, 7, 8]}, index=midx)

In [425]: df.to_panel()
Out[425]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 2 (major_axis) x 2 (minor_axis)
Items axis: A to B
Major_axis axis: one to two
Minor_axis axis: x to y
```

### 5.3.4 Item selection / addition / deletion

Similar to DataFrame functioning as a dict of Series, Panel is like a dict of DataFrames:

```
In [426]: wp['Item1']
Out[426]:
                   A         B         C         D
2000-01-01 -1.362139 -0.098512 -0.491067  0.048491
2000-01-02  2.287810 -0.403876 -1.076283 -0.155956
2000-01-03  0.388741 -1.284588 -0.508030  0.841173
2000-01-04 -0.555843 -0.030913 -0.289758  1.318467
2000-01-05  1.025903  0.195796  0.030198 -0.349406

In [427]: wp['Item3'] = wp['Item1'] / wp['Item2']
```

The API for insertion and deletion is the same as for DataFrame. And as with DataFrame, if the item is a valid python identifier, you can access it as an attribute and tab-complete it in IPython.

### 5.3.5 Transposing

A Panel can be rearranged using its `transpose` method (which does not make a copy by default unless the data are heterogeneous):

```
In [428]: wp.transpose(2, 0, 1)
Out[428]:
<class 'pandas.core.panel.Panel'>
Dimensions: 4 (items) x 3 (major_axis) x 5 (minor_axis)
Items axis: A to D
Major_axis axis: Item1 to Item3
Minor_axis axis: 2000-01-01 00:00:00 to 2000-01-05 00:00:00
```

### 5.3.6 Indexing / Selection

| Operation | Syntax | Result |
|---|---|---|
| Select item | `wp[item]` | DataFrame |
| Get slice at major_axis label | `wp.major_xs(val)` | DataFrame |
| Get slice at minor_axis label | `wp.minor_xs(val)` | DataFrame |

For example, using the earlier example data, we could do:

```
In [429]: wp['Item1']
Out[429]:
                   A         B         C         D
2000-01-01 -1.362139 -0.098512 -0.491067  0.048491
2000-01-02  2.287810 -0.403876 -1.076283 -0.155956
2000-01-03  0.388741 -1.284588 -0.508030  0.841173
2000-01-04 -0.555843 -0.030913 -0.289758  1.318467
2000-01-05  1.025903  0.195796  0.030198 -0.349406

In [430]: wp.major_xs(wp.major_axis[2])
Out[430]:
      Item1     Item2     Item3
A  0.388741  1.076202  0.361216
B -1.284588 -0.464905  2.763121
C -0.508030  0.432658 -1.174206
D  0.841173 -0.623043 -1.350105

In [431]: wp.minor_axis
Out[431]: Index([A, B, C, D], dtype=object)

In [432]: wp.minor_xs('C')
Out[432]:
                Item1     Item2     Item3
2000-01-01 -0.491067 -0.530157  0.926267
2000-01-02 -1.076283 -0.692498  1.554205
2000-01-03 -0.508030  0.432658 -1.174206
2000-01-04 -0.289758  1.771692 -0.163549
2000-01-05  0.030198 -0.016490 -1.831272
```

### 5.3.7 Conversion to DataFrame

A Panel can be represented in 2D form as a hierarchically indexed DataFrame. See the section *hierarchical indexing* for more on this. To convert a Panel to a DataFrame, use the `to_frame` method:

```
In [433]: panel = Panel(np.random.randn(3, 5, 4), items=['one', 'two', 'three'],
   .....:               major_axis=date_range('1/1/2000', periods=5),
   .....:               minor_axis=['a', 'b', 'c', 'd'])
   .....:

In [434]: panel.to_frame()
Out[434]:
                       one       two     three
major      minor
2000-01-01 a      1.219834 -0.842503  1.130688
           b     -0.185793 -0.585949  1.348831
           c     -1.016665 -0.864916 -0.709279
           d      0.170971  0.031573 -0.125291
2000-01-02 a      0.411316 -1.170645 -1.746865
           b     -0.773663 -0.655575 -0.802833
           c     -0.028610 -1.297237 -0.824150
           d      0.532592 -1.739996 -0.056603
2000-01-03 a      0.579638 -0.093661  1.443225
           b     -1.514892  0.873783 -1.013384
           c      1.528058 -1.803206 -0.591932
           d      0.954347 -0.134374  0.679775
2000-01-04 a     -0.635819 -0.100241 -0.921819
```

```
           b      0.009356  0.837864 -0.549326
           c     -1.639594  1.326922  0.273431
           d     -0.699057  1.224153 -0.189170
2000-01-05 a     -1.027240 -0.856153 -1.699029
           b     -0.489779 -0.038563  0.589825
           c      0.046080  0.521149 -0.065580
           d     -0.104689 -1.270389  0.877266
```

## 5.4 Panel4D (Experimental)

`Panel4D` is a 4-Dimensional named container very much like a `Panel`, but having 4 named dimensions. It is intended as a test bed for more N-Dimensional named containers.

- **labels**: axis 0, each item corresponds to a Panel contained inside
- **items**: axis 1, each item corresponds to a DataFrame contained inside
- **major_axis**: axis 2, it is the **index** (rows) of each of the DataFrames
- **minor_axis**: axis 3, it is the **columns** of each of the DataFrames

`Panel4D` is a sub-class of `Panel`, so most methods that work on Panels are applicable to Panel4D. The following methods are disabled:

- `join , to_frame , to_excel , to_sparse , groupby`

Construction of Panel4D works in a very similar manner to a `Panel`

### 5.4.1 From 4D ndarray with optional axis labels

```
In [435]: p4d = Panel4D(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 [436]: p4d
Out[436]:
<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
```

### 5.4.2 From dict of Panel objects

```
In [437]: data = { 'Label1' : Panel({ 'Item1' : DataFrame(randn(4, 3)) }),
   .....:          'Label2' : Panel({ 'Item2' : DataFrame(randn(4, 2)) }) }
   .....:

In [438]: Panel4D(data)
Out[438]:
<class 'pandas.core.panelnd.Panel4D'>
```

```
Dimensions: 2 (labels) x 2 (items) x 4 (major_axis) x 3 (minor_axis)
Labels axis: Label1 to Label2
Items axis: Item1 to Item2
Major_axis axis: 0 to 3
Minor_axis axis: 0 to 2
```

Note that the values in the dict need only be **convertible to Panels**. Thus, they can be any of the other valid inputs to Panel as per above.

### 5.4.3 Slicing

Slicing works in a similar manner to a Panel. `[]` slices the first dimension. `.ix` allows you to slice abitrarily and get back lower dimensional objects

```
In [439]: p4d['Label1']
Out[439]:
<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
```

4D -> Panel

```
In [440]: p4d.ix[:,:,:,'A']
Out[440]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 2 (major_axis) x 5 (minor_axis)
Items axis: Label1 to Label2
Major_axis axis: Item1 to Item2
Minor_axis axis: 2000-01-01 00:00:00 to 2000-01-05 00:00:00
```

4D -> DataFrame

```
In [441]: p4d.ix[:,:,0,'A']
Out[441]:
         Label1    Label2
Item1  2.301716 -0.045494
Item2  1.454477  1.420470
```

4D -> Series

```
In [442]: p4d.ix[:,0,0,'A']
Out[442]:
Label1    2.301716
Label2   -0.045494
Name: A, dtype: float64
```

### 5.4.4 Transposing

A Panel4D can be rearranged using its `transpose` method (which does not make a copy by default unless the data are heterogeneous):

```
In [443]: p4d.transpose(3, 2, 1, 0)
Out[443]:
<class 'pandas.core.panelnd.Panel4D'>
Dimensions: 4 (labels) x 5 (items) x 2 (major_axis) x 2 (minor_axis)
```

```
Labels axis: A to D
Items axis: 2000-01-01 00:00:00 to 2000-01-05 00:00:00
Major_axis axis: Item1 to Item2
Minor_axis axis: Label1 to Label2
```

## 5.5 PanelND (Experimental)

PanelND is a module with a set of factory functions to enable a user to construct N-dimensional named containers like Panel4D, with a custom set of axis labels. Thus a domain-specific container can easily be created.

The following creates a Panel5D. A new panel type object must be sliceable into a lower dimensional object. Here we slice to a Panel4D.

```
In [444]: from pandas.core import panelnd

In [445]: Panel5D = panelnd.create_nd_panel_factory(
   .....:     klass_name   = 'Panel5D',
   .....:     axis_orders  = [ 'cool', 'labels','items','major_axis','minor_axis'],
   .....:     axis_slices  = { 'labels' : 'labels', 'items' : 'items',
   .....:                      'major_axis' : 'major_axis', 'minor_axis' : 'minor_axis' },
   .....:     slicer       = Panel4D,
   .....:     axis_aliases = { 'major' : 'major_axis', 'minor' : 'minor_axis' },
   .....:     stat_axis    = 2)
   .....:

In [446]: p5d = Panel5D(dict(C1 = p4d))

In [447]: p5d
Out[447]:
<class 'pandas.core.panelnd.Panel5D'>
Dimensions: 1 (cool) x 2 (labels) x 2 (items) x 5 (major_axis) x 4 (minor_axis)
Cool axis: C1 to C1
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

# print a slice of our 5D
In [448]: p5d.ix['C1',:,:,0:3,:]
Out[448]:
<class 'pandas.core.panelnd.Panel4D'>
Dimensions: 2 (labels) x 2 (items) x 3 (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 2000-01-03 00:00:00
Minor_axis axis: A to D

# transpose it
In [449]: p5d.transpose(1,2,3,4,0)
Out[449]:
<class 'pandas.core.panelnd.Panel5D'>
Dimensions: 2 (cool) x 2 (labels) x 5 (items) x 4 (major_axis) x 1 (minor_axis)
Cool axis: Label1 to Label2
Labels axis: Item1 to Item2
Items axis: 2000-01-01 00:00:00 to 2000-01-05 00:00:00
Major_axis axis: A to D
```

```
Minor_axis axis: C1 to C1

# look at the shape & dim
In [450]: p5d.shape
Out[450]: [1, 2, 2, 5, 4]

In [451]: p5d.ndim
Out[451]: 5
```

CHAPTER

SIX

# ESSENTIAL BASIC FUNCTIONALITY

Here we discuss a lot of the essential functionality common to the pandas data structures. Here's how to create some of the objects used in the examples from the previous section:

```
In [1]: index = date_range('1/1/2000', periods=8)

In [2]: s = Series(randn(5), index=['a', 'b', 'c', 'd', 'e'])

In [3]: df = DataFrame(randn(8, 3), index=index,
   ...:                columns=['A', 'B', 'C'])
   ...:

In [4]: wp = Panel(randn(2, 5, 4), items=['Item1', 'Item2'],
   ...:            major_axis=date_range('1/1/2000', periods=5),
   ...:            minor_axis=['A', 'B', 'C', 'D'])
   ...:
```

## 6.1 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 [5]: long_series = Series(randn(1000))

In [6]: long_series.head()
Out[6]:
0    1.162813
1    0.870161
2    2.792723
3    0.776395
4   -1.181190
dtype: float64

In [7]: long_series.tail(3)
Out[7]:
997    0.545698
998    0.008194
999    1.452061
dtype: float64
```

## 6.2 Attributes and the raw ndarray(s)

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*
  - **Panel**: *items*, *major_axis*, and *minor_axis*

Note, **these attributes can be safely assigned to**!

```
In [8]: df[:2]
Out[8]:
                   A         B         C
2000-01-01 -1.007761  0.561990  0.560802
2000-01-02  0.770819 -0.972052  0.896288

In [9]: df.columns = [x.lower() for x in df.columns]

In [10]: df
Out[10]:
                   a         b         c
2000-01-01 -1.007761  0.561990  0.560802
2000-01-02  0.770819 -0.972052  0.896288
2000-01-03 -0.718942  0.329576  1.169925
2000-01-04  0.958928 -0.935316 -0.827036
2000-01-05 -1.240656  0.834546 -0.160635
2000-01-06 -3.590370 -1.247926 -1.445820
2000-01-07 -0.042194  0.906744 -0.471145
2000-01-08 -0.256360 -0.098316 -0.770393
```

To get the actual data inside a data structure, one need only access the **values** property:

```
In [11]: s.values
Out[11]: array([-0.5347, -0.0236, -0.9306, -0.2505, -0.1546])

In [12]: df.values
Out[12]:
array([[-1.0078,  0.562 ,  0.5608],
       [ 0.7708, -0.9721,  0.8963],
       [-0.7189,  0.3296,  1.1699],
       [ 0.9589, -0.9353, -0.827 ],
       [-1.2407,  0.8345, -0.1606],
       [-3.5904, -1.2479, -1.4458],
       [-0.0422,  0.9067, -0.4711],
       [-0.2564, -0.0983, -0.7704]])

In [13]: wp.values
Out[13]:
array([[[-0.5695,  0.917 ,  0.4495, -0.8452],
        [-0.5009,  0.4569,  0.4477,  0.2638],
        [ 1.3112, -0.0522,  0.508 , -0.7318],
        [-2.1767, -0.5234, -0.2092, -0.1431],
        [-1.0446,  0.5449,  0.0648,  0.4873]],
       [[ 0.0002, -1.3767, -0.7805,  0.6007],
        [-0.8252,  0.4755,  0.7108, -1.3615],
```

```
       [-0.4196, -0.701 , -1.3045, -0.2533],
       [ 0.0741, -1.3842, -0.5871, -0.3562],
       [ 1.8788,  1.788 , -1.2921, -0.2672]]])
```

If a DataFrame or Panel 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.

## 6.3 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.

### 6.3.1 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 [14]: d = {'one' : Series(randn(3), index=['a', 'b', 'c']),
   ....:      'two' : Series(randn(4), index=['a', 'b', 'c', 'd']),
   ....:      'three' : Series(randn(3), index=['b', 'c', 'd'])}
   ....:

In [15]: df = DataFrame(d)

In [16]: df
Out[16]:
        one     three       two
a  0.133865       NaN -0.352795
b -0.319644 -1.325203  0.934622
c  1.083374  0.512254 -1.658054
d       NaN -0.019298  1.929479

In [17]: row = df.ix[1]

In [18]: column = df['two']

In [19]: df.sub(row, axis='columns')
Out[19]:
        one     three       two
a  0.453509       NaN -1.287417
b  0.000000  0.000000  0.000000
c  1.403018  1.837457 -2.592677
d       NaN  1.305906  0.994857
```

```
In [20]: df.sub(row, axis=1)
Out[20]:
        one     three       two
a  0.453509       NaN -1.287417
b  0.000000  0.000000  0.000000
c  1.403018  1.837457 -2.592677
d       NaN  1.305906  0.994857

In [21]: df.sub(column, axis='index')
Out[21]:
        one     three  two
a  0.486660       NaN    0
b -1.254266 -2.259826    0
c  2.741429  2.170308    0
d       NaN -1.948777    0

In [22]: df.sub(column, axis=0)
Out[22]:
        one     three  two
a  0.486660       NaN    0
b -1.254266 -2.259826    0
c  2.741429  2.170308    0
d       NaN -1.948777    0
```

With Panel, describing the matching behavior is a bit more difficult, so the arithmetic methods instead (and perhaps confusingly?) give you the option to specify the *broadcast axis*. For example, suppose we wished to demean the data over a particular axis. This can be accomplished by taking the mean over an axis and broadcasting over the same axis:

```
In [23]: major_mean = wp.mean(axis='major')

In [24]: major_mean
Out[24]:
      Item1     Item2
A -0.596094  0.141658
B  0.268630 -0.239671
C  0.252154 -0.650685
D -0.193792 -0.327499

In [25]: wp.sub(major_mean, axis='major')
Out[25]:
<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
```

And similarly for `axis="items"` and `axis="minor"`.

---

**Note:** I could be convinced to make the **axis** argument in the DataFrame methods match the broadcasting behavior of Panel. Though it would require a transition period so users can change their code...

---

### 6.3.2 Missing data / operations with fill values

In Series and DataFrame (though not yet in Panel), 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 [26]: df
Out[26]:
        one     three       two
a  0.133865       NaN -0.352795
b -0.319644 -1.325203  0.934622
c  1.083374  0.512254 -1.658054
d       NaN -0.019298  1.929479

In [27]: df2
Out[27]:
        one     three       two
a  0.133865  1.000000 -0.352795
b -0.319644 -1.325203  0.934622
c  1.083374  0.512254 -1.658054
d       NaN -0.019298  1.929479

In [28]: df + df2
Out[28]:
        one     three       two
a  0.267730       NaN -0.705590
b -0.639288 -2.650407  1.869244
c  2.166748  1.024507 -3.316109
d       NaN -0.038595  3.858958

In [29]: df.add(df2, fill_value=0)
Out[29]:
        one     three       two
a  0.267730  1.000000 -0.705590
b -0.639288 -2.650407  1.869244
c  2.166748  1.024507 -3.316109
d       NaN -0.038595  3.858958
```

### 6.3.3 Flexible Comparisons

Starting in v0.8, pandas introduced binary comparison methods eq, ne, lt, gt, le, and ge to Series and DataFrame whose behavior is analogous to the binary arithmetic operations described above:

```
In [30]: df.gt(df2)
Out[30]:
     one  three    two
a  False  False  False
b  False  False  False
c  False  False  False
d  False  False  False

In [31]: df2.ne(df)
Out[31]:
     one  three    two
a  False   True  False
b  False  False  False
c  False  False  False
d   True  False  False
```

### 6.3.4 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 [32]: df1 = DataFrame({'A' : [1., np.nan, 3., 5., np.nan],
   ....:                  'B' : [np.nan, 2., 3., np.nan, 6.]})
   ....:

In [33]: df2 = DataFrame({'A' : [5., 2., 4., np.nan, 3., 7.],
   ....:                  'B' : [np.nan, np.nan, 3., 4., 6., 8.]})
   ....:

In [34]: df1
Out[34]:
    A   B
0   1 NaN
1 NaN   2
2   3   3
3   5 NaN
4 NaN   6

In [35]: df2
Out[35]:
    A   B
0   5 NaN
1   2 NaN
2   4   3
3 NaN   4
4   3   6
5   7   8

In [36]: df1.combine_first(df2)
Out[36]:
   A   B
0  1 NaN
1  2   2
2  3   3
3  5   4
4  3   6
5  7   8
```

### 6.3.5 General DataFrame Combine

The `combine_first` method above calls the more general DataFrame method `combine`. This method takes another DataFrame and a combiner function, aligns the input DataFrame and then passes the combiner function pairs of Series (ie, columns whose names are the same).

So, for instance, to reproduce `combine_first` as above:

```
In [37]: combiner = lambda x, y: np.where(isnull(x), y, x)

In [38]: df1.combine(df2, combiner)
```

```
Out[38]:
   A   B
0  1 NaN
1  2   2
2  3   3
3  5   4
4  3   6
5  7   8
```

## 6.4 Descriptive statistics

A large number of methods for computing descriptive statistics and other related operations on *Series*, *DataFrame*, and *Panel*. 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)
- **Panel**: "items" (axis=0), "major" (axis=1, default), "minor" (axis=2)

For example:

```
In [39]: df
Out[39]:
        one     three       two
a  0.133865       NaN -0.352795
b -0.319644 -1.325203  0.934622
c  1.083374  0.512254 -1.658054
d       NaN -0.019298  1.929479

In [40]: df.mean(0)
Out[40]:
one      0.299198
three   -0.277416
two      0.213313
dtype: float64

In [41]: df.mean(1)
Out[41]:
a   -0.109465
b   -0.236742
c   -0.020809
d    0.955091
dtype: float64
```

All such methods have a `skipna` option signaling whether to exclude missing data (`True` by default):

```
In [42]: df.sum(0, skipna=False)
Out[42]:
one           NaN
three         NaN
two      0.853252
dtype: float64

In [43]: df.sum(axis=1, skipna=True)
Out[43]:
```

```
a   -0.218930
b   -0.710225
c   -0.062427
d    1.910181
dtype: float64
```

Combined with the broadcasting / arithmetic behavior, one can describe various statistical procedures, like standardization (rendering data zero mean and standard deviation 1), very concisely:

```
In [44]: ts_stand = (df - df.mean()) / df.std()

In [45]: ts_stand.std()
Out[45]:
one      1
three    1
two      1
dtype: float64

In [46]: xs_stand = df.sub(df.mean(1), axis=0).div(df.std(1), axis=0)

In [47]: xs_stand.std(1)
Out[47]:
a    1
b    1
c    1
d    1
dtype: float64
```

Note that methods like **cumsum** and **cumprod** preserve the location of NA values:

```
In [48]: df.cumsum()
Out[48]:
        one     three       two
a  0.133865       NaN -0.352795
b -0.185779 -1.325203  0.581827
c  0.897595 -0.812950 -1.076228
d       NaN -0.832247  0.853252
```

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-null observations |
| sum | Sum of values |
| mean | Mean of values |
| mad | Mean absolute deviation |
| median | Arithmetic median of values |
| min | Minimum |
| max | Maximum |
| abs | Absolute Value |
| prod | Product of values |
| std | Unbiased standard deviation |
| var | Unbiased variance |
| skew | Unbiased skewness (3rd moment) |
| kurt | Unbiased 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 [49]: np.mean(df['one'])
Out[49]: 0.29919834342181954

In [50]: np.mean(df['one'].values)
Out[50]: nan
```

`Series` also has a method `nunique` which will return the number of unique non-null values:

```
In [51]: series = Series(randn(500))

In [52]: series[20:500] = np.nan

In [53]: series[10:20]  = 5

In [54]: series.nunique()
Out[54]: 11
```

### 6.4.1 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 [55]: series = Series(randn(1000))

In [56]: series[::2] = np.nan

In [57]: series.describe()
Out[57]:
count    500.000000
mean      -0.007877
std        0.911618
min       -2.400248
25%       -0.659261
50%        0.023054
```

```
75%         0.610466
max         2.548590
dtype: float64

In [58]: frame = DataFrame(randn(1000, 5), columns=['a', 'b', 'c', 'd', 'e'])

In [59]: frame.ix[::2] = np.nan

In [60]: frame.describe()
Out[60]:
                a           b           c           d           e
count  500.000000  500.000000  500.000000  500.000000  500.000000
mean     0.027404   -0.062202   -0.085482    0.047872    0.040049
std      1.009556    0.934708    1.020247    0.997085    0.981213
min     -2.820839   -2.629643   -2.907401   -2.678674   -2.439790
25%     -0.699926   -0.660646   -0.746925   -0.646927   -0.580899
50%      0.037665   -0.062781   -0.029457   -0.020508    0.016222
75%      0.708078    0.533449    0.571614    0.769260    0.731781
max      3.169764    2.790953    3.218046    2.766216    2.978102
```

For a non-numerical Series object, *describe* will give a simple summary of the number of unique values and most frequently occurring values:

```
In [61]: s = Series(['a', 'a', 'b', 'b', 'a', 'a', np.nan, 'c', 'd', 'a'])

In [62]: s.describe()
Out[62]:
count     9
unique    4
top       a
freq      5
dtype: object
```

There also is a utility function, `value_range` which takes a DataFrame and returns a series with the minimum/maximum values in the DataFrame.

### 6.4.2 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 [63]: s1 = Series(randn(5))

In [64]: s1
Out[64]:
0    0.190816
1    1.570470
2    0.579992
3   -0.570663
4    0.653770
dtype: float64

In [65]: s1.idxmin(), s1.idxmax()
Out[65]: (3, 1)

In [66]: df1 = DataFrame(randn(5,3), columns=['A','B','C'])
```

```
In [67]: df1
Out[67]:
          A         B         C
0  0.010475 -1.886886  0.703759
1  0.567838  0.954075  0.283241
2  0.156650 -1.192535 -1.015856
3  0.413254 -0.530874  0.030274
4 -0.298383 -0.866317 -0.725995

In [68]: df1.idxmin(axis=0)
Out[68]:
A    4
B    0
C    2
dtype: int64

In [69]: df1.idxmax(axis=1)
Out[69]:
0    C
1    B
2    A
3    A
4    A
dtype: object
```

When there are multiple rows (or columns) matching the minimum or maximum value, `idxmin` and `idxmax` return the first matching index:

```
In [70]: df3 = DataFrame([2, 1, 1, 3, np.nan], columns=['A'], index=list('edcba'))

In [71]: df3
Out[71]:
    A
e   2
d   1
c   1
b   3
a NaN

In [72]: df3['A'].idxmin()
Out[72]: 'd'
```

### 6.4.3 Value counts (histogramming)

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 [73]: data = np.random.randint(0, 7, size=50)

In [74]: data
Out[74]:
array([2, 3, 1, 4, 0, 4, 0, 2, 3, 0, 3, 3, 4, 3, 0, 3, 6, 6, 0, 6, 2, 0, 0,
       0, 6, 2, 0, 2, 4, 2, 3, 0, 6, 5, 1, 6, 3, 6, 6, 4, 2, 3, 1, 6, 5, 5,
       2, 0, 4, 5])

In [75]: s = Series(data)
```

```
In [76]: s.value_counts()
Out[76]:
0    11
6     9
3     9
2     8
4     6
5     4
1     3
dtype: int64

In [77]: value_counts(data)
Out[77]:
0    11
6     9
3     9
2     8
4     6
5     4
1     3
dtype: int64
```

### 6.4.4 Discretization and quantiling

Continuous values can be discretized using the `cut` (bins based on values) and `qcut` (bins based on sample quantiles) functions:

```
In [78]: arr = np.random.randn(20)

In [79]: factor = cut(arr, 4)

In [80]: factor
Out[80]:
Categorical:
array([(-1.841, -0.823], (-0.823, 0.19], (0.19, 1.204], (0.19, 1.204],
       (1.204, 2.218], (-1.841, -0.823], (-1.841, -0.823], (0.19, 1.204],
       (0.19, 1.204], (0.19, 1.204], (-0.823, 0.19], (-1.841, -0.823],
       (-0.823, 0.19], (0.19, 1.204], (-0.823, 0.19], (1.204, 2.218],
       (1.204, 2.218], (-0.823, 0.19], (-1.841, -0.823], (-0.823, 0.19]], dtype=object)
Levels (4): Index([(-1.841, -0.823], (-0.823, 0.19], (0.19, 1.204],
                   (1.204, 2.218]], dtype=object)

In [81]: factor = cut(arr, [-5, -1, 0, 1, 5])

In [82]: factor
Out[82]:
Categorical:
array([(-5, -1], (-1, 0], (0, 1], (0, 1], (1, 5], (-5, -1], (-1, 0],
       (0, 1], (1, 5], (0, 1], (-1, 0], (-5, -1], (-1, 0], (0, 1], (-1, 0],
       (1, 5], (1, 5], (-1, 0], (-5, -1], (0, 1]], dtype=object)
Levels (4): Index([(-5, -1], (-1, 0], (0, 1], (1, 5]], dtype=object)
```

`qcut` computes sample quantiles. For example, we could slice up some normally distributed data into equal-size quartiles like so:

```
In [83]: arr = np.random.randn(30)
```

```
In [84]: factor = qcut(arr, [0, .25, .5, .75, 1])

In [85]: factor
Out[85]:
Categorical:
array([(-0.145, 0.333], (-0.591, -0.145], (0.333, 1.453], (-0.145, 0.333],
       (-0.591, -0.145], [-2.506, -0.591], [-2.506, -0.591],
       (0.333, 1.453], (0.333, 1.453], (-0.145, 0.333], (-0.591, -0.145],
       [-2.506, -0.591], [-2.506, -0.591], [-2.506, -0.591],
       (-0.591, -0.145], (-0.145, 0.333], (0.333, 1.453], (0.333, 1.453],
       (-0.591, -0.145], (0.333, 1.453], [-2.506, -0.591], (-0.145, 0.333],
       (-0.145, 0.333], (0.333, 1.453], (-0.591, -0.145], [-2.506, -0.591],
       (-0.591, -0.145], (-0.145, 0.333], (0.333, 1.453], [-2.506, -0.591]], dtype=object)
Levels (4): Index([[-2.506, -0.591], (-0.591, -0.145], (-0.145, 0.333],
                   (0.333, 1.453]], dtype=object)

In [86]: value_counts(factor)
Out[86]:
(0.333, 1.453]      8
[-2.506, -0.591]    8
(-0.145, 0.333]     7
(-0.591, -0.145]    7
dtype: int64
```

## 6.5 Function application

Arbitrary functions can be applied along the axes of a DataFrame or Panel using the `apply` method, which, like the descriptive statistics methods, take an optional `axis` argument:

```
In [87]: df.apply(np.mean)
Out[87]:
one      0.299198
three   -0.277416
two      0.213313
dtype: float64

In [88]: df.apply(np.mean, axis=1)
Out[88]:
a   -0.109465
b   -0.236742
c   -0.020809
d    0.955091
dtype: float64

In [89]: df.apply(lambda x: x.max() - x.min())
Out[89]:
one      1.403018
three    1.837457
two      3.587534
dtype: float64

In [90]: df.apply(np.cumsum)
Out[90]:
        one     three       two
a  0.133865       NaN -0.352795
b -0.185779 -1.325203  0.581827
```

```
c  0.897595 -0.812950 -1.076228
d       NaN -0.832247  0.853252

In [91]: df.apply(np.exp)
Out[91]:
        one     three       two
a  1.143239       NaN  0.702721
b  0.726408  0.265749  2.546251
c  2.954632  1.669048  0.190509
d       NaN  0.980887  6.885923
```

Depending on the return type of the function passed to `apply`, the result will either be of lower dimension or the same dimension.

`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 [92]: tsdf = DataFrame(randn(1000, 3), columns=['A', 'B', 'C'],
   ....:                  index=date_range('1/1/2000', periods=1000))
   ....:

In [93]: tsdf.apply(lambda x: x.index[x.dropna().argmax()])
Out[93]:
A   2000-11-22 00:00:00
B   2001-09-03 00:00:00
C   2002-05-01 00:00:00
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 [94]: tsdf
Out[94]:
                   A         B         C
2000-01-01  1.162731  0.246389 -0.834775
2000-01-02  1.434571  1.158517  1.031740
2000-01-03 -0.187711 -0.206570  1.435722
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  1.378860 -1.534015  0.464984
2000-01-09  0.494635 -0.344982 -0.178994
2000-01-10  0.369649 -0.345704 -1.047580

In [95]: tsdf.apply(Series.interpolate)
Out[95]:
                   A         B         C
2000-01-01  1.162731  0.246389 -0.834775
2000-01-02  1.434571  1.158517  1.031740
2000-01-03 -0.187711 -0.206570  1.435722
```

```
2000-01-04  0.125603 -0.472059  1.241574
2000-01-05  0.438917 -0.737548  1.047427
2000-01-06  0.752232 -1.003037  0.853279
2000-01-07  1.065546 -1.268526  0.659131
2000-01-08  1.378860 -1.534015  0.464984
2000-01-09  0.494635 -0.344982 -0.178994
2000-01-10  0.369649 -0.345704 -1.047580
```

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.

**See Also:**

The section on *GroupBy* demonstrates related, flexible functionality for grouping by some criterion, applying, and combining the results into a Series, DataFrame, etc.

### 6.5.1 Applying elementwise Python 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 [96]: f = lambda x: len(str(x))

In [97]: df['one'].map(f)
Out[97]:
a    14
b    15
c    13
d     3
Name: one, dtype: int64

In [98]: df.applymap(f)
Out[98]:
   one  three  two
a   14      3   15
b   15     14   13
c   13     14   14
d    3     16   13
```

`Series.map` has an additional feature which is that it can be used to easily "link" or "map" values defined by a secondary series. This is closely related to *merging/joining functionality*:

```
In [99]: s = Series(['six', 'seven', 'six', 'seven', 'six'],
   ....:            index=['a', 'b', 'c', 'd', 'e'])
   ....:

In [100]: t = Series({'six' : 6., 'seven' : 7.})

In [101]: s
Out[101]:
a      six
b    seven
c      six
d    seven
e      six
dtype: object
```

```
In [102]: s.map(t)
Out[102]:
a    6
b    7
c    6
d    7
e    6
dtype: float64
```

## 6.6 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 [103]: s = Series(randn(5), index=['a', 'b', 'c', 'd', 'e'])

In [104]: s
Out[104]:
a    1.143520
b    0.143515
c    1.717025
d   -0.366994
e   -1.255767
dtype: float64

In [105]: s.reindex(['e', 'b', 'f', 'd'])
Out[105]:
e   -1.255767
b    0.143515
f         NaN
d   -0.366994
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 [106]: df
Out[106]:
        one     three       two
a  0.133865       NaN -0.352795
b -0.319644 -1.325203  0.934622
c  1.083374  0.512254 -1.658054
d       NaN -0.019298  1.929479

In [107]: df.reindex(index=['c', 'f', 'b'], columns=['three', 'two', 'one'])
Out[107]:
      three       two       one
```

```
c  0.512254 -1.658054  1.083374
f       NaN       NaN       NaN
b -1.325203  0.934622 -0.319644
```

For convenience, you may utilize the `reindex_axis` method, which takes the labels and a keyword `axis` parameter.

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 [108]: rs = s.reindex(df.index)

In [109]: rs
Out[109]:
a    1.143520
b    0.143515
c    1.717025
d   -0.366994
dtype: float64

In [110]: rs.index is df.index
Out[110]: True
```

This means that the reindexed Series's index is the same Python object as the DataFrame's index.

**See Also:**

*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 sprinking a few explicit `reindex` calls here and there can have an impact.

---

### 6.6.1 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 [111]: df
Out[111]:
        one     three       two
a  0.133865       NaN -0.352795
b -0.319644 -1.325203  0.934622
c  1.083374  0.512254 -1.658054
d       NaN -0.019298  1.929479

In [112]: df2
Out[112]:
        one       two
a -0.165333  0.005947
b -0.618842  1.293365
c  0.784176 -1.299312

In [113]: df.reindex_like(df2)
Out[113]:
```

```
        one       two
a  0.133865 -0.352795
b -0.319644  0.934622
c  1.083374 -1.658054
```

### 6.6.2 Reindexing with `reindex_axis`

### 6.6.3 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
- `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 [114]: s = Series(randn(5), index=['a', 'b', 'c', 'd', 'e'])

In [115]: s1 = s[:4]

In [116]: s2 = s[1:]

In [117]: s1.align(s2)
Out[117]:
(a    0.615848
b   -0.016043
c   -1.447277
d    0.946345
e         NaN
dtype: float64,
 a         NaN
b   -0.016043
c   -1.447277
d    0.946345
e    0.723322
dtype: float64)

In [118]: s1.align(s2, join='inner')
Out[118]:
(b   -0.016043
c   -1.447277
d    0.946345
dtype: float64,
 b   -0.016043
c   -1.447277
d    0.946345
dtype: float64)

In [119]: s1.align(s2, join='left')
Out[119]:
(a    0.615848
b   -0.016043
```

```
c   -1.447277
d    0.946345
dtype: float64,
 a         NaN
b   -0.016043
c   -1.447277
d    0.946345
dtype: float64)
```

For DataFrames, the join method will be applied to both the index and the columns by default:

```
In [120]: df.align(df2, join='inner')
Out[120]:
(        one       two
a  0.133865 -0.352795
b -0.319644  0.934622
c  1.083374 -1.658054,
        one       two
a -0.165333  0.005947
b -0.618842  1.293365
c  0.784176 -1.299312)
```

You can also pass an `axis` option to only align on the specified axis:

```
In [121]: df.align(df2, join='inner', axis=0)
Out[121]:
(        one     three       two
a  0.133865       NaN -0.352795
b -0.319644 -1.325203  0.934622
c  1.083374  0.512254 -1.658054,
        one       two
a -0.165333  0.005947
b -0.618842  1.293365
c  0.784176 -1.299312)
```

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 [122]: df.align(df2.ix[0], axis=1)
Out[122]:
(        one     three       two
a  0.133865       NaN -0.352795
b -0.319644 -1.325203  0.934622
c  1.083374  0.512254 -1.658054
d       NaN -0.019298  1.929479,
 one     -0.165333
three         NaN
two      0.005947
Name: a, dtype: float64)
```

### 6.6.4 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 |

Other fill methods could be added, of course, but these are the two most commonly used for time series data. In a way they only make sense for time series or otherwise ordered data, but you may have an application on non-time series data where this sort of "interpolation" logic is the correct thing to do. More sophisticated interpolation of missing values would be an obvious extension.

We illustrate these fill methods on a simple TimeSeries:

```
In [123]: rng = date_range('1/3/2000', periods=8)

In [124]: ts = Series(randn(8), index=rng)

In [125]: ts2 = ts[[0, 3, 6]]

In [126]: ts
Out[126]:
2000-01-03    0.990340
2000-01-04   -0.070005
2000-01-05   -0.157860
2000-01-06    0.233077
2000-01-07    0.475897
2000-01-08   -1.029480
2000-01-09   -1.079405
2000-01-10   -0.079334
Freq: D, dtype: float64

In [127]: ts2
Out[127]:
2000-01-03    0.990340
2000-01-06    0.233077
2000-01-09   -1.079405
dtype: float64

In [128]: ts2.reindex(ts.index)
Out[128]:
2000-01-03    0.990340
2000-01-04         NaN
2000-01-05         NaN
2000-01-06    0.233077
2000-01-07         NaN
2000-01-08         NaN
2000-01-09   -1.079405
2000-01-10         NaN
Freq: D, dtype: float64

In [129]: ts2.reindex(ts.index, method='ffill')
Out[129]:
2000-01-03    0.990340
2000-01-04    0.990340
2000-01-05    0.990340
2000-01-06    0.233077
2000-01-07    0.233077
2000-01-08    0.233077
2000-01-09   -1.079405
2000-01-10   -1.079405
Freq: D, dtype: float64

In [130]: ts2.reindex(ts.index, method='bfill')
Out[130]:
2000-01-03    0.990340
```

```
2000-01-04    0.233077
2000-01-05    0.233077
2000-01-06    0.233077
2000-01-07   -1.079405
2000-01-08   -1.079405
2000-01-09   -1.079405
2000-01-10         NaN
Freq: D, dtype: float64
```

Note the same result could have been achieved using *fillna*:

```
In [131]: ts2.reindex(ts.index).fillna(method='ffill')
Out[131]:
2000-01-03    0.990340
2000-01-04    0.990340
2000-01-05    0.990340
2000-01-06    0.233077
2000-01-07    0.233077
2000-01-08    0.233077
2000-01-09   -1.079405
2000-01-10   -1.079405
Freq: D, dtype: float64
```

Note these methods generally assume that the indexes are **sorted**. They may be modified in the future to be a bit more flexible but as time series data is ordered most of the time anyway, this has not been a major priority.

### 6.6.5 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 [132]: df
Out[132]:
        one     three       two
a  0.133865       NaN -0.352795
b -0.319644 -1.325203  0.934622
c  1.083374  0.512254 -1.658054
d       NaN -0.019298  1.929479

In [133]: df.drop(['a', 'd'], axis=0)
Out[133]:
        one     three       two
b -0.319644 -1.325203  0.934622
c  1.083374  0.512254 -1.658054

In [134]: df.drop(['one'], axis=1)
Out[134]:
      three       two
a       NaN -0.352795
b -1.325203  0.934622
c  0.512254 -1.658054
d -0.019298  1.929479
```

Note that the following also works, but is a bit less obvious / clean:

```
In [135]: df.reindex(df.index - ['a', 'd'])
Out[135]:
        one     three       two
```

```
b -0.319644 -1.325203  0.934622
c  1.083374  0.512254 -1.658054
```

### 6.6.6 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 [136]: s
Out[136]:
a    0.615848
b   -0.016043
c   -1.447277
d    0.946345
e    0.723322
dtype: float64

In [137]: s.rename(str.upper)
Out[137]:
A    0.615848
B   -0.016043
C   -1.447277
D    0.946345
E    0.723322
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). But if you pass a dict or Series, it need only contain a subset of the labels as keys:

```
In [138]: df.rename(columns={'one' : 'foo', 'two' : 'bar'},
   .....:           index={'a' : 'apple', 'b' : 'banana', 'd' : 'durian'})
   .....:
Out[138]:
             foo     three       bar
apple   0.133865       NaN -0.352795
banana -0.319644 -1.325203  0.934622
c       1.083374  0.512254 -1.658054
durian       NaN -0.019298  1.929479
```

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. The Panel class has a related `rename_axis` class which can rename any of its three axes.

## 6.7 Iteration

Because Series is array-like, basic iteration produces the values. Other data structures follow the dict-like convention of iterating over the “keys” of the objects. In short:

- **Series**: values
- **DataFrame**: column labels
- **Panel**: item labels

Thus, for example:

```
In [139]: for col in df:
   .....:     print col
   .....:
one
three
two
```

### 6.7.1 iteritems

Consistent with the dict-like interface, **iteritems** iterates through key-value pairs:

- **Series**: (index, scalar value) pairs
- **DataFrame**: (column, Series) pairs
- **Panel**: (item, DataFrame) pairs

For example:

```
In [140]: for item, frame in wp.iteritems():
   .....:     print item
   .....:     print frame
   .....:
Item1
                   A         B         C         D
2000-01-01 -0.569502  0.916952  0.449538 -0.845226
2000-01-02 -0.500946  0.456865  0.447653  0.263834
2000-01-03  1.311241 -0.052172  0.508033 -0.731786
2000-01-04 -2.176710 -0.523424 -0.209228 -0.143088
2000-01-05 -1.044551  0.544929  0.064773  0.487304
Item2
                   A         B         C         D
2000-01-01  0.000200 -1.376720 -0.780456  0.600739
2000-01-02 -0.825227  0.475548  0.710782 -1.361472
2000-01-03 -0.419611 -0.700988 -1.304530 -0.253342
2000-01-04  0.074107 -1.384211 -0.587086 -0.356223
2000-01-05  1.878822  1.788014 -1.292132 -0.267198
```

### 6.7.2 iterrows

New in v0.7 is the ability to iterate efficiently through rows of a DataFrame. It returns an iterator yielding each index value along with a Series containing the data in each row:

```
In [141]: for row_index, row in df2.iterrows():
   .....:     print '%s\n%s' % (row_index, row)
   .....:
a
one   -0.165333
two    0.005947
Name: a, dtype: float64
b
one   -0.618842
two    1.293365
Name: b, dtype: float64
c
one    0.784176
```

```
two   -1.299312
Name: c, dtype: float64
```

For instance, a contrived way to transpose the dataframe would be:

```
In [142]: df2 = DataFrame({'x': [1, 2, 3], 'y': [4, 5, 6]})

In [143]: print df2
   x  y
0  1  4
1  2  5
2  3  6

In [144]: print df2.T
   0  1  2
x  1  2  3
y  4  5  6

In [145]: df2_t = DataFrame(dict((idx,values) for idx, values in df2.iterrows()))

In [146]: print df2_t
   0  1  2
x  1  2  3
y  4  5  6
```

### 6.7.3 itertuples

This method will return an iterator yielding a tuple 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 proper.

For instance,

```
In [147]: for r in df2.itertuples(): print r
(0, 1, 4)
(1, 2, 5)
(2, 3, 6)
```

## 6.8 Vectorized string methods

Series is equipped (as of pandas 0.8.1) 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) build-in string methods:

```
In [148]: s = Series(['A', 'B', 'C', 'Aaba', 'Baca', np.nan, 'CABA', 'dog', 'cat'])

In [149]: s.str.lower()
Out[149]:
0       a
1       b
2       c
3    aaba
4    baca
5     NaN
6    caba
```

```
7     dog
8     cat
dtype: object

In [150]: s.str.upper()
Out[150]:
0       A
1       B
2       C
3    AABA
4    BACA
5     NaN
6    CABA
7     DOG
8     CAT
dtype: object

In [151]: s.str.len()
Out[151]:
0     1
1     1
2     1
3     4
4     4
5   NaN
6     4
7     3
8     3
dtype: float64
```

Methods like `split` return a Series of lists:

```
In [152]: s2 = Series(['a_b_c', 'c_d_e', np.nan, 'f_g_h'])

In [153]: s2.str.split('_')
Out[153]:
0    [a, b, c]
1    [c, d, e]
2          NaN
3    [f, g, h]
dtype: object
```

Elements in the split lists can be accessed using `get` or `[]` notation:

```
In [154]: s2.str.split('_').str.get(1)
Out[154]:
0      b
1      d
2    NaN
3      g
dtype: object

In [155]: s2.str.split('_').str[1]
Out[155]:
0      b
1      d
2    NaN
3      g
dtype: object
```

Methods like `replace` and `findall` take regular expressions, too:

```
In [156]: s3 = Series(['A', 'B', 'C', 'Aaba', 'Baca',
   .....:              '', np.nan, 'CABA', 'dog', 'cat'])
   .....:

In [157]: s3
Out[157]:
0       A
1       B
2       C
3    Aaba
4    Baca
5
6     NaN
7    CABA
8     dog
9     cat
dtype: object

In [158]: s3.str.replace('^.a|dog', 'XX-XX ', case=False)
Out[158]:
0           A
1           B
2           C
3    XX-XX ba
4    XX-XX ca
5
6         NaN
7    XX-XX BA
8      XX-XX
9     XX-XX t
dtype: object
```

Methods like `contains`, `startswith`, and `endswith` takes an extra `na` arguement so missing values can be considered True or False:

```
In [159]: s4 = Series(['A', 'B', 'C', 'Aaba', 'Baca', np.nan, 'CABA', 'dog', 'cat'])

In [160]: s4.str.contains('A', na=False)
Out[160]:
0     True
1    False
2    False
3     True
4    False
5    False
6     True
7    False
8    False
dtype: bool
```

| Method | Description |
|---|---|
| cat | Concatenate strings |
| split | Split strings on delimiter |
| get | Index into each element (retrieve i-th element) |
| join | Join strings in each element of the Series with passed separator |
| contains | Return boolean array if each string contains pattern/regex |
| replace | Replace occurrences of pattern/regex with some other string |
| 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 `pad(side='both')` |
| 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 |
| endswidth | 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 |
| len | Compute string lengths |
| strip | Equivalent to `str.strip` |
| rstrip | Equivalent to `str.rstrip` |
| lstrip | Equivalent to `str.lstrip` |
| lower | Equivalent to `str.lower` |
| upper | Equivalent to `str.upper` |

## 6.9 Sorting by index and value

There are two obvious kinds of sorting that you may be interested in: sorting by label and sorting by actual values. The primary method for sorting axis labels (indexes) across data structures is the `sort_index` method.

```
In [161]: unsorted_df = df.reindex(index=['a', 'd', 'c', 'b'],
   .....:                          columns=['three', 'two', 'one'])
   .....:

In [162]: unsorted_df.sort_index()
Out[162]:
      three       two       one
a       NaN -0.352795  0.133865
b -1.325203  0.934622 -0.319644
c  0.512254 -1.658054  1.083374
d -0.019298  1.929479       NaN

In [163]: unsorted_df.sort_index(ascending=False)
Out[163]:
      three       two       one
d -0.019298  1.929479       NaN
c  0.512254 -1.658054  1.083374
b -1.325203  0.934622 -0.319644
a       NaN -0.352795  0.133865

In [164]: unsorted_df.sort_index(axis=1)
Out[164]:
        one     three       two
a  0.133865       NaN -0.352795
d       NaN -0.019298  1.929479
```

```
c  1.083374  0.512254 -1.658054
b -0.319644 -1.325203  0.934622
```

`DataFrame.sort_index` can accept an optional `by` argument for `axis=0` which will use an arbitrary vector or a column name of the DataFrame to determine the sort order:

```
In [165]: df.sort_index(by='two')
Out[165]:
        one     three       two
c  1.083374  0.512254 -1.658054
a  0.133865       NaN -0.352795
b -0.319644 -1.325203  0.934622
d       NaN -0.019298  1.929479
```

The `by` argument can take a list of column names, e.g.:

```
In [166]: df = DataFrame({'one':[2,1,1,1],'two':[1,3,2,4],'three':[5,4,3,2]})

In [167]: df[['one', 'two', 'three']].sort_index(by=['one','two'])
Out[167]:
   one  two  three
2    1    2      3
1    1    3      4
3    1    4      2
0    2    1      5
```

Series has the method `order` (analogous to R's order function) which sorts by value, with special treatment of NA values via the `na_last` argument:

```
In [168]: s[2] = np.nan

In [169]: s.order()
Out[169]:
0       A
3    Aaba
1       B
4    Baca
6    CABA
8     cat
7     dog
2     NaN
5     NaN
dtype: object

In [170]: s.order(na_last=False)
Out[170]:
2     NaN
5     NaN
0       A
3    Aaba
1       B
4    Baca
6    CABA
8     cat
7     dog
dtype: object
```

Some other sorting notes / nuances:

- `Series.sort` sorts a Series by value in-place. This is to provide compatibility with NumPy methods which expect the `ndarray.sort` behavior.

- `DataFrame.sort` takes a `column` argument instead of `by`. This method will likely be deprecated in a future release in favor of just using `sort_index`.

## 6.10 Copying, type casting

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 methods have the side effect of modifying your data; almost all methods return new objects, leaving the original object untouched. If data is modified, it is because you did so explicitly.

Data can be explicitly cast to a NumPy dtype by using the `astype` method or alternately passing the `dtype` keyword argument to the object constructor.

```
In [171]: df = DataFrame(np.arange(12).reshape((4, 3)))

In [172]: df[0].dtype
Out[172]: dtype('int64')

In [173]: df.astype(float)[0].dtype
Out[173]: dtype('float64')

In [174]: df = DataFrame(np.arange(12).reshape((4, 3)), dtype=float)

In [175]: df[0].dtype
Out[175]: dtype('float64')
```

### 6.10.1 Inferring better types for object columns

The `convert_objects` DataFrame method will attempt to convert `dtype=object` columns to a better NumPy dtype. Occasionally (after transposing multiple times, for example), a mixed-type DataFrame will end up with everything as `dtype=object`. This method attempts to fix that:

```
In [176]: df = DataFrame(randn(6, 3), columns=['a', 'b', 'c'])

In [177]: df['d'] = 'foo'

In [178]: df
Out[178]:
          a         b         c    d
0  1.031643 -0.189461 -0.437520  foo
1  0.239650  0.056665 -0.950583  foo
2  0.406598 -1.327319 -0.764997  foo
3  0.619450 -0.158757  1.182297  foo
4  0.345184  0.096056  0.724360  foo
5 -2.790083 -0.168660  0.039725  foo

In [179]: df = df.T.T
```

```
In [180]: df.dtypes
Out[180]:
a    object
b    object
c    object
d    object
dtype: object

In [181]: converted = df.convert_objects()

In [182]: converted.dtypes
Out[182]:
a    float64
b    float64
c    float64
d     object
dtype: object
```

## 6.11 Pickling and serialization

All pandas objects are equipped with `save` methods which use Python's `cPickle` module to save data structures to disk using the pickle format.

```
In [183]: df
Out[183]:
           a           b           c    d
0   1.031643  -0.1894613  -0.4375196  foo
1  0.2396501  0.05666547   -0.950583  foo
2  0.4065984   -1.327319  -0.7649967  foo
3  0.6194499  -0.1587574    1.182297  foo
4   0.345184  0.09605619   0.7243603  foo
5  -2.790083  -0.1686605  0.03972503  foo

In [184]: df.save('foo.pickle')
```

The `load` function in the `pandas` namespace can be used to load any pickled pandas object (or any other pickled object) from file:

```
In [185]: load('foo.pickle')
Out[185]:
           a           b           c    d
0   1.031643  -0.1894613  -0.4375196  foo
1  0.2396501  0.05666547   -0.950583  foo
2  0.4065984   -1.327319  -0.7649967  foo
3  0.6194499  -0.1587574    1.182297  foo
4   0.345184  0.09605619   0.7243603  foo
5  -2.790083  -0.1686605  0.03972503  foo
```

There is also a `save` function which takes any object as its first argument:

```
In [186]: save(df, 'foo.pickle')

In [187]: load('foo.pickle')
Out[187]:
           a           b           c    d
0   1.031643  -0.1894613  -0.4375196  foo
```

```
1  0.2396501  0.05666547   -0.950583  foo
2  0.4065984   -1.327319  -0.7649967  foo
3  0.6194499  -0.1587574    1.182297  foo
4   0.345184  0.09605619   0.7243603  foo
5  -2.790083  -0.1686605  0.03972503  foo
```

## 6.12 Working with package options

Introduced in 0.10.0, pandas supports a new system for working with options. 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 [188]: import pandas as pd

In [189]: pd.options.display.max_rows
Out[189]: 100

In [190]: pd.options.display.max_rows = 999

In [191]: pd.options.display.max_rows
Out[191]: 999
```

There is also an API composed of 4 relavent functions, available directly from the `pandas` namespace, and they are:

- `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.

**Note:** developers can check out pandas/core/config.py for more info.

but all of the functions above accept a regexp pattern (`re.search` style) as argument, so passing in a substring will work - as long as it is unambiguous :

```
In [192]: get_option("display.max_rows")
Out[192]: 999

In [193]: set_option("display.max_rows",101)

In [194]: get_option("display.max_rows")
Out[194]: 101

In [195]: set_option("max_r",102)

In [196]: get_option("display.max_rows")
Out[196]: 102
```

However, the following will **not work** because it matches multiple option names, e.g.‘‘display.max_colwidth‘‘, `display.max_rows`, `display.max_columns`:

```
In [197]: try:
   .....:     get_option("display.max_")
   .....: except KeyError as e:
   .....:     print(e)
   .....:
  File "<ipython-input-197-7ccb78c48d28>", line 3
    except KeyError as e:
```

```
                         ^
IndentationError: unindent does not match any outer indentation level
```

**Note:** Using this form of convenient shorthand may make your code break if new options with similar names are added in future versions.

The docstrings of all the functions document the available options, but you can also get a list of available options and their descriptions with `describe_option`. When called with no argument `describe_option` will print out descriptions for all available options.

```
In [198]: describe_option()
display.chop_threshold: [default: None] [currently: None]
: 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.
display.colheader_justify: [default: right] [currently: right]
: 'left'/'right'
        Controls the justification of column headers. used by DataFrameFormatter.
display.column_space: [default: 12] [currently: 12]No description available.
display.date_dayfirst: [default: False] [currently: False]
: boolean
        When True, prints and parses dates with the day first, eg 20/01/2005
display.date_yearfirst: [default: False] [currently: False]
: boolean
        When True, prints and parses dates with the year first, eg 2005/01/20
display.encoding: [default: UTF-8] [currently: UTF-8]
: 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.
display.expand_frame_repr: [default: True] [currently: True]
: boolean
        Whether to print out the full DataFrame repr for wide DataFrames
        across multiple lines.
        If False, the summary representation is shown.
display.float_format: [default: None] [currently: None]
: 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 core.format.EngFormatter for an example.
display.line_width: [default: 80] [currently: 80]
: int
        When printing wide DataFrames, this is the width of each line.
display.max_columns: [default: 20] [currently: 20]
: int
        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.
        Either one, or both can be set to 0 (experimental). Pandas will figure
        out how big the terminal is and will not display more rows or/and
        columns that can fit on it.
display.max_colwidth: [default: 50] [currently: 50]
: int
        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.
display.max_info_columns: [default: 100] [currently: 100]
: int
        max_info_columns is used in DataFrame.info method to decide if
```

```
        per column information will be printed.
display.max_info_rows: [default: 1000000] [currently: 1000000]
: int or None
        max_info_rows is the maximum number of rows for which a frame will
        perform a null check on its columns when repr'ing To a console.
        The default is 1,000,000 rows. So, if a DataFrame has more
        1,000,000 rows there will be no null check performed on the
        columns and thus the representation will take much less time to
        display in an interactive session. A value of None means always
        perform a null check when repr'ing.
display.max_rows: [default: 100] [currently: 102]
: int
        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 an summary repr.
display.max_seq_items: [default: None] [currently: None]
: int or None

        when pretty-printing a long sequence, no more then `max_seq_items`
        will be printed. If items are ommitted, 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.multi_sparse: [default: True] [currently: True]
: boolean
        "sparsify" MultiIndex display (don't display repeated
        elements in outer levels within groups)
display.notebook_repr_html: [default: True] [currently: True]
: boolean
        When True, IPython notebook will use html representation for
        pandas objects (if it is available).
display.pprint_nest_depth: [default: 3] [currently: 3]
: int
        Controls the number of nested levels to process when pretty-printing
display.precision: [default: 7] [currently: 7]
: int
        Floating point output precision (number of significant digits). This is
        only a suggestion
mode.sim_interactive: [default: False] [currently: False]
: boolean
        Whether to simulate interactive mode for purposes of testing
mode.use_inf_as_null: [default: False] [currently: False]
: boolean
        True means treat None, NaN, INF, -INF as null (old way),
        False means None and NaN are null, but INF, -INF are not null
        (new way).
```

or you can get the description for just the options that match the regexp you pass in:

```
In [199]: describe_option("date")
display.date_dayfirst: [default: False] [currently: False]
: boolean
        When True, prints and parses dates with the day first, eg 20/01/2005
display.date_yearfirst: [default: False] [currently: False]
: boolean
        When True, prints and parses dates with the year first, eg 2005/01/20
```

All options also have a default value, and you can use the `reset_option` to do just that:

```
In [200]: get_option("display.max_rows")
Out[200]: 100

In [201]: set_option("display.max_rows",999)

In [202]: get_option("display.max_rows")
Out[202]: 999

In [203]: reset_option("display.max_rows")

In [204]: get_option("display.max_rows")
Out[204]: 100
```

and you also set multiple options at once:

```
In [205]: reset_option("^display\.")
```

## 6.13 Console Output Formatting

**Note:** `set_printoptions`/ `reset_printoptions` are now deprecated (but functioning), and both, as well as `set_eng_float_format`, use the options API behind the scenes. The corresponding options now live under "print.XYZ", and you can set them directly with `get/set_option`.

Use the `set_eng_float_format` function in the `pandas.core.common` module to alter the floating-point formatting of pandas objects to produce a particular format.

For instance:

```
In [206]: set_eng_float_format(accuracy=3, use_eng_prefix=True)

In [207]: df['a']/1.e3
Out[207]:
0      1.032m
1    239.650u
2    406.598u
3    619.450u
4    345.184u
5     -2.790m
Name: a, dtype: object

In [208]: df['a']/1.e6
Out[208]:
0      1.032u
1    239.650n
2    406.598n
3    619.450n
4    345.184n
5     -2.790u
Name: a, dtype: object
```

The `set_printoptions` function has a number of options for controlling how floating point numbers are formatted (using hte `precision` argument) in the console and . The `max_rows` and `max_columns` control how many rows and columns of DataFrame objects are shown by default. If `max_columns` is set to 0 (the default, in fact), the library will attempt to fit the DataFrame's string representation into the current terminal width, and defaulting to the summary view otherwise.

CHAPTER

SEVEN

# 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 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 / chapter, 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. Expect more work to be invested higher-dimensional data structures (including Panel) in the future, especially in label-based advanced indexing.

## 7.1 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. Thus,

- **Series**: `series[label]` returns a scalar value
- **DataFrame**: `frame[colname]` returns a Series corresponding to the passed column name
- **Panel**: `panel[itemname]` returns a DataFrame corresponding to the passed item name

Here we construct a simple time series data set to use for illustrating the indexing functionality:

```
In [620]: dates = np.asarray(date_range('1/1/2000', periods=8))

In [621]: df = DataFrame(randn(8, 4), index=dates, columns=['A', 'B', 'C', 'D'])

In [622]: df
Out[622]:
                   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
```

```
In [623]: panel = Panel({'one' : df, 'two' : df - df.mean()})

In [624]: panel
Out[624]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 8 (major_axis) x 4 (minor_axis)
Items axis: one to two
Major_axis axis: 2000-01-01 00:00:00 to 2000-01-08 00:00:00
Minor_axis axis: A to D
```

**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 [625]: s = df['A']

In [626]: s[dates[5]]
Out[626]: -0.67368970808837059

In [627]: panel['two']
Out[627]:
                   A         B         C         D
2000-01-01  0.409571  0.113086 -0.610826 -0.936507
2000-01-02  1.152571  0.222735  1.017442 -0.845111
2000-01-03 -0.921390 -1.708620  0.403304  1.270929
2000-01-04  0.662014 -0.310822 -0.141342  0.470985
2000-01-05 -0.484513  0.962970  1.174465 -0.888276
2000-01-06 -0.733231  0.509598 -0.580194  0.724113
2000-01-07  0.345164  0.972995 -0.816769 -0.840143
2000-01-08 -0.430188 -0.761943 -0.446079  1.044010
```

### 7.1.1 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 `get_value` method, which is implemented on all of the data structures:

```
In [628]: s.get_value(dates[5])
Out[628]: -0.67368970808837059

In [629]: df.get_value(dates[5], 'A')
Out[629]: -0.67368970808837059
```

There is an analogous `set_value` method which has the additional capability of enlarging an object. This method *always* returns a reference to the object it modified, which in the case of enlargement, will be a **new object**:

```
In [630]: df.set_value(dates[5], 'E', 7)
Out[630]:
                   A         B         C         D    E
2000-01-01  0.469112 -0.282863 -1.509059 -1.135632  NaN
2000-01-02  1.212112 -0.173215  0.119209 -1.044236  NaN
2000-01-03 -0.861849 -2.104569 -0.494929  1.071804  NaN
2000-01-04  0.721555 -0.706771 -1.039575  0.271860  NaN
2000-01-05 -0.424972  0.567020  0.276232 -1.087401  NaN
2000-01-06 -0.673690  0.113648 -1.478427  0.524988    7
```

```
2000-01-07  0.404705  0.577046 -1.715002 -1.039268 NaN
2000-01-08 -0.370647 -1.157892 -1.344312  0.844885 NaN
```

### 7.1.2 Additional Column Access

You may access a column on a dataframe directly as an attribute:

```
In [631]: df.A
Out[631]:
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
Name: A, dtype: float64
```

If you are using the IPython environment, you may also use tab-completion to see the accessible columns of a DataFrame.

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 [632]: df
Out[632]:
                   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

In [633]: df[['B', 'A']] = df[['A', 'B']]

In [634]: df
Out[634]:
                   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.

### 7.1.3 Data slices on other axes

It's certainly possible to retrieve data slices along the other axes of a DataFrame or Panel. We tend to refer to these slices as *cross-sections*. DataFrame has the `xs` function for retrieving rows as Series and Panel has the analogous major_xs and minor_xs functions for retrieving slices as DataFrames for a given major_axis or minor_axis label, respectively.

```
In [635]: date = dates[5]

In [636]: df.xs(date)
Out[636]:
A    0.113648
B   -0.673690
C   -1.478427
D    0.524988
Name: 2000-01-06 00:00:00, dtype: float64

In [637]: panel.major_xs(date)
Out[637]:
        one       two
A -0.673690 -0.733231
B  0.113648  0.509598
C -1.478427 -0.580194
D  0.524988  0.724113

In [638]: panel.minor_xs('A')
Out[638]:
                 one       two
2000-01-01  0.469112  0.409571
2000-01-02  1.212112  1.152571
2000-01-03 -0.861849 -0.921390
2000-01-04  0.721555  0.662014
2000-01-05 -0.424972 -0.484513
2000-01-06 -0.673690 -0.733231
2000-01-07  0.404705  0.345164
2000-01-08 -0.370647 -0.430188
```

### 7.1.4 Slicing ranges

The most robust and consistent way of slicing ranges along arbitrary axes is described in the *Advanced indexing* section detailing the .ix 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 [639]: s[:5]
Out[639]:
2000-01-01   -0.282863
2000-01-02   -0.173215
2000-01-03   -2.104569
2000-01-04   -0.706771
2000-01-05    0.567020
Name: A, dtype: float64

In [640]: s[::2]
Out[640]:
2000-01-01   -0.282863
2000-01-03   -2.104569
2000-01-05    0.567020
2000-01-07    0.577046
Name: A, dtype: float64

In [641]: s[::-1]
```

```
Out[641]:
2000-01-08   -1.157892
2000-01-07    0.577046
2000-01-06    0.113648
2000-01-05    0.567020
2000-01-04   -0.706771
2000-01-03   -2.104569
2000-01-02   -0.173215
2000-01-01   -0.282863
Name: A, dtype: float64
```

Note that setting works as well:

```
In [642]: s2 = s.copy()

In [643]: s2[:5] = 0

In [644]: s2
Out[644]:
2000-01-01    0.000000
2000-01-02    0.000000
2000-01-03    0.000000
2000-01-04    0.000000
2000-01-05    0.000000
2000-01-06    0.113648
2000-01-07    0.577046
2000-01-08   -1.157892
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 [645]: df[:3]
Out[645]:
                   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

In [646]: df[::-1]
Out[646]:
                   A         B         C         D
2000-01-08 -1.157892 -0.370647 -1.344312  0.844885
2000-01-07  0.577046  0.404705 -1.715002 -1.039268
2000-01-06  0.113648 -0.673690 -1.478427  0.524988
2000-01-05  0.567020 -0.424972  0.276232 -1.087401
2000-01-04 -0.706771  0.721555 -1.039575  0.271860
2000-01-03 -2.104569 -0.861849 -0.494929  1.071804
2000-01-02 -0.173215  1.212112  0.119209 -1.044236
2000-01-01 -0.282863  0.469112 -1.509059 -1.135632
```

### 7.1.5 Boolean indexing

Another common operation is the use of boolean vectors to filter the data.

Using a boolean vector to index a Series works exactly as in a numpy ndarray:

```
In [647]: s[s > 0]
Out[647]:
2000-01-05    0.567020
2000-01-06    0.113648
2000-01-07    0.577046
Name: A, dtype: float64

In [648]: s[(s < 0) & (s > -0.5)]
Out[648]:
2000-01-01   -0.282863
2000-01-02   -0.173215
Name: A, dtype: float64

In [649]: s[(s < -1) | (s > 1 )]
Out[649]:
2000-01-03   -2.104569
2000-01-08   -1.157892
Name: A, dtype: float64
```

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 [650]: df[df['A'] > 0]
Out[650]:
                   A         B         C         D
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
```

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 [651]: df2 = DataFrame({'a' : ['one', 'one', 'two', 'three', 'two', 'one', 'six'],
   .....:                  'b' : ['x', 'y', 'y', 'x', 'y', 'x', 'x'],
   .....:                  'c' : randn(7)})
   .....:

In [652]: df2[df2['a'].isin(['one', 'two'])]
Out[652]:
     a  b         c
0  one  x  1.075770
1  one  y -0.109050
2  two  y  1.643563
4  two  y  0.357021
5  one  x -0.674600
```

List comprehensions and `map` method of Series can also be used to produce more complex criteria:

```
# only want 'two' or 'three'
In [653]: criterion = df2['a'].map(lambda x: x.startswith('t'))

In [654]: df2[criterion]
Out[654]:
       a  b         c
2    two  y  1.643563
3  three  x -1.469388
4    two  y  0.357021

# equivalent but slower
```

```
In [655]: df2[[x.startswith('t') for x in df2['a']]]
Out[655]:
       a  b         c
2    two  y  1.643563
3  three  x -1.469388
4    two  y  0.357021

# Multiple criteria
In [656]: df2[criterion & (df2['b'] == 'x')]
Out[656]:
       a  b         c
3  three  x -1.469388
```

Note, with the *advanced indexing* `ix` method, you may select along more than one axis using boolean vectors combined with other indexing expressions.

### 7.1.6 Where 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`.

```
# return only the selected rows
In [657]: s[s > 0]
Out[657]:
2000-01-05    0.567020
2000-01-06    0.113648
2000-01-07    0.577046
Name: A, dtype: float64

# return a Series of the same shape as the original
In [658]: s.where(s > 0)
Out[658]:
2000-01-01         NaN
2000-01-02         NaN
2000-01-03         NaN
2000-01-04         NaN
2000-01-05    0.567020
2000-01-06    0.113648
2000-01-07    0.577046
2000-01-08         NaN
Name: A, dtype: float64
```

Selecting values from a DataFrame with a boolean critierion now also preserves input data shape. `where` is used under the hood as the implementation.

```
# return a DataFrame of the same shape as the original
# this is equiavalent to ''df.where(df < 0)''
In [659]: df[df < 0]
Out[659]:
                   A         B         C         D
2000-01-01 -0.282863       NaN -1.509059 -1.135632
2000-01-02 -0.173215       NaN       NaN -1.044236
2000-01-03 -2.104569 -0.861849 -0.494929       NaN
2000-01-04 -0.706771       NaN -1.039575       NaN
2000-01-05       NaN -0.424972       NaN -1.087401
2000-01-06       NaN -0.673690 -1.478427       NaN
2000-01-07       NaN       NaN -1.715002 -1.039268
```

```
2000-01-08 -1.157892 -0.370647 -1.344312       NaN
```

In addition, `where` takes an optional `other` argument for replacement of values where the condition is False, in the returned copy.

```
In [660]: df.where(df < 0, -df)
Out[660]:
                   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 wish to set values based on some boolean criteria. This can be done intuitively like so:

```
In [661]: s2 = s.copy()

In [662]: s2[s2 < 0] = 0

In [663]: s2
Out[663]:
2000-01-01    0.000000
2000-01-02    0.000000
2000-01-03    0.000000
2000-01-04    0.000000
2000-01-05    0.567020
2000-01-06    0.113648
2000-01-07    0.577046
2000-01-08    0.000000
Name: A, dtype: float64

In [664]: df2 = df.copy()

In [665]: df2[df2 < 0] = 0

In [666]: df2
Out[666]:
                   A         B         C         D
2000-01-01  0.000000  0.469112  0.000000  0.000000
2000-01-02  0.000000  1.212112  0.119209  0.000000
2000-01-03  0.000000  0.000000  0.000000  1.071804
2000-01-04  0.000000  0.721555  0.000000  0.271860
2000-01-05  0.567020  0.000000  0.276232  0.000000
2000-01-06  0.113648  0.000000  0.000000  0.524988
2000-01-07  0.577046  0.404705  0.000000  0.000000
2000-01-08  0.000000  0.000000  0.000000  0.844885
```

Furthermore, `where` aligns the input boolean condition (ndarray or DataFrame), such that partial selection with setting is possible. This is analagous to partial setting via `.ix` (but on the contents rather than the axis labels)

```
In [667]: df2 = df.copy()

In [668]: df2[ df2[1:4] > 0 ] = 3

In [669]: df2
```

```
Out[669]:
                   A         B         C         D
2000-01-01 -0.282863  0.469112 -1.509059 -1.135632
2000-01-02 -0.173215  3.000000  3.000000 -1.044236
2000-01-03 -2.104569 -0.861849 -0.494929  3.000000
2000-01-04 -0.706771  3.000000 -1.039575  3.000000
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
```

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 [670]: df_orig = df.copy()

In [671]: df_orig.where(df > 0, -df, inplace=True);
In [671]: df_orig
Out[671]:
                   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
```

`mask` is the inverse boolean operation of `where`.

```
In [672]: s.mask(s >= 0)
Out[672]:
2000-01-01   -0.282863
2000-01-02   -0.173215
2000-01-03   -2.104569
2000-01-04   -0.706771
2000-01-05         NaN
2000-01-06         NaN
2000-01-07         NaN
2000-01-08   -1.157892
Name: A, dtype: float64

In [673]: df.mask(df >= 0)
Out[673]:
                   A         B         C         D
2000-01-01 -0.282863       NaN -1.509059 -1.135632
2000-01-02 -0.173215       NaN       NaN -1.044236
2000-01-03 -2.104569 -0.861849 -0.494929       NaN
2000-01-04 -0.706771       NaN -1.039575       NaN
2000-01-05       NaN -0.424972       NaN -1.087401
2000-01-06       NaN -0.673690 -1.478427       NaN
2000-01-07       NaN       NaN -1.715002 -1.039268
2000-01-08 -1.157892 -0.370647 -1.344312       NaN
```

### 7.1.7 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.

```
In [674]: index = Index(randint(0, 1000, 10))

In [675]: index
Out[675]: Int64Index([969, 412, 496, 195, 288, 101, 881, 900, 732, 658], dtype=int64)

In [676]: positions = [0, 9, 3]

In [677]: index[positions]
Out[677]: Int64Index([969, 658, 195], dtype=int64)

In [678]: index.take(positions)
Out[678]: Int64Index([969, 658, 195], dtype=int64)

In [679]: ser = Series(randn(10))

In [680]: ser.ix[positions]
Out[680]:
0   -0.968914
9   -1.131345
3    1.247642
dtype: float64

In [681]: ser.take(positions)
Out[681]:
0   -0.968914
9   -1.131345
3    1.247642
dtype: float64
```

For DataFrames, the given indices should be a 1d list or ndarray that specifies row or column positions.

```
In [682]: frm = DataFrame(randn(5, 3))

In [683]: frm.take([1, 4, 3])
Out[683]:
          0         1         2
1 -0.932132  1.956030  0.017587
4 -0.077118 -0.408530 -0.862495
3 -1.143704  0.215897  1.193555

In [684]: frm.take([0, 2], axis=1)
Out[684]:
          0         2
0 -0.089329 -0.945867
1 -0.932132  0.017587
2 -0.016692  0.254161
3 -1.143704  1.193555
4 -0.077118 -0.862495
```

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 [685]: arr = randn(10)

In [686]: arr.take([False, False, True, True])
Out[686]: array([ 1.3461,  1.3461,  1.5118,  1.5118])

In [687]: arr[[0, 1]]
Out[687]: array([ 1.3461,  1.5118])

In [688]: ser = Series(randn(10))

In [689]: ser.take([False, False, True, True])
Out[689]:
0   -0.105381
0   -0.105381
1   -0.532532
1   -0.532532
dtype: float64

In [690]: ser.ix[[0, 1]]
Out[690]:
0   -0.105381
1   -0.532532
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.

### 7.1.8 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 `take_last` parameter that indicates the last observed row should be taken instead.

```
In [691]: df2 = DataFrame({'a' : ['one', 'one', 'two', 'three', 'two', 'one', 'six'],
   .....:                  'b' : ['x', 'y', 'y', 'x', 'y', 'x', 'x'],
   .....:                  'c' : np.random.randn(7)})
   .....:

In [692]: df2.duplicated(['a','b'])
Out[692]:
0    False
1    False
2    False
3    False
4     True
5     True
6    False
dtype: bool

In [693]: df2.drop_duplicates(['a','b'])
Out[693]:
```

```
       a  b         c
0    one  x -0.339355
1    one  y  0.593616
2    two  y  0.884345
3  three  x  1.591431
6    six  x  0.435589

In [694]: df2.drop_duplicates(['a','b'], take_last=True)
Out[694]:
       a  b         c
1    one  y  0.593616
3  three  x  1.591431
4    two  y  0.141809
5    one  x  0.220390
6    six  x  0.435589
```

### 7.1.9 Dictionary-like `get` method

Each of Series, DataFrame, and Panel have a `get` method which can return a default value.

```
In [695]: s = Series([1,2,3], index=['a','b','c'])

In [696]: s.get('a')               # equivalent to s['a']
Out[696]: 1

In [697]: s.get('x', default=-1)
Out[697]: -1
```

## 7.2 Advanced indexing with labels

We have avoided excessively overloading the `[]` / `__getitem__` operator to keep the basic functionality of the pandas objects straightforward and simple. However, there are often times when you may wish get a subset (or analogously set a subset) of the data in a way that is not straightforward using the combination of `reindex` and `[]`. Complicated setting operations are actually quite difficult because `reindex` usually returns a copy.

By *advanced* indexing we are referring to a special `.ix` attribute on pandas objects which enable you to do getting/setting operations on a DataFrame, for example, with matrix/ndarray-like semantics. Thus you can combine the following kinds of indexing:

- An integer or single label, e.g. `5` or `'a'`
- A list or array of labels `['a', 'b', 'c']` or integers `[4, 3, 0]`
- A slice object with ints `1:7` or labels `'a':'f'`
- A boolean array

We'll illustrate all of these methods. First, note that this provides a concise way of reindexing on multiple axes at once:

```
In [698]: subindex = dates[[3,4,5]]

In [699]: df.reindex(index=subindex, columns=['C', 'B'])
Out[699]:
                   C         B
2000-01-04 -1.039575  0.721555
2000-01-05  0.276232 -0.424972
```

```
2000-01-06 -1.478427 -0.673690

In [700]: df.ix[subindex, ['C', 'B']]
Out[700]:
                   C         B
2000-01-04 -1.039575  0.721555
2000-01-05  0.276232 -0.424972
2000-01-06 -1.478427 -0.673690
```

Assignment / setting values is possible when using `ix`:

```
In [701]: df2 = df.copy()

In [702]: df2.ix[subindex, ['C', 'B']] = 0

In [703]: df2
Out[703]:
                   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  0.000000  0.000000  0.271860
2000-01-05  0.567020  0.000000  0.000000 -1.087401
2000-01-06  0.113648  0.000000  0.000000  0.524988
2000-01-07  0.577046  0.404705 -1.715002 -1.039268
2000-01-08 -1.157892 -0.370647 -1.344312  0.844885
```

Indexing with an array of integers can also be done:

```
In [704]: df.ix[[4,3,1]]
Out[704]:
                   A         B         C         D
2000-01-05  0.567020 -0.424972  0.276232 -1.087401
2000-01-04 -0.706771  0.721555 -1.039575  0.271860
2000-01-02 -0.173215  1.212112  0.119209 -1.044236

In [705]: df.ix[dates[[4,3,1]]]
Out[705]:
                   A         B         C         D
2000-01-05  0.567020 -0.424972  0.276232 -1.087401
2000-01-04 -0.706771  0.721555 -1.039575  0.271860
2000-01-02 -0.173215  1.212112  0.119209 -1.044236
```

**Slicing** has standard Python semantics for integer slices:

```
In [706]: df.ix[1:7, :2]
Out[706]:
                   A         B
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
```

Slicing with labels is semantically slightly different because the slice start and stop are **inclusive** in the label-based case:

```
In [707]: date1, date2 = dates[[2, 4]]
```

```
In [708]: print date1, date2
1970-01-11 232:00:00 1970-01-11 24:00:00

In [709]: df.ix[date1:date2]
Out[709]:
Empty DataFrame
Columns: [A, B, C, D]
Index: []

In [710]: df['A'].ix[date1:date2]
Out[710]: Series([], dtype: float64)
```

Getting and setting rows in a DataFrame, especially by their location, is much easier:

```
In [711]: df2 = df[:5].copy()

In [712]: df2.ix[3]
Out[712]:
A   -0.706771
B    0.721555
C   -1.039575
D    0.271860
Name: 2000-01-04 00:00:00, dtype: float64

In [713]: df2.ix[3] = np.arange(len(df2.columns))

In [714]: df2
Out[714]:
                   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  0.000000  1.000000  2.000000  3.000000
2000-01-05  0.567020 -0.424972  0.276232 -1.087401
```

Column or row selection can be combined as you would expect with arrays of labels or even boolean vectors:

```
In [715]: df.ix[df['A'] > 0, 'B']
Out[715]:
2000-01-05   -0.424972
2000-01-06   -0.673690
2000-01-07    0.404705
Name: B, dtype: float64

In [716]: df.ix[date1:date2, 'B']
Out[716]: Series([], dtype: float64)

In [717]: df.ix[date1, 'B']
Out[717]: -0.86184896334779992
```

Slicing with labels is closely related to the `truncate` method which does precisely `.ix[start:stop]` but returns a copy (for legacy reasons).

### 7.2.1 Returning a view versus a copy

The rules about when a view on the data is returned are entirely dependent on NumPy. Whenever an array of labels or a boolean vector are involved in the indexing operation, the result will be a copy. With single label / scalar indexing and slicing, e.g. `df.ix[3:6]` or `df.ix[:, 'A']`, a view will be returned.

### 7.2.2 The `select` method

Another way to extract slices from an object is with the `select` method of Series, DataFrame, and Panel. This method should be used only when there is no more direct way. `select` takes a function which operates on labels along `axis` and returns a boolean. For instance:

```
In [718]: df.select(lambda x: x == 'A', axis=1)
Out[718]:
                   A
2000-01-01 -0.282863
2000-01-02 -0.173215
2000-01-03 -2.104569
2000-01-04 -0.706771
2000-01-05  0.567020
2000-01-06  0.113648
2000-01-07  0.577046
2000-01-08 -1.157892
```

### 7.2.3 The `lookup` method

Sometimes you want to extract a set of values given a sequence of row labels and column labels, and the `lookup` method allows for this and returns a numpy array. For instance,

```
In [719]: dflookup = DataFrame(np.random.rand(20,4), columns = ['A','B','C','D'])

In [720]: dflookup.lookup(xrange(0,10,2), ['B','C','A','B','D'])
Out[720]: array([ 0.0227,  0.4199,  0.529 ,  0.9674,  0.5357])
```

### 7.2.4 Advanced indexing with integer labels

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 `.ix`. The following code will generate exceptions:

```
s = Series(range(5))
s[-1]
df = DataFrame(np.random.randn(5, 4))
df
df.ix[-2:]
```

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).

### 7.2.5 Setting values in mixed-type DataFrame

Setting values on a mixed-type DataFrame or Panel is supported when using scalar values, though setting arbitrary vectors is not yet supported:

```
In [721]: df2 = df[:4]

In [722]: df2['foo'] = 'bar'

In [723]: print df2
```

```
                   A         B         C         D  foo
2000-01-01 -0.282863  0.469112 -1.509059 -1.135632  bar
2000-01-02 -0.173215  1.212112  0.119209 -1.044236  bar
2000-01-03 -2.104569 -0.861849 -0.494929  1.071804  bar
2000-01-04 -0.706771  0.721555 -1.039575  0.271860  bar

In [724]: df2.ix[2] = np.nan

In [725]: print df2
                   A         B         C         D  foo
2000-01-01 -0.282863  0.469112 -1.509059 -1.135632  bar
2000-01-02 -0.173215  1.212112  0.119209 -1.044236  bar
2000-01-03       NaN       NaN       NaN       NaN  NaN
2000-01-04 -0.706771  0.721555 -1.039575  0.271860  bar

In [726]: print df2.dtypes
A       float64
B       float64
C       float64
D       float64
foo      object
dtype: object
```

## 7.3 Index objects

The pandas Index class and its subclasses can be viewed as implementing an *ordered set* in addition to providing the support infrastructure necessary for lookups, data alignment, and reindexing. The easiest way to create one directly is to pass a list or other sequence to `Index`:

```
In [727]: index = Index(['e', 'd', 'a', 'b'])

In [728]: index
Out[728]: Index([e, d, a, b], dtype=object)

In [729]: 'd' in index
Out[729]: True
```

You can also pass a `name` to be stored in the index:

```
In [730]: index = Index(['e', 'd', 'a', 'b'], name='something')

In [731]: index.name
Out[731]: 'something'
```

Starting with pandas 0.5, the name, if set, will be shown in the console display:

```
In [732]: index = Index(range(5), name='rows')

In [733]: columns = Index(['A', 'B', 'C'], name='cols')

In [734]: df = DataFrame(np.random.randn(5, 3), index=index, columns=columns)

In [735]: df
Out[735]:
cols          A         B         C
rows
```

```
0     0.192451  0.629675 -1.425966
1     1.857704 -1.193545  0.677510
2    -0.153931  0.520091 -1.475051
3     0.722570 -0.322646 -1.601631
4     0.778033 -0.289342  0.233141

In [736]: df['A']
Out[736]:
rows
0       0.192451
1       1.857704
2      -0.153931
3       0.722570
4       0.778033
Name: A, dtype: float64
```

### 7.3.1 Set operations on Index objects

The three main operations are `union (|)`, `intersection (&)`, and `diff (-)`. These can be directly called as instance methods or used via overloaded operators:

```
In [737]: a = Index(['c', 'b', 'a'])

In [738]: b = Index(['c', 'e', 'd'])

In [739]: a.union(b)
Out[739]: Index([a, b, c, d, e], dtype=object)

In [740]: a | b
Out[740]: Index([a, b, c, d, e], dtype=object)

In [741]: a & b
Out[741]: Index([c], dtype=object)

In [742]: a - b
Out[742]: Index([a, b], dtype=object)
```

### 7.3.2 `isin` method of Index objects

One additional operation is the `isin` method that works analogously to the `Series.isin` method found *here*.

## 7.4 Hierarchical indexing (MultiIndex)

Hierarchical indexing (also referred to as "multi-level" indexing) is brand new in the pandas 0.4 release. It 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 the 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.

**Note:** Given that hierarchical indexing is so new to the library, it is definitely "bleeding-edge" functionality but is certainly suitable for production. But, there may inevitably be some minor API changes as more use cases are explored and any weaknesses in the design / implementation are identified. pandas aims to be "eminently usable" so any feedback about new functionality like this is extremely helpful.

### 7.4.1 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` an array of tuples where each tuple is unique. A `MultiIndex` can be created from a list of arrays (using `MultiIndex.from_arrays`) or an array of tuples (using `MultiIndex.from_tuples`).

```
In [743]: arrays = [['bar', 'bar', 'baz', 'baz', 'foo', 'foo', 'qux', 'qux'],
   .....:           ['one', 'two', 'one', 'two', 'one', 'two', 'one', 'two']]
   .....:

In [744]: tuples = zip(*arrays)

In [745]: tuples
Out[745]:
[('bar', 'one'),
 ('bar', 'two'),
 ('baz', 'one'),
 ('baz', 'two'),
 ('foo', 'one'),
 ('foo', 'two'),
 ('qux', 'one'),
 ('qux', 'two')]

In [746]: index = MultiIndex.from_tuples(tuples, names=['first', 'second'])

In [747]: s = Series(randn(8), index=index)

In [748]: s
Out[748]:
first  second
bar    one      -0.223540
       two       0.542054
baz    one      -0.688585
       two      -0.352676
foo    one      -0.711411
       two      -2.122599
qux    one       1.962935
       two       1.672027
dtype: float64
```

As a convenience, you can pass a list of arrays directly into Series or DataFrame to construct a MultiIndex automatically:

```
In [749]: arrays = [np.array(['bar', 'bar', 'baz', 'baz', 'foo', 'foo', 'qux', 'qux']),
   .....:           np.array(['one', 'two', 'one', 'two', 'one', 'two', 'one', 'two'])]
   .....:

In [750]: s = Series(randn(8), index=arrays)

In [751]: s
```

```
Out[751]:
bar  one   -0.880984
     two    0.997289
baz  one   -1.693316
     two   -0.179129
foo  one   -1.598062
     two    0.936914
qux  one    0.912560
     two   -1.003401
dtype: float64

In [752]: df = DataFrame(randn(8, 4), index=arrays)

In [753]: df
Out[753]:
                0         1         2         3
bar one  1.632781 -0.724626  0.178219  0.310610
    two -0.108002 -0.974226 -1.147708 -2.281374
baz one  0.760010 -0.742532  1.533318  2.495362
    two -0.432771 -0.068954  0.043520  0.112246
foo one  0.871721 -0.816064 -0.784880  1.030659
    two  0.187483 -1.933946  0.377312  0.734122
qux one  2.141616 -0.011225  0.048869 -1.360687
    two -0.479010 -0.859661 -0.231595 -0.527750
```

All of the `MultiIndex` constructors accept a `names` argument which stores string names for the levels themselves. If no names are provided, some arbitrary ones will be assigned:

```
In [754]: index.names
Out[754]: ['first', 'second']
```

This index can back any axis of a pandas object, and the number of **levels** of the index is up to you:

```
In [755]: df = DataFrame(randn(3, 8), index=['A', 'B', 'C'], columns=index)

In [756]: df
Out[756]:
first        bar                 baz                 foo                 qux
second       one       two       one       two       one       two       one       two
A      -1.296337  0.150680  0.123836  0.571764  1.555563 -0.823761  0.535420 -1.032853
B       1.469725  1.304124  1.449735  0.203109 -1.032011  0.969818 -0.962723  1.382083
C      -0.938794  0.669142 -0.433567 -0.273610  0.680433 -0.308450 -0.276099 -1.821168

In [757]: DataFrame(randn(6, 6), index=index[:6], columns=index[:6])
Out[757]:
first               bar                 baz                 foo
second              one       two       one       two       one       two
first second
bar   one     -1.993606 -1.927385 -2.027924  1.624972  0.551135  3.059267
      two      0.455264 -0.030740  0.935716  1.061192 -2.107852  0.199905
baz   one      0.323586 -0.641630 -0.587514  0.053897  0.194889 -0.381994
      two      0.318587  2.089075 -0.728293 -0.090255 -0.748199  1.318931
foo   one     -2.029766  0.792652  0.461007 -0.542749 -0.305384 -0.479195
      two      0.095031 -0.270099 -0.707140 -0.773882  0.229453  0.304418
```

We've "sparsified" the higher levels of the indexes to make the console output a bit easier on the eyes.

It's worth keeping in mind that there's nothing preventing you from using tuples as atomic labels on an axis:

```
In [758]: Series(randn(8), index=tuples)
Out[758]:
(bar, one)    0.736135
(bar, two)   -0.859631
(baz, one)   -0.424100
(baz, two)   -0.776114
(foo, one)    1.279293
(foo, two)    0.943798
(qux, one)   -1.001859
(qux, two)    0.306546
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.

Note that how the index is displayed by be controlled using the `multi_sparse` option in `pandas.set_printoptions`:

```
In [759]: pd.set_printoptions(multi_sparse=False)

In [760]: df
Out[760]:
first        bar       bar       baz       baz       foo       foo       qux       qux
second       one       two       one       two       one       two       one       two
A      -1.296337  0.150680  0.123836  0.571764  1.555563 -0.823761  0.535420 -1.032853
B       1.469725  1.304124  1.449735  0.203109 -1.032011  0.969818 -0.962723  1.382083
C      -0.938794  0.669142 -0.433567 -0.273610  0.680433 -0.308450 -0.276099 -1.821168

In [761]: pd.set_printoptions(multi_sparse=True)
```

### 7.4.2 Reconstructing the level labels

The method `get_level_values` will return a vector of the labels for each location at a particular level:

```
In [762]: index.get_level_values(0)
Out[762]: Index([bar, bar, baz, baz, foo, foo, qux, qux], dtype=object)

In [763]: index.get_level_values('second')
Out[763]: Index([one, two, one, two, one, two, one, two], dtype=object)
```

### 7.4.3 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 [764]: df['bar']
Out[764]:
second       one       two
A      -1.296337  0.150680
B       1.469725  1.304124
C      -0.938794  0.669142

In [765]: df['bar', 'one']
```

```
Out[765]:
A   -1.296337
B    1.469725
C   -0.938794
Name: (bar, one), dtype: float64

In [766]: df['bar']['one']
Out[766]:
A   -1.296337
B    1.469725
C   -0.938794
Name: one, dtype: float64

In [767]: s['qux']
Out[767]:
one    0.912560
two   -1.003401
dtype: float64
```

### 7.4.4 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 [768]: s + s[:-2]
Out[768]:
bar  one   -1.761968
     two    1.994577
baz  one   -3.386631
     two   -0.358257
foo  one   -3.196125
     two    1.873828
qux  one         NaN
     two         NaN
dtype: float64

In [769]: s + s[::2]
Out[769]:
bar  one   -1.761968
     two         NaN
baz  one   -3.386631
     two         NaN
foo  one   -3.196125
     two         NaN
qux  one    1.825119
     two         NaN
dtype: float64
```

`reindex` can be called with another `MultiIndex` or even a list or array of tuples:

```
In [770]: s.reindex(index[:3])
Out[770]:
first  second
bar    one      -0.880984
       two       0.997289
baz    one      -1.693316
dtype: float64
```

```
In [771]: s.reindex([('foo', 'two'), ('bar', 'one'), ('qux', 'one'), ('baz', 'one')])
Out[771]:
foo  two    0.936914
bar  one   -0.880984
qux  one    0.912560
baz  one   -1.693316
dtype: float64
```

### 7.4.5 Advanced indexing with hierarchical index

Syntactically integrating `MultiIndex` in advanced indexing with `.ix` is a bit challenging, but we've made every effort to do so. for example the following works as you would expect:

```
In [772]: df = df.T

In [773]: df
Out[773]:
                     A         B         C
first second
bar   one    -1.296337  1.469725 -0.938794
      two     0.150680  1.304124  0.669142
baz   one     0.123836  1.449735 -0.433567
      two     0.571764  0.203109 -0.273610
foo   one     1.555563 -1.032011  0.680433
      two    -0.823761  0.969818 -0.308450
qux   one     0.535420 -0.962723 -0.276099
      two    -1.032853  1.382083 -1.821168

In [774]: df.ix['bar']
Out[774]:
               A         B         C
second
one    -1.296337  1.469725 -0.938794
two     0.150680  1.304124  0.669142

In [775]: df.ix['bar', 'two']
Out[775]:
A    0.150680
B    1.304124
C    0.669142
Name: (bar, two), dtype: float64
```

"Partial" slicing also works quite nicely:

```
In [776]: df.ix['baz':'foo']
Out[776]:
                     A         B         C
first second
baz   one     0.123836  1.449735 -0.433567
      two     0.571764  0.203109 -0.273610
foo   one     1.555563 -1.032011  0.680433
      two    -0.823761  0.969818 -0.308450

In [777]: df.ix[('baz', 'two'):('qux', 'one')]
Out[777]:
                     A         B         C
first second
```

```
baz   two     0.571764  0.203109 -0.273610
foo   one     1.555563 -1.032011  0.680433
      two    -0.823761  0.969818 -0.308450
qux   one     0.535420 -0.962723 -0.276099

In [778]: df.ix[('baz', 'two'):'foo']
Out[778]:
                     A         B         C
first second
baz   two     0.571764  0.203109 -0.273610
foo   one     1.555563 -1.032011  0.680433
      two    -0.823761  0.969818 -0.308450
```

Passing a list of labels or tuples works similar to reindexing:

```
In [779]: df.ix[[('bar', 'two'), ('qux', 'one')]]
Out[779]:
                    A         B         C
first second
bar   two     0.15068  1.304124  0.669142
qux   one     0.53542 -0.962723 -0.276099
```

The following does not work, and it's not clear if it should or not:

```
>>> df.ix[['bar', 'qux']]
```

The code for implementing `.ix` makes every attempt to "do the right thing" but as you use it you may uncover corner cases or unintuitive behavior. If you do find something like this, do not hesitate to report the issue or ask on the mailing list.

### 7.4.6 Cross-section with hierarchical index

The `xs` method of `DataFrame` additionally takes a level argument to make selecting data at a particular level of a MultiIndex easier.

```
In [780]: df.xs('one', level='second')
Out[780]:
              A         B         C
first
bar   -1.296337  1.469725 -0.938794
baz    0.123836  1.449735 -0.433567
foo    1.555563 -1.032011  0.680433
qux    0.535420 -0.962723 -0.276099
```

### 7.4.7 Advanced reindexing and alignment with hierarchical index

The parameter `level` has been added to the `reindex` and `align` methods of pandas objects. This is useful to broadcast values across a level. For instance:

```
In [781]: midx = MultiIndex(levels=[['zero', 'one'], ['x','y']],
   .....:                   labels=[[1,1,0,0],[1,0,1,0]])
   .....:

In [782]: df = DataFrame(randn(4,2), index=midx)

In [783]: print df
```

```
                0         1
one  y  0.307453 -0.906534
     x -1.505397  1.392009
zero y -0.027793 -0.631023
     x -0.662357  2.725042

In [784]: df2 = df.mean(level=0)

In [785]: print df2
              0         1
zero -0.345075  1.047010
one  -0.598972  0.242737

In [786]: print df2.reindex(df.index, level=0)
                0         1
one  y -0.598972  0.242737
     x -0.598972  0.242737
zero y -0.345075  1.047010
     x -0.345075  1.047010

In [787]: df_aligned, df2_aligned = df.align(df2, level=0)

In [788]: print df_aligned
                0         1
one  y  0.307453 -0.906534
     x -1.505397  1.392009
zero y -0.027793 -0.631023
     x -0.662357  2.725042

In [789]: print df2_aligned
                0         1
one  y -0.598972  0.242737
     x -0.598972  0.242737
zero y -0.345075  1.047010
     x -0.345075  1.047010
```

### 7.4.8 The need for sortedness

**Caveat emptor**: the present implementation of `MultiIndex` requires that the labels be sorted for some of the slicing / indexing routines to work correctly. You can think about breaking the axis into unique groups, where at the hierarchical level of interest, each distinct group shares a label, but no two have the same label. However, the `MultiIndex` does not enforce this: **you are responsible for ensuring that things are properly sorted**. There is an important new method `sortlevel` to sort an axis within a `MultiIndex` so that its labels are grouped and sorted by the original ordering of the associated factor at that level. Note that this does not necessarily mean the labels will be sorted lexicographically!

```
In [790]: import random; random.shuffle(tuples)

In [791]: s = Series(randn(8), index=MultiIndex.from_tuples(tuples))

In [792]: s
Out[792]:
baz  one   -1.847240
     two   -0.529247
foo  two    0.614656
bar  two   -1.590742
```

```
qux  one   -0.156479
foo  one   -1.696377
qux  two    0.819712
bar  one   -2.107728
dtype: float64

In [793]: s.sortlevel(0)
Out[793]:
bar  one   -2.107728
     two   -1.590742
baz  one   -1.847240
     two   -0.529247
foo  one   -1.696377
     two    0.614656
qux  one   -0.156479
     two    0.819712
dtype: float64

In [794]: s.sortlevel(1)
Out[794]:
bar  one   -2.107728
baz  one   -1.847240
foo  one   -1.696377
qux  one   -0.156479
bar  two   -1.590742
baz  two   -0.529247
foo  two    0.614656
qux  two    0.819712
dtype: float64
```

Note, you may also pass a level name to `sortlevel` if the MultiIndex levels are named.

```
In [795]: s.index.names = ['L1', 'L2']

In [796]: s.sortlevel(level='L1')
Out[796]:
L1   L2
bar  one   -2.107728
     two   -1.590742
baz  one   -1.847240
     two   -0.529247
foo  one   -1.696377
     two    0.614656
qux  one   -0.156479
     two    0.819712
dtype: float64

In [797]: s.sortlevel(level='L2')
Out[797]:
L1   L2
bar  one   -2.107728
baz  one   -1.847240
foo  one   -1.696377
qux  one   -0.156479
bar  two   -1.590742
baz  two   -0.529247
foo  two    0.614656
qux  two    0.819712
```

```
dtype: float64
```

Some indexing will work even if the data are not sorted, but will be rather inefficient and will also return a copy of the data rather than a view:

```
In [798]: s['qux']
Out[798]:
L2
one   -0.156479
two    0.819712
dtype: float64

In [799]: s.sortlevel(1)['qux']
Out[799]:
L2
one   -0.156479
two    0.819712
dtype: float64
```

On higher dimensional objects, you can sort any of the other axes by level if they have a MultiIndex:

```
In [800]: df.T.sortlevel(1, axis=1)
Out[800]:
       zero       one      zero       one
          x         x         y         y
0 -0.662357 -1.505397 -0.027793  0.307453
1  2.725042  1.392009 -0.631023 -0.906534
```

The `MultiIndex` object has code to **explicity check the sort depth**. Thus, if you try to index at a depth at which the index is not sorted, it will raise an exception. Here is a concrete example to illustrate this:

```
In [801]: tuples = [('a', 'a'), ('a', 'b'), ('b', 'a'), ('b', 'b')]

In [802]: idx = MultiIndex.from_tuples(tuples)

In [803]: idx.lexsort_depth
Out[803]: 2

In [804]: reordered = idx[[1, 0, 3, 2]]

In [805]: reordered.lexsort_depth
Out[805]: 1

In [806]: s = Series(randn(4), index=reordered)

In [807]: s.ix['a':'a']
Out[807]:
a  b   -0.488326
   a    0.851918
dtype: float64
```

However:

```
>>> s.ix[('a', 'b'):('b', 'a')]
Exception: MultiIndex lexsort depth 1, key was length 2
```

### 7.4.9 Swapping levels with `swaplevel`

The `swaplevel` function can switch the order of two levels:

```
In [808]: df[:5]
Out[808]:
               0         1
one  y  0.307453 -0.906534
     x -1.505397  1.392009
zero y -0.027793 -0.631023
     x -0.662357  2.725042

In [809]: df[:5].swaplevel(0, 1, axis=0)
Out[809]:
               0         1
y one   0.307453 -0.906534
x one  -1.505397  1.392009
y zero -0.027793 -0.631023
x zero -0.662357  2.725042
```

### 7.4.10 Reordering levels with `reorder_levels`

The `reorder_levels` function generalizes the `swaplevel` function, allowing you to permute the hierarchical index levels in one step:

```
In [810]: df[:5].reorder_levels([1,0], axis=0)
Out[810]:
               0         1
y one   0.307453 -0.906534
x one  -1.505397  1.392009
y zero -0.027793 -0.631023
x zero -0.662357  2.725042
```

### 7.4.11 Some gory internal details

Internally, the `MultiIndex` consists of a few things: the **levels**, the integer **labels**, and the level **names**:

```
In [811]: index
Out[811]:
MultiIndex
[bar  one,      two, baz  one,      two, foo  one,      two, qux  one,      two]

In [812]: index.levels
Out[812]: [Index([bar, baz, foo, qux], dtype=object), Index([one, two], dtype=object)]

In [813]: index.labels
Out[813]: [array([0, 0, 1, 1, 2, 2, 3, 3]), array([0, 1, 0, 1, 0, 1, 0, 1])]

In [814]: index.names
Out[814]: ['first', 'second']
```

You can probably guess that the labels 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 labels 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 labels yourself, please be careful.

## 7.5 Adding an index to an existing DataFrame

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.

### 7.5.1 Add an index using DataFrame columns

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, indexed DataFrame:

```
In [815]: data
Out[815]:
     a    b  c  d
0  bar  one  z  1
1  bar  two  y  2
2  foo  one  x  3
3  foo  two  w  4

In [816]: indexed1 = data.set_index('c')

In [817]: indexed1
Out[817]:
     a    b  d
c
z  bar  one  1
y  bar  two  2
x  foo  one  3
w  foo  two  4

In [818]: indexed2 = data.set_index(['a', 'b'])

In [819]: indexed2
Out[819]:
         c  d
a   b
bar one  z  1
    two  y  2
foo one  x  3
    two  w  4
```

The `append` keyword option allow you to keep the existing index and append the given columns to a MultiIndex:

```
In [820]: frame = data.set_index('c', drop=False)

In [821]: frame = frame.set_index(['a', 'b'], append=True)

In [822]: frame
Out[822]:
           c  d
c a   b
z bar one  z  1
y bar two  y  2
x foo one  x  3
w foo two  w  4
```

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 [823]: data.set_index('c', drop=False)
Out[823]:
     a    b  c  d
c
z  bar  one  z  1
y  bar  two  y  2
x  foo  one  x  3
w  foo  two  w  4

In [824]: data.set_index(['a', 'b'], inplace=True)
Out[824]:
         c  d
a   b
bar one  z  1
    two  y  2
foo one  x  3
    two  w  4

In [825]: data
Out[825]:
         c  d
a   b
bar one  z  1
    two  y  2
foo one  x  3
    two  w  4
```

### 7.5.2 Remove / reset the index, reset_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 to `set_index`

```
In [826]: data
Out[826]:
         c  d
a   b
bar one  z  1
    two  y  2
foo one  x  3
    two  w  4

In [827]: data.reset_index()
Out[827]:
     a    b  c  d
0  bar  one  z  1
1  bar  two  y  2
2  foo  one  x  3
3  foo  two  w  4
```

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 [828]: frame
Out[828]:
           c  d
c a   b
```

```
z bar one  z  1
y bar two  y  2
x foo one  x  3
w foo two  w  4

In [829]: frame.reset_index(level=1)
Out[829]:
         a  c  d
c b
z one  bar  z  1
y two  bar  y  2
x one  foo  x  3
w two  foo  w  4
```

`reset_index` takes an optional parameter `drop` which if true simply discards the index, instead of putting index values in the DataFrame's columns.

**Note:** The `reset_index` method used to be called `delevel` which is now deprecated.

### 7.5.3 Adding an ad hoc index

If you create an index yourself, you can just assign it to the `index` field:

```
data.index = index
```

## 7.6 Indexing internal details

**Note:** The following is largely relevant for those actually working on the pandas codebase. And the source code is still the best place to look at the specifics of how things are implemented.

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
- `MultiIndex`: the standard hierarchical index object
- `date_range`: fixed frequency date range generated from a time rule or DateOffset. An ndarray of Python datetime objects

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
- `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

CHAPTER

EIGHT

# COMPUTATIONAL TOOLS

## 8.1 Statistical functions

### 8.1.1 Percent Change

Both `Series` and `DataFrame` has a method `pct_change` to compute the percent change over a given number of periods (using `fill_method` to fill NA/null values).

```
In [209]: ser = Series(randn(8))

In [210]: ser.pct_change()
Out[210]:
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 [211]: df = DataFrame(randn(10, 4))

In [212]: df.pct_change(periods=3)
Out[212]:
          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
```

### 8.1.2 Covariance

The `Series` object has a method `cov` to compute covariance between series (excluding NA/null values).

```
In [213]: s1 = Series(randn(1000))

In [214]: s2 = Series(randn(1000))

In [215]: s1.cov(s2)
Out[215]: 0.00068010881743109321
```

Analogously, `DataFrame` has a method `cov` to compute pairwise covariances among the series in the DataFrame, also excluding NA/null values.

```
In [216]: frame = DataFrame(randn(1000, 5), columns=['a', 'b', 'c', 'd', 'e'])

In [217]: frame.cov()
Out[217]:
          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 [218]: frame = DataFrame(randn(20, 3), columns=['a', 'b', 'c'])

In [219]: frame.ix[:5, 'a'] = np.nan

In [220]: frame.ix[5:10, 'b'] = np.nan

In [221]: frame.cov()
Out[221]:
          a         b         c
a  1.210090 -0.430629  0.018002
b -0.430629  1.240960  0.347188
c  0.018002  0.347188  1.301149

In [222]: frame.cov(min_periods=12)
Out[222]:
          a         b         c
a  1.210090       NaN  0.018002
b       NaN  1.240960  0.347188
c  0.018002  0.347188  1.301149
```

### 8.1.3 Correlation

Several methods for computing correlations are provided. Several kinds of correlation methods 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.

```
In [223]: frame = DataFrame(randn(1000, 5), columns=['a', 'b', 'c', 'd', 'e'])

In [224]: frame.ix[::2] = np.nan
```

```
# Series with Series
In [225]: frame['a'].corr(frame['b'])
Out[225]: 0.013479040400098763

In [226]: frame['a'].corr(frame['b'], method='spearman')
Out[226]: -0.0072898851595406388

# Pairwise correlation of DataFrame columns
In [227]: frame.corr()
Out[227]:
          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 [228]: frame = DataFrame(randn(20, 3), columns=['a', 'b', 'c'])

In [229]: frame.ix[:5, 'a'] = np.nan

In [230]: frame.ix[5:10, 'b'] = np.nan

In [231]: frame.corr()
Out[231]:
          a         b         c
a  1.000000 -0.076520  0.160092
b -0.076520  1.000000  0.135967
c  0.160092  0.135967  1.000000

In [232]: frame.corr(min_periods=12)
Out[232]:
          a         b         c
a  1.000000       NaN  0.160092
b       NaN  1.000000  0.135967
c  0.160092  0.135967  1.000000
```

A related method `corrwith` is implemented on DataFrame to compute the correlation between like-labeled Series contained in different DataFrame objects.

```
In [233]: index = ['a', 'b', 'c', 'd', 'e']

In [234]: columns = ['one', 'two', 'three', 'four']

In [235]: df1 = DataFrame(randn(5, 4), index=index, columns=columns)

In [236]: df2 = DataFrame(randn(4, 4), index=index[:4], columns=columns)

In [237]: df1.corrwith(df2)
Out[237]:
one     -0.125501
two     -0.493244
three    0.344056
four     0.004183
dtype: float64
```

```
In [238]: df2.corrwith(df1, axis=1)
Out[238]:
a   -0.675817
b    0.458296
c    0.190809
d   -0.186275
e         NaN
dtype: float64
```

### 8.1.4 Data ranking

The `rank` method produces a data ranking with ties being assigned the mean of the ranks (by default) for the group:

```
In [239]: s = Series(np.random.randn(5), index=list('abcde'))

In [240]: s['d'] = s['b'] # so there's a tie

In [241]: s.rank()
Out[241]:
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 [242]: df = DataFrame(np.random.randn(10, 6))

In [243]: df[4] = df[2][:5] # some ties

In [244]: df
Out[244]:
          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 [245]: df.rank(1)
Out[245]:
   0  1    2  3    4  5
0  4  3  1.5  5  1.5  6
1  2  6  4.5  1  4.5  3
2  1  6  3.5  5  3.5  2
3  4  5  1.5  3  1.5  6
4  5  3  1.5  4  1.5  6
5  1  2  5.0  3  NaN  4
6  4  5  3.0  1  NaN  2
```

```
7  2  5  3.0  4  NaN  1
8  2  5  3.0  4  NaN  1
9  2  3  1.0  4  NaN  5
```

`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

**Note:** These methods are significantly faster (around 10-20x) than `scipy.stats.rankdata`.

## 8.2 Moving (rolling) statistics / moments

For working with time series data, a number of functions are provided for computing common *moving* or *rolling* statistics. Among these are count, sum, mean, median, correlation, variance, covariance, standard deviation, skewness, and kurtosis. All of these methods are in the `pandas` namespace, but otherwise they can be found in `pandas.stats.moments`.

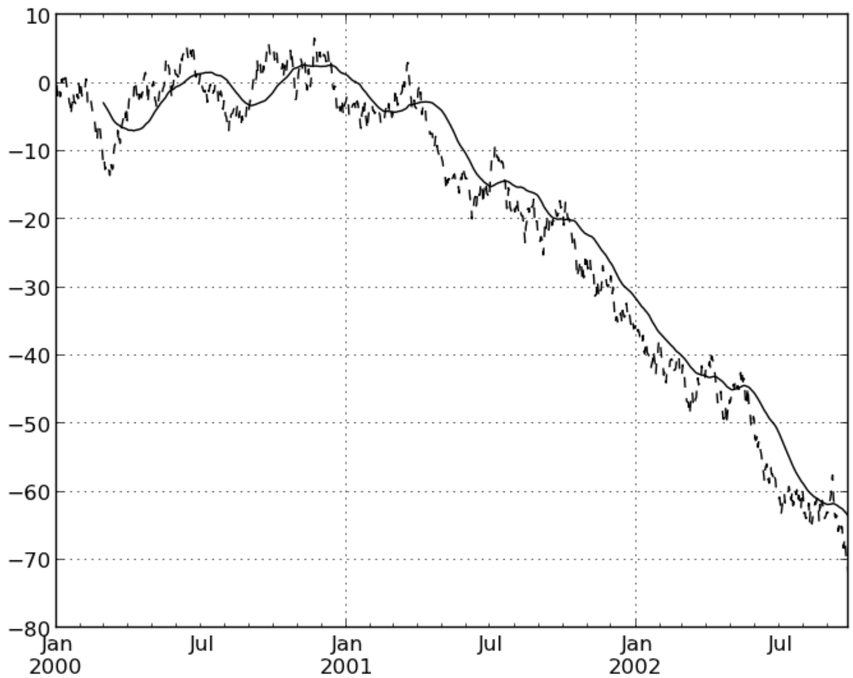
| Function | Description |
|---|---|
| `rolling_count` | Number of non-null observations |
| `rolling_sum` | Sum of values |
| `rolling_mean` | Mean of values |
| `rolling_median` | Arithmetic median of values |
| `rolling_min` | Minimum |
| `rolling_max` | Maximum |
| `rolling_std` | Unbiased standard deviation |
| `rolling_var` | Unbiased variance |
| `rolling_skew` | Unbiased skewness (3rd moment) |
| `rolling_kurt` | Unbiased kurtosis (4th moment) |
| `rolling_quantile` | Sample quantile (value at %) |
| `rolling_apply` | Generic apply |
| `rolling_cov` | Unbiased covariance (binary) |
| `rolling_corr` | Correlation (binary) |
| `rolling_corr_pairwise` | Pairwise correlation of DataFrame columns |
| `rolling_window` | Moving window function |

Generally these methods all have the same interface. The binary operators (e.g. `rolling_corr`) take two Series or DataFrames. Otherwise, they all accept the following arguments:

- `window`: size of moving window
- `min_periods`: threshold of non-null data points to require (otherwise result is NA)
- `freq`: optionally specify a *frequency string* or *DateOffset* to pre-conform the data to. Note that prior to pandas v0.8.0, a keyword argument `time_rule` was used instead of `freq` that referred to the legacy time rule constants

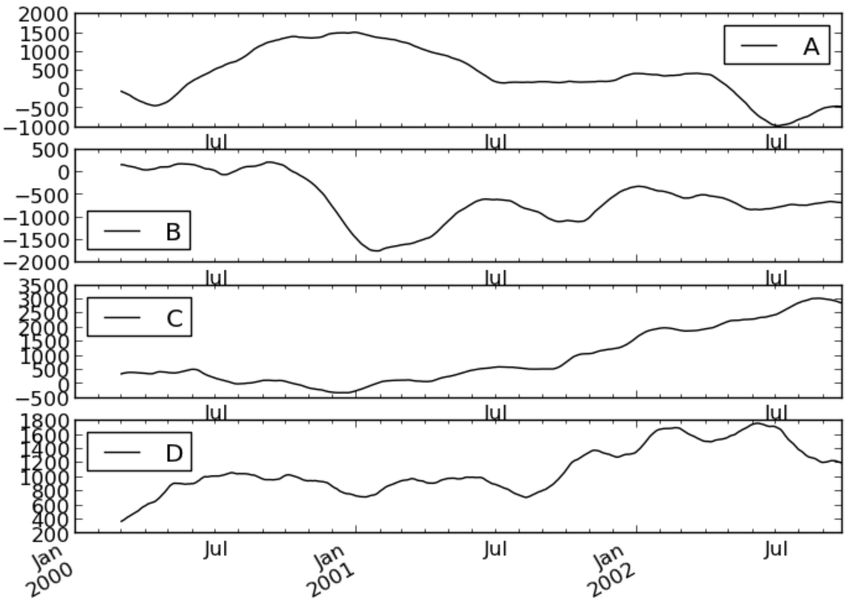
These functions can be applied to ndarrays or Series objects:

```
In [246]: ts = Series(randn(1000), index=date_range('1/1/2000', periods=1000))

In [247]: ts = ts.cumsum()

In [248]: ts.plot(style='k--')
Out[248]: <matplotlib.axes.AxesSubplot at 0x6691590>

In [249]: rolling_mean(ts, 60).plot(style='k')
Out[249]: <matplotlib.axes.AxesSubplot at 0x6691590>
```



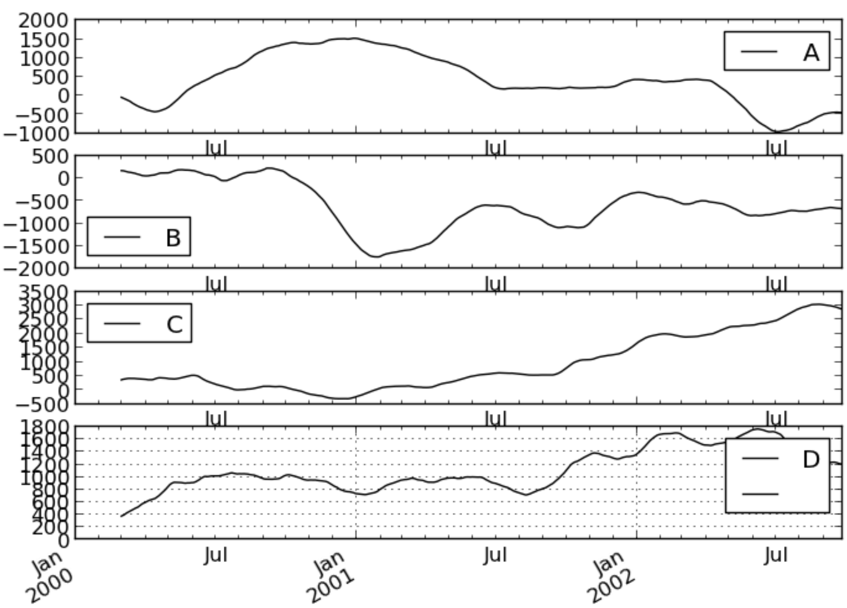

They can also be applied to DataFrame objects. This is really just syntactic sugar for applying the moving window operator to all of the DataFrame's columns:

```
In [250]: df = DataFrame(randn(1000, 4), index=ts.index,
   .....:                columns=['A', 'B', 'C', 'D'])
   .....:

In [251]: df = df.cumsum()

In [252]: rolling_sum(df, 60).plot(subplots=True)
Out[252]:
array([Axes(0.125,0.747826;0.775x0.152174),
       Axes(0.125,0.565217;0.775x0.152174),
       Axes(0.125,0.382609;0.775x0.152174), Axes(0.125,0.2;0.775x0.152174)], dtype=object)
```




The `rolling_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. Suppose we wanted to compute the mean absolute deviation on a rolling basis:

```
In [253]: mad = lambda x: np.fabs(x - x.mean()).mean()

In [254]: rolling_apply(ts, 60, mad).plot(style='k')
Out[254]: <matplotlib.axes.AxesSubplot at 0x6d4f750>
```




The `rolling_window` function performs a generic rolling window computation on the input data. The weights used in the window are specified by the `win_type` keyword. The list of recognized types are:

- `boxcar`
- `triang`
- `blackman`

- `hamming`
- `bartlett`
- `parzen`
- `bohman`
- `blackmanharris`
- `nuttall`
- `barthann`
- `kaiser` (needs beta)
- `gaussian` (needs std)
- `general_gaussian` (needs power, width)
- `slepian` (needs width).

```
In [255]: ser = Series(randn(10), index=date_range('1/1/2000', periods=10))

In [256]: rolling_window(ser, 5, 'triang')
Out[256]:
2000-01-01         NaN
2000-01-02         NaN
2000-01-03         NaN
2000-01-04         NaN
2000-01-05   -0.622722
2000-01-06   -0.460623
2000-01-07   -0.229918
2000-01-08   -0.237308
2000-01-09   -0.335064
2000-01-10   -0.403449
Freq: D, dtype: float64
```

Note that the `boxcar` window is equivalent to `rolling_mean`:

```
In [257]: rolling_window(ser, 5, 'boxcar')
Out[257]:
2000-01-01         NaN
2000-01-02         NaN
2000-01-03         NaN
2000-01-04         NaN
2000-01-05   -0.841164
2000-01-06   -0.779948
2000-01-07   -0.565487
2000-01-08   -0.502815
2000-01-09   -0.553755
2000-01-10   -0.472211
Freq: D, dtype: float64

In [258]: rolling_mean(ser, 5)
Out[258]:
2000-01-01         NaN
2000-01-02         NaN
2000-01-03         NaN
2000-01-04         NaN
2000-01-05   -0.841164
2000-01-06   -0.779948
2000-01-07   -0.565487
```

```
2000-01-08   -0.502815
2000-01-09   -0.553755
2000-01-10   -0.472211
Freq: D, dtype: float64
```

For some windowing functions, additional parameters must be specified:

```
In [259]: rolling_window(ser, 5, 'gaussian', std=0.1)
Out[259]:
2000-01-01         NaN
2000-01-02         NaN
2000-01-03         NaN
2000-01-04         NaN
2000-01-05   -0.261998
2000-01-06   -0.230600
2000-01-07    0.121276
2000-01-08   -0.136220
2000-01-09   -0.057945
2000-01-10   -0.199326
Freq: D, dtype: float64
```

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. This keyword is available in other rolling functions as well.

```
In [260]: rolling_window(ser, 5, 'boxcar')
Out[260]:
2000-01-01         NaN
2000-01-02         NaN
2000-01-03         NaN
2000-01-04         NaN
2000-01-05   -0.841164
2000-01-06   -0.779948
2000-01-07   -0.565487
2000-01-08   -0.502815
2000-01-09   -0.553755
2000-01-10   -0.472211
Freq: D, dtype: float64

In [261]: rolling_window(ser, 5, 'boxcar', center=True)
Out[261]:
2000-01-01         NaN
2000-01-02         NaN
2000-01-03   -0.841164
2000-01-04   -0.779948
2000-01-05   -0.565487
2000-01-06   -0.502815
2000-01-07   -0.553755
2000-01-08   -0.472211
2000-01-09         NaN
2000-01-10         NaN
Freq: D, dtype: float64

In [262]: rolling_mean(ser, 5, center=True)
Out[262]:
2000-01-01         NaN
2000-01-02         NaN
2000-01-03   -0.841164
2000-01-04   -0.779948
2000-01-05   -0.565487
```

```
2000-01-06   -0.502815
2000-01-07   -0.553755
2000-01-08   -0.472211
2000-01-09         NaN
2000-01-10         NaN
Freq: D, dtype: float64
```

### 8.2.1 Binary rolling moments

`rolling_cov` and `rolling_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`: compute statistic for matching column names, returning a DataFrame

For example:

```
In [263]: df2 = df[:20]

In [264]: rolling_corr(df2, df2['B'], window=5)
Out[264]:
                   A    B         C         D
2000-01-01       NaN  NaN       NaN       NaN
2000-01-02       NaN  NaN       NaN       NaN
2000-01-03       NaN  NaN       NaN       NaN
2000-01-04       NaN  NaN       NaN       NaN
2000-01-05 -0.262853    1  0.334449  0.193380
2000-01-06 -0.083745    1 -0.521587 -0.556126
2000-01-07 -0.292940    1 -0.658532 -0.458128
2000-01-08  0.840416    1  0.796505 -0.498672
2000-01-09 -0.135275    1  0.753895 -0.634445
2000-01-10 -0.346229    1 -0.682232 -0.645681
2000-01-11 -0.365524    1 -0.775831 -0.561991
2000-01-12 -0.204761    1 -0.855874 -0.382232
2000-01-13  0.575218    1 -0.747531  0.167892
2000-01-14  0.519499    1 -0.687277  0.192822
2000-01-15  0.048982    1  0.167669 -0.061463
2000-01-16  0.217190    1  0.167564 -0.326034
2000-01-17  0.641180    1 -0.164780 -0.111487
2000-01-18  0.130422    1  0.322833  0.632383
2000-01-19  0.317278    1  0.384528  0.813656
2000-01-20  0.293598    1  0.159538  0.742381
```

### 8.2.2 Computing rolling pairwise correlations

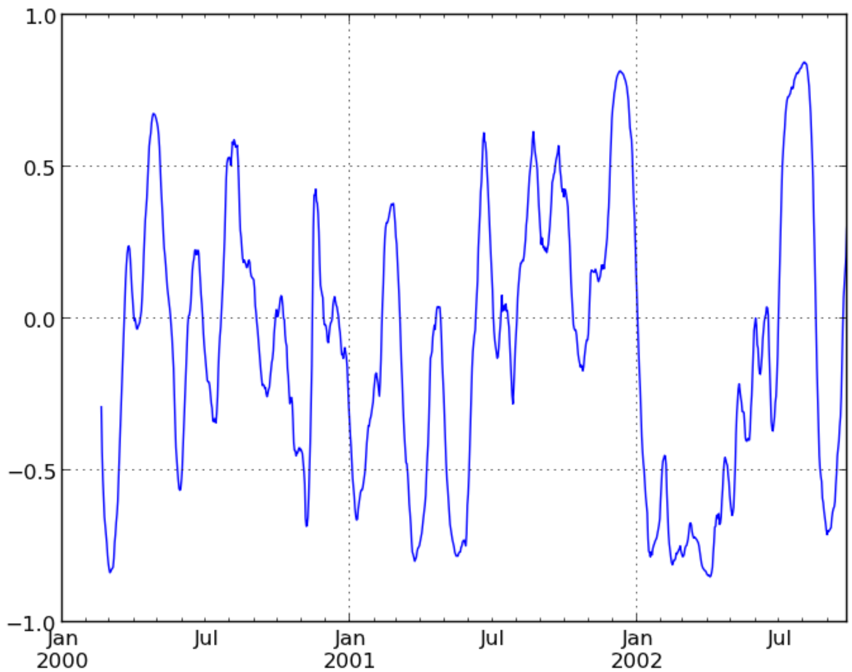
In financial data analysis and other fields it's common to compute correlation matrices for a collection of time series. More difficult is to compute a moving-window correlation matrix. This can be done using the `rolling_corr_pairwise` function, which yields a `Panel` whose `items` are the dates in question:

```
In [265]: correls = rolling_corr_pairwise(df, 50)

In [266]: correls[df.index[-50]]
Out[266]:
```

```
          A         B         C         D
A  1.000000  0.604221  0.767429 -0.776170
B  0.604221  1.000000  0.461484 -0.381148
C  0.767429  0.461484  1.000000 -0.748863
D -0.776170 -0.381148 -0.748863  1.000000
```

You can efficiently retrieve the time series of correlations between two columns using `ix` indexing:

```
In [267]: correls.ix[:, 'A', 'C'].plot()
Out[267]: <matplotlib.axes.AxesSubplot at 0x6d76590>
```




## 8.3 Expanding window moment functions

A common alternative to rolling statistics is to use an *expanding* window, which yields the value of the statistic with all the data available up to that point in time. As these calculations are a special case of rolling statistics, they are implemented in pandas such that the following two calls are equivalent:

```
In [268]: rolling_mean(df, window=len(df), min_periods=1)[:5]
Out[268]:
                   A         B         C         D
2000-01-01 -1.388345  3.317290  0.344542 -0.036968
2000-01-02 -1.123132  3.622300  1.675867  0.595300
2000-01-03 -0.628502  3.626503  2.455240  1.060158
2000-01-04 -0.768740  3.888917  2.451354  1.281874
2000-01-05 -0.824034  4.108035  2.556112  1.140723

In [269]: expanding_mean(df)[:5]
Out[269]:
                   A         B         C         D
2000-01-01 -1.388345  3.317290  0.344542 -0.036968
2000-01-02 -1.123132  3.622300  1.675867  0.595300
2000-01-03 -0.628502  3.626503  2.455240  1.060158
```

```
2000-01-04 -0.768740  3.888917  2.451354  1.281874
2000-01-05 -0.824034  4.108035  2.556112  1.140723
```

Like the `rolling_` functions, the following methods are included in the `pandas` namespace or can be located in `pandas.stats.moments`.

| Function | Description |
|---|---|
| `expanding_count` | Number of non-null observations |
| `expanding_sum` | Sum of values |
| `expanding_mean` | Mean of values |
| `expanding_median` | Arithmetic median of values |
| `expanding_min` | Minimum |
| `expanding_max` | Maximum |
| `expanding_std` | Unbiased standard deviation |
| `expanding_var` | Unbiased variance |
| `expanding_skew` | Unbiased skewness (3rd moment) |
| `expanding_kurt` | Unbiased kurtosis (4th moment) |
| `expanding_quantile` | Sample quantile (value at %) |
| `expanding_apply` | Generic apply |
| `expanding_cov` | Unbiased covariance (binary) |
| `expanding_corr` | Correlation (binary) |
| `expanding_corr_pairwise` | Pairwise correlation of DataFrame columns |

Aside from not having a `window` parameter, these functions have the same interfaces as their `rolling_` counterpart. Like above, the parameters they all accept are:

- `min_periods`: threshold of non-null data points to require. Defaults to minimum needed to compute statistic. No `NaNs` will be output once `min_periods` non-null data points have been seen.
- `freq`: optionally specify a *frequency string* or *DateOffset* to pre-conform the data to. Note that prior to pandas v0.8.0, a keyword argument `time_rule` was used instead of `freq` that referred to the legacy time rule constants

**Note:** The output of the `rolling_` and `expanding_` functions do not return a `NaN` if there are at least `min_periods` non-null values in the current window. This differs from `cumsum`, `cumprod`, `cummax`, and `cummin`, which return `NaN` in the output wherever a `NaN` is encountered in the input.

An expanding window statistic will be more stable (and less responsive) than its rolling window counterpart as the increasing window size decreases the relative impact of an individual data point. As an example, here is the `expanding_mean` output for the previous time series dataset:

```
In [270]: ts.plot(style='k--')
Out[270]: <matplotlib.axes.AxesSubplot at 0x74323d0>

In [271]: expanding_mean(ts).plot(style='k')
Out[271]: <matplotlib.axes.AxesSubplot at 0x74323d0>
```


## 8.4 Exponentially weighted moment functions

A related set of functions are exponentially weighted versions of many of the above statistics. A number of EW (exponentially weighted) functions are provided using the blending method. For example, where $y_t$ is the result and $x_t$ the input, we compute an exponentially weighted moving average as

$$y_t = \alpha y_{t-1} + (1 - \alpha)x_t$$

One must have $0 < \alpha \leq 1$, but rather than pass $\alpha$ directly, it's easier to think about either the **span** or **center of mass (com)** of an EW moment:

$$\alpha = \begin{cases} \frac{2}{s+1}, s = \text{span} \\ \frac{1}{c+1}, c = \text{center of mass} \end{cases}$$

You can pass one or the other to these functions but not both. **Span** corresponds to what is commonly called a "20-day EW moving average" for example. **Center of mass** has a more physical interpretation. For example, **span** = 20 corresponds to **com** = 9.5. Here is the list of functions available:

| Function | Description |
|---|---|
| `ewma` | EW moving average |
| `ewmvar` | EW moving variance |
| `ewmstd` | EW moving standard deviation |
| `ewmcorr` | EW moving correlation |
| `ewmcov` | EW moving covariance |

Here are an example for a univariate time series:

```
In [272]: plt.close('all')

In [273]: ts.plot(style='k--')
Out[273]: <matplotlib.axes.AxesSubplot at 0x77b2950>
```

```
In [274]: ewma(ts, span=20).plot(style='k')
Out[274]: <matplotlib.axes.AxesSubplot at 0x77b2950>
```


**Note:** The EW functions perform a standard adjustment to the initial observations whereby if there are fewer observations than called for in the span, those observations are reweighted accordingly.

## 8.5 Linear and panel regression

**Note:** We plan to move this functionality to statsmodels for the next release. Some of the result attributes may change names in order to foster naming consistency with the rest of statsmodels. We will provide every effort to provide compatibility with older versions of pandas, however.

We have implemented a very fast set of *moving-window linear regression* classes in pandas. Two different types of regressions are supported:

- Standard ordinary least squares (OLS) multiple regression
- Multiple regression (OLS-based) on panel data including with fixed-effects (also known as entity or individual effects) or time-effects.

Both kinds of linear models are accessed through the `ols` function in the pandas namespace. They all take the following arguments to specify either a static (full sample) or dynamic (moving window) regression:

- `window_type`: `'full sample'` (default), `'expanding'`, or `rolling`
- `window`: size of the moving window in the `window_type='rolling'` case. If `window` is specified, `window_type` will be automatically set to `'rolling'`
- `min_periods`: minimum number of time periods to require to compute the regression coefficients

Generally speaking, the `ols` works by being given a `y` (response) object and an `x` (predictors) object. These can take many forms:

- `y`: a Series, ndarray, or DataFrame (panel model)
- `x`: Series, DataFrame, dict of Series, dict of DataFrame or Panel

Based on the types of `y` and `x`, the model will be inferred to either a panel model or a regular linear model. If the `y` variable is a DataFrame, the result will be a panel model. In this case, the `x` variable must either be a Panel, or a dict of DataFrame (which will be coerced into a Panel).

### 8.5.1 Standard OLS regression

Let's pull in some sample data:

```
In [275]: from pandas.io.data import DataReader

In [276]: symbols = ['MSFT', 'GOOG', 'AAPL']

In [277]: data = dict((sym, DataReader(sym, "yahoo"))
   .....:             for sym in symbols)
   .....:

In [278]: panel = Panel(data).swapaxes('items', 'minor')

In [279]: close_px = panel['Close']

# convert closing prices to returns
In [280]: rets = close_px / close_px.shift(1) - 1

In [281]: rets.info()
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 830 entries, 2010-01-04 00:00:00 to 2013-04-22 00:00:00
Data columns:
AAPL    829  non-null values
GOOG    829  non-null values
MSFT    829  non-null values
dtypes: float64(3)
```

Let's do a static regression of `AAPL` returns on `GOOG` returns:

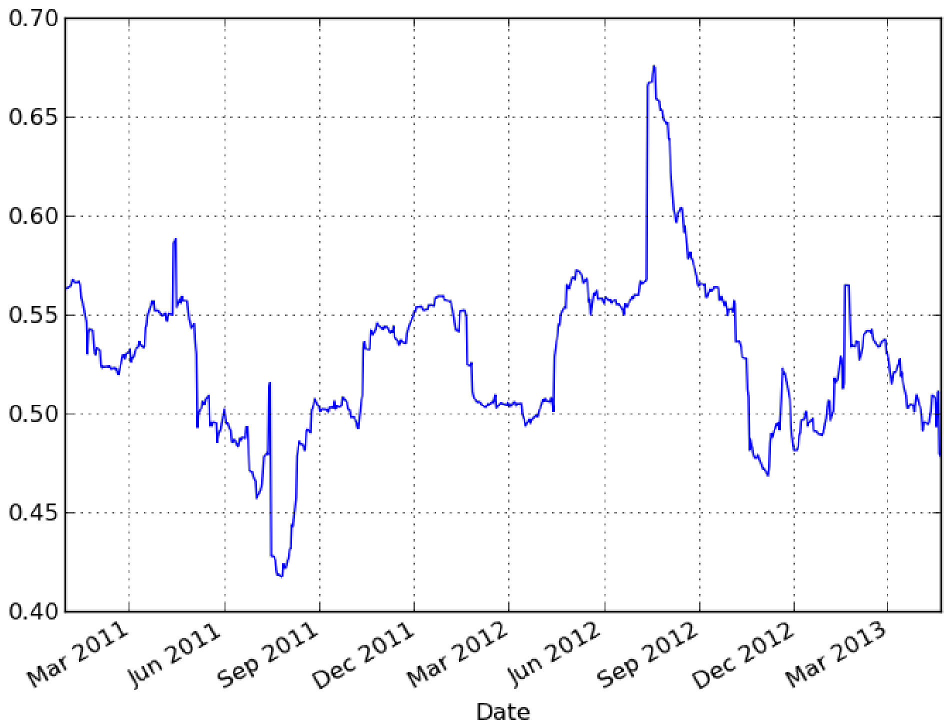
```
In [282]: model = ols(y=rets['AAPL'], x=rets.ix[:, ['GOOG']])

In [283]: model
Out[283]:
-------------------------Summary of Regression Analysis-------------------------
Formula: Y ~ <GOOG> + <intercept>
Number of Observations:         829
Number of Degrees of Freedom:   2
R-squared:         0.2372
Adj R-squared:     0.2363
Rmse:              0.0157
F-stat (1, 827):   257.2205, p-value:     0.0000
Degrees of Freedom: model 1, resid 827
-----------------------Summary of Estimated Coefficients------------------------
      Variable       Coef    Std Err     t-stat    p-value    CI 2.5%   CI 97.5%
--------------------------------------------------------------------------------
          GOOG     0.5267     0.0328      16.04     0.0000     0.4623     0.5910
     intercept     0.0007     0.0005       1.25     0.2101    -0.0004     0.0018
```

```
---------------------------------End of Summary---------------------------------

In [284]: model.beta
Out[284]:
GOOG         0.526664
intercept    0.000685
dtype: float64
```

If we had passed a Series instead of a DataFrame with the single GOOG column, the model would have assigned the generic name x to the sole right-hand side variable.

We can do a moving window regression to see how the relationship changes over time:

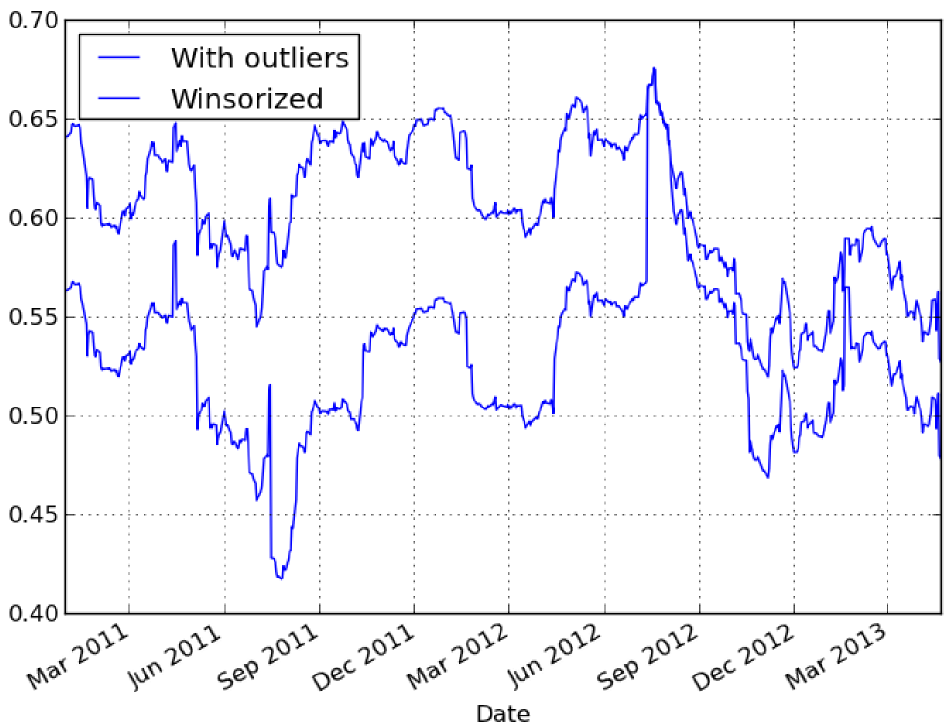
```
In [285]: model = ols(y=rets['AAPL'], x=rets.ix[:, ['GOOG']],
   .....:             window=250)
   .....:

# just plot the coefficient for GOOG
In [286]: model.beta['GOOG'].plot()
Out[286]: <matplotlib.axes.AxesSubplot at 0x8160410>
```




It looks like there are some outliers rolling in and out of the window in the above regression, influencing the results. We could perform a simple winsorization at the 3 STD level to trim the impact of outliers:

```
In [287]: winz = rets.copy()

In [288]: std_1year = rolling_std(rets, 250, min_periods=20)

# cap at 3 * 1 year standard deviation
In [289]: cap_level = 3 * np.sign(winz) * std_1year

In [290]: winz[np.abs(winz) > 3 * std_1year] = cap_level
```

```
In [291]: winz_model = ols(y=winz['AAPL'], x=winz.ix[:, ['GOOG']],
   .....:                  window=250)
   .....:

In [292]: model.beta['GOOG'].plot(label="With outliers")
Out[292]: <matplotlib.axes.AxesSubplot at 0x8d91dd0>

In [293]: winz_model.beta['GOOG'].plot(label="Winsorized"); plt.legend(loc='best')
Out[293]: <matplotlib.legend.Legend at 0x8eb97d0>
```




So in this simple example we see the impact of winsorization is actually quite significant. Note the correlation after winsorization remains high:

```
In [294]: winz.corrwith(rets)
Out[294]:
AAPL    0.988868
GOOG    0.973599
MSFT    0.998398
dtype: float64
```

Multiple regressions can be run by passing a DataFrame with multiple columns for the predictors `x`:

```
In [295]: ols(y=winz['AAPL'], x=winz.drop(['AAPL'], axis=1))
Out[295]:
-------------------------Summary of Regression Analysis-------------------------
Formula: Y ~ <GOOG> + <MSFT> + <intercept>
Number of Observations:         829
Number of Degrees of Freedom:   3
R-squared:         0.3217
Adj R-squared:     0.3200
Rmse:              0.0140
F-stat (2, 826):   195.8485, p-value:     0.0000
Degrees of Freedom: model 2, resid 826
```

```
-----------------------Summary of Estimated Coefficients------------------------
      Variable       Coef    Std Err     t-stat    p-value    CI 2.5%   CI 97.5%
--------------------------------------------------------------------------------
          GOOG     0.4636     0.0380      12.20     0.0000     0.3892     0.5381
          MSFT     0.2956     0.0418       7.07     0.0000     0.2136     0.3777
     intercept     0.0007     0.0005       1.38     0.1666    -0.0003     0.0016
---------------------------------End of Summary---------------------------------
```

### 8.5.2 Panel regression

We've implemented moving window panel regression on potentially unbalanced panel data (see this article if this means nothing to you). Suppose we wanted to model the relationship between the magnitude of the daily return and trading volume among a group of stocks, and we want to pool all the data together to run one big regression. This is actually quite easy:

```
# make the units somewhat comparable
In [296]: volume = panel['Volume'] / 1e8

In [297]: model = ols(y=volume, x={'return' : np.abs(rets)})

In [298]: model
Out[298]:
-------------------------Summary of Regression Analysis-------------------------
Formula: Y ~ <return> + <intercept>
Number of Observations:         2487
Number of Degrees of Freedom:   2
R-squared:         0.0211
Adj R-squared:     0.0207
Rmse:              0.2654
F-stat (1, 2485):    53.6545, p-value:     0.0000
Degrees of Freedom: model 1, resid 2485
-----------------------Summary of Estimated Coefficients------------------------
      Variable       Coef    Std Err     t-stat    p-value    CI 2.5%   CI 97.5%
--------------------------------------------------------------------------------
        return     3.4208     0.4670       7.32     0.0000     2.5055     4.3362
     intercept     0.2227     0.0076      29.38     0.0000     0.2079     0.2376
---------------------------------End of Summary---------------------------------
```

In a panel model, we can insert dummy (0-1) variables for the "entities" involved (here, each of the stocks) to account the a entity-specific effect (intercept):

```
In [299]: fe_model = ols(y=volume, x={'return' : np.abs(rets)},
   .....:                entity_effects=True)
   .....:

In [300]: fe_model
Out[300]:
-------------------------Summary of Regression Analysis-------------------------
Formula: Y ~ <return> + <FE_GOOG> + <FE_MSFT> + <intercept>
Number of Observations:         2487
Number of Degrees of Freedom:   4
R-squared:         0.7401
Adj R-squared:     0.7398
Rmse:              0.1368
F-stat (3, 2483):  2357.1701, p-value:     0.0000
Degrees of Freedom: model 3, resid 2483
-----------------------Summary of Estimated Coefficients------------------------
```

```
      Variable       Coef    Std Err     t-stat    p-value    CI 2.5%   CI 97.5%
--------------------------------------------------------------------------------
        return     4.5616     0.2420      18.85     0.0000     4.0872     5.0360
       FE_GOOG    -0.1540     0.0067     -22.87     0.0000    -0.1672    -0.1408
       FE_MSFT     0.3873     0.0068      57.34     0.0000     0.3741     0.4006
     intercept     0.1318     0.0057      23.04     0.0000     0.1206     0.1430
---------------------------------End of Summary---------------------------------
```

Because we ran the regression with an intercept, one of the dummy variables must be dropped or the design matrix will not be full rank. If we do not use an intercept, all of the dummy variables will be included:

```
In [301]: fe_model = ols(y=volume, x={'return' : np.abs(rets)},
   .....:                entity_effects=True, intercept=False)
   .....:

In [302]: fe_model
Out[302]:
-------------------------Summary of Regression Analysis-------------------------
Formula: Y ~ <return> + <FE_AAPL> + <FE_GOOG> + <FE_MSFT>
Number of Observations:         2487
Number of Degrees of Freedom:   4
R-squared:         0.7401
Adj R-squared:     0.7398
Rmse:              0.1368
F-stat (4, 2483):  2357.1701, p-value:     0.0000
Degrees of Freedom: model 3, resid 2483
-----------------------Summary of Estimated Coefficients------------------------
      Variable       Coef    Std Err     t-stat    p-value    CI 2.5%   CI 97.5%
--------------------------------------------------------------------------------
        return     4.5616     0.2420      18.85     0.0000     4.0872     5.0360
       FE_AAPL     0.1318     0.0057      23.04     0.0000     0.1206     0.1430
       FE_GOOG    -0.0223     0.0055      -4.07     0.0000    -0.0330    -0.0115
       FE_MSFT     0.5191     0.0054      96.76     0.0000     0.5086     0.5296
---------------------------------End of Summary---------------------------------
```

We can also include *time effects*, which demeans the data cross-sectionally at each point in time (equivalent to including dummy variables for each date). More mathematical care must be taken to properly compute the standard errors in this case:

```
In [303]: te_model = ols(y=volume, x={'return' : np.abs(rets)},
   .....:                time_effects=True, entity_effects=True)
   .....:

In [304]: te_model
Out[304]:
-------------------------Summary of Regression Analysis-------------------------
Formula: Y ~ <return> + <FE_GOOG> + <FE_MSFT>
Number of Observations:         2487
Number of Degrees of Freedom:   832
R-squared:         0.8159
Adj R-squared:     0.7235
Rmse:              0.1320
F-stat (3, 1655):     8.8284, p-value:     0.0000
Degrees of Freedom: model 831, resid 1655
-----------------------Summary of Estimated Coefficients------------------------
      Variable       Coef    Std Err     t-stat    p-value    CI 2.5%   CI 97.5%
--------------------------------------------------------------------------------
        return     3.7304     0.3422      10.90     0.0000     3.0597     4.4011
       FE_GOOG    -0.1556     0.0065     -23.89     0.0000    -0.1684    -0.1428
```

```
      FE_MSFT     0.3850     0.0066      58.72     0.0000     0.3721     0.3978
---------------------------------End of Summary---------------------------------
```

Here the intercept (the mean term) is dropped by default because it will be 0 according to the model assumptions, having subtracted off the group means.

### 8.5.3 Result fields and tests

We'll leave it to the user to explore the docstrings and source, especially as we'll be moving this code into statsmodels in the near future.

CHAPTER

NINE

# 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. It differs from the MaskedArray approach of, for example, `scikits.timeseries`. We are hopeful that NumPy will soon be able to provide a native NA type solution (similar to R) performant enough to be used in pandas.

## 9.1 Missing data basics

### 9.1.1 When / why does data become missing?

Some might quibble over our usage of *missing*. By "missing" we simply mean **null** or "not present for whatever reason". Many data sets simply arrive with missing data, either because it exists and was not collected or it never existed. For example, in a collection of financial time series, some of the time series might start on different dates. Thus, values prior to the start date would generally be marked as missing.

In pandas, one of the most common ways that missing data is **introduced** into a data set is by reindexing. For example

```
In [1159]: df = DataFrame(randn(5, 3), index=['a', 'c', 'e', 'f', 'h'],
   ......:                columns=['one', 'two', 'three'])
   ......:

In [1160]: df['four'] = 'bar'

In [1161]: df['five'] = df['one'] > 0

In [1162]: df
Out[1162]:
        one       two     three four   five
a  0.059117  1.138469 -2.400634  bar   True
c -0.280853  0.025653 -1.386071  bar  False
e  0.863937  0.252462  1.500571  bar   True
f  1.053202 -2.338595 -0.374279  bar   True
h -2.359958 -1.157886 -0.551865  bar  False

In [1163]: df2 = df.reindex(['a', 'b', 'c', 'd', 'e', 'f', 'g', 'h'])

In [1164]: df2
Out[1164]:
        one       two     three four   five
```

```
a  0.059117  1.138469 -2.400634  bar   True
b       NaN       NaN       NaN  NaN    NaN
c -0.280853  0.025653 -1.386071  bar  False
d       NaN       NaN       NaN  NaN    NaN
e  0.863937  0.252462  1.500571  bar   True
f  1.053202 -2.338595 -0.374279  bar   True
g       NaN       NaN       NaN  NaN    NaN
h -2.359958 -1.157886 -0.551865  bar  False
```

### 9.1.2 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 "null".

Until recently, for legacy reasons `inf` and `-inf` were also considered to be "null" in computations. This is no longer the case by default; use the `mode.use_inf_as_null` option to recover it. To make detecting missing values easier (and across different array dtypes), pandas provides the `isnull()` and `notnull()` functions, which are also methods on `Series` objects:

```
In [1165]: df2['one']
Out[1165]:
a    0.059117
b         NaN
c   -0.280853
d         NaN
e    0.863937
f    1.053202
g         NaN
h   -2.359958
Name: one, dtype: float64

In [1166]: isnull(df2['one'])
Out[1166]:
a    False
b     True
c    False
d     True
e    False
f    False
g     True
h    False
Name: one, dtype: bool

In [1167]: df2['four'].notnull()
Out[1167]:
a     True
b    False
c     True
d    False
e     True
f     True
g    False
h     True
dtype: bool
```

**Summary:** `NaN` and `None` (in object arrays) are considered missing by the `isnull` and `notnull` functions. `inf` and `-inf` are no longer considered missing by default.

## 9.2 Calculations with missing data

Missing values propagate naturally through arithmetic operations between pandas objects.

```
In [1168]: a
Out[1168]:
        one       two
a  0.059117  1.138469
b  0.059117  1.138469
c -0.280853  0.025653
d -0.280853  0.025653
e  0.863937  0.252462

In [1169]: b
Out[1169]:
        one       two     three
a  0.059117  1.138469 -2.400634
b       NaN       NaN       NaN
c -0.280853  0.025653 -1.386071
d       NaN       NaN       NaN
e  0.863937  0.252462  1.500571

In [1170]: a + b
Out[1170]:
        one  three       two
a  0.118234    NaN  2.276938
b       NaN    NaN       NaN
c -0.561707    NaN  0.051306
d       NaN    NaN       NaN
e  1.727874    NaN  0.504923
```

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 NA
- Methods like **cumsum** and **cumprod** ignore NA values, but preserve them in the resulting arrays

```
In [1171]: df
Out[1171]:
        one       two     three
a  0.059117  1.138469 -2.400634
b       NaN       NaN       NaN
c -0.280853  0.025653 -1.386071
d       NaN       NaN       NaN
e  0.863937  0.252462  1.500571
f  1.053202 -2.338595 -0.374279
g       NaN       NaN       NaN
h -2.359958 -1.157886 -0.551865

In [1172]: df['one'].sum()
Out[1172]: -0.66455558290247652
```

```
In [1173]: df.mean(1)
Out[1173]:
a   -0.401016
b         NaN
c   -0.547090
d         NaN
e    0.872323
f   -0.553224
g         NaN
h   -1.356570
dtype: float64

In [1174]: df.cumsum()
Out[1174]:
        one       two     three
a  0.059117  1.138469 -2.400634
b       NaN       NaN       NaN
c -0.221736  1.164122 -3.786705
d       NaN       NaN       NaN
e  0.642200  1.416584 -2.286134
f  1.695403 -0.922011 -2.660413
g       NaN       NaN       NaN
h -0.664556 -2.079897 -3.212278
```

### 9.2.1 NA values in GroupBy

NA groups in GroupBy are automatically excluded. This behavior is consistent with R, for example.

## 9.3 Cleaning / filling missing data

pandas objects are equipped with various data manipulation methods for dealing with missing data.

### 9.3.1 Filling missing values: fillna

The **fillna** function can "fill in" NA values with non-null data in a couple of ways, which we illustrate:

**Replace NA with a scalar value**

```
In [1175]: df2
Out[1175]:
        one       two     three four   five
a  0.059117  1.138469 -2.400634  bar   True
b       NaN       NaN       NaN  NaN    NaN
c -0.280853  0.025653 -1.386071  bar  False
d       NaN       NaN       NaN  NaN    NaN
e  0.863937  0.252462  1.500571  bar   True
f  1.053202 -2.338595 -0.374279  bar   True
g       NaN       NaN       NaN  NaN    NaN
h -2.359958 -1.157886 -0.551865  bar  False

In [1176]: df2.fillna(0)
Out[1176]:
        one       two     three four   five
a  0.059117  1.138469 -2.400634  bar   True
```

```
b  0.000000  0.000000  0.000000    0      0
c -0.280853  0.025653 -1.386071  bar  False
d  0.000000  0.000000  0.000000    0      0
e  0.863937  0.252462  1.500571  bar   True
f  1.053202 -2.338595 -0.374279  bar   True
g  0.000000  0.000000  0.000000    0      0
h -2.359958 -1.157886 -0.551865  bar  False

In [1177]: df2['four'].fillna('missing')
Out[1177]:
a        bar
b    missing
c        bar
d    missing
e        bar
f        bar
g    missing
h        bar
Name: four, dtype: object
```

#### Fill gaps forward or backward

Using the same filling arguments as *reindexing*, we can propagate non-null values forward or backward:

```
In [1178]: df
Out[1178]:
        one       two     three
a  0.059117  1.138469 -2.400634
b       NaN       NaN       NaN
c -0.280853  0.025653 -1.386071
d       NaN       NaN       NaN
e  0.863937  0.252462  1.500571
f  1.053202 -2.338595 -0.374279
g       NaN       NaN       NaN
h -2.359958 -1.157886 -0.551865

In [1179]: df.fillna(method='pad')
Out[1179]:
        one       two     three
a  0.059117  1.138469 -2.400634
b  0.059117  1.138469 -2.400634
c -0.280853  0.025653 -1.386071
d -0.280853  0.025653 -1.386071
e  0.863937  0.252462  1.500571
f  1.053202 -2.338595 -0.374279
g  1.053202 -2.338595 -0.374279
h -2.359958 -1.157886 -0.551865
```

#### 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 [1180]: df
Out[1180]:
        one       two     three
a  0.059117  1.138469 -2.400634
b       NaN       NaN       NaN
c       NaN       NaN       NaN
d       NaN       NaN       NaN
e  0.863937  0.252462  1.500571
```

```
f  1.053202 -2.338595 -0.374279
g       NaN       NaN       NaN
h -2.359958 -1.157886 -0.551865

In [1181]: df.fillna(method='pad', limit=1)
Out[1181]:
        one       two     three
a  0.059117  1.138469 -2.400634
b  0.059117  1.138469 -2.400634
c       NaN       NaN       NaN
d       NaN       NaN       NaN
e  0.863937  0.252462  1.500571
f  1.053202 -2.338595 -0.374279
g  1.053202 -2.338595 -0.374279
h -2.359958 -1.157886 -0.551865
```

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.

### 9.3.2 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 the **dropna** method:

```
In [1182]: df
Out[1182]:
        one       two     three
a  0.059117  1.138469 -2.400634
b       NaN  0.000000  0.000000
c       NaN  0.000000  0.000000
d       NaN  0.000000  0.000000
e  0.863937  0.252462  1.500571
f  1.053202 -2.338595 -0.374279
g       NaN  0.000000  0.000000
h -2.359958 -1.157886 -0.551865

In [1183]: df.dropna(axis=0)
Out[1183]:
        one       two     three
a  0.059117  1.138469 -2.400634
e  0.863937  0.252462  1.500571
f  1.053202 -2.338595 -0.374279
h -2.359958 -1.157886 -0.551865

In [1184]: df.dropna(axis=1)
Out[1184]:
        two     three
a  1.138469 -2.400634
b  0.000000  0.000000
c  0.000000  0.000000
d  0.000000  0.000000
e  0.252462  1.500571
f -2.338595 -0.374279
```

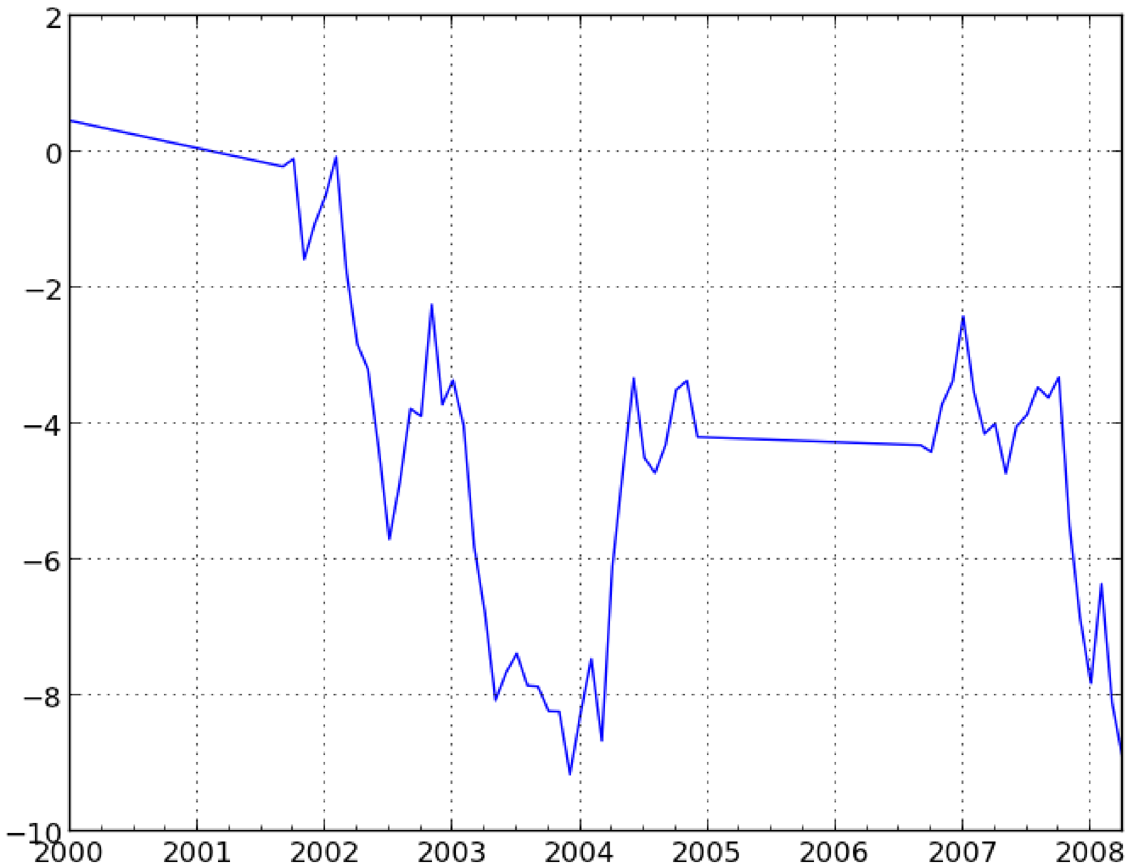
```
g  0.000000  0.000000
h -1.157886 -0.551865

In [1185]: df['one'].dropna()
Out[1185]:
a    0.059117
e    0.863937
f    1.053202
h   -2.359958
Name: one, dtype: float64
```

**dropna** is presently only implemented for Series and DataFrame, but will be eventually added to Panel. Series.dropna is a simpler method as it only has one axis to consider. DataFrame.dropna has considerably more options, which can be examined *in the API*.

### 9.3.3 Interpolation

A linear **interpolate** method has been implemented on Series. The default interpolation assumes equally spaced points.

```
In [1186]: ts.count()
Out[1186]: 61

In [1187]: ts.head()
Out[1187]:
2000-01-31    0.469112
2000-02-29         NaN
2000-03-31         NaN
2000-04-28         NaN
2000-05-31         NaN
Freq: BM, dtype: float64

In [1188]: ts.interpolate().count()
Out[1188]: 100

In [1189]: ts.interpolate().head()
Out[1189]:
2000-01-31    0.469112
2000-02-29    0.435428
2000-03-31    0.401743
2000-04-28    0.368059
2000-05-31    0.334374
Freq: BM, dtype: float64

In [1190]: ts.interpolate().plot()
Out[1190]: <matplotlib.axes.AxesSubplot at 0xeece490>
```




Index aware interpolation is available via the `method` keyword:

```
In [1191]: ts
Out[1191]:
2000-01-31    0.469112
2000-02-29         NaN
2002-07-31   -5.689738
2005-01-31         NaN
2008-04-30   -8.916232
dtype: float64

In [1192]: ts.interpolate()
Out[1192]:
2000-01-31    0.469112
2000-02-29   -2.610313
2002-07-31   -5.689738
2005-01-31   -7.302985
2008-04-30   -8.916232
dtype: float64

In [1193]: ts.interpolate(method='time')
Out[1193]:
2000-01-31    0.469112
2000-02-29    0.273272
2002-07-31   -5.689738
2005-01-31   -7.095568
2008-04-30   -8.916232
dtype: float64
```

For a floating-point index, use `method='values'`:

```
In [1194]: ser
Out[1194]:
0      0
1    NaN
10    10
dtype: float64

In [1195]: ser.interpolate()
Out[1195]:
0      0
1      5
10    10
dtype: float64

In [1196]: ser.interpolate(method='values')
Out[1196]:
0      0
1      1
10    10
dtype: float64
```

### 9.3.4 Replacing Generic Values

Often times we want to replace arbitrary values with other values. New in v0.8 is the `replace` method in Series/DataFrame that 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 [1197]: ser = Series([0., 1., 2., 3., 4.])

In [1198]: ser.replace(0, 5)
Out[1198]:
0    5
1    1
2    2
3    3
4    4
dtype: float64
```

You can replace a list of values by a list of other values:

```
In [1199]: ser.replace([0, 1, 2, 3, 4], [4, 3, 2, 1, 0])
Out[1199]:
0    4
1    3
2    2
3    1
4    0
dtype: float64
```

You can also specify a mapping dict:

```
In [1200]: ser.replace({0: 10, 1: 100})
Out[1200]:
0     10
1    100
```

```
2      2
3      3
4      4
dtype: float64
```

For a DataFrame, you can specify individual values by column:

```
In [1201]: df = DataFrame({'a': [0, 1, 2, 3, 4], 'b': [5, 6, 7, 8, 9]})

In [1202]: df.replace({'a': 0, 'b': 5}, 100)
Out[1202]:
     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 [1203]: ser.replace([1, 2, 3], method='pad')
Out[1203]:
0    0
1    0
2    0
3    0
4    4
dtype: float64
```

## 9.4 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 reindexing will cause missing data to be introduced into, say, a Series or DataFrame. Here they are:

| data type | Cast to |
|---|---|
| integer | float |
| boolean | object |
| float | no cast |
| object | no cast |

For example:

```
In [1204]: s = Series(randn(5), index=[0, 2, 4, 6, 7])

In [1205]: s > 0
Out[1205]:
0    False
2     True
4     True
6     True
7     True
dtype: bool

In [1206]: (s > 0).dtype
Out[1206]: dtype('bool')
```

```
In [1207]: crit = (s > 0).reindex(range(8))

In [1208]: crit
Out[1208]:
0    False
1      NaN
2     True
3      NaN
4     True
5      NaN
6     True
7     True
dtype: object

In [1209]: crit.dtype
Out[1209]: dtype('object')
```

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 [1210]: reindexed = s.reindex(range(8)).fillna(0)

In [1211]: reindexed[crit]
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-1211-2da204ed1ac7> in <module>()
----> 1 reindexed[crit]
/home/wesm/code/pandasplus/pandas/core/series.pyc in __getitem__(self, key)
    622         # special handling of boolean data with NAs stored in object
    623         # arrays. Since we can't represent NA with dtype=bool
--> 624         if _is_bool_indexer(key):
    625             key = _check_bool_indexer(self.index, key)
    626
/home/wesm/code/pandasplus/pandas/core/common.pyc in _is_bool_indexer(key)
   1070         if not lib.is_bool_array(key):
   1071             if isnull(key).any():
-> 1072                 raise ValueError('cannot index with vector containing '
   1073                                  'NA / NaN values')
   1074             return False
ValueError: cannot index with vector containing NA / NaN values
```

However, these can be filled in using **fillna** and it will work fine:

```
In [1212]: reindexed[crit.fillna(False)]
Out[1212]:
2    1.314232
4    0.690579
6    0.995761
7    2.396780
dtype: float64

In [1213]: reindexed[crit.fillna(True)]
Out[1213]:
1    0.000000
2    1.314232
3    0.000000
4    0.690579
5    0.000000
```

```
6    0.995761
7    2.396780
dtype: float64
```

CHAPTER

TEN

# 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

Of these, the split step is the most straightforward. In fact, in many situations you may wish to split the data set into groups and do something with those groups yourself. In the apply step, we might wish to one of the following:

- **Aggregation**: computing a summary statistic (or statistics) about each group. Some examples:
  - Compute group sums or means
  - Compute group sizes / counts
- **Transformation**: perform some group-specific computations and return a like-indexed. Some examples:
  - Standardizing data (zscore) within group
  - Filling NAs within groups with a value derived from each group
- 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 method 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.

## 10.1 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 do the following:

```
>>> grouped = obj.groupby(key)
>>> grouped = obj.groupby(key, axis=1)
>>> grouped = obj.groupby([key1, key2])
```

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 a column to be used to group. Of course `df.groupby('A')` is just syntactic sugar for `df.groupby(df['A'])`, but it makes life simpler
- A list of any of the above things

Collectively we refer to the grouping objects as the **keys**. For example, consider the following DataFrame:

```
In [518]: df = DataFrame({'A' : ['foo', 'bar', 'foo', 'bar',
   .....:                        'foo', 'bar', 'foo', 'foo'],
   .....:                 'B' : ['one', 'one', 'two', 'three',
   .....:                        'two', 'two', 'one', 'three'],
   .....:                 'C' : randn(8), 'D' : randn(8)})
   .....:

In [519]: df
Out[519]:
     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
```

We could naturally group by either the `A` or `B` columns or both:

```
In [520]: grouped = df.groupby('A')

In [521]: grouped = df.groupby(['A', 'B'])
```

These will split the DataFrame on its index (rows). We could also split by the columns:

```
In [522]: def get_letter_type(letter):
   .....:     if letter.lower() in 'aeiou':
   .....:         return 'vowel'
   .....:     else:
   .....:         return 'consonant'
   .....:

In [523]: grouped = df.groupby(get_letter_type, axis=1)
```

Starting with 0.8, pandas Index objects now supports 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 [524]: lst = [1, 2, 3, 1, 2, 3]

In [525]: s = Series([1, 2, 3, 10, 20, 30], lst)

In [526]: grouped = s.groupby(level=0)

In [527]: grouped.first()
```

```
Out[527]:
1    1
2    2
3    3
dtype: float64

In [528]: grouped.last()
Out[528]:
1    10
2    20
3    30
dtype: float64

In [529]: grouped.sum()
Out[529]:
1    11
2    22
3    33
dtype: float64
```

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.

---

### 10.1.1 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 [530]: df.groupby('A').groups
Out[530]: {'bar': [1, 3, 5], 'foo': [0, 2, 4, 6, 7]}

In [531]: df.groupby(get_letter_type, axis=1).groups
Out[531]: {'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 [532]: grouped = df.groupby(['A', 'B'])

In [533]: grouped.groups
Out[533]:
{('bar', 'one'): [1],
 ('bar', 'three'): [3],
 ('bar', 'two'): [5],
 ('foo', 'one'): [0, 6],
 ('foo', 'three'): [7],
 ('foo', 'two'): [2, 4]}

In [534]: len(grouped)
Out[534]: 6
```

By default the group keys are sorted during the groupby operation. You may however pass `sort``=``False` for potential speedups:

```
In [535]: df2 = DataFrame({'X' : ['B', 'B', 'A', 'A'], 'Y' : [1, 2, 3, 4]})

In [536]: df2.groupby(['X'], sort=True).sum()
Out[536]:
   Y
X
A  7
B  3

In [537]: df2.groupby(['X'], sort=False).sum()
Out[537]:
   Y
X
B  3
A  7
```

### 10.1.2 GroupBy with MultiIndex

With *hierarchically-indexed data*, it's quite natural to group by one of the levels of the hierarchy.

```
In [538]: s
Out[538]:
first  second
bar    one      -0.424972
       two       0.567020
baz    one       0.276232
       two      -1.087401
foo    one      -0.673690
       two       0.113648
qux    one      -1.478427
       two       0.524988
dtype: float64

In [539]: grouped = s.groupby(level=0)

In [540]: grouped.sum()
Out[540]:
first
bar      0.142048
baz     -0.811169
foo     -0.560041
qux     -0.953439
dtype: float64
```

If the MultiIndex has names specified, these can be passed instead of the level number:

```
In [541]: s.groupby(level='second').sum()
Out[541]:
second
one      -2.300857
two       0.118256
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 [542]: s.sum(level='second')
Out[542]:
second
one      -2.300857
two       0.118256
dtype: float64
```

Also as of v0.6, grouping with multiple levels is supported.

```
In [543]: s
Out[543]:
first  second  third
bar    doo     one       0.404705
               two       0.577046
baz    bee     one      -1.715002
               two      -1.039268
foo    bop     one      -0.370647
               two      -1.157892
qux    bop     one      -1.344312
               two       0.844885
dtype: float64

In [544]: s.groupby(level=['first','second']).sum()
Out[544]:
first  second
bar    doo       0.981751
baz    bee      -2.754270
foo    bop      -1.528539
qux    bop      -0.499427
dtype: float64
```

More on the sum function and aggregation later.

### 10.1.3 DataFrame column selection in GroupBy

Once you have created the GroupBy object from a DataFrame, for example, 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 [545]: grouped = df.groupby(['A'])

In [546]: grouped_C = grouped['C']

In [547]: grouped_D = grouped['D']
```

This is mainly syntactic sugar for the alternative and much more verbose:

```
In [548]: df['C'].groupby(df['A'])
Out[548]: <pandas.core.groupby.SeriesGroupBy at 0xb42d610>
```

Additionally this method avoids recomputing the internal grouping information derived from the passed key.

## 10.2 Iterating through groups

With the GroupBy object in hand, iterating through the grouped data is very natural and functions similarly to `itertools.groupby`:

```
In [549]: grouped = df.groupby('A')

In [550]: for name, group in grouped:
   .....:        print name
   .....:        print group
   .....:
bar
     A      B         C         D
1  bar    one -0.282863 -2.104569
3  bar  three -1.135632  1.071804
5  bar    two -0.173215 -0.706771
foo
     A      B         C         D
0  foo    one  0.469112 -0.861849
2  foo    two -1.509059 -0.494929
4  foo    two  1.212112  0.721555
6  foo    one  0.119209 -1.039575
7  foo  three -1.044236  0.271860
```

In the case of grouping by multiple keys, the group name will be a tuple:

```
In [551]: for name, group in df.groupby(['A', 'B']):
   .....:        print name
   .....:        print group
   .....:
('bar', 'one')
     A    B         C         D
1  bar  one -0.282863 -2.104569
('bar', 'three')
     A      B         C         D
3  bar  three -1.135632  1.071804
('bar', 'two')
     A    B         C         D
5  bar  two -0.173215 -0.706771
('foo', 'one')
     A    B         C         D
0  foo  one  0.469112 -0.861849
6  foo  one  0.119209 -1.039575
('foo', 'three')
     A      B         C        D
7  foo  three -1.044236  0.27186
('foo', 'two')
     A    B         C         D
2  foo  two -1.509059 -0.494929
4  foo  two  1.212112  0.721555
```

It's standard Python-fu but remember you can unpack the tuple in the for loop statement if you wish: `for (k1, k2), group in grouped:`.

## 10.3 Aggregation

Once the GroupBy object has been created, several methods are available to perform a computation on the grouped data. An obvious one is aggregation via the `aggregate` or equivalently `agg` method:

```
In [552]: grouped = df.groupby('A')

In [553]: grouped.aggregate(np.sum)
```

```
Out[553]:
            C         D
A
bar -1.591710 -1.739537
foo -0.752861 -1.402938

In [554]: grouped = df.groupby(['A', 'B'])

In [555]: grouped.aggregate(np.sum)
Out[555]:
                  C         D
A   B
bar one   -0.282863 -2.104569
    three -1.135632  1.071804
    two   -0.173215 -0.706771
foo one    0.588321 -1.901424
    three -1.044236  0.271860
    two   -0.296946  0.226626
```

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 [556]: grouped = df.groupby(['A', 'B'], as_index=False)

In [557]: grouped.aggregate(np.sum)
Out[557]:
     A      B         C         D
0  bar    one -0.282863 -2.104569
1  bar  three -1.135632  1.071804
2  bar    two -0.173215 -0.706771
3  foo    one  0.588321 -1.901424
4  foo  three -1.044236  0.271860
5  foo    two -0.296946  0.226626

In [558]: df.groupby('A', as_index=False).sum()
Out[558]:
     A         C         D
0  bar -1.591710 -1.739537
1  foo -0.752861 -1.402938
```

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 [559]: df.groupby(['A', 'B']).sum().reset_index()
Out[559]:
     A      B         C         D
0  bar    one -0.282863 -2.104569
1  bar  three -1.135632  1.071804
2  bar    two -0.173215 -0.706771
3  foo    one  0.588321 -1.901424
4  foo  three -1.044236  0.271860
5  foo    two -0.296946  0.226626
```

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 [560]: grouped.size()
Out[560]:
```

```
A    B
bar  one      1
     three    1
     two      1
foo  one      2
     three    1
     two      2
dtype: int64
```

### 10.3.1 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 [561]: grouped = df.groupby('A')

In [562]: grouped['C'].agg([np.sum, np.mean, np.std])
Out[562]:
          sum      mean       std
A
bar -1.591710 -0.530570  0.526860
foo -0.752861 -0.150572  1.113308
```

If a dict is passed, the keys will be used to name the columns. Otherwise the function's name (stored in the function object) will be used.

```
In [563]: grouped['D'].agg({'result1' : np.sum,
   .....:                   'result2' : np.mean})
   .....:
Out[563]:
      result2   result1
A
bar -0.579846 -1.739537
foo -0.280588 -1.402938
```

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 [564]: grouped.agg([np.sum, np.mean, np.std])
Out[564]:
            C                             D
          sum      mean       std       sum      mean       std
A
bar -1.591710 -0.530570  0.526860 -1.739537 -0.579846  1.591986
foo -0.752861 -0.150572  1.113308 -1.402938 -0.280588  0.753219
```

Passing a dict of functions has different behavior by default, see the next section.

### 10.3.2 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 [565]: grouped.agg({'C' : np.sum,
   .....:              'D' : lambda x: np.std(x, ddof=1)})
   .....:
Out[565]:
            C         D
A
```

```
bar -1.591710  1.591986
foo -0.752861  0.753219
```

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 [566]: grouped.agg({'C' : 'sum', 'D' : 'std'})
Out[566]:
            C         D
A
bar -1.591710  1.591986
foo -0.752861  0.753219
```

### 10.3.3 Cython-optimized aggregation functions

Some common aggregations, currently only `sum`, `mean`, and `std`, have optimized Cython implementations:

```
In [567]: df.groupby('A').sum()
Out[567]:
            C         D
A
bar -1.591710 -1.739537
foo -0.752861 -1.402938

In [568]: df.groupby(['A', 'B']).mean()
Out[568]:
                  C         D
A   B
bar one   -0.282863 -2.104569
    three -1.135632  1.071804
    two   -0.173215 -0.706771
foo one    0.294161 -0.950712
    three -1.044236  0.271860
    two   -0.148473  0.113313
```

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).

## 10.4 Transformation

The `transform` method returns an object that is indexed the same (same size) as the one being grouped. Thus, the passed transform function should return a result that is the same size as the group chunk. For example, suppose we wished to standardize the data within each group:

```
In [569]: index = date_range('10/1/1999', periods=1100)

In [570]: ts = Series(np.random.normal(0.5, 2, 1100), index)

In [571]: ts = rolling_mean(ts, 100, 100).dropna()

In [572]: ts.head()
Out[572]:
2000-01-08    0.536925
2000-01-09    0.494448
2000-01-10    0.496114
```

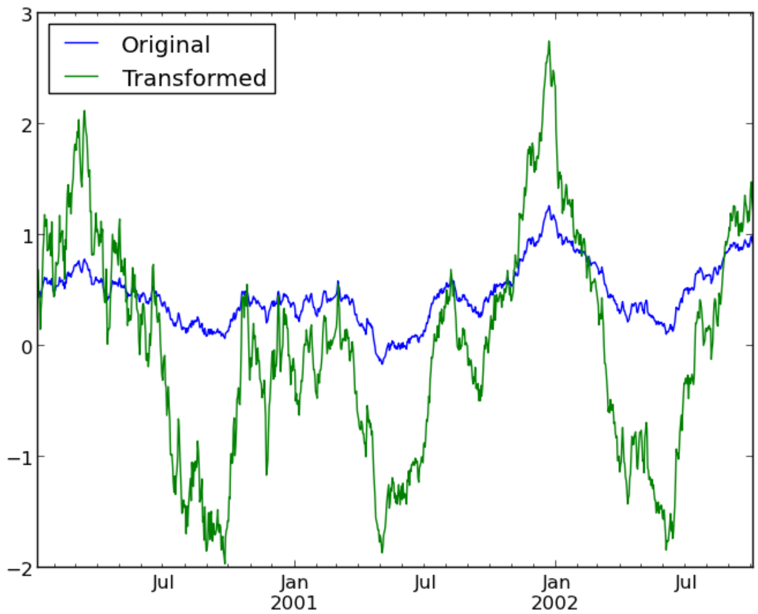
```
2000-01-11    0.443475
2000-01-12    0.474744
Freq: D, dtype: float64

In [573]: ts.tail()
Out[573]:
2002-09-30    0.978859
2002-10-01    0.994704
2002-10-02    0.953789
2002-10-03    0.932345
2002-10-04    0.915581
Freq: D, dtype: float64

In [574]: key = lambda x: x.year

In [575]: zscore = lambda x: (x - x.mean()) / x.std()

In [576]: transformed = ts.groupby(key).transform(zscore)
```

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 [577]: grouped = ts.groupby(key)

In [578]: grouped.mean()
Out[578]:
2000    0.416344
2001    0.416987
2002    0.599380
dtype: float64

In [579]: grouped.std()
Out[579]:
2000    0.174755
2001    0.309640
2002    0.266172
dtype: float64

# Transformed Data
In [580]: grouped_trans = transformed.groupby(key)

In [581]: grouped_trans.mean()
Out[581]:
2000   -3.122696e-16
2001   -2.688869e-16
2002   -1.499001e-16
dtype: float64

In [582]: grouped_trans.std()
Out[582]:
2000    1
2001    1
2002    1
dtype: float64
```

We can also visually compare the original and transformed data sets.

```
In [583]: compare = DataFrame({'Original': ts, 'Transformed': transformed})

In [584]: compare.plot()
Out[584]: <matplotlib.axes.AxesSubplot at 0xaa1e1d0>
```




Another common data transform is to replace missing data with the group mean.

```
In [585]: data_df
Out[585]:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1000 entries, 0 to 999
Data columns:
A    908  non-null values
B    953  non-null values
C    820  non-null values
dtypes: float64(3)

In [586]: countries = np.array(['US', 'UK', 'GR', 'JP'])

In [587]: key = countries[np.random.randint(0, 4, 1000)]

In [588]: grouped = data_df.groupby(key)

# Non-NA count in each group
In [589]: grouped.count()
Out[589]:
      A    B    C
GR  219  223  194
JP  238  250  211
UK  228  239  213
US  223  241  202

In [590]: f = lambda x: x.fillna(x.mean())

In [591]: transformed = grouped.transform(f)
```

We can verify that the group means have not changed in the transformed data and that the transformed data contains no NAs.

```
In [592]: grouped_trans = transformed.groupby(key)

In [593]: grouped.mean() # original group means
Out[593]:
           A         B         C
GR  0.093655 -0.004978 -0.049883
JP -0.067605  0.025828  0.006752
UK -0.054246  0.031742  0.068974
US  0.084334 -0.013433  0.056589

In [594]: grouped_trans.mean() # transformation did not change group means
Out[594]:
           A         B         C
GR  0.093655 -0.004978 -0.049883
JP -0.067605  0.025828  0.006752
UK -0.054246  0.031742  0.068974
US  0.084334 -0.013433  0.056589

In [595]: grouped.count() # original has some missing data points
Out[595]:
      A    B    C
GR  219  223  194
JP  238  250  211
UK  228  239  213
US  223  241  202

In [596]: grouped_trans.count() # counts after transformation
Out[596]:
      A    B    C
GR  234  234  234
JP  264  264  264
UK  251  251  251
US  251  251  251

In [597]: grouped_trans.size() # Verify non-NA count equals group size
Out[597]:
GR    234
JP    264
UK    251
US    251
dtype: int64
```

## 10.5 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 [598]: grouped = df.groupby('A')

In [599]: grouped.agg(lambda x: x.std())
Out[599]:
      B         C         D
A
bar NaN  0.526860  1.591986
foo NaN  1.113308  0.753219
```

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 [600]: grouped.std()
Out[600]:
            C         D
A
bar  0.526860  1.591986
foo  1.113308  0.753219
```

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 [601]: tsdf = DataFrame(randn(1000, 3),
   .....:                  index=date_range('1/1/2000', periods=1000),
   .....:                  columns=['A', 'B', 'C'])
   .....:

In [602]: tsdf.ix[::2] = np.nan

In [603]: grouped = tsdf.groupby(lambda x: x.year)

In [604]: grouped.fillna(method='pad')
Out[604]:
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 1000 entries, 2000-01-01 00:00:00 to 2002-09-26 00:00:00
Freq: D
Data columns:
A    998  non-null values
B    998  non-null values
C    998  non-null values
dtypes: float64(3)
```

In this example, we chopped the collection of time series into yearly chunks then independently called *fillna* on the groups.

## 10.6 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 [605]: df
Out[605]:
     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
```

```
In [606]: grouped = df.groupby('A')

# could also just call .describe()
In [607]: grouped['C'].apply(lambda x: x.describe())
Out[607]:
A
bar  count    3.000000
     mean    -0.530570
     std      0.526860
     min     -1.135632
     25%     -0.709248
     50%     -0.282863
     75%     -0.228039
     max     -0.173215
foo  count    5.000000
     mean    -0.150572
     std      1.113308
     min     -1.509059
     25%     -1.044236
     50%      0.119209
     75%      0.469112
     max      1.212112
dtype: float64
```

The dimension of the returned result can also change:

```
In [608]: grouped = df.groupby('A')['C']

In [609]: def f(group):
   .....:     return DataFrame({'original' : group,
   .....:                       'demeaned' : group - group.mean()})
   .....:

In [610]: grouped.apply(f)
Out[610]:
   demeaned  original
0  0.619685  0.469112
1  0.247707 -0.282863
2 -1.358486 -1.509059
3 -0.605062 -1.135632
4  1.362684  1.212112
5  0.357355 -0.173215
6  0.269781  0.119209
7 -0.893664 -1.044236
```

`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 [611]: def f(x):
   .....:       return Series([ x, x**2 ], index = ['x', 'x^s'])
   .....:

In [612]: s = Series(np.random.rand(5))

In [613]: s
Out[613]:
0    0.785887
1    0.498525
2    0.933703
```

```
3    0.154106
4    0.271779
dtype: float64

In [614]: s.apply(f)
Out[614]:
          x       x^s
0  0.785887  0.617619
1  0.498525  0.248528
2  0.933703  0.871801
3  0.154106  0.023749
4  0.271779  0.073864
```

## 10.7 Other useful features

### 10.7.1 Automatic exclusion of "nuisance" columns

Again consider the example DataFrame we've been looking at:

```
In [615]: df
Out[615]:
     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
```

Supposed we wished 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 [616]: df.groupby('A').std()
Out[616]:
            C         D
A
bar  0.526860  1.591986
foo  1.113308  0.753219
```

### 10.7.2 NA group handling

If there are any NaN values in the grouping key, these will be automatically excluded. So there will never be an "NA 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).

### 10.7.3 Grouping with ordered factors

Categorical variables represented as instance of pandas's `Factor` class can be used as group keys. If so, the order of the levels will be preserved:

```
In [617]: data = Series(np.random.randn(100))

In [618]: factor = qcut(data, [0, .25, .5, .75, 1.])

In [619]: data.groupby(factor).mean()
Out[619]:
[-3.469, -0.737]   -1.269581
(-0.737, 0.214]    -0.216269
(0.214, 1.0572]     0.680402
(1.0572, 3.0762]    1.629338
dtype: float64
```

CHAPTER

ELEVEN

# MERGE, JOIN, AND CONCATENATE

pandas provides various facilities for easily combining together Series, DataFrame, and Panel objects with various kinds of set logic for the indexes and relational algebra functionality in the case of join / merge-type operations.

## 11.1 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 [1055]: df = DataFrame(np.random.randn(10, 4))

In [1056]: df
Out[1056]:
          0         1         2         3
0  0.469112 -0.282863 -1.509059 -1.135632
1  1.212112 -0.173215  0.119209 -1.044236
2 -0.861849 -2.104569 -0.494929  1.071804
3  0.721555 -0.706771 -1.039575  0.271860
4 -0.424972  0.567020  0.276232 -1.087401
5 -0.673690  0.113648 -1.478427  0.524988
6  0.404705  0.577046 -1.715002 -1.039268
7 -0.370647 -1.157892 -1.344312  0.844885
8  1.075770 -0.109050  1.643563 -1.469388
9  0.357021 -0.674600 -1.776904 -0.968914

# break it into pieces
In [1057]: pieces = [df[:3], df[3:7], df[7:]]

In [1058]: concatenated = concat(pieces)

In [1059]: concatenated
Out[1059]:
          0         1         2         3
0  0.469112 -0.282863 -1.509059 -1.135632
1  1.212112 -0.173215  0.119209 -1.044236
2 -0.861849 -2.104569 -0.494929  1.071804
3  0.721555 -0.706771 -1.039575  0.271860
4 -0.424972  0.567020  0.276232 -1.087401
5 -0.673690  0.113648 -1.478427  0.524988
6  0.404705  0.577046 -1.715002 -1.039268
```

```
7 -0.370647 -1.157892 -1.344312  0.844885
8  1.075770 -0.109050  1.643563 -1.469388
9  0.357021 -0.674600 -1.776904 -0.968914
```

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":

```
concat(objs, axis=0, join='outer', join_axes=None, ignore_index=False,
       keys=None, levels=None, names=None, verify_integrity=False)
```

- `objs`: list or dict of Series, DataFrame, or Panel 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)
- `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
- `join_axes`: list of Index objects. Specific indexes to use for the other n - 1 axes instead of performing inner/outer set logic
- `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. If keys passed, specific levels to use for the resulting 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
- `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.

Without a little bit of context and example many of these arguments don't make much sense. Let's take 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 [1060]: concatenated = concat(pieces, keys=['first', 'second', 'third'])

In [1061]: concatenated
Out[1061]:
                 0         1         2         3
first  0  0.469112 -0.282863 -1.509059 -1.135632
       1  1.212112 -0.173215  0.119209 -1.044236
       2 -0.861849 -2.104569 -0.494929  1.071804
second 3  0.721555 -0.706771 -1.039575  0.271860
       4 -0.424972  0.567020  0.276232 -1.087401
       5 -0.673690  0.113648 -1.478427  0.524988
       6  0.404705  0.577046 -1.715002 -1.039268
third  7 -0.370647 -1.157892 -1.344312  0.844885
       8  1.075770 -0.109050  1.643563 -1.469388
       9  0.357021 -0.674600 -1.776904 -0.968914
```

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 do stuff like select out each chunk by key:

```
In [1062]: concatenated.ix['second']
Out[1062]:
          0         1         2         3
3  0.721555 -0.706771 -1.039575  0.271860
4 -0.424972  0.567020  0.276232 -1.087401
5 -0.673690  0.113648 -1.478427  0.524988
6  0.404705  0.577046 -1.715002 -1.039268
```

It's not a stretch to see how this can be very useful. More detail on this functionality below.

### 11.1.1 Set logic on the other axes

When gluing together multiple DataFrames (or Panels or...), for example, you have a choice of how to handle the other axes (other than the one being concatenated). This can be done in three ways:

- Take the (sorted) union of them all, `join='outer'`. This is the default option as it results in zero information loss.
- Take the intersection, `join='inner'`.
- Use a specific index (in the case of DataFrame) or indexes (in the case of Panel or future higher dimensional objects), i.e. the `join_axes` argument

Here is a example of each of these methods. First, the default `join='outer'` behavior:

```
In [1063]: from pandas.util.testing import rands

In [1064]: df = DataFrame(np.random.randn(10, 4), columns=['a', 'b', 'c', 'd'],
   ......:                index=[rands(5) for _ in xrange(10)])
   ......:

In [1065]: df
Out[1065]:
              a         b         c         d
AGx0N -1.294524  0.413738  0.276662 -0.472035
MlI4H -0.013960 -0.362543 -0.006154 -0.923061
AkPA8  0.895717  0.805244 -1.206412  2.565646
oGYzQ  1.431256  1.340309 -1.170299 -0.226169
ZRFIw  0.410835  0.813850  0.132003 -0.827317
HRxqM -0.076467 -1.187678  1.130127 -1.436737
HxpJj -1.413681  1.607920  1.024180  0.569605
JlMQH  0.875906 -2.211372  0.974466 -2.006747
sAcFy -0.410001 -0.078638  0.545952 -1.219217
UOsfn -1.226825  0.769804 -1.281247 -0.727707

In [1066]: concat([df.ix[:7, ['a', 'b']], df.ix[2:-2, ['c']],
   ......:         df.ix[-7:, ['d']]], axis=1)
   ......:
Out[1066]:
              a         b         c         d
AGx0N -1.294524  0.413738       NaN       NaN
AkPA8  0.895717  0.805244 -1.206412       NaN
HRxqM -0.076467 -1.187678  1.130127 -1.436737
HxpJj -1.413681  1.607920  1.024180  0.569605
JlMQH       NaN       NaN  0.974466 -2.006747
MlI4H -0.013960 -0.362543       NaN       NaN
UOsfn       NaN       NaN       NaN -0.727707
ZRFIw  0.410835  0.813850  0.132003 -0.827317
```

```
oGYzQ  1.431256  1.340309 -1.170299 -0.226169
sAcFy       NaN       NaN       NaN -1.219217
```

Note that the row indexes have been unioned and sorted. Here is the same thing with `join='inner'`:

```
In [1067]: concat([df.ix[:7, ['a', 'b']], df.ix[2:-2, ['c']],
   ......:         df.ix[-7:, ['d']]], axis=1, join='inner')
   ......:
Out[1067]:
              a         b         c         d
oGYzQ  1.431256  1.340309 -1.170299 -0.226169
ZRFIw  0.410835  0.813850  0.132003 -0.827317
HRxqM -0.076467 -1.187678  1.130127 -1.436737
HxpJj -1.413681  1.607920  1.024180  0.569605
```

Lastly, suppose we just wanted to reuse the *exact index* from the original DataFrame:

```
In [1068]: concat([df.ix[:7, ['a', 'b']], df.ix[2:-2, ['c']],
   ......:         df.ix[-7:, ['d']]], axis=1, join_axes=[df.index])
   ......:
Out[1068]:
              a         b         c         d
AGx0N -1.294524  0.413738       NaN       NaN
MlI4H -0.013960 -0.362543       NaN       NaN
AkPA8  0.895717  0.805244 -1.206412       NaN
oGYzQ  1.431256  1.340309 -1.170299 -0.226169
ZRFIw  0.410835  0.813850  0.132003 -0.827317
HRxqM -0.076467 -1.187678  1.130127 -1.436737
HxpJj -1.413681  1.607920  1.024180  0.569605
JlMQH       NaN       NaN  0.974466 -2.006747
sAcFy       NaN       NaN       NaN -1.219217
UOsfn       NaN       NaN       NaN -0.727707
```

### 11.1.2 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 [1069]: s = Series(randn(10), index=np.arange(10))

In [1070]: s1 = s[:5] # note we're slicing with labels here, so 5 is included

In [1071]: s2 = s[6:]

In [1072]: s1.append(s2)
Out[1072]:
0   -0.121306
1   -0.097883
2    0.695775
3    0.341734
4    0.959726
6   -0.619976
7    0.149748
8   -0.732339
9    0.687738
dtype: float64
```

In the case of DataFrame, the indexes must be disjoint but the columns do not need to be:

```
In [1073]: df = DataFrame(randn(6, 4), index=date_range('1/1/2000', periods=6),
   ......:                 columns=['A', 'B', 'C', 'D'])
   ......:

In [1074]: df1 = df.ix[:3]

In [1075]: df2 = df.ix[3:, :3]

In [1076]: df1
Out[1076]:
                   A         B         C         D
2000-01-01  0.176444  0.403310 -0.154951  0.301624
2000-01-02 -2.179861 -1.369849 -0.954208  1.462696
2000-01-03 -1.743161 -0.826591 -0.345352  1.314232

In [1077]: df2
Out[1077]:
                   A         B         C
2000-01-04  0.690579  0.995761  2.396780
2000-01-05  3.357427 -0.317441 -1.236269
2000-01-06 -0.487602 -0.082240 -2.182937

In [1078]: df1.append(df2)
Out[1078]:
                   A         B         C         D
2000-01-01  0.176444  0.403310 -0.154951  0.301624
2000-01-02 -2.179861 -1.369849 -0.954208  1.462696
2000-01-03 -1.743161 -0.826591 -0.345352  1.314232
2000-01-04  0.690579  0.995761  2.396780       NaN
2000-01-05  3.357427 -0.317441 -1.236269       NaN
2000-01-06 -0.487602 -0.082240 -2.182937       NaN
```

`append` may take multiple objects to concatenate:

```
In [1079]: df1 = df.ix[:2]

In [1080]: df2 = df.ix[2:4]

In [1081]: df3 = df.ix[4:]

In [1082]: df1.append([df2,df3])
Out[1082]:
                   A         B         C         D
2000-01-01  0.176444  0.403310 -0.154951  0.301624
2000-01-02 -2.179861 -1.369849 -0.954208  1.462696
2000-01-03 -1.743161 -0.826591 -0.345352  1.314232
2000-01-04  0.690579  0.995761  2.396780  0.014871
2000-01-05  3.357427 -0.317441 -1.236269  0.896171
2000-01-06 -0.487602 -0.082240 -2.182937  0.380396
```

**Note:** Unlike *list.append* method, which appends to the original list and returns nothing, `append` here **does not** modify `df1` and returns its copy with `df2` appended.

### 11.1.3 Ignoring indexes on the concatenation axis

For DataFrames which don't have a meaningful index, you may wish to append them and ignore the fact that they may have overlapping indexes:

```
In [1083]: df1 = DataFrame(randn(6, 4), columns=['A', 'B', 'C', 'D'])

In [1084]: df2 = DataFrame(randn(3, 4), columns=['A', 'B', 'C', 'D'])

In [1085]: df1
Out[1085]:
          A         B         C         D
0  0.084844  0.432390  1.519970 -0.493662
1  0.600178  0.274230  0.132885 -0.023688
2  2.410179  1.450520  0.206053 -0.251905
3 -2.213588  1.063327  1.266143  0.299368
4 -0.863838  0.408204 -1.048089 -0.025747
5 -0.988387  0.094055  1.262731  1.289997

In [1086]: df2
Out[1086]:
          A         B         C         D
0  0.082423 -0.055758  0.536580 -0.489682
1  0.369374 -0.034571 -2.484478 -0.281461
2  0.030711  0.109121  1.126203 -0.977349
```

To do this, use the `ignore_index` argument:

```
In [1087]: concat([df1, df2], ignore_index=True)
Out[1087]:
          A         B         C         D
0  0.084844  0.432390  1.519970 -0.493662
1  0.600178  0.274230  0.132885 -0.023688
2  2.410179  1.450520  0.206053 -0.251905
3 -2.213588  1.063327  1.266143  0.299368
4 -0.863838  0.408204 -1.048089 -0.025747
5 -0.988387  0.094055  1.262731  1.289997
6  0.082423 -0.055758  0.536580 -0.489682
7  0.369374 -0.034571 -2.484478 -0.281461
8  0.030711  0.109121  1.126203 -0.977349
```

This is also a valid argument to `DataFrame.append`:

```
In [1088]: df1.append(df2, ignore_index=True)
Out[1088]:
          A         B         C         D
0  0.084844  0.432390  1.519970 -0.493662
1  0.600178  0.274230  0.132885 -0.023688
2  2.410179  1.450520  0.206053 -0.251905
3 -2.213588  1.063327  1.266143  0.299368
4 -0.863838  0.408204 -1.048089 -0.025747
5 -0.988387  0.094055  1.262731  1.289997
6  0.082423 -0.055758  0.536580 -0.489682
7  0.369374 -0.034571 -2.484478 -0.281461
8  0.030711  0.109121  1.126203 -0.977349
```

### 11.1.4 More concatenating with group keys

Let's consider a variation on the first example presented:

```
In [1089]: df = DataFrame(np.random.randn(10, 4))

In [1090]: df
Out[1090]:
          0         1         2         3
0  1.474071 -0.064034 -1.282782  0.781836
1 -1.071357  0.441153  2.353925  0.583787
2  0.221471 -0.744471  0.758527  1.729689
3 -0.964980 -0.845696 -1.340896  1.846883
4 -1.328865  1.682706 -1.717693  0.888782
5  0.228440  0.901805  1.171216  0.520260
6 -1.197071 -1.066969 -0.303421 -0.858447
7  0.306996 -0.028665  0.384316  1.574159
8  1.588931  0.476720  0.473424 -0.242861
9 -0.014805 -0.284319  0.650776 -1.461665

# break it into pieces
In [1091]: pieces = [df.ix[:, [0, 1]], df.ix[:, [2]], df.ix[:, [3]]]

In [1092]: result = concat(pieces, axis=1, keys=['one', 'two', 'three'])

In [1093]: result
Out[1093]:
        one                 two     three
          0         1         2         3
0  1.474071 -0.064034 -1.282782  0.781836
1 -1.071357  0.441153  2.353925  0.583787
2  0.221471 -0.744471  0.758527  1.729689
3 -0.964980 -0.845696 -1.340896  1.846883
4 -1.328865  1.682706 -1.717693  0.888782
5  0.228440  0.901805  1.171216  0.520260
6 -1.197071 -1.066969 -0.303421 -0.858447
7  0.306996 -0.028665  0.384316  1.574159
8  1.588931  0.476720  0.473424 -0.242861
9 -0.014805 -0.284319  0.650776 -1.461665
```

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 [1094]: pieces = {'one': df.ix[:, [0, 1]],
   ......:           'two': df.ix[:, [2]],
   ......:           'three': df.ix[:, [3]]}
   ......:

In [1095]: concat(pieces, axis=1)
Out[1095]:
        one               three       two
          0         1         3         2
0  1.474071 -0.064034  0.781836 -1.282782
1 -1.071357  0.441153  0.583787  2.353925
2  0.221471 -0.744471  1.729689  0.758527
3 -0.964980 -0.845696  1.846883 -1.340896
4 -1.328865  1.682706  0.888782 -1.717693
5  0.228440  0.901805  0.520260  1.171216
6 -1.197071 -1.066969 -0.858447 -0.303421
```

```
7  0.306996 -0.028665  1.574159  0.384316
8  1.588931  0.476720 -0.242861  0.473424
9 -0.014805 -0.284319 -1.461665  0.650776

In [1096]: concat(pieces, keys=['three', 'two'])
Out[1096]:
                2         3
three 0       NaN  0.781836
      1       NaN  0.583787
      2       NaN  1.729689
      3       NaN  1.846883
      4       NaN  0.888782
      5       NaN  0.520260
      6       NaN -0.858447
      7       NaN  1.574159
      8       NaN -0.242861
      9       NaN -1.461665
two   0 -1.282782       NaN
      1  2.353925       NaN
      2  0.758527       NaN
      3 -1.340896       NaN
      4 -1.717693       NaN
      5  1.171216       NaN
      6 -0.303421       NaN
      7  0.384316       NaN
      8  0.473424       NaN
      9  0.650776       NaN
```

The MultiIndex created has levels that are constructed from the passed keys and the columns of the DataFrame pieces:

```
In [1097]: result.columns.levels
Out[1097]: [Index([one, two, three], dtype=object), Int64Index([0, 1, 2, 3], dtype=int64)]
```

If you wish to specify other levels (as will occasionally be the case), you can do so using the `levels` argument:

```
In [1098]: result = concat(pieces, axis=1, keys=['one', 'two', 'three'],
   ......:                 levels=[['three', 'two', 'one', 'zero']],
   ......:                 names=['group_key'])
   ......:

In [1099]: result
Out[1099]:
group_key       one                 two     three
                  0         1         2         3
0          1.474071 -0.064034 -1.282782  0.781836
1         -1.071357  0.441153  2.353925  0.583787
2          0.221471 -0.744471  0.758527  1.729689
3         -0.964980 -0.845696 -1.340896  1.846883
4         -1.328865  1.682706 -1.717693  0.888782
5          0.228440  0.901805  1.171216  0.520260
6         -1.197071 -1.066969 -0.303421 -0.858447
7          0.306996 -0.028665  0.384316  1.574159
8          1.588931  0.476720  0.473424 -0.242861
9         -0.014805 -0.284319  0.650776 -1.461665

In [1100]: result.columns.levels
Out[1100]:
[Index([three, two, one, zero], dtype=object),
 Int64Index([0, 1, 2, 3], dtype=int64)]
```

Yes, this is fairly esoteric, but is actually necessary for implementing things like GroupBy where the order of a categorical variable is meaningful.

### 11.1.5 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 [1101]: df = DataFrame(np.random.randn(8, 4), columns=['A','B','C','D'])

In [1102]: df
Out[1102]:
          A         B         C         D
0 -1.137707 -0.891060 -0.693921  1.613616
1  0.464000  0.227371 -0.496922  0.306389
2 -2.290613 -1.134623 -1.561819 -0.260838
3  0.281957  1.523962 -0.902937  0.068159
4 -0.057873 -0.368204 -1.144073  0.861209
5  0.800193  0.782098 -1.069094 -1.099248
6  0.255269  0.009750  0.661084  0.379319
7 -0.008434  1.952541 -1.056652  0.533946

In [1103]: s = df.xs(3)

In [1104]: df.append(s, ignore_index=True)
Out[1104]:
          A         B         C         D
0 -1.137707 -0.891060 -0.693921  1.613616
1  0.464000  0.227371 -0.496922  0.306389
2 -2.290613 -1.134623 -1.561819 -0.260838
3  0.281957  1.523962 -0.902937  0.068159
4 -0.057873 -0.368204 -1.144073  0.861209
5  0.800193  0.782098 -1.069094 -1.099248
6  0.255269  0.009750  0.661084  0.379319
7 -0.008434  1.952541 -1.056652  0.533946
8  0.281957  1.523962 -0.902937  0.068159
```

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 [1105]: df = DataFrame(np.random.randn(5, 4),
   ......:                columns=['foo', 'bar', 'baz', 'qux'])
   ......:

In [1106]: dicts = [{'foo': 1, 'bar': 2, 'baz': 3, 'peekaboo': 4},
   ......:          {'foo': 5, 'bar': 6, 'baz': 7, 'peekaboo': 8}]
   ......:

In [1107]: result = df.append(dicts, ignore_index=True)

In [1108]: result
Out[1108]:
        bar       baz       foo  peekaboo       qux
0  0.040403 -0.507516 -1.226970       NaN -0.230096
1 -1.934370 -1.652499  0.394500       NaN  1.488753
2  0.576897  1.146000 -0.896484       NaN  1.487349
```

```
3  2.121453  0.597701  0.604603       NaN  0.563700
4 -1.057909  1.375020  0.967661       NaN -0.928797
5  2.000000  3.000000  1.000000         4       NaN
6  6.000000  7.000000  5.000000         8       NaN
```

## 11.2 Database-style DataFrame 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 internal layout of the data in DataFrame.

pandas provides a single function, `merge`, as the entry point for all standard database join operations between DataFrame objects:

```
merge(left, right, how='left', on=None, left_on=None, right_on=None,
      left_index=False, right_index=False, sort=True,
      suffixes=('_x', '_y'), copy=True)
```

Here's a description of what each argument is for:

- `left`: A DataFrame object
- `right`: Another DataFrame object
- `on`: Columns (names) to join on. Must be found in both the left and right DataFrame objects. If not passed and `left_index` and `right_index` are `False`, the intersection of the columns in the DataFrames will be inferred to be the join keys
- `left_on`: Columns from the left DataFrame to use as keys. Can either be column names or arrays with length equal to the length of the DataFrame
- `right_on`: Columns from the right DataFrame to use as keys. Can either be column names or arrays with length equal to the length of the DataFrame
- `left_index`: If `True`, use the index (row labels) from the left DataFrame as its join key(s). In the case of a DataFrame with a MultiIndex (hierarchical), the number of levels must match the number of join keys from the right DataFrame
- `right_index`: Same usage as `left_index` for the right DataFrame
- `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 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.

`merge` is a function in the pandas namespace, and it is also available as a DataFrame instance method, with the calling DataFrame being implicitly considered the left object in the join.

The related `DataFrame.join` method, uses `merge` internally for the index-on-index and index-on-column(s) joins, but *joins on indexes* by default rather than trying to join on common columns (the default behavior for `merge`). If you are joining on index, you may wish to use `DataFrame.join` to save yourself some typing.

### 11.2.1 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 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 [1109]: left = DataFrame({'key': ['foo', 'foo'], 'lval': [1, 2]})

In [1110]: right = DataFrame({'key': ['foo', 'foo'], 'rval': [4, 5]})

In [1111]: left
Out[1111]:
   key  lval
0  foo     1
1  foo     2

In [1112]: right
Out[1112]:
   key  rval
0  foo     4
1  foo     5

In [1113]: merge(left, right, on='key')
Out[1113]:
   key  lval  rval
0  foo     1     4
1  foo     1     5
2  foo     2     4
3  foo     2     5
```

Here is a more complicated example with multiple join keys:

```
In [1114]: left = DataFrame({'key1': ['foo', 'foo', 'bar'],
   ......:                   'key2': ['one', 'two', 'one'],
   ......:                   'lval': [1, 2, 3]})
   ......:

In [1115]: right = DataFrame({'key1': ['foo', 'foo', 'bar', 'bar'],
   ......:                    'key2': ['one', 'one', 'one', 'two'],
   ......:                    'rval': [4, 5, 6, 7]})
   ......:

In [1116]: merge(left, right, how='outer')
Out[1116]:
  key1 key2  lval  rval
```

```
0  foo  one     1     4
1  foo  one     1     5
2  foo  two     2   NaN
3  bar  one     3     6
4  bar  two   NaN     7

In [1117]: merge(left, right, how='inner')
Out[1117]:
  key1 key2  lval  rval
0  foo  one     1     4
1  foo  one     1     5
2  bar  one     3     6
```

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 |

### 11.2.2 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 [1118]: df = DataFrame(np.random.randn(8, 4), columns=['A','B','C','D'])

In [1119]: df1 = df.ix[1:, ['A', 'B']]

In [1120]: df2 = df.ix[:5, ['C', 'D']]

In [1121]: df1
Out[1121]:
          A         B
1 -2.461467 -1.553902
2  1.771740 -0.670027
3 -3.201750  0.792716
4 -0.747169 -0.309038
5  0.936527  1.255746
6  0.062297 -0.110388
7  0.077849  0.629498

In [1122]: df2
Out[1122]:
          C         D
0  0.377953  0.493672
1  2.015523 -1.833722
2  0.049307 -0.521493
3  0.146111  1.903247
4  0.393876  1.861468
5 -2.655452  1.219492

In [1123]: df1.join(df2)
Out[1123]:
```

```
          A         B         C         D
1 -2.461467 -1.553902  2.015523 -1.833722
2  1.771740 -0.670027  0.049307 -0.521493
3 -3.201750  0.792716  0.146111  1.903247
4 -0.747169 -0.309038  0.393876  1.861468
5  0.936527  1.255746 -2.655452  1.219492
6  0.062297 -0.110388       NaN       NaN
7  0.077849  0.629498       NaN       NaN

In [1124]: df1.join(df2, how='outer')
Out[1124]:
          A         B         C         D
0       NaN       NaN  0.377953  0.493672
1 -2.461467 -1.553902  2.015523 -1.833722
2  1.771740 -0.670027  0.049307 -0.521493
3 -3.201750  0.792716  0.146111  1.903247
4 -0.747169 -0.309038  0.393876  1.861468
5  0.936527  1.255746 -2.655452  1.219492
6  0.062297 -0.110388       NaN       NaN
7  0.077849  0.629498       NaN       NaN

In [1125]: df1.join(df2, how='inner')
Out[1125]:
          A         B         C         D
1 -2.461467 -1.553902  2.015523 -1.833722
2  1.771740 -0.670027  0.049307 -0.521493
3 -3.201750  0.792716  0.146111  1.903247
4 -0.747169 -0.309038  0.393876  1.861468
5  0.936527  1.255746 -2.655452  1.219492
```

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 [1126]: merge(df1, df2, left_index=True, right_index=True, how='outer')
Out[1126]:
          A         B         C         D
0       NaN       NaN  0.377953  0.493672
1 -2.461467 -1.553902  2.015523 -1.833722
2  1.771740 -0.670027  0.049307 -0.521493
3 -3.201750  0.792716  0.146111  1.903247
4 -0.747169 -0.309038  0.393876  1.861468
5  0.936527  1.255746 -2.655452  1.219492
6  0.062297 -0.110388       NaN       NaN
7  0.077849  0.629498       NaN       NaN
```

### 11.2.3 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)
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 [1127]: df['key'] = ['foo', 'bar'] * 4

In [1128]: to_join = DataFrame(randn(2, 2), index=['bar', 'foo'],
   ......:                     columns=['j1', 'j2'])
   ......:

In [1129]: df
Out[1129]:
          A         B         C         D  key
0 -0.308853 -0.681087  0.377953  0.493672  foo
1 -2.461467 -1.553902  2.015523 -1.833722  bar
2  1.771740 -0.670027  0.049307 -0.521493  foo
3 -3.201750  0.792716  0.146111  1.903247  bar
4 -0.747169 -0.309038  0.393876  1.861468  foo
5  0.936527  1.255746 -2.655452  1.219492  bar
6  0.062297 -0.110388 -1.184357 -0.558081  foo
7  0.077849  0.629498 -1.035260 -0.438229  bar

In [1130]: to_join
Out[1130]:
           j1        j2
bar  0.503703  0.413086
foo -1.139050  0.660342

In [1131]: df.join(to_join, on='key')
Out[1131]:
          A         B         C         D  key        j1        j2
0 -0.308853 -0.681087  0.377953  0.493672  foo -1.139050  0.660342
1 -2.461467 -1.553902  2.015523 -1.833722  bar  0.503703  0.413086
2  1.771740 -0.670027  0.049307 -0.521493  foo -1.139050  0.660342
3 -3.201750  0.792716  0.146111  1.903247  bar  0.503703  0.413086
4 -0.747169 -0.309038  0.393876  1.861468  foo -1.139050  0.660342
5  0.936527  1.255746 -2.655452  1.219492  bar  0.503703  0.413086
6  0.062297 -0.110388 -1.184357 -0.558081  foo -1.139050  0.660342
7  0.077849  0.629498 -1.035260 -0.438229  bar  0.503703  0.413086

In [1132]: merge(df, to_join, left_on='key', right_index=True,
   ......:       how='left', sort=False)
   ......:
Out[1132]:
          A         B         C         D  key        j1        j2
0 -0.308853 -0.681087  0.377953  0.493672  foo -1.139050  0.660342
1 -2.461467 -1.553902  2.015523 -1.833722  bar  0.503703  0.413086
2  1.771740 -0.670027  0.049307 -0.521493  foo -1.139050  0.660342
3 -3.201750  0.792716  0.146111  1.903247  bar  0.503703  0.413086
4 -0.747169 -0.309038  0.393876  1.861468  foo -1.139050  0.660342
5  0.936527  1.255746 -2.655452  1.219492  bar  0.503703  0.413086
6  0.062297 -0.110388 -1.184357 -0.558081  foo -1.139050  0.660342
7  0.077849  0.629498 -1.035260 -0.438229  bar  0.503703  0.413086
```

To join on multiple keys, the passed DataFrame must have a `MultiIndex`:

```
In [1133]: index = 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=['first', 'second'])
   ......:
```

```
In [1134]: to_join = DataFrame(np.random.randn(10, 3), index=index,
   ......:                     columns=['j_one', 'j_two', 'j_three'])
   ......:

# a little relevant example with NAs
In [1135]: key1 = ['bar', 'bar', 'bar', 'foo', 'foo', 'baz', 'baz', 'qux',
   ......:         'qux', 'snap']
   ......:

In [1136]: key2 = ['two', 'one', 'three', 'one', 'two', 'one', 'two', 'two',
   ......:         'three', 'one']
   ......:

In [1137]: data = np.random.randn(len(key1))

In [1138]: data = DataFrame({'key1' : key1, 'key2' : key2,
   ......:                   'data' : data})
   ......:

In [1139]: data
Out[1139]:
       data  key1   key2
0 -1.004168   bar    two
1 -1.377627   bar    one
2  0.499281   bar  three
3 -1.405256   foo    one
4  0.162565   foo    two
5 -0.067785   baz    one
6 -1.260006   baz    two
7 -1.132896   qux    two
8 -2.006481   qux  three
9  0.301016  snap    one

In [1140]: to_join
Out[1140]:
                 j_one     j_two   j_three
first second
foo   one     0.464794 -0.309337 -0.649593
      two     0.683758 -0.643834  0.421287
      three   1.032814 -1.290493  0.787872
bar   one     1.515707 -0.276487 -0.223762
      two     1.397431  1.503874 -0.478905
baz   two    -0.135950 -0.730327 -0.033277
      three   0.281151 -1.298915 -2.819487
qux   one    -0.851985 -1.106952 -0.937731
      two    -1.537770  0.555759 -2.277282
      three  -0.390201  1.207122  0.178690
```

Now this can be joined by passing the two key column names:

```
In [1141]: data.join(to_join, on=['key1', 'key2'])
Out[1141]:
       data  key1   key2     j_one     j_two   j_three
0 -1.004168   bar    two  1.397431  1.503874 -0.478905
1 -1.377627   bar    one  1.515707 -0.276487 -0.223762
2  0.499281   bar  three       NaN       NaN       NaN
3 -1.405256   foo    one  0.464794 -0.309337 -0.649593
4  0.162565   foo    two  0.683758 -0.643834  0.421287
5 -0.067785   baz    one       NaN       NaN       NaN
```

```
6 -1.260006   baz    two -0.135950 -0.730327 -0.033277
7 -1.132896   qux    two -1.537770  0.555759 -2.277282
8 -2.006481   qux  three -0.390201  1.207122  0.178690
9  0.301016  snap    one       NaN       NaN       NaN
```

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 [1142]: data.join(to_join, on=['key1', 'key2'], how='inner')
Out[1142]:
       data key1   key2     j_one     j_two   j_three
0 -1.004168  bar    two  1.397431  1.503874 -0.478905
1 -1.377627  bar    one  1.515707 -0.276487 -0.223762
3 -1.405256  foo    one  0.464794 -0.309337 -0.649593
4  0.162565  foo    two  0.683758 -0.643834  0.421287
6 -1.260006  baz    two -0.135950 -0.730327 -0.033277
7 -1.132896  qux    two -1.537770  0.555759 -2.277282
8 -2.006481  qux  three -0.390201  1.207122  0.178690
```

As you can see, this drops any rows where there was no match.

### 11.2.4 Overlapping value columns

The merge `suffixes` argument takes a tuple of list of strings to append to overlapping column names in the input DataFrames to disambiguate the result columns:

```
In [1143]: left = DataFrame({'key': ['foo', 'foo'], 'value': [1, 2]})

In [1144]: right = DataFrame({'key': ['foo', 'foo'], 'value': [4, 5]})

In [1145]: merge(left, right, on='key', suffixes=['_left', '_right'])
Out[1145]:
   key  value_left  value_right
0  foo           1            4
1  foo           1            5
2  foo           2            4
3  foo           2            5
```

`DataFrame.join` has `lsuffix` and `rsuffix` arguments which behave similarly.

### 11.2.5 Merging Ordered Data

New in v0.8.0 is the ordered_merge function for combining time series and other ordered data. In particular it has an optional `fill_method` keyword to fill/interpolate missing data:

```
In [1146]: A
Out[1146]:
  group key  lvalue
0     a   a       1
1     a   c       2
2     a   e       3
3     b   a       1
4     b   c       2
5     b   e       3
```

```
In [1147]: B
Out[1147]:
  key  rvalue
0   b       1
1   c       2
2   d       3

In [1148]: ordered_merge(A, B, fill_method='ffill', left_by='group')
Out[1148]:
  group key  lvalue  rvalue
0     a   a       1     NaN
1     a   b       1       1
2     a   c       2       2
3     a   d       2       3
4     a   e       3       3
5     b   a       1     NaN
6     b   b       1       1
7     b   c       2       2
8     b   d       2       3
9     b   e       3       3
```

### 11.2.6 Joining multiple DataFrame or Panel objects

A list or tuple of DataFrames can also be passed to `DataFrame.join` to join them together on their indexes. The same is true for `Panel.join`.

```
In [1149]: df1 = df.ix[:, ['A', 'B']]

In [1150]: df2 = df.ix[:, ['C', 'D']]

In [1151]: df3 = df.ix[:, ['key']]

In [1152]: df1
Out[1152]:
          A         B
0 -0.308853 -0.681087
1 -2.461467 -1.553902
2  1.771740 -0.670027
3 -3.201750  0.792716
4 -0.747169 -0.309038
5  0.936527  1.255746
6  0.062297 -0.110388
7  0.077849  0.629498

In [1153]: df1.join([df2, df3])
Out[1153]:
          A         B         C         D  key
0 -0.308853 -0.681087  0.377953  0.493672  foo
1 -2.461467 -1.553902  2.015523 -1.833722  bar
2  1.771740 -0.670027  0.049307 -0.521493  foo
3 -3.201750  0.792716  0.146111  1.903247  bar
4 -0.747169 -0.309038  0.393876  1.861468  foo
5  0.936527  1.255746 -2.655452  1.219492  bar
6  0.062297 -0.110388 -1.184357 -0.558081  foo
7  0.077849  0.629498 -1.035260 -0.438229  bar
```

### 11.2.7 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 [1154]: df1 = DataFrame([[nan, 3., 5.], [-4.6, np.nan, nan],
   ......:                  [nan, 7., nan]])
   ......:

In [1155]: df2 = DataFrame([[-42.6, np.nan, -8.2], [-5., 1.6, 4]],
   ......:                 index=[1, 2])
   ......:
```

For this, use the `combine_first` method:

```
In [1156]: df1.combine_first(df2)
Out[1156]:
     0    1    2
0  NaN    3  5.0
1 -4.6  NaN -8.2
2 -5.0    7  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 inplace:

```
In [1157]: df1.update(df2)

In [1158]: df1
Out[1158]:
      0    1    2
0   NaN  3.0  5.0
1 -42.6  NaN -8.2
2  -5.0  1.6  4.0
```

CHAPTER

TWELVE

# RESHAPING AND PIVOT TABLES

## 12.1 Reshaping by pivoting DataFrame objects

Data is often stored in CSV files or databases in so-called "stacked" or "record" format:

```
In [1225]: df
Out[1225]:
                   date variable     value
0   2000-01-03 00:00:00        A  0.469112
1   2000-01-04 00:00:00        A -0.282863
2   2000-01-05 00:00:00        A -1.509059
3   2000-01-03 00:00:00        B -1.135632
4   2000-01-04 00:00:00        B  1.212112
5   2000-01-05 00:00:00        B -0.173215
6   2000-01-03 00:00:00        C  0.119209
7   2000-01-04 00:00:00        C -1.044236
8   2000-01-05 00:00:00        C -0.861849
9   2000-01-03 00:00:00        D -2.104569
10  2000-01-04 00:00:00        D -0.494929
11  2000-01-05 00:00:00        D  1.071804
```

For the curious here is how the above DataFrame was created:

```
import pandas.util.testing as tm; tm.N = 3
def unpivot(frame):
    N, K = frame.shape
    data = {'value' : frame.values.ravel('F'),
            'variable' : np.asarray(frame.columns).repeat(N),
            'date' : np.tile(np.asarray(frame.index), K)}
    return DataFrame(data, columns=['date', 'variable', 'value'])
df = unpivot(tm.makeTimeDataFrame())
```

To select out everything for variable `A` we could do:

```
In [1226]: df[df['variable'] == 'A']
Out[1226]:
                  date variable     value
0 2000-01-03 00:00:00        A  0.469112
1 2000-01-04 00:00:00        A -0.282863
2 2000-01-05 00:00:00        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, use the `pivot` function:

```
In [1227]: df.pivot(index='date', columns='variable', values='value')
Out[1227]:
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 [1228]: df['value2'] = df['value'] * 2

In [1229]: pivoted = df.pivot('date', 'variable')

In [1230]: pivoted
Out[1230]:
               value                                  value2                      \
variable           A         B         C         D         A         B         C
date
2000-01-03  0.469112 -1.135632  0.119209 -2.104569  0.938225 -2.271265  0.238417
2000-01-04 -0.282863  1.212112 -1.044236 -0.494929 -0.565727  2.424224 -2.088472
2000-01-05 -1.509059 -0.173215 -0.861849  1.071804 -3.018117 -0.346429 -1.723698

variable           D
date
2000-01-03 -4.209138
2000-01-04 -0.989859
2000-01-05  2.143608
```

You of course can then select subsets from the pivoted DataFrame:

```
In [1231]: pivoted['value2']
Out[1231]:
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.

## 12.2 Reshaping by stacking and unstacking

Closely related to the `pivot` function are the related `stack` and `unstack` functions currently available on Series and DataFrame. These functions are designed to work together with `MultiIndex` objects (see the section on *hierarchical indexing*). Here are essentially what these functions 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 from `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 [1232]: tuples = zip(*[['bar', 'bar', 'baz', 'baz',
   ......:                  'foo', 'foo', 'qux', 'qux'],
   ......:                 ['one', 'two', 'one', 'two',
   ......:                  'one', 'two', 'one', 'two']])
   ......:

In [1233]: index = MultiIndex.from_tuples(tuples, names=['first', 'second'])

In [1234]: df = DataFrame(randn(8, 2), index=index, columns=['A', 'B'])

In [1235]: df2 = df[:4]

In [1236]: df2
Out[1236]:
                     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 [1237]: stacked = df2.stack()

In [1238]: stacked
Out[1238]:
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 [1239]: stacked.unstack()
Out[1239]:
                     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 [1240]: stacked.unstack(1)
Out[1240]:
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 [1241]: stacked.unstack(0)
Out[1241]:
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 [1242]: stacked.unstack('second')
Out[1242]:
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
```

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.

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 `sortlevel`, of course). Here is a more complex example:

```
In [1243]: columns = MultiIndex.from_tuples([('A', 'cat'), ('B', 'dog'),
   ......:                                   ('B', 'cat'), ('A', 'dog')],
   ......:                                  names=['exp', 'animal'])
   ......:

In [1244]: df = DataFrame(randn(8, 4), index=index, columns=columns)

In [1245]: df2 = df.ix[[0, 1, 2, 4, 5, 7]]

In [1246]: df2
Out[1246]:
exp                  A         B                   A
animal             cat       dog       cat       dog
first second
bar   one    -0.370647 -1.157892 -1.344312  0.844885
      two     1.075770 -0.109050  1.643563 -1.469388
baz   one     0.357021 -0.674600 -1.776904 -0.968914
foo   one    -0.013960 -0.362543 -0.006154 -0.923061
      two     0.895717  0.805244 -1.206412  2.565646
qux   two     0.410835  0.813850  0.132003 -0.827317
```

As mentioned above, `stack` can be called with a `level` argument to select which level in the columns to stack:

```
In [1247]: df2.stack('exp')
Out[1247]:
animal                 cat       dog
```

```
first second exp
bar   one    A   -0.370647  0.844885
             B   -1.344312 -1.157892
      two    A    1.075770 -1.469388
             B    1.643563 -0.109050
baz   one    A    0.357021 -0.968914
             B   -1.776904 -0.674600
foo   one    A   -0.013960 -0.923061
             B   -0.006154 -0.362543
      two    A    0.895717  2.565646
             B   -1.206412  0.805244
qux   two    A    0.410835 -0.827317
             B    0.132003  0.813850

In [1248]: df2.stack('animal')
Out[1248]:
exp                          A         B
first second animal
bar   one    cat    -0.370647 -1.344312
             dog     0.844885 -1.157892
      two    cat     1.075770  1.643563
             dog    -1.469388 -0.109050
baz   one    cat     0.357021 -1.776904
             dog    -0.968914 -0.674600
foo   one    cat    -0.013960 -0.006154
             dog    -0.923061 -0.362543
      two    cat     0.895717 -1.206412
             dog     2.565646  0.805244
qux   two    cat     0.410835  0.132003
             dog    -0.827317  0.813850
```

Unstacking when the columns are a `MultiIndex` is also careful about doing the right thing:

```
In [1249]: df[:3].unstack(0)
Out[1249]:
exp             A                   B                                     A
animal        cat                 dog                 cat                 dog
first         bar       baz       bar      baz        bar       baz       bar       baz
second
one     -0.370647  0.357021 -1.157892 -0.6746 -1.344312 -1.776904  0.844885 -0.968914
two      1.075770       NaN -0.109050      NaN  1.643563       NaN -1.469388       NaN

In [1250]: df2.unstack(1)
Out[1250]:
exp             A                   B                                         A
animal        cat                 dog                     cat                 dog
second        one       two       one       two       one       two       one       two
first
bar     -0.370647  1.075770 -1.157892 -0.109050 -1.344312  1.643563  0.844885 -1.469388
baz      0.357021       NaN -0.674600       NaN -1.776904       NaN -0.968914       NaN
foo     -0.013960  0.895717 -0.362543  0.805244 -0.006154 -1.206412 -0.923061  2.565646
qux           NaN  0.410835       NaN  0.813850       NaN  0.132003       NaN -0.827317
```

## 12.3 Reshaping by Melt

The melt function found in pandas.core.reshape is useful to massage a DataFrame into a format where one or more columns are identifier variables, while all other columns, considered measured variables, are "pivoted" to the row axis, leaving just two non-identifier columns, "variable" and "value".

For instance,

```
In [1251]: cheese = DataFrame({'first' : ['John', 'Mary'],
   ......:                     'last' : ['Doe', 'Bo'],
   ......:                     'height' : [5.5, 6.0],
   ......:                     'weight' : [130, 150]})
   ......:

In [1252]: cheese
Out[1252]:
  first  height last  weight
0  John     5.5  Doe     130
1  Mary     6.0   Bo     150

In [1253]: melt(cheese, id_vars=['first', 'last'])
Out[1253]:
  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
```

## 12.4 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 [1254]: df
Out[1254]:
exp                  A         B                   A
animal             cat       dog       cat       dog
first second
bar   one    -0.370647 -1.157892 -1.344312  0.844885
      two     1.075770 -0.109050  1.643563 -1.469388
baz   one     0.357021 -0.674600 -1.776904 -0.968914
      two    -1.294524  0.413738  0.276662 -0.472035
foo   one    -0.013960 -0.362543 -0.006154 -0.923061
      two     0.895717  0.805244 -1.206412  2.565646
qux   one     1.431256  1.340309 -1.170299 -0.226169
      two     0.410835  0.813850  0.132003 -0.827317

In [1255]: df.stack().mean(1).unstack()
Out[1255]:
animal             cat       dog
first second
bar   one    -0.857479 -0.156504
      two     1.359666 -0.789219
baz   one    -0.709942 -0.821757
      two    -0.508931 -0.029148
foo   one    -0.010057 -0.642802
```

```
      two    -0.155347  1.685445
qux   one     0.130479  0.557070
      two     0.271419 -0.006733

# same result, another way
In [1256]: df.groupby(level=1, axis=1).mean()
Out[1256]:
animal             cat       dog
first second
bar   one    -0.857479 -0.156504
      two     1.359666 -0.789219
baz   one    -0.709942 -0.821757
      two    -0.508931 -0.029148
foo   one    -0.010057 -0.642802
      two    -0.155347  1.685445
qux   one     0.130479  0.557070
      two     0.271419 -0.006733

In [1257]: df.stack().groupby(level=1).mean()
Out[1257]:
exp            A         B
second
one     0.016301 -0.644049
two     0.110588  0.346200

In [1258]: df.mean().unstack(0)
Out[1258]:
exp            A         B
animal
cat     0.311433 -0.431481
dog    -0.184544  0.133632
```

## 12.5 Pivot tables and cross-tabulations

The function `pandas.pivot_table` can be used to create spreadsheet-style pivot tables. It takes a number of arguments

- `data`: A DataFrame object
- `values`: a column or a list of columns to aggregate
- `rows`: list of columns to group by on the table rows
- `cols`: list of columns to group by on the table columns
- `aggfunc`: function to use for aggregation, defaulting to `numpy.mean`

Consider a data set like this:

```
In [1259]: df = 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)})
   ......:

In [1260]: df
Out[1260]:
```

```
        A  B    C         D         E
0     one  A  foo -0.076467  0.959726
1     one  B  foo -1.187678 -1.110336
2     two  C  foo  1.130127 -0.619976
3   three  A  bar -1.436737  0.149748
4     one  B  bar -1.413681 -0.732339
5     one  C  bar  1.607920  0.687738
6     two  A  foo  1.024180  0.176444
7   three  B  foo  0.569605  0.403310
8     one  C  foo  0.875906 -0.154951
9     one  A  bar -2.211372  0.301624
10    two  B  bar  0.974466 -2.179861
11  three  C  bar -2.006747 -1.369849
12    one  A  foo -0.410001 -0.954208
13    one  B  foo -0.078638  1.462696
14    two  C  foo  0.545952 -1.743161
15  three  A  bar -1.219217 -0.826591
16    one  B  bar -1.226825 -0.345352
17    one  C  bar  0.769804  1.314232
18    two  A  foo -1.281247  0.690579
19  three  B  foo -0.727707  0.995761
20    one  C  foo -0.121306  2.396780
21    one  A  bar -0.097883  0.014871
22    two  B  bar  0.695775  3.357427
23  three  C  bar  0.341734 -0.317441
```

We can produce pivot tables from this data very easily:

```
In [1261]: pivot_table(df, values='D', rows=['A', 'B'], cols=['C'])
Out[1261]:
C              bar       foo
A     B
one   A -1.154627 -0.243234
      B -1.320253 -0.633158
      C  1.188862  0.377300
three A -1.327977       NaN
      B       NaN -0.079051
      C -0.832506       NaN
two   A       NaN -0.128534
      B  0.835120       NaN
      C       NaN  0.838040

In [1262]: pivot_table(df, values='D', rows=['B'], cols=['A', 'C'], aggfunc=np.sum)
Out[1262]:
A       one                three                 two
C       bar       foo       bar       foo       bar       foo
B
A -2.309255 -0.486468 -2.655954       NaN       NaN -0.257067
B -2.640506 -1.266315       NaN -0.158102  1.670241       NaN
C  2.377724  0.754600 -1.665013       NaN       NaN  1.676079

In [1263]: pivot_table(df, values=['D','E'], rows=['B'], cols=['A', 'C'], aggfunc=np.sum)
Out[1263]:
          D                                                           E             \
A       one                three                 two                one
C       bar       foo       bar       foo       bar       foo       bar       foo
B
A -2.309255 -0.486468 -2.655954       NaN       NaN -0.257067  0.316495  0.005518
B -2.640506 -1.266315       NaN -0.158102  1.670241       NaN -1.077692  0.352360
```

```
C  2.377724  0.754600 -1.665013       NaN       NaN  1.676079  2.001971  2.241830

A     three                two
C       bar      foo       bar       foo
B
A -0.676843      NaN       NaN  0.867024
B       NaN  1.39907  1.177566       NaN
C -1.687290      NaN       NaN -2.363137
```

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 [1264]: pivot_table(df, rows=['A', 'B'], cols=['C'])
Out[1264]:
                  D                   E
C               bar       foo       bar       foo
A     B
one   A -1.154627 -0.243234  0.158248  0.002759
      B -1.320253 -0.633158 -0.538846  0.176180
      C  1.188862  0.377300  1.000985  1.120915
three A -1.327977       NaN -0.338421       NaN
      B       NaN -0.079051       NaN  0.699535
      C -0.832506       NaN -0.843645       NaN
two   A       NaN -0.128534       NaN  0.433512
      B  0.835120       NaN  0.588783       NaN
      C       NaN  0.838040       NaN -1.181568
```

You can render a nice output of the table omitting the missing values by calling `to_string` if you wish:

```
In [1265]: table = pivot_table(df, rows=['A', 'B'], cols=['C'])

In [1266]: print table.to_string(na_rep='')
                  D                   E
C               bar       foo       bar       foo
A     B
one   A -1.154627 -0.243234  0.158248  0.002759
      B -1.320253 -0.633158 -0.538846  0.176180
      C  1.188862  0.377300  1.000985  1.120915
three A -1.327977           -0.338421
      B           -0.079051            0.699535
      C -0.832506           -0.843645
two   A           -0.128534            0.433512
      B  0.835120            0.588783
      C            0.838040           -1.181568
```

Note that `pivot_table` is also available as an instance method on DataFrame.

### 12.5.1 Cross tabulations

Use the `crosstab` function 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

- `rows`: array-like, values to group by in the rows
- `cols`: 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)

Any Series passed will have their name attributes used unless row or column names for the cross-tabulation are specified

For example:

```
In [1267]: foo, bar, dull, shiny, one, two = 'foo', 'bar', 'dull', 'shiny', 'one', 'two'

In [1268]: a = np.array([foo, foo, bar, bar, foo, foo], dtype=object)

In [1269]: b = np.array([one, one, two, one, two, one], dtype=object)

In [1270]: c = np.array([dull, dull, shiny, dull, dull, shiny], dtype=object)

In [1271]: crosstab(a, [b, c], rownames=['a'], colnames=['b', 'c'])
Out[1271]:
b     one        two
c    dull  shiny dull  shiny
a
bar     1      0    0      1
foo     2      1    1      0
```

### 12.5.2 Adding margins (partial aggregates)

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 [1272]: df.pivot_table(rows=['A', 'B'], cols='C', margins=True, aggfunc=np.std)
Out[1272]:
                D                             E
C             bar       foo       All       bar       foo       All
A     B
one   A  1.494463  0.235844  1.019752  0.202765  1.353355  0.795165
      B  0.132127  0.784210  0.606779  0.273641  1.819408  1.139647
      C  0.592638  0.705136  0.708771  0.442998  1.804346  1.074910
three A  0.153810       NaN  0.153810  0.690376       NaN  0.690376
      B       NaN  0.917338  0.917338       NaN  0.418926  0.418926
      C  1.660627       NaN  1.660627  0.744165       NaN  0.744165
two   A       NaN  1.630183  1.630183       NaN  0.363548  0.363548
      B  0.197065       NaN  0.197065  3.915454       NaN  3.915454
      C       NaN  0.413074  0.413074       NaN  0.794212  0.794212
All      1.294620  0.824989  1.064129  1.403041  1.188419  1.248988
```

## 12.6 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 [1273]: ages = np.array([10, 15, 13, 12, 23, 25, 28, 59, 60])

In [1274]: cut(ages, bins=3)
Out[1274]:
Categorical:
array([(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],
       (43.333, 60]], dtype=object)
Levels (3): Index([(9.95, 26.667], (26.667, 43.333], (43.333, 60]], dtype=object)
```

If the `bins` keyword is an integer, then equal-width bins are formed. Alternatively we can specify custom bin-edges:

```
In [1275]: cut(ages, bins=[0, 18, 35, 70])
Out[1275]:
Categorical:
array([(0, 18], (0, 18], (0, 18], (0, 18], (18, 35], (18, 35], (18, 35],
       (35, 70], (35, 70]], dtype=object)
Levels (3): Index([(0, 18], (18, 35], (35, 70]], dtype=object)
```

CHAPTER

THIRTEEN

# TIME SERIES / DATE FUNCTIONALITY

pandas has proven very successful as a tool for working with time series data, especially in the financial data analysis space. With the 0.8 release, we have further improved the time series API in pandas by leaps and bounds. Using the new NumPy `datetime64` dtype, we have 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.

In working with time series data, we will frequently seek to:

- generate sequences of fixed-frequency dates and time spans
- conform or convert time series to a particular frequency
- compute "relative" dates based on various non-standard time increments (e.g. 5 business days before the last business day of the year), or "roll" dates forward or backward

pandas provides a relatively compact and self-contained set of tools for performing the above tasks.

Create a range of dates:

```
# 72 hours starting with midnight Jan 1st, 2011
In [1299]: rng = date_range('1/1/2011', periods=72, freq='H')

In [1300]: rng[:5]
Out[1300]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2011-01-01 00:00:00, ..., 2011-01-01 04:00:00]
Length: 5, Freq: H, Timezone: None
```

Index pandas objects with dates:

```
In [1301]: ts = Series(randn(len(rng)), index=rng)

In [1302]: ts.head()
Out[1302]:
2011-01-01 00:00:00    0.469112
2011-01-01 01:00:00   -0.282863
2011-01-01 02:00:00   -1.509059
2011-01-01 03:00:00   -1.135632
2011-01-01 04:00:00    1.212112
Freq: H, dtype: float64
```

Change frequency and fill gaps:

```
# to 45 minute frequency and forward fill
In [1303]: converted = ts.asfreq('45Min', method='pad')
```

```
In [1304]: converted.head()
Out[1304]:
2011-01-01 00:00:00    0.469112
2011-01-01 00:45:00    0.469112
2011-01-01 01:30:00   -0.282863
2011-01-01 02:15:00   -1.509059
2011-01-01 03:00:00   -1.135632
Freq: 45T, dtype: float64
```

Resample:

```
# Daily means
In [1305]: ts.resample('D', how='mean')
Out[1305]:
2011-01-01   -0.319569
2011-01-02   -0.337703
2011-01-03    0.117258
Freq: D, dtype: float64
```

## 13.1 Time Stamps vs. Time Spans

Time-stamped data is the most basic type of timeseries data that associates values with points in time. For pandas objects it means using the points in time to create the index

```
In [1306]: dates = [datetime(2012, 5, 1), datetime(2012, 5, 2), datetime(2012, 5, 3)]

In [1307]: ts = Series(np.random.randn(3), dates)

In [1308]: type(ts.index)
Out[1308]: pandas.tseries.index.DatetimeIndex

In [1309]: ts
Out[1309]:
2012-05-01   -0.410001
2012-05-02   -0.078638
2012-05-03    0.545952
dtype: float64
```

However, in many cases it is more natural to associate things like change variables with a time span instead.

For example:

```
In [1310]: periods = PeriodIndex([Period('2012-01'), Period('2012-02'),
   ......:                        Period('2012-03')])
   ......:

In [1311]: ts = Series(np.random.randn(3), periods)

In [1312]: type(ts.index)
Out[1312]: pandas.tseries.period.PeriodIndex

In [1313]: ts
Out[1313]:
2012-01   -1.219217
2012-02   -1.226825
2012-03    0.769804
Freq: M, dtype: float64
```

Starting with 0.8, 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.

## 13.2 Generating Ranges of Timestamps

To generate an index with time stamps, you can use either the DatetimeIndex or Index constructor and pass in a list of datetime objects:

```
In [1314]: dates = [datetime(2012, 5, 1), datetime(2012, 5, 2), datetime(2012, 5, 3)]

In [1315]: index = DatetimeIndex(dates)

In [1316]: index # Note the frequency information
Out[1316]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2012-05-01 00:00:00, ..., 2012-05-03 00:00:00]
Length: 3, Freq: None, Timezone: None

In [1317]: index = Index(dates)

In [1318]: index # Automatically converted to DatetimeIndex
Out[1318]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2012-05-01 00:00:00, ..., 2012-05-03 00:00:00]
Length: 3, Freq: None, Timezone: None
```

Practically, 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 pandas functions `date_range` and `bdate_range` to create timestamp indexes.

```
In [1319]: index = date_range('2000-1-1', periods=1000, freq='M')

In [1320]: index
Out[1320]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2000-01-31 00:00:00, ..., 2083-04-30 00:00:00]
Length: 1000, Freq: M, Timezone: None

In [1321]: index = bdate_range('2012-1-1', periods=250)

In [1322]: index
Out[1322]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2012-01-02 00:00:00, ..., 2012-12-14 00:00:00]
Length: 250, Freq: B, Timezone: None
```

Convenience functions like `date_range` and `bdate_range` utilize a variety of frequency aliases. The default frequency for `date_range` is a **calendar day** while the default for `bdate_range` is a **business day**

```
In [1323]: start = datetime(2011, 1, 1)

In [1324]: end = datetime(2012, 1, 1)

In [1325]: rng = date_range(start, end)
```

```
In [1326]: rng
Out[1326]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2011-01-01 00:00:00, ..., 2012-01-01 00:00:00]
Length: 366, Freq: D, Timezone: None

In [1327]: rng = bdate_range(start, end)

In [1328]: rng
Out[1328]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2011-01-03 00:00:00, ..., 2011-12-30 00:00:00]
Length: 260, Freq: B, Timezone: None
```

`date_range` and `bdate_range` makes it easy to generate a range of dates using various combinations of parameters like `start`, `end`, `periods`, and `freq`:

```
In [1329]: date_range(start, end, freq='BM')
Out[1329]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2011-01-31 00:00:00, ..., 2011-12-30 00:00:00]
Length: 12, Freq: BM, Timezone: None

In [1330]: date_range(start, end, freq='W')
Out[1330]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2011-01-02 00:00:00, ..., 2012-01-01 00:00:00]
Length: 53, Freq: W-SUN, Timezone: None

In [1331]: bdate_range(end=end, periods=20)
Out[1331]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2011-12-05 00:00:00, ..., 2011-12-30 00:00:00]
Length: 20, Freq: B, Timezone: None

In [1332]: bdate_range(start=start, periods=20)
Out[1332]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2011-01-03 00:00:00, ..., 2011-01-28 00:00:00]
Length: 20, Freq: B, Timezone: None
```

The start and end dates are strictly inclusive. So it will not generate any dates outside of those dates if specified.

### 13.2.1 DatetimeIndex

One of the main uses for `DatetimeIndex` is as an index for pandas objects. The `DatetimeIndex` class contains many timeseries 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` and `tshift` 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` can be used like a regular index and offers all of its intelligent functionality like selection, slicing, etc.

```
In [1333]: rng = date_range(start, end, freq='BM')

In [1334]: ts = Series(randn(len(rng)), index=rng)

In [1335]: ts.index
Out[1335]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2011-01-31 00:00:00, ..., 2011-12-30 00:00:00]
Length: 12, Freq: BM, Timezone: None

In [1336]: ts[:5].index
Out[1336]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2011-01-31 00:00:00, ..., 2011-05-31 00:00:00]
Length: 5, Freq: BM, Timezone: None

In [1337]: ts[::2].index
Out[1337]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2011-01-31 00:00:00, ..., 2011-11-30 00:00:00]
Length: 6, Freq: 2BM, Timezone: None
```

You can pass in dates and strings that parses to dates as indexing parameters:

```
In [1338]: ts['1/31/2011']
Out[1338]: -1.2812473076599531

In [1339]: ts[datetime(2011, 12, 25):]
Out[1339]:
2011-12-30    0.687738
Freq: BM, dtype: float64

In [1340]: ts['10/31/2011':'12/31/2011']
Out[1340]:
2011-10-31    0.149748
2011-11-30   -0.732339
2011-12-30    0.687738
Freq: BM, dtype: float64
```

A `truncate` convenience function is provided that is equivalent to slicing:

```
In [1341]: ts.truncate(before='10/31/2011', after='12/31/2011')
Out[1341]:
2011-10-31    0.149748
2011-11-30   -0.732339
2011-12-30    0.687738
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 [1342]: ts['2011']
Out[1342]:
2011-01-31   -1.281247
2011-02-28   -0.727707
2011-03-31   -0.121306
```

```
2011-04-29   -0.097883
2011-05-31    0.695775
2011-06-30    0.341734
2011-07-29    0.959726
2011-08-31   -1.110336
2011-09-30   -0.619976
2011-10-31    0.149748
2011-11-30   -0.732339
2011-12-30    0.687738
Freq: BM, dtype: float64

In [1343]: ts['2011-6']
Out[1343]:
2011-06-30    0.341734
Freq: BM, dtype: float64
```

Even complicated fancy indexing that breaks the DatetimeIndex's frequency regularity will result in a `DatetimeIndex` (but frequency is lost):

```
In [1344]: ts[[0, 2, 6]].index
Out[1344]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2011-01-31 00:00:00, ..., 2011-07-29 00:00:00]
Length: 3, Freq: None, Timezone: None
```

DatetimeIndex objects has all the basic functionality of regular Index objects and a smorgasbord of advanced timeseries-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. So please be careful.

## 13.3 DateOffset objects

In the preceding examples, we created DatetimeIndex objects at various frequencies by passing in frequency strings like 'M', 'W', and 'BM to the `freq` keyword. Under the hood, these frequency strings are being translated into an instance of pandas `DateOffset`, which represents a regular frequency increment. Specific offset logic like "month", "business day", or "one hour" is represented in its various subclasses.

| Class name | Description |
|---|---|
| DateOffset | Generic offset class, defaults to 1 calendar day |
| BDay | business day (weekday) |
| Week | one week, optionally anchored on a day of the week |
| WeekOfMonth | the x-th day of the y-th week of each month |
| MonthEnd | calendar month end |
| MonthBegin | calendar month begin |
| BMonthEnd | business month end |
| BMonthBegin | business month begin |
| QuarterEnd | calendar quarter end |
| QuarterBegin | calendar quarter begin |
| BQuarterEnd | business quarter end |
| BQuarterBegin | business quarter begin |
| YearEnd | calendar year end |
| YearBegin | calendar year begin |
| BYearEnd | business year end |
| BYearBegin | business year begin |
| Hour | one hour |
| Minute | one minute |
| Second | one second |
| Milli | one millisecond |
| Micro | one microsecond |

The basic `DateOffset` takes the same arguments as `dateutil.relativedelta`, which works like:

```
In [1345]: d = datetime(2008, 8, 18)

In [1346]: d + relativedelta(months=4, days=5)
Out[1346]: datetime.datetime(2008, 12, 23, 0, 0)
```

We could have done the same thing with `DateOffset`:

```
In [1347]: from pandas.tseries.offsets import *

In [1348]: d + DateOffset(months=4, days=5)
Out[1348]: datetime.datetime(2008, 12, 23, 0, 0)
```

The key features of a `DateOffset` object are:

- it can be added / subtracted to/from a datetime object to obtain a shifted date
- it can be multiplied by an integer (positive or negative) so that the increment will be applied multiple times
- it has `rollforward` and `rollback` methods for moving a date forward or backward to the next or previous "offset date"

Subclasses of `DateOffset` define the `apply` function which dictates custom date increment logic, such as adding business days:

```
class BDay(DateOffset):
    """DateOffset increments between business days"""
    def apply(self, other):
        ...
```

```
In [1349]: d - 5 * BDay()
Out[1349]: datetime.datetime(2008, 8, 11, 0, 0)

In [1350]: d + BMonthEnd()
Out[1350]: datetime.datetime(2008, 8, 29, 0, 0)
```

The `rollforward` and `rollback` methods do exactly what you would expect:

```
In [1351]: d
Out[1351]: datetime.datetime(2008, 8, 18, 0, 0)

In [1352]: offset = BMonthEnd()

In [1353]: offset.rollforward(d)
Out[1353]: datetime.datetime(2008, 8, 29, 0, 0)

In [1354]: offset.rollback(d)
Out[1354]: datetime.datetime(2008, 7, 31, 0, 0)
```

It's definitely worth exploring the `pandas.tseries.offsets` module and the various docstrings for the classes.

### 13.3.1 Parametric offsets

Some of the offsets can be "parameterized" when created to result in different behavior. 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 [1355]: d + Week()
Out[1355]: datetime.datetime(2008, 8, 25, 0, 0)

In [1356]: d + Week(weekday=4)
Out[1356]: datetime.datetime(2008, 8, 22, 0, 0)

In [1357]: (d + Week(weekday=4)).weekday()
Out[1357]: 4
```

Another example is parameterizing `YearEnd` with the specific ending month:

```
In [1358]: d + YearEnd()
Out[1358]: datetime.datetime(2008, 12, 31, 0, 0)

In [1359]: d + YearEnd(month=6)
Out[1359]: datetime.datetime(2009, 6, 30, 0, 0)
```

### 13.3.2 Offset Aliases

A number of string aliases are given to useful common time series frequencies. We will refer to these aliases as *offset aliases* (referred to as *time rules* prior to v0.8.0).

| Alias | Description |
|---|---|
| B | business day frequency |
| D | calendar day frequency |
| W | weekly frequency |
| M | month end frequency |
| BM | business month end frequency |
| MS | month start frequency |
| BMS | business month start frequency |
| Q | quarter end frequency |
| BQ | business quarter endfrequency |
| QS | quarter start frequency |
| BQS | business quarter start frequency |
| A | year end frequency |
| BA | business year end frequency |
| AS | year start frequency |
| BAS | business year start frequency |
| H | hourly frequency |
| T | minutely frequency |
| S | secondly frequency |
| L | milliseonds |
| U | microseconds |

### 13.3.3 Combining Aliases

As we have seen previously, the alias and the offset instance are fungible in most functions:

```
In [1360]: date_range(start, periods=5, freq='B')
Out[1360]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2011-01-03 00:00:00, ..., 2011-01-07 00:00:00]
Length: 5, Freq: B, Timezone: None

In [1361]: date_range(start, periods=5, freq=BDay())
Out[1361]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2011-01-03 00:00:00, ..., 2011-01-07 00:00:00]
Length: 5, Freq: B, Timezone: None
```

You can combine together day and intraday offsets:

```
In [1362]: date_range(start, periods=10, freq='2h20min')
Out[1362]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2011-01-01 00:00:00, ..., 2011-01-01 21:00:00]
Length: 10, Freq: 140T, Timezone: None

In [1363]: date_range(start, periods=10, freq='1D10U')
Out[1363]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2011-01-01 00:00:00, ..., 2011-01-10 00:00:00.000090]
Length: 10, Freq: 86400000010U, Timezone: None
```

### 13.3.4 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' |
| (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.

### 13.3.5 Legacy Aliases

Note that prior to v0.8.0, time rules had a slightly different look. Pandas will continue to support the legacy time rules for the time being but it is strongly recommended that you switch to using the new offset aliases.

| Legacy Time Rule | Offset Alias |
|---|---|
| WEEKDAY | B |
| EOM | BM |
| W@MON | W-MON |
| W@TUE | W-TUE |
| W@WED | W-WED |
| W@THU | W-THU |
| W@FRI | W-FRI |
| W@SAT | W-SAT |
| W@SUN | W-SUN |
| Q@JAN | BQ-JAN |
| Q@FEB | BQ-FEB |
| Q@MAR | BQ-MAR |
| A@JAN | BA-JAN |
| A@FEB | BA-FEB |
| A@MAR | BA-MAR |
| A@APR | BA-APR |
| A@MAY | BA-MAY |
| A@JUN | BA-JUN |
| A@JUL | BA-JUL |
| A@AUG | BA-AUG |
| A@SEP | BA-SEP |
| A@OCT | BA-OCT |
| A@NOV | BA-NOV |
| A@DEC | BA-DEC |
| min | T |
| ms | L |
| us: "U" | |

As you can see, legacy quarterly and annual frequencies are business quarter and business year ends. Please also note the legacy time rule for milliseconds `ms` versus the new offset alias for month start `MS`. This means that offset alias parsing is case sensitive.

## 13.4 Time series-related instance methods

### 13.4.1 Shifting / lagging

One may want to *shift* or *lag* the values in a TimeSeries back and forward in time. The method for this is `shift`, which is available on all of the pandas objects. In DataFrame, `shift` will currently only shift along the `index` and in Panel along the `major_axis`.

```
In [1364]: ts = ts[:5]

In [1365]: ts.shift(1)
Out[1365]:
2011-01-31         NaN
2011-02-28   -1.281247
2011-03-31   -0.727707
2011-04-29   -0.121306
2011-05-31   -0.097883
Freq: BM, dtype: float64
```

The shift method accepts an `freq` argument which can accept a `DateOffset` class or other `timedelta`-like object or also a *offset alias*:

```
In [1366]: ts.shift(5, freq=datetools.bday)
Out[1366]:
2011-02-07   -1.281247
2011-03-07   -0.727707
2011-04-07   -0.121306
2011-05-06   -0.097883
2011-06-07    0.695775
dtype: float64

In [1367]: ts.shift(5, freq='BM')
Out[1367]:
2011-06-30   -1.281247
2011-07-29   -0.727707
2011-08-31   -0.121306
2011-09-30   -0.097883
2011-10-31    0.695775
Freq: BM, dtype: float64
```

Rather than changing the alignment of the data and the index, `DataFrame` and `TimeSeries` objects also have a `tshift` convenience method that changes all the dates in the index by a specified number of offsets:

```
In [1368]: ts.tshift(5, freq='D')
Out[1368]:
2011-02-05   -1.281247
2011-03-05   -0.727707
2011-04-05   -0.121306
2011-05-04   -0.097883
2011-06-05    0.695775
dtype: float64
```

Note that with `tshift`, the leading entry is no longer NaN because the data is not being realigned.

### 13.4.2 Frequency conversion

The primary function for changing frequencies is the `asfreq` function. For a `DatetimeIndex`, this is basically just a thin, but convenient wrapper around `reindex` which generates a `date_range` and calls `reindex`.

```
In [1369]: dr = date_range('1/1/2010', periods=3, freq=3 * datetools.bday)

In [1370]: ts = Series(randn(3), index=dr)

In [1371]: ts
Out[1371]:
2010-01-01    0.176444
2010-01-06    0.403310
2010-01-11   -0.154951
Freq: 3B, dtype: float64

In [1372]: ts.asfreq(BDay())
Out[1372]:
2010-01-01    0.176444
2010-01-04         NaN
2010-01-05         NaN
2010-01-06    0.403310
2010-01-07         NaN
2010-01-08         NaN
```

```
2010-01-11   -0.154951
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 [1373]: ts.asfreq(BDay(), method='pad')
Out[1373]:
2010-01-01    0.176444
2010-01-04    0.176444
2010-01-05    0.176444
2010-01-06    0.403310
2010-01-07    0.403310
2010-01-08    0.403310
2010-01-11   -0.154951
Freq: B, dtype: float64
```

### 13.4.3 Filling forward / backward

Related to `asfreq` and `reindex` is the `fillna` function documented in the *missing data section*.

## 13.5 Up- and downsampling

With 0.8, pandas introduces 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.

```
In [1374]: rng = date_range('1/1/2012', periods=100, freq='S')

In [1375]: ts = Series(randint(0, 500, len(rng)), index=rng)

In [1376]: ts.resample('5Min', how='sum')
Out[1376]:
2012-01-01    25792
Freq: 5T, dtype: float64
```

The `resample` function is very flexible and allows you to specify many different parameters to control the frequency conversion and resampling operation.

The `how` parameter can be a function name or numpy array function that takes an array and produces aggregated values:

```
In [1377]: ts.resample('5Min') # default is mean
Out[1377]:
2012-01-01    257.92
Freq: 5T, dtype: float64

In [1378]: ts.resample('5Min', how='ohlc')
Out[1378]:
            open  high  low  close
2012-01-01   230   492    0    214

In [1379]: ts.resample('5Min', how=np.max)
Out[1379]:
```

```
2012-01-01    NaN
Freq: 5T, dtype: float64
```

Any function available via *dispatching* can be given to the `how` parameter by name, including `sum`, `mean`, `std`, `max`, `min`, `median`, `first`, `last`, `ohlc`.

For downsampling, `closed` can be set to 'left' or 'right' to specify which end of the interval is closed:

```
In [1380]: ts.resample('5Min', closed='right')
Out[1380]:
2011-12-31 23:55:00    230.00000
2012-01-01 00:00:00    258.20202
Freq: 5T, dtype: float64

In [1381]: ts.resample('5Min', closed='left')
Out[1381]:
2012-01-01    257.92
Freq: 5T, dtype: float64
```

For upsampling, the `fill_method` and `limit` parameters can be specified to interpolate over the gaps that are created:

```
# from secondly to every 250 milliseconds
In [1382]: ts[:2].resample('250L')
Out[1382]:
2012-01-01 00:00:00.250000    NaN
2012-01-01 00:00:00.500000    NaN
2012-01-01 00:00:00.750000    NaN
2012-01-01 00:00:01           202
2012-01-01 00:00:01.250000    NaN
Freq: 250L, dtype: float64

In [1383]: ts[:2].resample('250L', fill_method='pad')
Out[1383]:
2012-01-01 00:00:00.250000    230
2012-01-01 00:00:00.500000    230
2012-01-01 00:00:00.750000    230
2012-01-01 00:00:01           202
2012-01-01 00:00:01.250000    202
Freq: 250L, dtype: int64

In [1384]: ts[:2].resample('250L', fill_method='pad', limit=2)
Out[1384]:
2012-01-01 00:00:00.250000    230
2012-01-01 00:00:00.500000    230
2012-01-01 00:00:00.750000    NaN
2012-01-01 00:00:01           202
2012-01-01 00:00:01.250000    202
Freq: 250L, dtype: float64
```

Parameters like `label` and `loffset` are used to manipulate the resulting labels. `label` specifies whether the result is labeled with the beginning or the end of the interval. `loffset` performs a time adjustment on the output labels.

```
In [1385]: ts.resample('5Min') # by default label='right'
Out[1385]:
2012-01-01    257.92
Freq: 5T, dtype: float64

In [1386]: ts.resample('5Min', label='left')
```

```
Out[1386]:
2012-01-01    257.92
Freq: 5T, dtype: float64

In [1387]: ts.resample('5Min', label='left', loffset='1s')
Out[1387]:
2012-01-01 00:00:01    257.92
dtype: float64
```

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 time-stamp 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.

Note that 0.8 marks a watershed in the timeseries functionality in pandas. In previous versions, resampling had to be done using a combination of `date_range`, `groupby` with `asof`, and then calling an aggregation function on the grouped object. This was not nearly convenient or performant as the new pandas timeseries API.

## 13.6 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`.

### 13.6.1 Period

A `Period` represents a span of time (e.g., a day, a month, a quarter, etc). It can be created using a frequency alias:

```
In [1388]: Period('2012', freq='A-DEC')
Out[1388]: Period('2012', 'A-DEC')

In [1389]: Period('2012-1-1', freq='D')
Out[1389]: Period('2012-01-01', 'D')

In [1390]: Period('2012-1-1 19:00', freq='H')
Out[1390]: Period('2012-01-01 19:00', 'H')
```

Unlike time stamped data, pandas does not support frequencies at multiples of DateOffsets (e.g., '3Min') for periods.

Adding and subtracting integers from periods shifts the period by its own frequency.

```
In [1391]: p = Period('2012', freq='A-DEC')

In [1392]: p + 1
Out[1392]: Period('2013', 'A-DEC')

In [1393]: p - 3
Out[1393]: Period('2009', 'A-DEC')
```

Taking the difference of `Period` instances with the same frequency will return the number of frequency units between them:

```
In [1394]: Period('2012', freq='A-DEC') - Period('2002', freq='A-DEC')
Out[1394]: 10
```

### 13.6.2 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 [1395]: prng = period_range('1/1/2011', '1/1/2012', freq='M')

In [1396]: prng
Out[1396]:
<class 'pandas.tseries.period.PeriodIndex'>
freq: M
[2011-01, ..., 2012-01]
length: 13
```

The `PeriodIndex` constructor can also be used directly:

```
In [1397]: PeriodIndex(['2011-1', '2011-2', '2011-3'], freq='M')
Out[1397]:
<class 'pandas.tseries.period.PeriodIndex'>
freq: M
[2011-01, ..., 2011-03]
length: 3
```

Just like `DatetimeIndex`, a `PeriodIndex` can also be used to index pandas objects:

```
In [1398]: Series(randn(len(prng)), prng)
Out[1398]:
2011-01    0.301624
2011-02   -1.460489
2011-03    0.610679
2011-04    1.195856
2011-05   -0.008820
2011-06   -0.045729
2011-07   -1.051015
2011-08   -0.422924
2011-09   -0.028361
2011-10   -0.782386
2011-11    0.861980
2011-12    1.438604
2012-01   -0.525492
Freq: M, dtype: float64
```

### 13.6.3 Frequency Conversion and Resampling with PeriodIndex

The frequency of Periods and PeriodIndex can be converted via the `asfreq` method. Let's start with the fiscal year 2011, ending in December:

```
In [1399]: p = Period('2011', freq='A-DEC')

In [1400]: p
Out[1400]: 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 [1401]: p.asfreq('M', how='start')
Out[1401]: Period('2011-01', 'M')
```

```
In [1402]: p.asfreq('M', how='end')
Out[1402]: Period('2011-12', 'M')
```

The shorthands 's' and 'e' are provided for convenience:

```
In [1403]: p.asfreq('M', 's')
Out[1403]: Period('2011-01', 'M')

In [1404]: p.asfreq('M', 'e')
Out[1404]: 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 [1405]: p = Period('2011-12', freq='M')

In [1406]: p.asfreq('A-NOV')
Out[1406]: 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 start and ends. Thus, first quarter of 2011 could start in 2010 or a few months into 2011. Via anchored frequencies, pandas works all quarterly frequencies `Q-JAN` through `Q-DEC`.

`Q-DEC` define regular calendar quarters:

```
In [1407]: p = Period('2012Q1', freq='Q-DEC')

In [1408]: p.asfreq('D', 's')
Out[1408]: Period('2012-01-01', 'D')

In [1409]: p.asfreq('D', 'e')
Out[1409]: Period('2012-03-31', 'D')
```

`Q-MAR` defines fiscal year end in March:

```
In [1410]: p = Period('2011Q4', freq='Q-MAR')

In [1411]: p.asfreq('D', 's')
Out[1411]: Period('2011-01-01', 'D')

In [1412]: p.asfreq('D', 'e')
Out[1412]: Period('2011-03-31', 'D')
```

## 13.7 Converting between Representations

Timestamped data can be converted to PeriodIndex-ed data using `to_period` and vice-versa using `to_timestamp`:

```
In [1413]: rng = date_range('1/1/2012', periods=5, freq='M')

In [1414]: ts = Series(randn(len(rng)), index=rng)

In [1415]: ts
Out[1415]:
2012-01-31   -1.684469
```

```
2012-02-29    0.550605
2012-03-31    0.091955
2012-04-30    0.891713
2012-05-31    0.807078
Freq: M, dtype: float64

In [1416]: ps = ts.to_period()

In [1417]: ps
Out[1417]:
2012-01   -1.684469
2012-02    0.550605
2012-03    0.091955
2012-04    0.891713
2012-05    0.807078
Freq: M, dtype: float64

In [1418]: ps.to_timestamp()
Out[1418]:
2012-01-01   -1.684469
2012-02-01    0.550605
2012-03-01    0.091955
2012-04-01    0.891713
2012-05-01    0.807078
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 [1419]: ps.to_timestamp('D', how='s')
Out[1419]:
2012-01-01   -1.684469
2012-02-01    0.550605
2012-03-01    0.091955
2012-04-01    0.891713
2012-05-01    0.807078
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 [1420]: prng = period_range('1990Q1', '2000Q4', freq='Q-NOV')

In [1421]: ts = Series(randn(len(prng)), prng)

In [1422]: ts.index = (prng.asfreq('M', 'e') + 1).asfreq('H', 's') + 9

In [1423]: ts.head()
Out[1423]:
1990-03-01 09:00    0.221441
1990-06-01 09:00   -0.113139
1990-09-01 09:00   -1.812900
1990-12-01 09:00   -0.053708
1991-03-01 09:00   -0.114574
Freq: H, dtype: float64
```

## 13.8 Time Zone Handling

Using `pytz`, pandas provides rich support for working with timestamps in different time zones. By default, pandas objects are time zone unaware:

```
In [1424]: rng = date_range('3/6/2012 00:00', periods=15, freq='D')

In [1425]: print(rng.tz)
None
```

To supply the time zone, you can use the `tz` keyword to `date_range` and other functions:

```
In [1426]: rng_utc = date_range('3/6/2012 00:00', periods=10, freq='D', tz='UTC')

In [1427]: print(rng_utc.tz)
UTC
```

Timestamps, like Python's `datetime.datetime` object can be either time zone naive or time zone aware. Naive time series and DatetimeIndex objects can be *localized* using `tz_localize`:

```
In [1428]: ts = Series(randn(len(rng)), rng)

In [1429]: ts_utc = ts.tz_localize('UTC')

In [1430]: ts_utc
Out[1430]:
2012-03-06 00:00:00+00:00   -0.114722
2012-03-07 00:00:00+00:00    0.168904
2012-03-08 00:00:00+00:00   -0.048048
2012-03-09 00:00:00+00:00    0.801196
2012-03-10 00:00:00+00:00    1.392071
2012-03-11 00:00:00+00:00   -0.048788
2012-03-12 00:00:00+00:00   -0.808838
2012-03-13 00:00:00+00:00   -1.003677
2012-03-14 00:00:00+00:00   -0.160766
2012-03-15 00:00:00+00:00    1.758853
2012-03-16 00:00:00+00:00    0.729195
2012-03-17 00:00:00+00:00    1.359732
2012-03-18 00:00:00+00:00    2.006296
2012-03-19 00:00:00+00:00    0.870210
2012-03-20 00:00:00+00:00    0.043464
Freq: D, dtype: float64
```

You can use the `tz_convert` method to convert pandas objects to convert tz-aware data to another time zone:

```
In [1431]: ts_utc.tz_convert('US/Eastern')
Out[1431]:
2012-03-05 19:00:00-05:00   -0.114722
2012-03-06 19:00:00-05:00    0.168904
2012-03-07 19:00:00-05:00   -0.048048
2012-03-08 19:00:00-05:00    0.801196
2012-03-09 19:00:00-05:00    1.392071
2012-03-10 19:00:00-05:00   -0.048788
2012-03-11 20:00:00-04:00   -0.808838
2012-03-12 20:00:00-04:00   -1.003677
2012-03-13 20:00:00-04:00   -0.160766
2012-03-14 20:00:00-04:00    1.758853
2012-03-15 20:00:00-04:00    0.729195
2012-03-16 20:00:00-04:00    1.359732
```

```
2012-03-17 20:00:00-04:00    2.006296
2012-03-18 20:00:00-04:00    0.870210
2012-03-19 20:00:00-04:00    0.043464
Freq: D, dtype: float64
```

Under the hood, all timestamps are stored in UTC. Scalar values from a `DatetimeIndex` with a time zone will have their fields (day, hour, minute) 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 [1432]: rng_eastern = rng_utc.tz_convert('US/Eastern')

In [1433]: rng_berlin = rng_utc.tz_convert('Europe/Berlin')

In [1434]: rng_eastern[5]
Out[1434]: <Timestamp: 2012-03-10 19:00:00-0500 EST, tz=US/Eastern>

In [1435]: rng_berlin[5]
Out[1435]: <Timestamp: 2012-03-11 01:00:00+0100 CET, tz=Europe/Berlin>

In [1436]: rng_eastern[5] == rng_berlin[5]
Out[1436]: True
```

Like Series, DataFrame, and DatetimeIndex, Timestamps can be converted to other time zones using `tz_convert`:

```
In [1437]: rng_eastern[5]
Out[1437]: <Timestamp: 2012-03-10 19:00:00-0500 EST, tz=US/Eastern>

In [1438]: rng_berlin[5]
Out[1438]: <Timestamp: 2012-03-11 01:00:00+0100 CET, tz=Europe/Berlin>

In [1439]: rng_eastern[5].tz_convert('Europe/Berlin')
Out[1439]: <Timestamp: 2012-03-11 01:00:00+0100 CET, tz=Europe/Berlin>
```

Localization of Timestamps functions just like DatetimeIndex and TimeSeries:

```
In [1440]: rng[5]
Out[1440]: <Timestamp: 2012-03-11 00:00:00>

In [1441]: rng[5].tz_localize('Asia/Shanghai')
Out[1441]: <Timestamp: 2012-03-11 00:00:00+0800 CST, tz=Asia/Shanghai>
```

Operations between TimeSeries in difficult time zones will yield UTC TimeSeries, aligning the data on the UTC timestamps:

```
In [1442]: eastern = ts_utc.tz_convert('US/Eastern')

In [1443]: berlin = ts_utc.tz_convert('Europe/Berlin')

In [1444]: result = eastern + berlin

In [1445]: result
Out[1445]:
2012-03-06 00:00:00+00:00   -0.229443
2012-03-07 00:00:00+00:00    0.337809
2012-03-08 00:00:00+00:00   -0.096096
2012-03-09 00:00:00+00:00    1.602392
2012-03-10 00:00:00+00:00    2.784142
2012-03-11 00:00:00+00:00   -0.097575
2012-03-12 00:00:00+00:00   -1.617677
```

```
2012-03-13 00:00:00+00:00   -2.007353
2012-03-14 00:00:00+00:00   -0.321532
2012-03-15 00:00:00+00:00    3.517706
2012-03-16 00:00:00+00:00    1.458389
2012-03-17 00:00:00+00:00    2.719465
2012-03-18 00:00:00+00:00    4.012592
2012-03-19 00:00:00+00:00    1.740419
2012-03-20 00:00:00+00:00    0.086928
Freq: D, dtype: float64

In [1446]: result.index
Out[1446]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2012-03-06 00:00:00, ..., 2012-03-20 00:00:00]
Length: 15, Freq: D, Timezone: UTC
```

CHAPTER

FOURTEEN

# PLOTTING WITH MATPLOTLIB

**Note:** We intend to build more plotting integration with matplotlib as time goes on.

We use the standard convention for referencing the matplotlib API:

```
In [1447]: import matplotlib.pyplot as plt
```

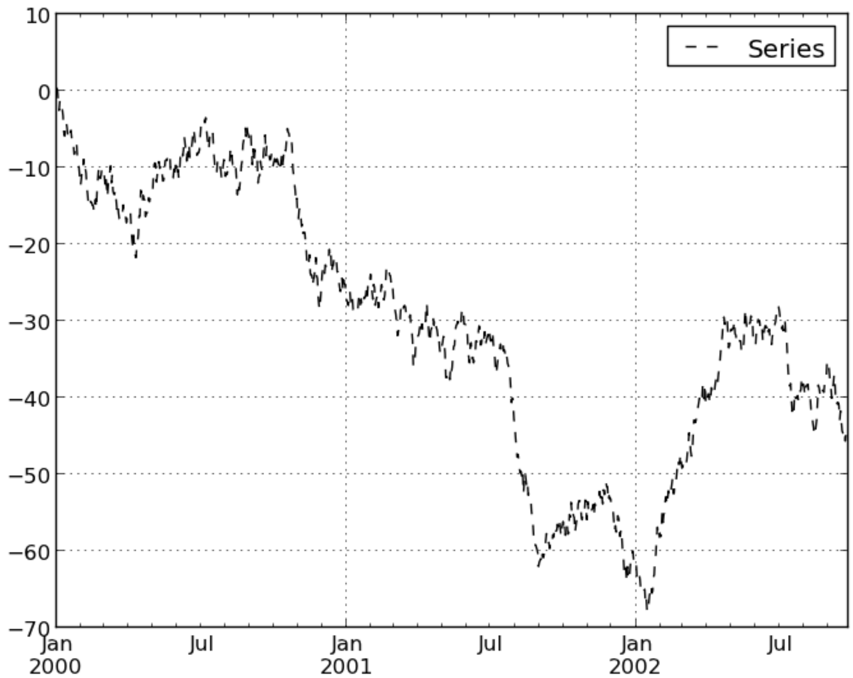
## 14.1 Basic plotting: `plot`

The `plot` method on Series and DataFrame is just a simple wrapper around `plt.plot`:

```
In [1448]: ts = Series(randn(1000), index=date_range('1/1/2000', periods=1000))

In [1449]: ts = ts.cumsum()

In [1450]: ts.plot()
Out[1450]: <matplotlib.axes.AxesSubplot at 0xacbdc10>
```

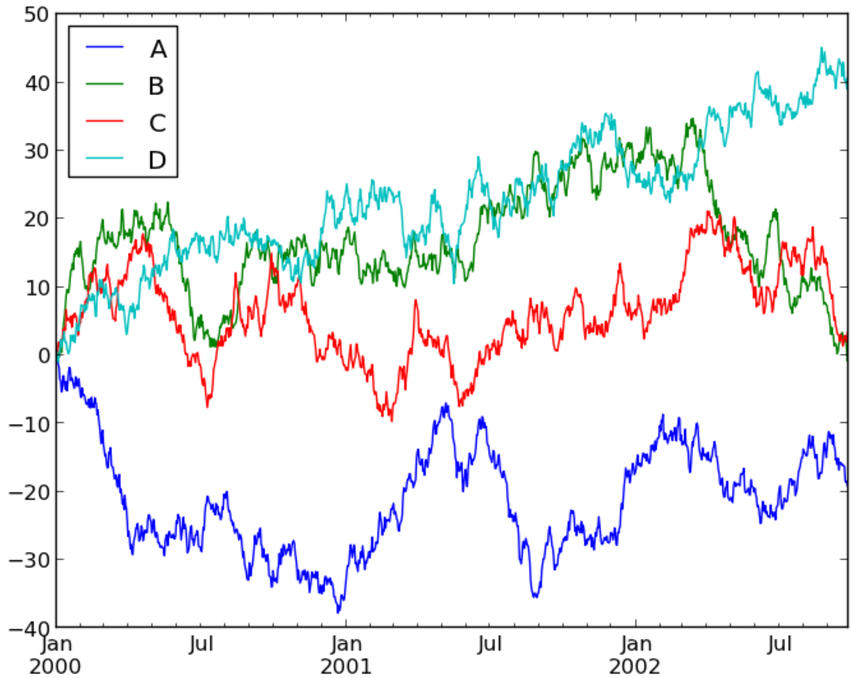
If the index consists of dates, it calls `gcf().autofmt_xdate()` to try to format the x-axis nicely as per above. The method takes a number of arguments for controlling the look of the plot:

```
In [1451]: plt.figure(); ts.plot(style='k--', label='Series'); plt.legend()
Out[1451]: <matplotlib.legend.Legend at 0x108d1610>
```



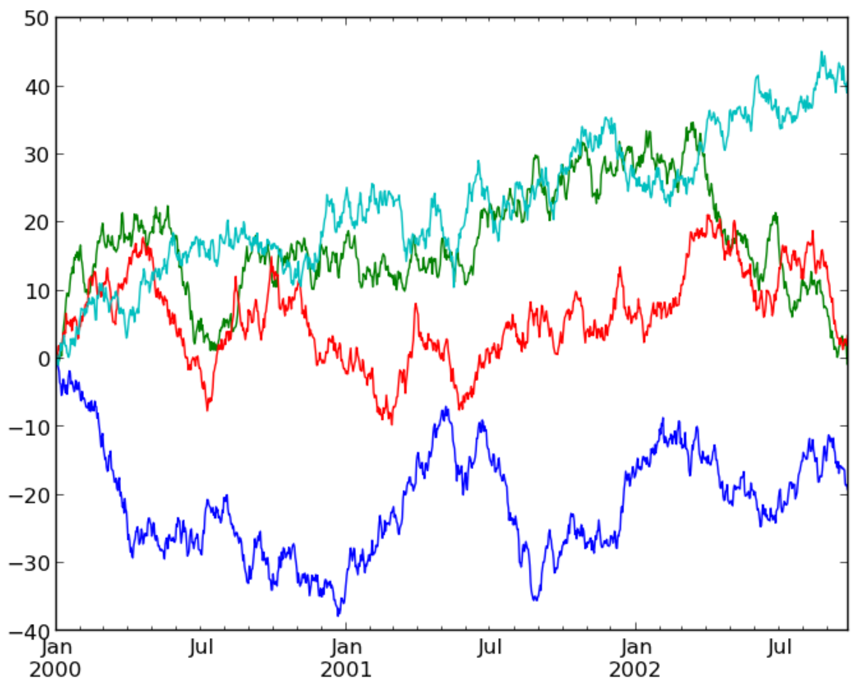

On DataFrame, `plot` is a convenience to plot all of the columns with labels:

```
In [1452]: df = DataFrame(randn(1000, 4), index=ts.index,
   ......:                 columns=['A', 'B', 'C', 'D'])
   ......:

In [1453]: df = df.cumsum()

In [1454]: plt.figure(); df.plot(); plt.legend(loc='best')
Out[1454]: <matplotlib.legend.Legend at 0x108c4450>
```



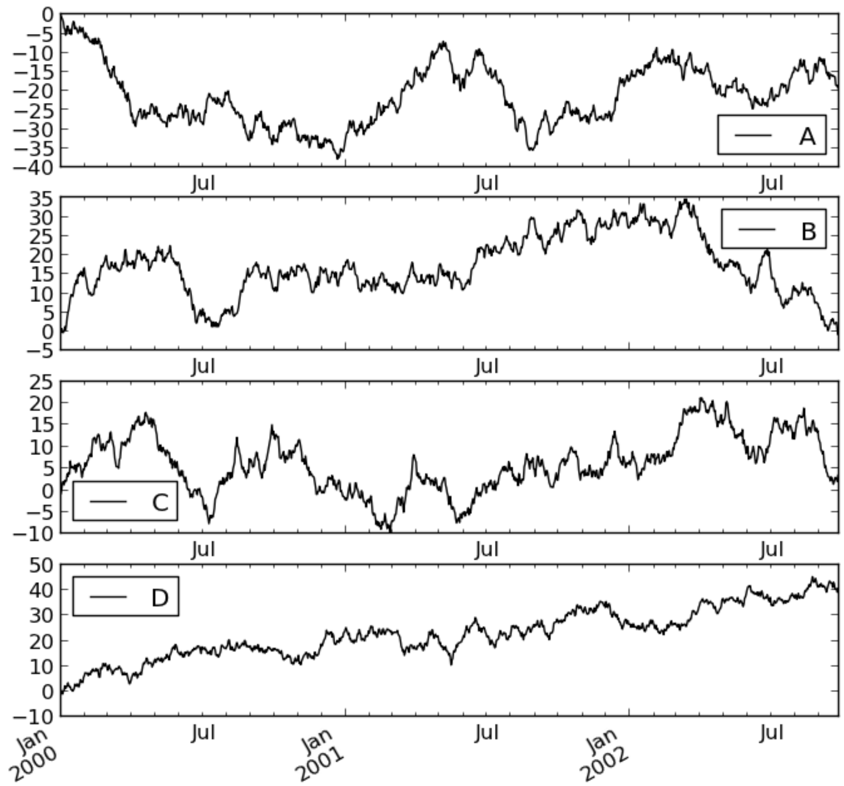

You may set the `legend` argument to `False` to hide the legend, which is shown by default.

```
In [1455]: df.plot(legend=False)
Out[1455]: <matplotlib.axes.AxesSubplot at 0x1132f8d0>
```



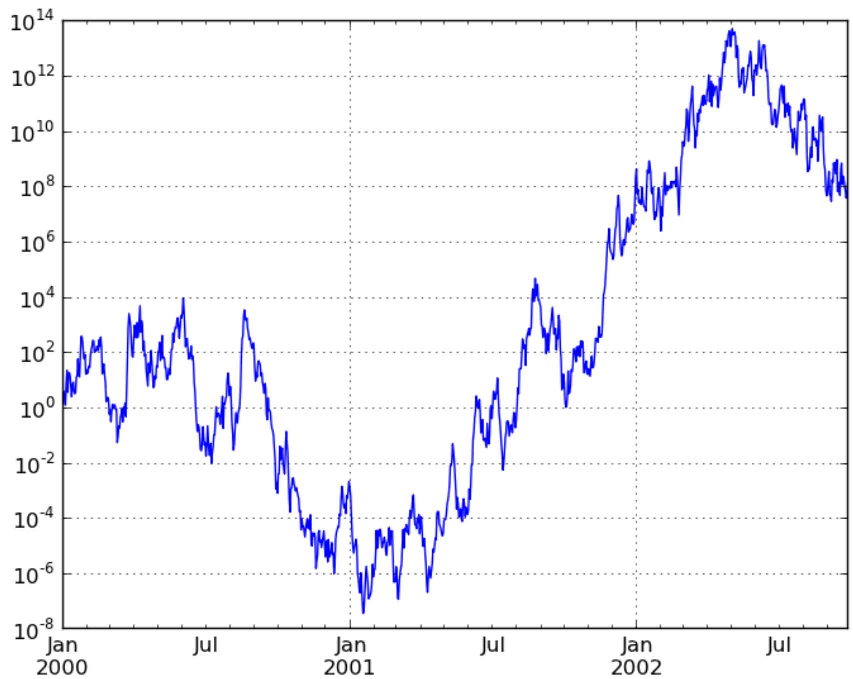

Some other options are available, like plotting each Series on a different axis:

```
In [1456]: df.plot(subplots=True, figsize=(8, 8)); plt.legend(loc='best')
Out[1456]: <matplotlib.legend.Legend at 0x1132fb10>
```



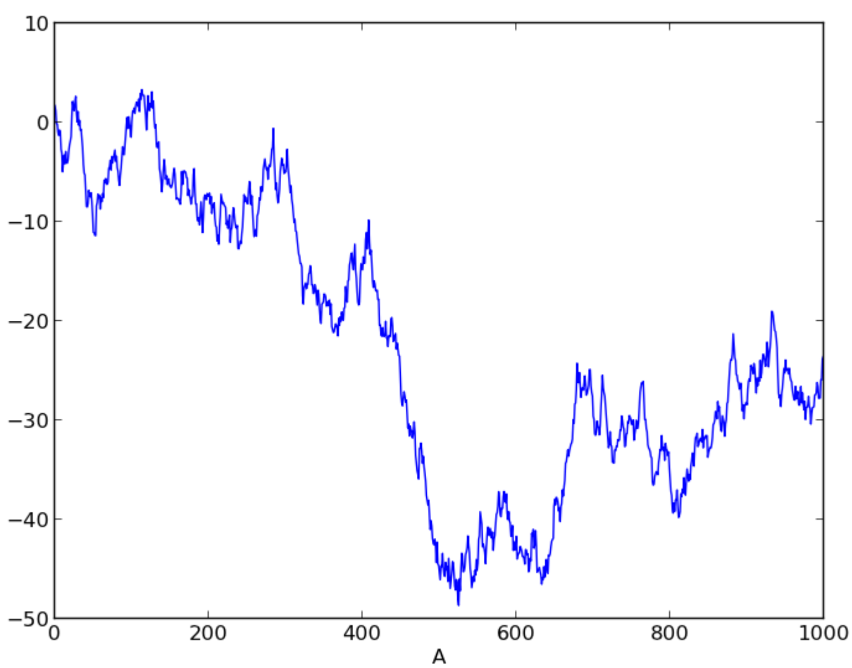

You may pass logy to get a log-scale Y axis.

```
In [1457]: plt.figure();
In [1457]: ts = Series(randn(1000), index=date_range('1/1/2000', periods=1000))

In [1458]: ts = np.exp(ts.cumsum())

In [1459]: ts.plot(logy=True)
Out[1459]: <matplotlib.axes.AxesSubplot at 0x124f7e10>
```




You can plot one column versus another using the *x* and *y* keywords in *DataFrame.plot*:

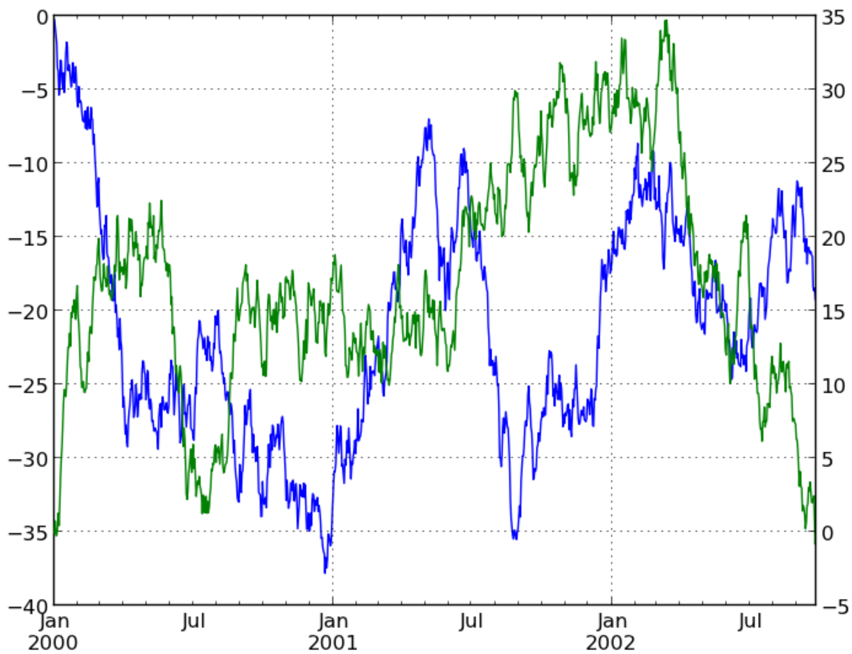
```
In [1460]: plt.figure()
Out[1460]: <matplotlib.figure.Figure at 0x11e1ec50>

In [1461]: df3 = DataFrame(np.random.randn(1000, 2), columns=['B', 'C']).cumsum()

In [1462]: df3['A'] = Series(range(len(df)))

In [1463]: df3.plot(x='A', y='B')
Out[1463]: <matplotlib.axes.AxesSubplot at 0x12d13c90>
```



### 14.1.1 Plotting on a Secondary Y-axis

To plot data on a secondary y-axis, use the `secondary_y` keyword:

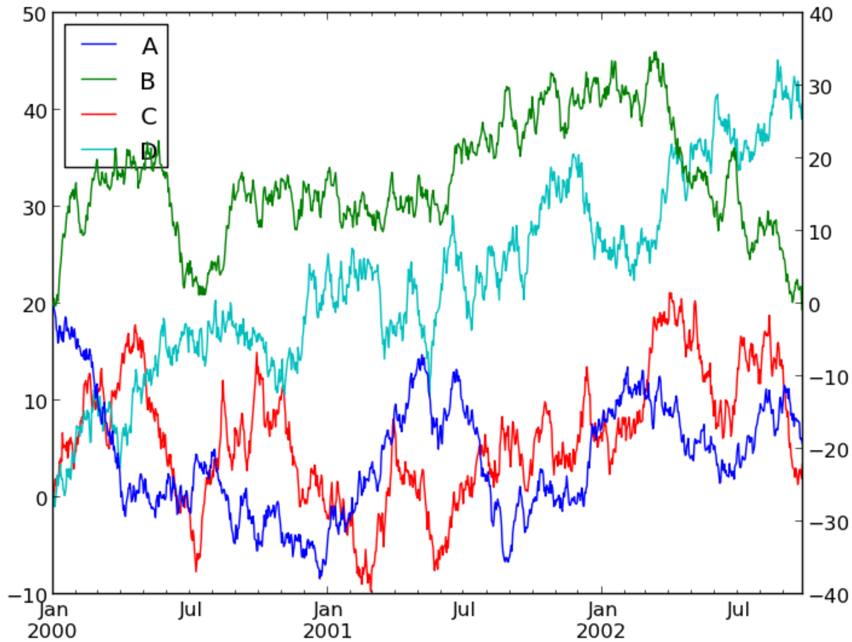
```
In [1464]: plt.figure()
Out[1464]: <matplotlib.figure.Figure at 0x12d22290>

In [1465]: df.A.plot()
Out[1465]: <matplotlib.axes.AxesSubplot at 0x1296d150>

In [1466]: df.B.plot(secondary_y=True, style='g')
Out[1466]: <matplotlib.axes.AxesSubplot at 0x1296d150>
```




### 14.1.2 Selective Plotting on Secondary Y-axis

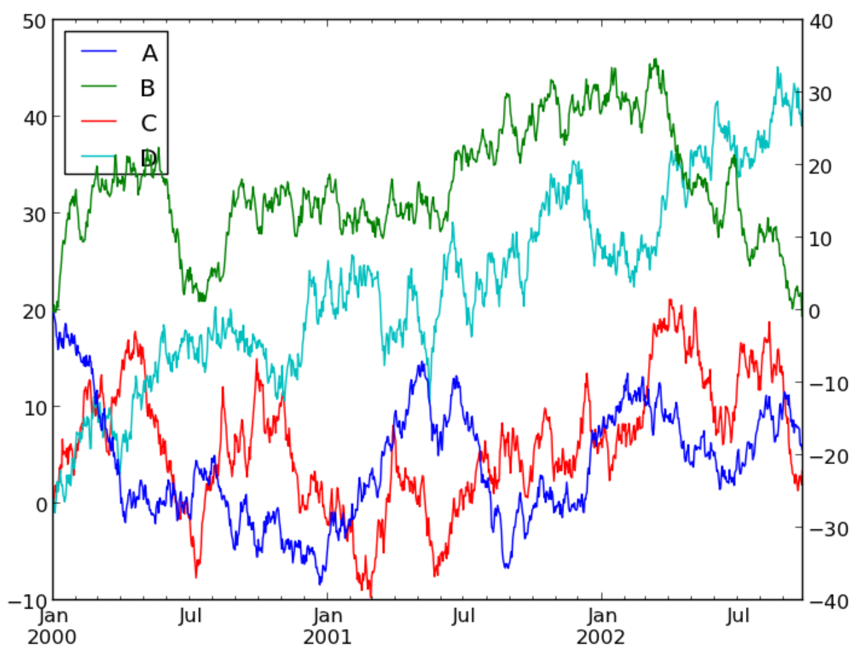
To plot some columns in a DataFrame, give the column names to the `secondary_y` keyword:

```
In [1467]: plt.figure()
Out[1467]: <matplotlib.figure.Figure at 0x130fbe90>

In [1468]: df.plot(secondary_y=['A', 'B'])
Out[1468]: <matplotlib.axes.AxesSubplot at 0x137563d0>
```




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 [1469]: plt.figure()
Out[1469]: <matplotlib.figure.Figure at 0x1354e210>

In [1470]: df.plot(secondary_y=['A', 'B'], mark_right=False)
Out[1470]: <matplotlib.axes.AxesSubplot at 0x13573b50>
```

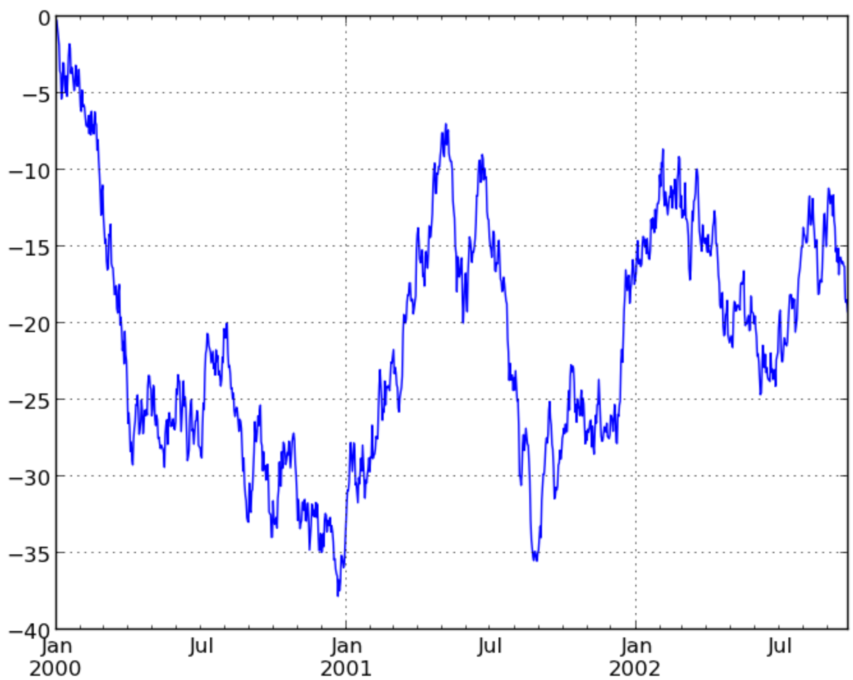


### 14.1.3 Suppressing tick resolution adjustment

Pandas includes automatically 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.

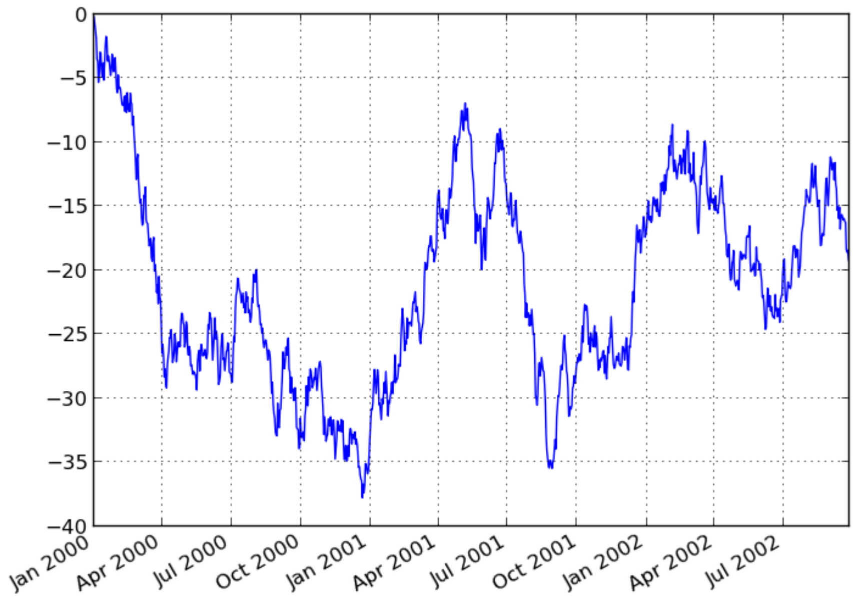
Here is the default behavior, notice how the x-axis tick labelling is performed:

```
In [1471]: plt.figure()
Out[1471]: <matplotlib.figure.Figure at 0x13573050>

In [1472]: df.A.plot()
Out[1472]: <matplotlib.axes.AxesSubplot at 0x1356be90>
```



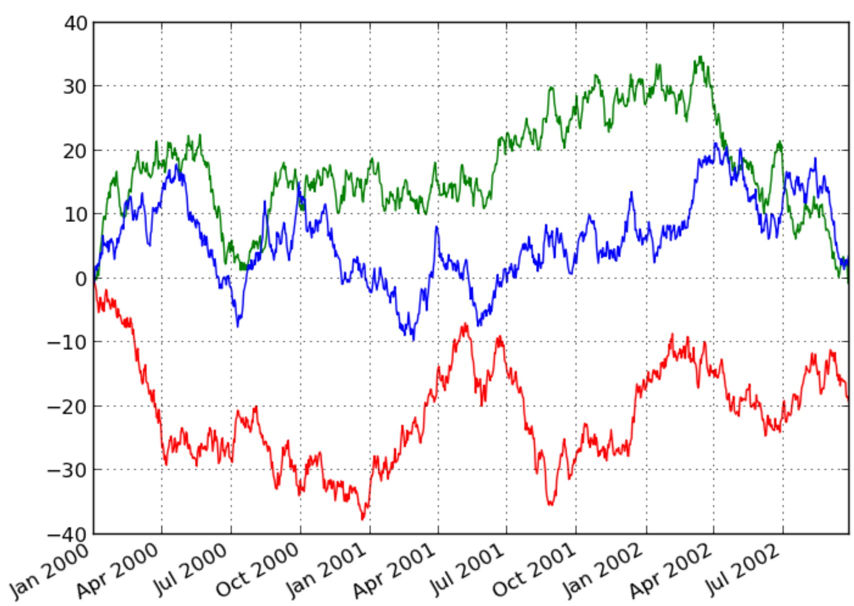

Using the `x_compat` parameter, you can suppress this bevahior:

```
In [1473]: plt.figure()
Out[1473]: <matplotlib.figure.Figure at 0x14954650>

In [1474]: df.A.plot(x_compat=True)
Out[1474]: <matplotlib.axes.AxesSubplot at 0x14077450>
```




If you have more than one plot that needs to be suppressed, the `use` method in `pandas.plot_params` can be used in a *with statement*:

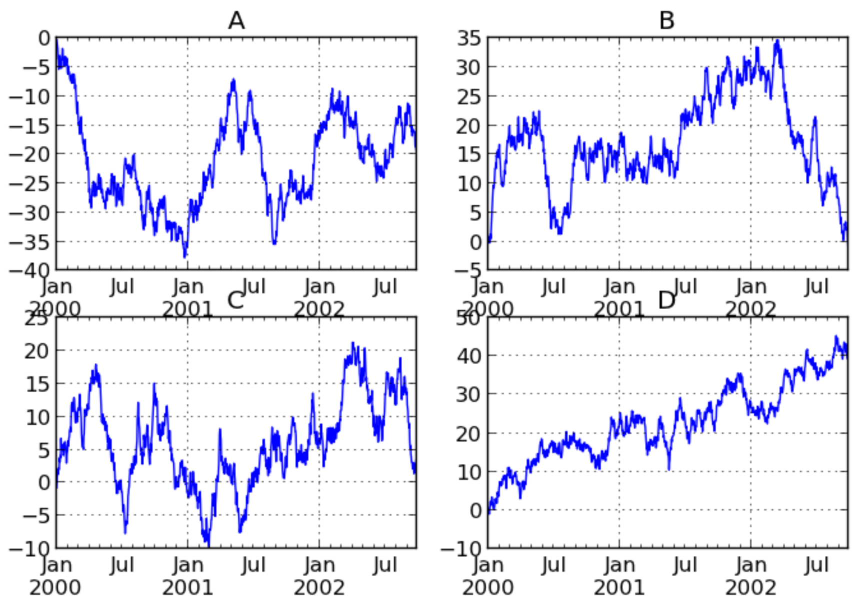
```
In [1475]: import pandas as pd

In [1476]: plt.figure()
Out[1476]: <matplotlib.figure.Figure at 0x1498e910>

In [1477]: with pd.plot_params.use('x_compat', True):
   ......:     df.A.plot(color='r')
   ......:     df.B.plot(color='g')
   ......:     df.C.plot(color='b')
   ......:
```



### 14.1.4 Targeting different subplots

You can pass an `ax` argument to `Series.plot` to plot on a particular axis:

```
In [1478]: fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(8, 5))

In [1479]: df['A'].plot(ax=axes[0,0]); axes[0,0].set_title('A')
Out[1479]: <matplotlib.text.Text at 0x14c74dd0>

In [1480]: df['B'].plot(ax=axes[0,1]); axes[0,1].set_title('B')
Out[1480]: <matplotlib.text.Text at 0x14fb5490>

In [1481]: df['C'].plot(ax=axes[1,0]); axes[1,0].set_title('C')
Out[1481]: <matplotlib.text.Text at 0x1530a990>

In [1482]: df['D'].plot(ax=axes[1,1]); axes[1,1].set_title('D')
Out[1482]: <matplotlib.text.Text at 0x1532c850>
```

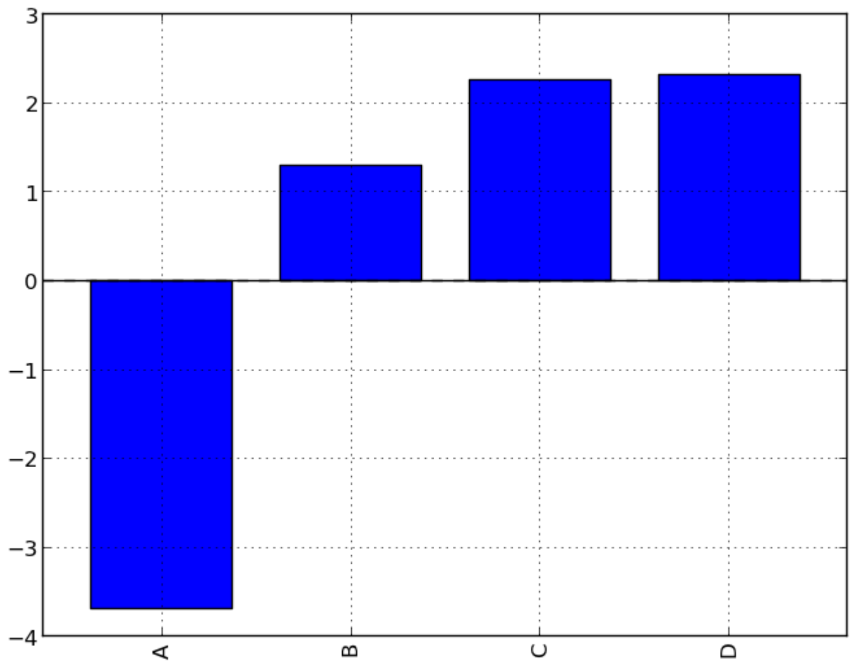



## 14.2 Other plotting features

### 14.2.1 Bar plots

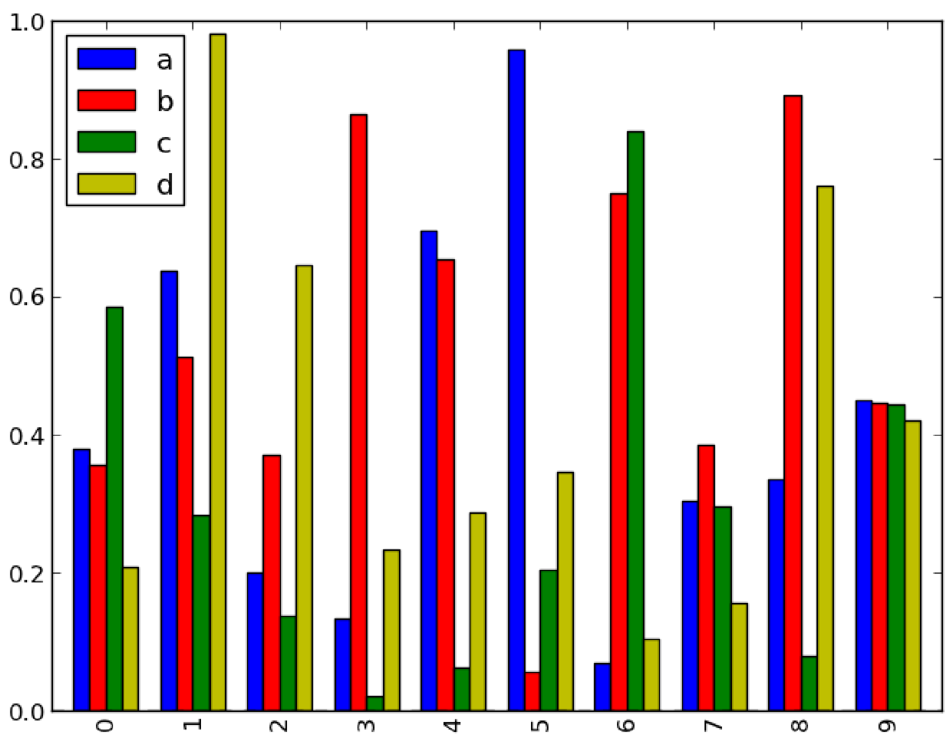
For labeled, non-time series data, you may wish to produce a bar plot:

```
In [1483]: plt.figure();
In [1483]: df.ix[5].plot(kind='bar'); plt.axhline(0, color='k')
Out[1483]: <matplotlib.lines.Line2D at 0x15cc0310>
```



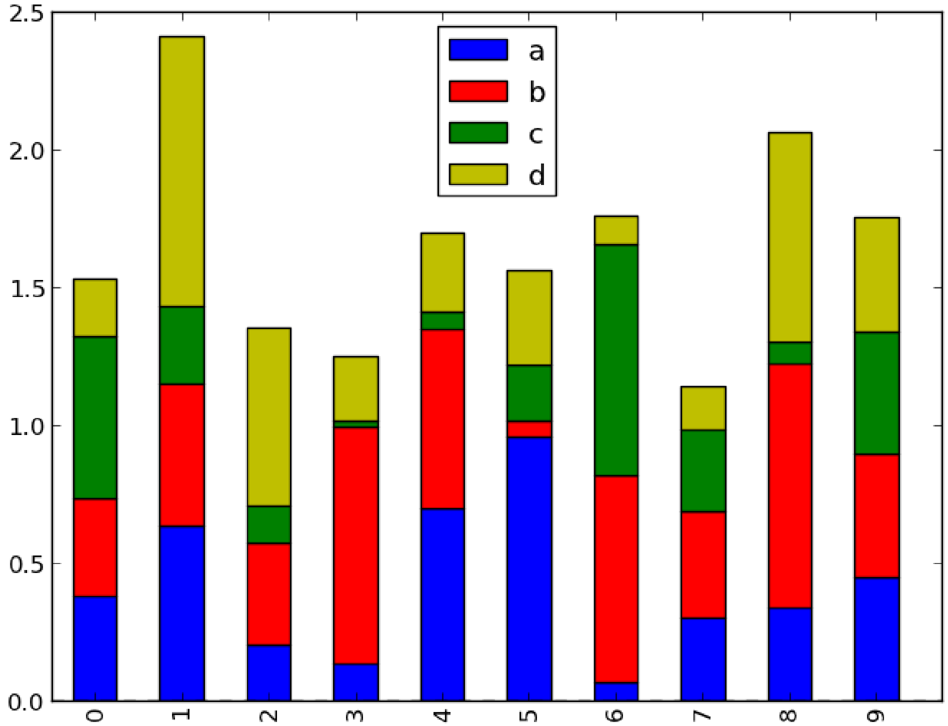

Calling a DataFrame's `plot` method with `kind='bar'` produces a multiple bar plot:

```
In [1484]: df2 = DataFrame(np.random.rand(10, 4), columns=['a', 'b', 'c', 'd'])

In [1485]: df2.plot(kind='bar');
```



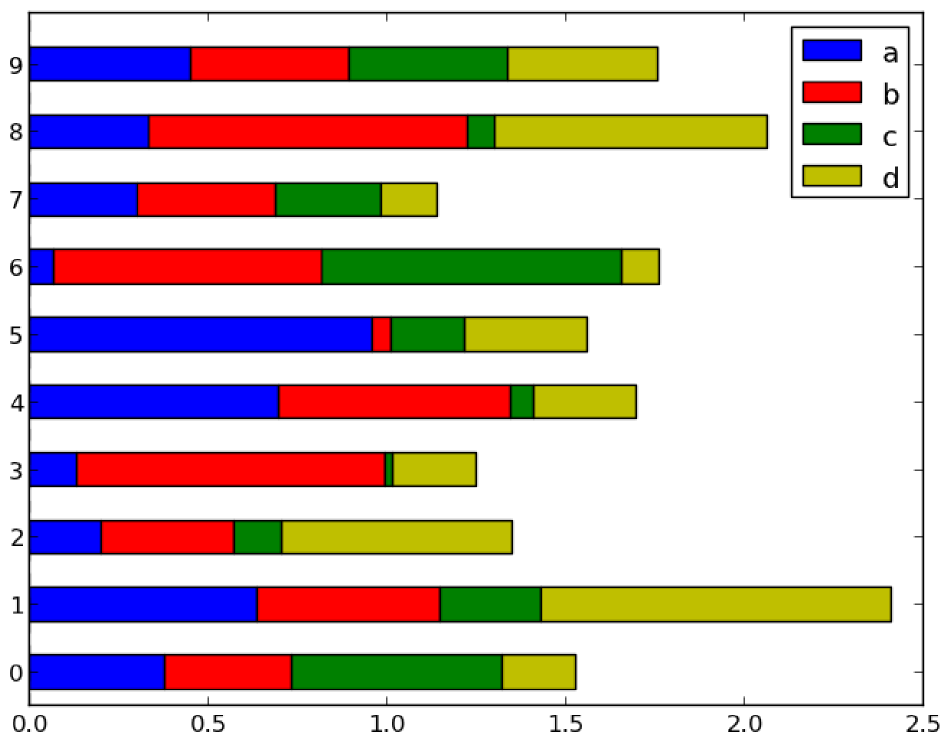

To produce a stacked bar plot, pass `stacked=True`:

```
In [1485]: df2.plot(kind='bar', stacked=True);
```



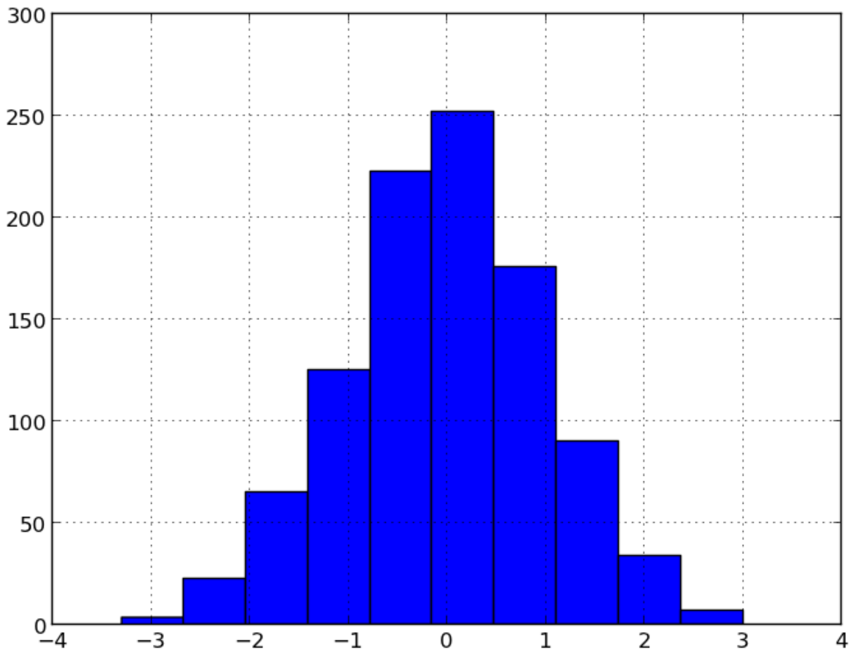

To get horizontal bar plots, pass `kind='barh'`:

```
In [1485]: df2.plot(kind='barh', stacked=True);
```



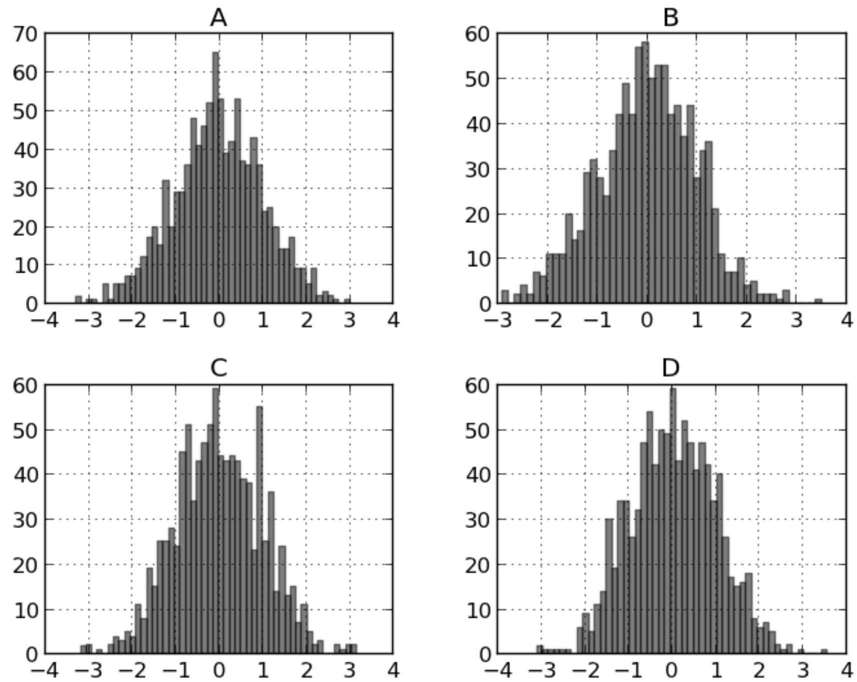
### 14.2.2 Histograms

```
In [1485]: plt.figure();
In [1485]: df['A'].diff().hist()
Out[1485]: <matplotlib.axes.AxesSubplot at 0x16756390>
```



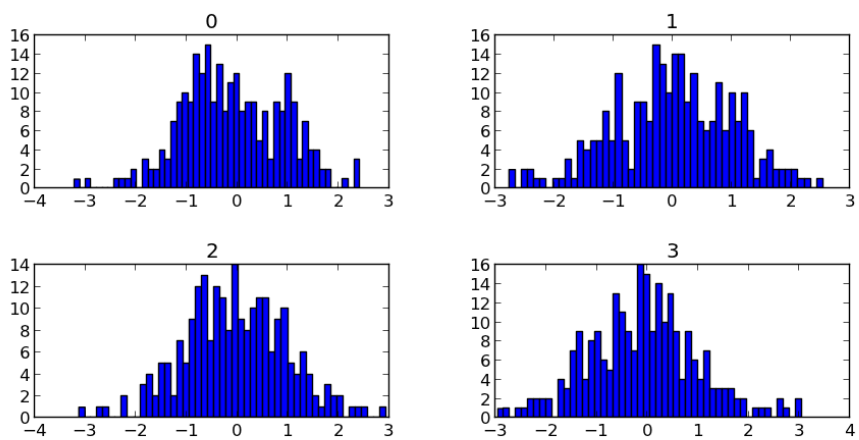

For a DataFrame, `hist` plots the histograms of the columns on multiple subplots:

```
In [1486]: plt.figure()
Out[1486]: <matplotlib.figure.Figure at 0x1675d2d0>

In [1487]: df.diff().hist(color='k', alpha=0.5, bins=50)
Out[1487]:
array([[Axes(0.125,0.552174;0.336957x0.347826),
        Axes(0.563043,0.552174;0.336957x0.347826)],
       [Axes(0.125,0.1;0.336957x0.347826),
        Axes(0.563043,0.1;0.336957x0.347826)]], dtype=object)
```




New since 0.10.0, the `by` keyword can be specified to plot grouped histograms:

```
In [1488]: data = Series(np.random.randn(1000))

In [1489]: data.hist(by=np.random.randint(0, 4, 1000))
Out[1489]:
array([[Axes(0.1,0.6;0.347826x0.3), Axes(0.552174,0.6;0.347826x0.3)],
       [Axes(0.1,0.15;0.347826x0.3), Axes(0.552174,0.15;0.347826x0.3)]], dtype=object)
```



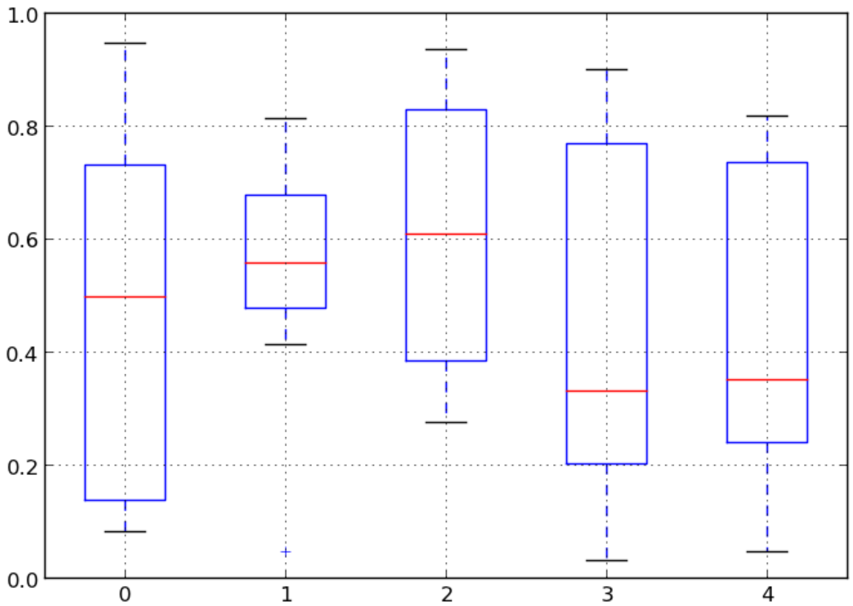

### 14.2.3 Box-Plotting

DataFrame has a `boxplot` method which allows you 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).

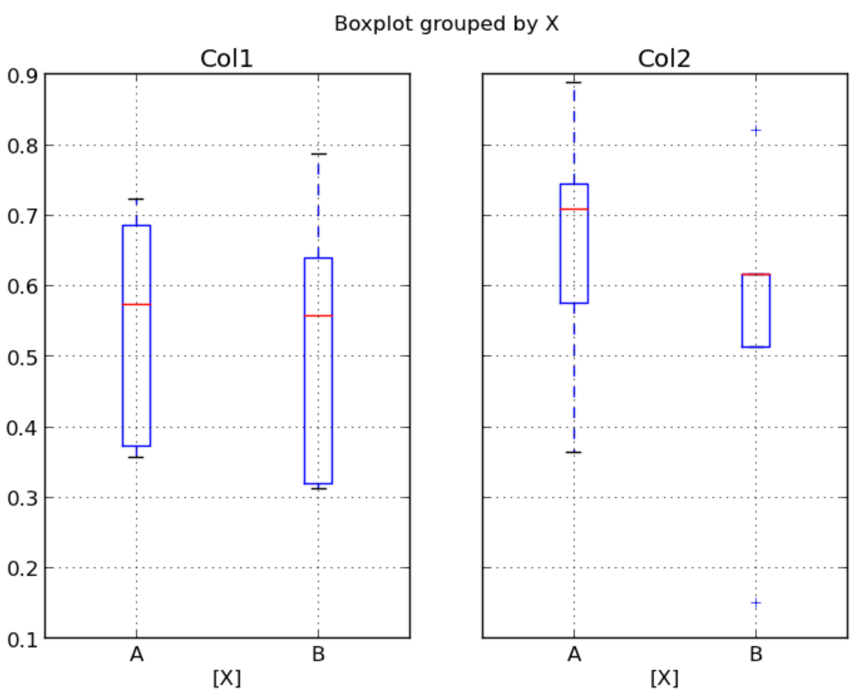
```
In [1490]: df = DataFrame(np.random.rand(10,5))
```

```
In [1491]: plt.figure();
In [1491]: bp = df.boxplot()
```



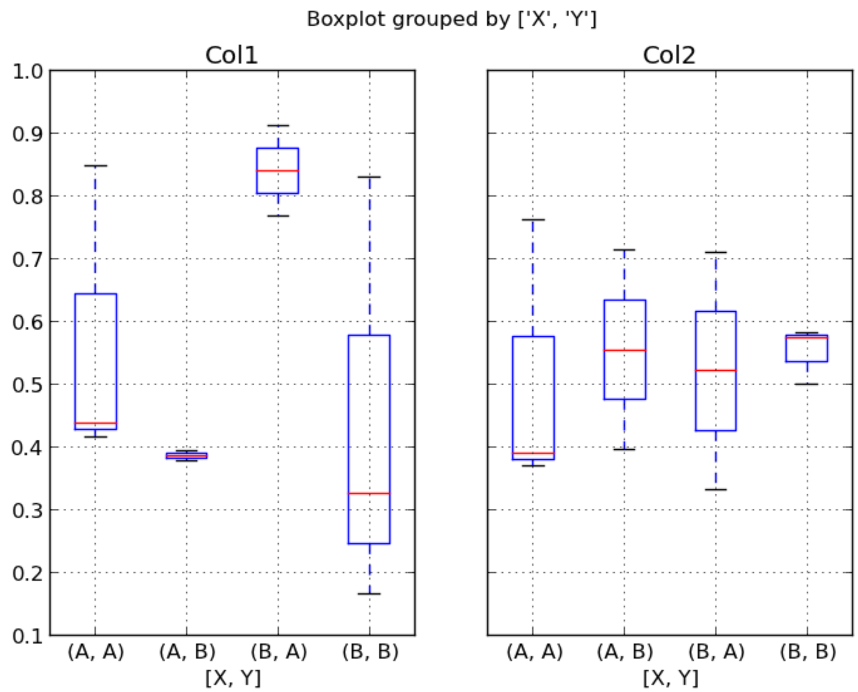

You can create a stratified boxplot using the by keyword argument to create groupings. For instance,

```
In [1492]: df = DataFrame(np.random.rand(10,2), columns=['Col1', 'Col2'] )

In [1493]: df['X'] = Series(['A','A','A','A','A','B','B','B','B','B'])

In [1494]: plt.figure();
In [1494]: bp = df.boxplot(by='X')
```



You can also pass a subset of columns to plot, as well as group by multiple columns:

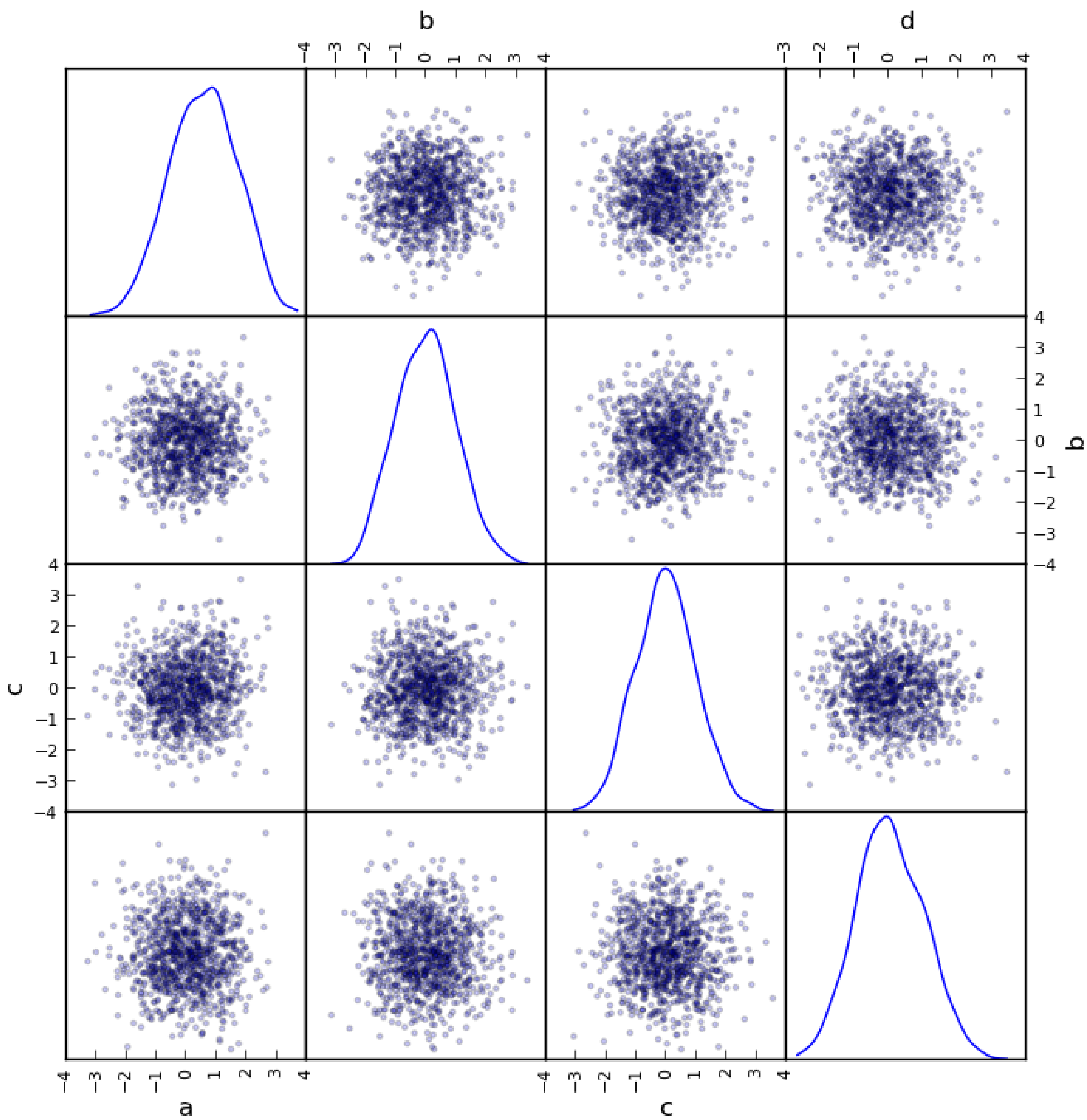
```
In [1495]: df = DataFrame(np.random.rand(10,3), columns=['Col1', 'Col2', 'Col3'])

In [1496]: df['X'] = Series(['A','A','A','A','A','B','B','B','B','B'])

In [1497]: df['Y'] = Series(['A','B','A','B','A','B','A','B','A','B'])

In [1498]: plt.figure();
In [1498]: bp = df.boxplot(column=['Col1','Col2'], by=['X','Y'])
```




### 14.2.4 Scatter plot matrix

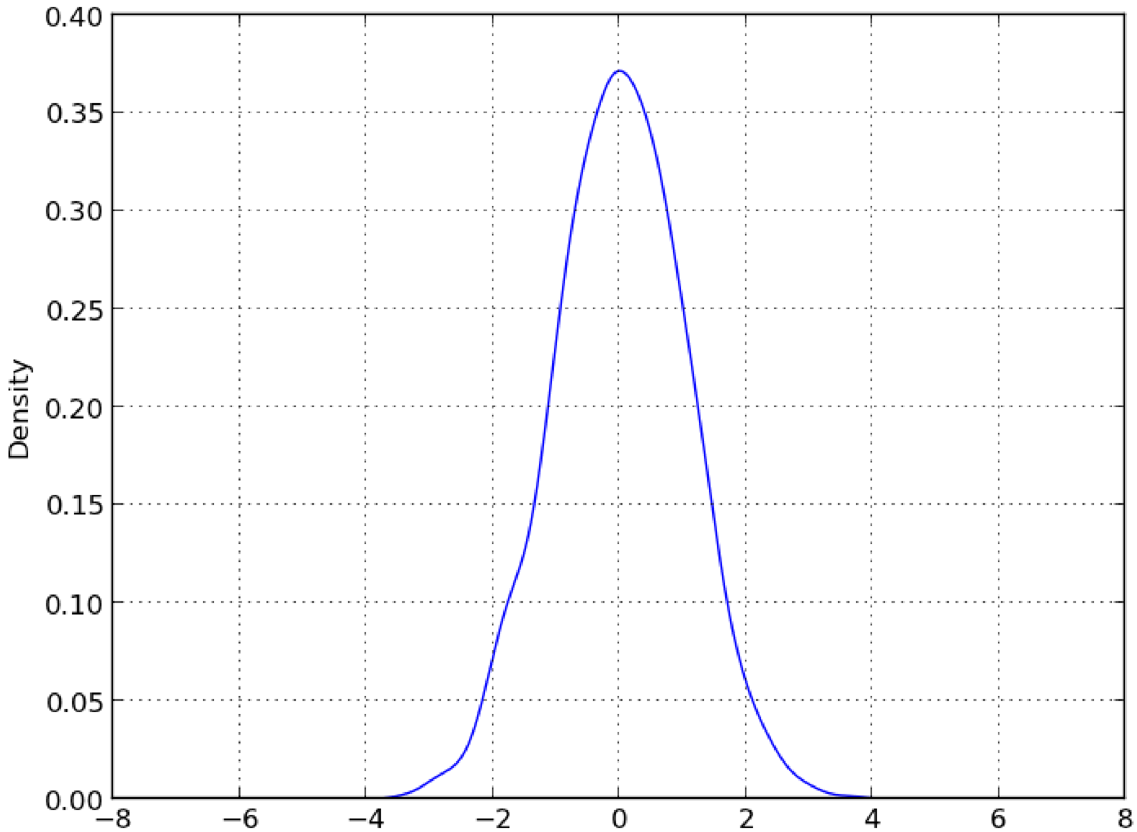
*New in 0.7.3.* **You can create a scatter plot matrix using the** `scatter_matrix` method in `pandas.tools.plotting`:

```
In [1499]: from pandas.tools.plotting import scatter_matrix

In [1500]: df = DataFrame(np.random.randn(1000, 4), columns=['a', 'b', 'c', 'd'])

In [1501]: scatter_matrix(df, alpha=0.2, figsize=(8, 8), diagonal='kde')
Out[1501]:
array([[Axes(0.125,0.7;0.19375x0.2), Axes(0.31875,0.7;0.19375x0.2),
         Axes(0.5125,0.7;0.19375x0.2), Axes(0.70625,0.7;0.19375x0.2)],
        [Axes(0.125,0.5;0.19375x0.2), Axes(0.31875,0.5;0.19375x0.2),
         Axes(0.5125,0.5;0.19375x0.2), Axes(0.70625,0.5;0.19375x0.2)],
        [Axes(0.125,0.3;0.19375x0.2), Axes(0.31875,0.3;0.19375x0.2),
         Axes(0.5125,0.3;0.19375x0.2), Axes(0.70625,0.3;0.19375x0.2)],
        [Axes(0.125,0.1;0.19375x0.2), Axes(0.31875,0.1;0.19375x0.2),
         Axes(0.5125,0.1;0.19375x0.2), Axes(0.70625,0.1;0.19375x0.2)]], dtype=object)
```




*New in 0.8.0* You can create density plots using the Series/DataFrame.plot and setting *kind='kde'*:

```
In [1502]: ser = Series(np.random.randn(1000))

In [1503]: ser.plot(kind='kde')
Out[1503]: <matplotlib.axes.AxesSubplot at 0x1aed1410>
```

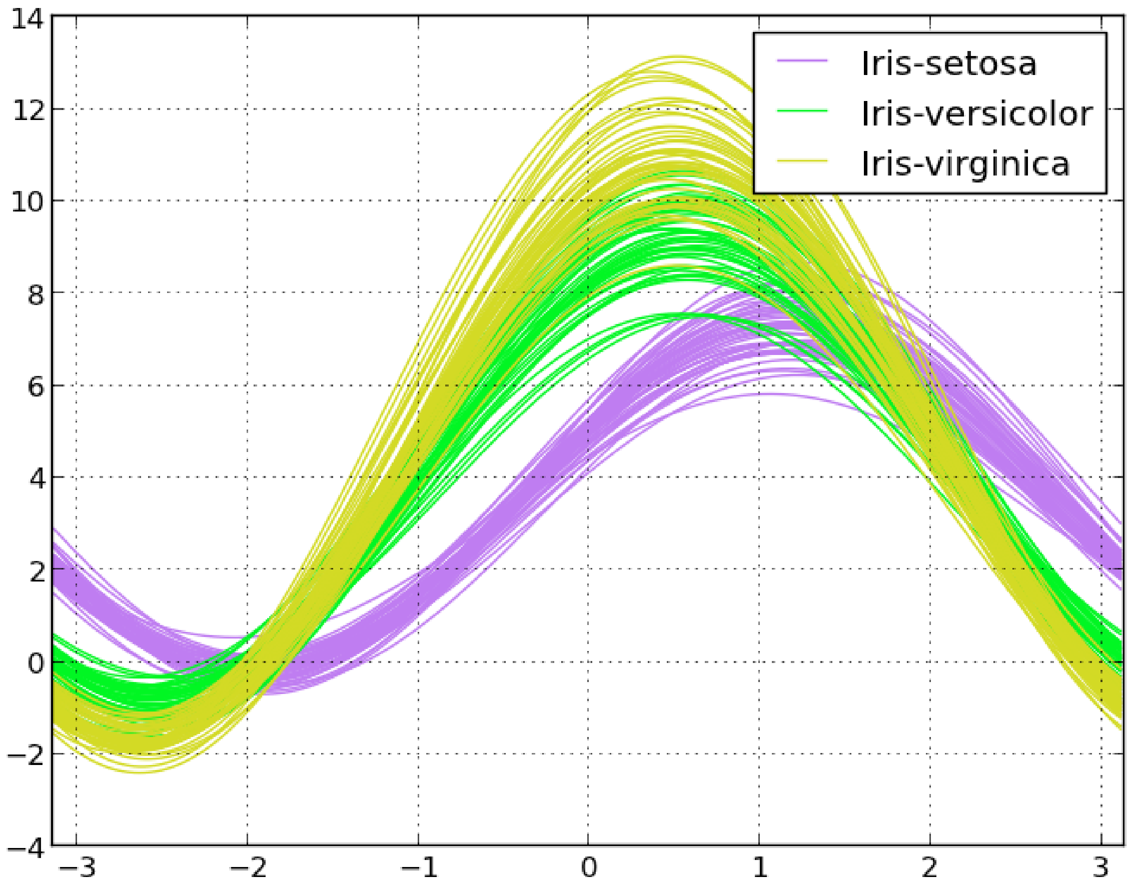



### 14.2.5 Andrews Curves

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. 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.

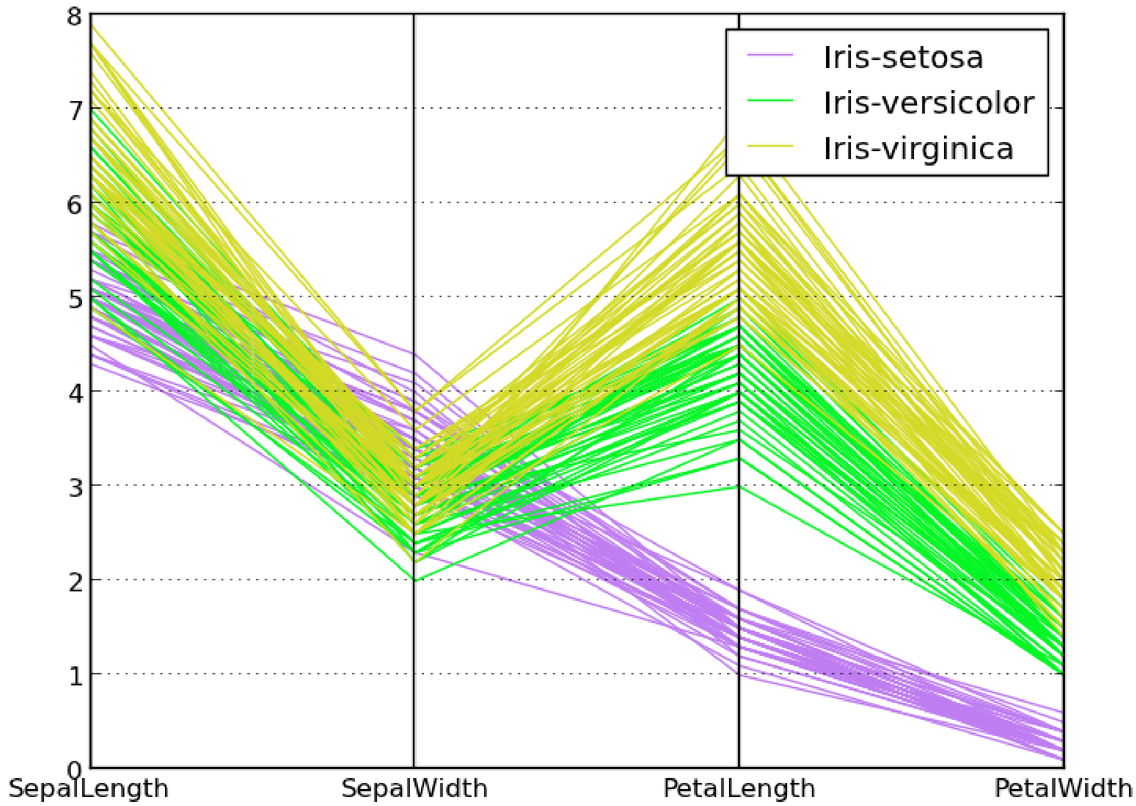
```
In [1504]: from pandas import read_csv

In [1505]: from pandas.tools.plotting import andrews_curves

In [1506]: data = read_csv('data/iris.data')

In [1507]: plt.figure()
Out[1507]: <matplotlib.figure.Figure at 0x1acf0990>

In [1508]: andrews_curves(data, 'Name')
Out[1508]: <matplotlib.axes.AxesSubplot at 0x1acfd890>
```




### 14.2.6 Parallel Coordinates

Parallel coordinates is a plotting technique for plotting multivariate data. It 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.

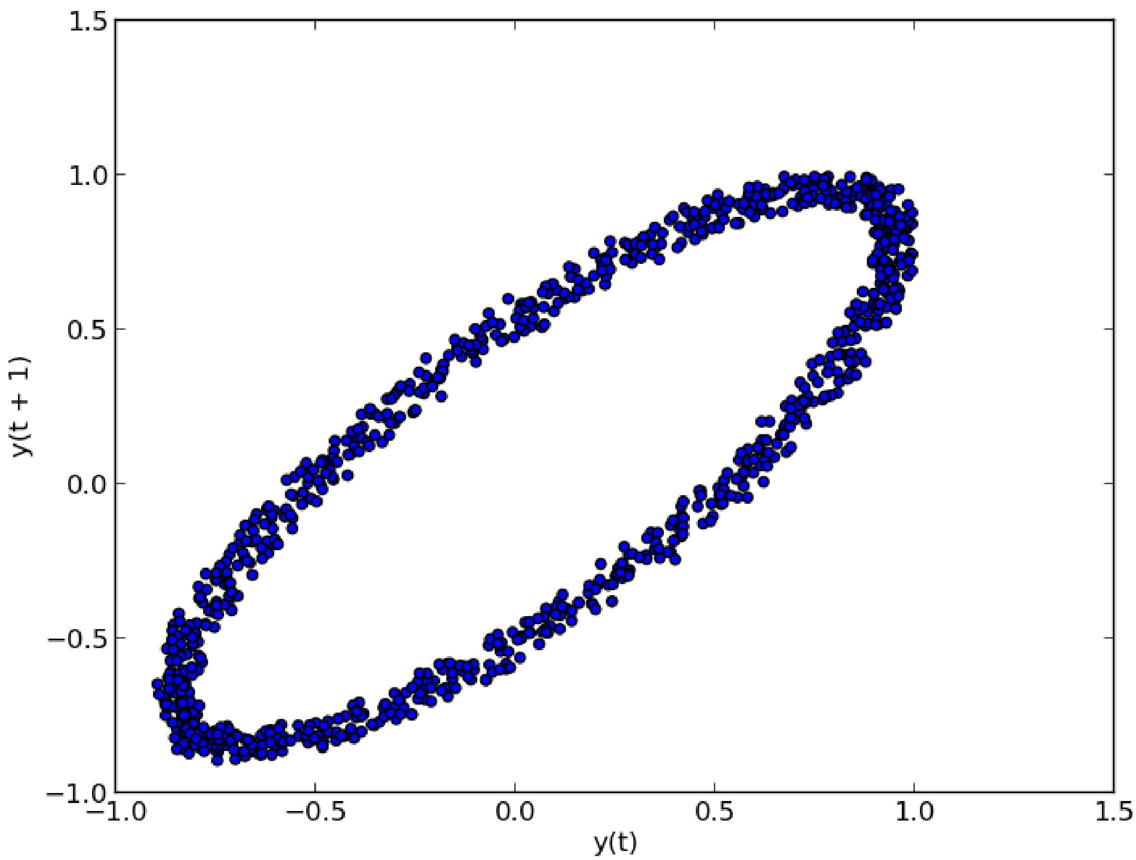
```
In [1509]: from pandas import read_csv

In [1510]: from pandas.tools.plotting import parallel_coordinates

In [1511]: data = read_csv('data/iris.data')

In [1512]: plt.figure()
Out[1512]: <matplotlib.figure.Figure at 0x1b591550>

In [1513]: parallel_coordinates(data, 'Name')
Out[1513]: <matplotlib.axes.AxesSubplot at 0x1b9c6250>
```




### 14.2.7 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.

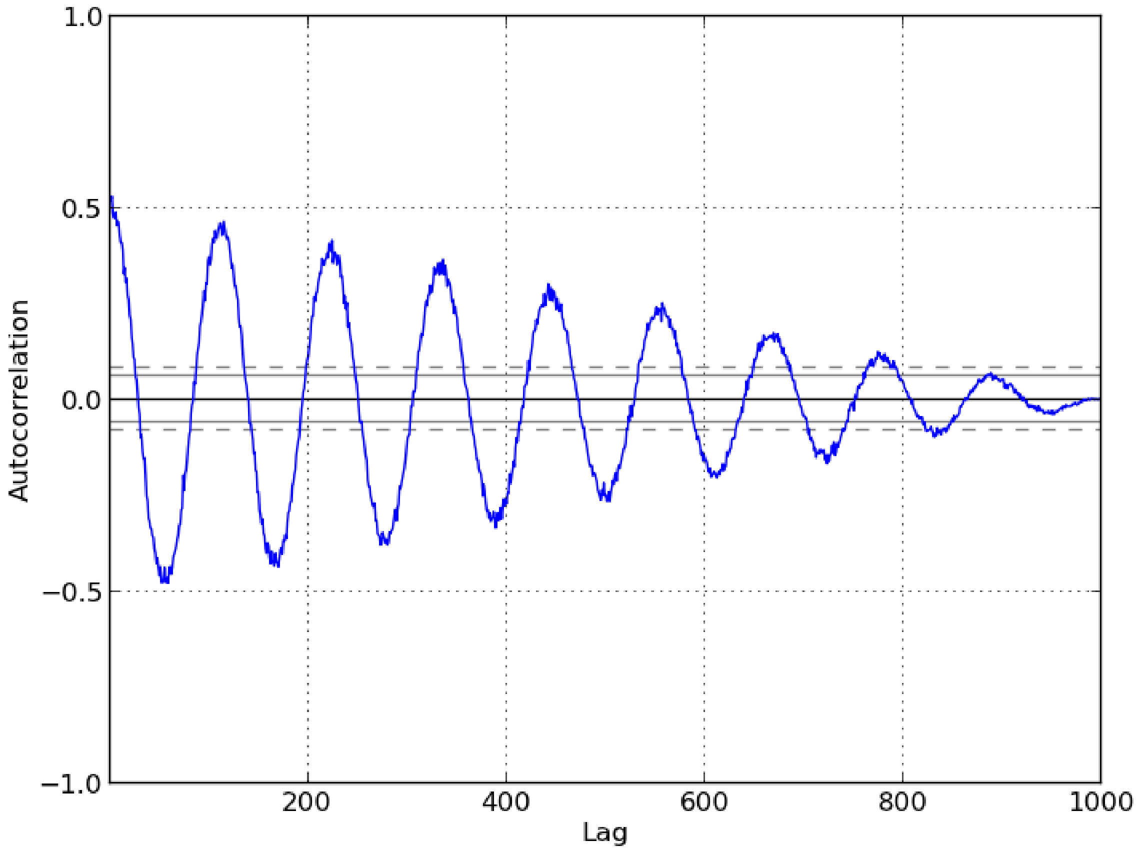
```
In [1514]: from pandas.tools.plotting import lag_plot

In [1515]: plt.figure()
Out[1515]: <matplotlib.figure.Figure at 0x1acf6590>

In [1516]: data = Series(0.1 * np.random.random(1000) +
   ......:     0.9 * np.sin(np.linspace(-99 * np.pi, 99 * np.pi, num=1000)))
   ......:

In [1517]: lag_plot(data)
Out[1517]: <matplotlib.axes.AxesSubplot at 0x1c20bfd0>
```




### 14.2.8 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.

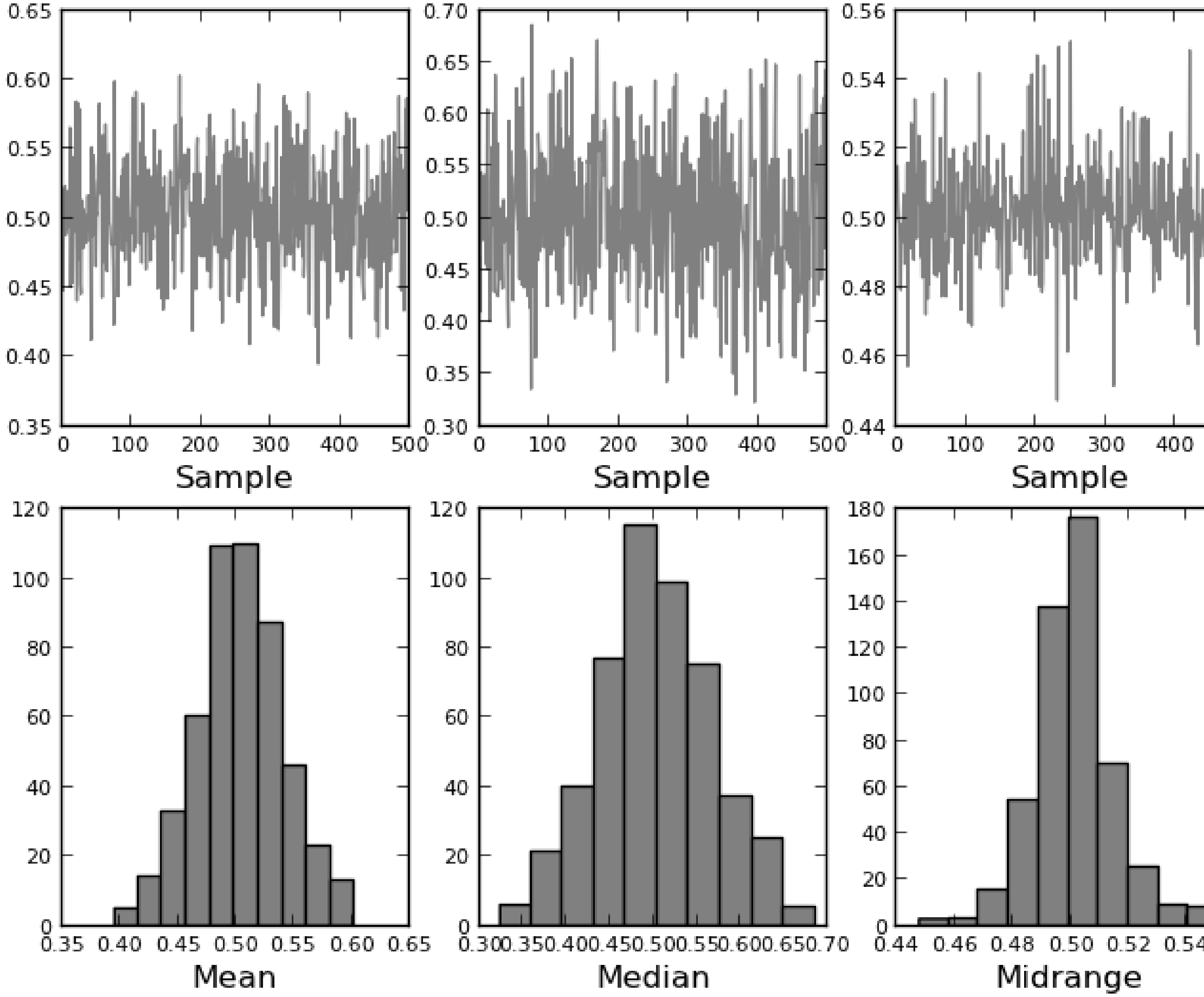
```
In [1518]: from pandas.tools.plotting import autocorrelation_plot

In [1519]: plt.figure()
Out[1519]: <matplotlib.figure.Figure at 0x1c206390>

In [1520]: data = Series(0.7 * np.random.random(1000) +
   ......:     0.3 * np.sin(np.linspace(-9 * np.pi, 9 * np.pi, num=1000)))
   ......:

In [1521]: autocorrelation_plot(data)
Out[1521]: <matplotlib.axes.AxesSubplot at 0x1c09d850>
```




### 14.2.9 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 [1522]: from pandas.tools.plotting import bootstrap_plot

In [1523]: data = Series(np.random.random(1000))

In [1524]: bootstrap_plot(data, size=50, samples=500, color='grey')
Out[1524]: <matplotlib.figure.Figure at 0x1c0958d0>
```



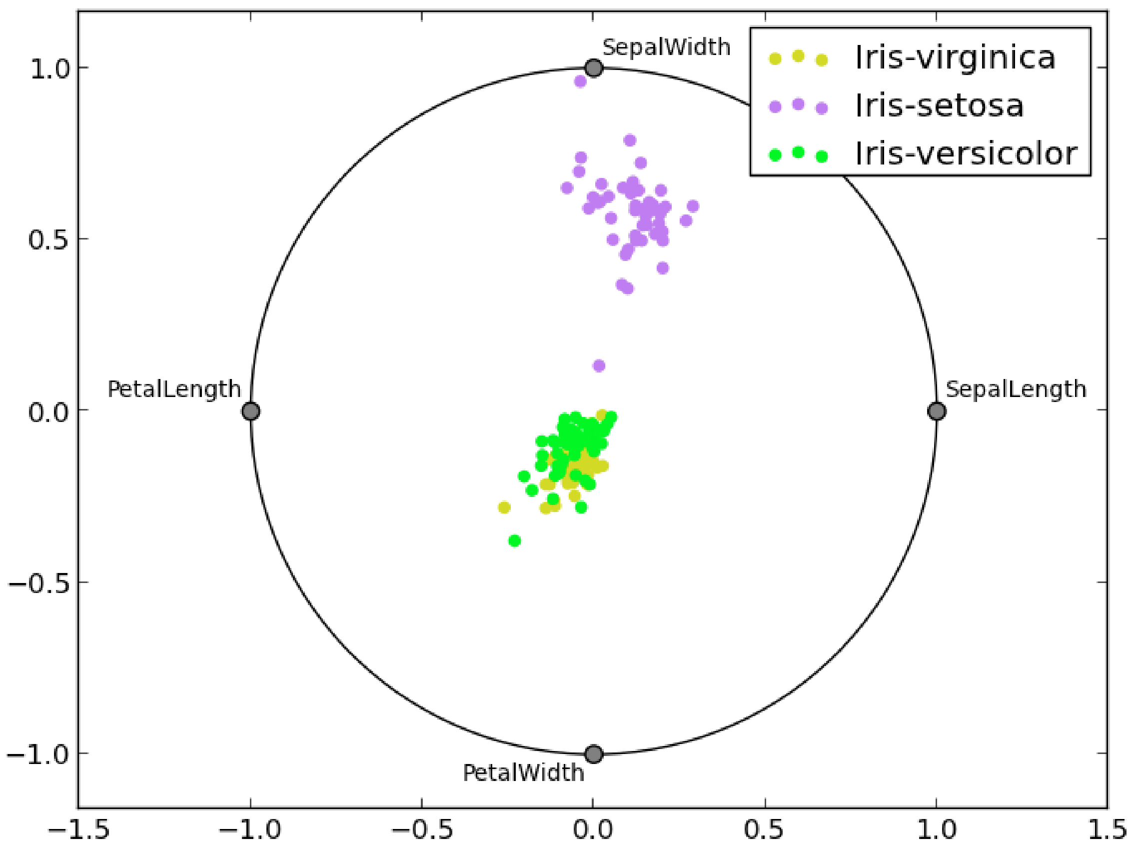

### 14.2.10 RadViz

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.

**Note**: The "Iris" dataset is available here.

```
In [1525]: from pandas import read_csv

In [1526]: from pandas.tools.plotting import radviz
```

```
In [1527]: data = read_csv('data/iris.data')

In [1528]: plt.figure()
Out[1528]: <matplotlib.figure.Figure at 0x1c20bad0>

In [1529]: radviz(data, 'Name')
Out[1529]: <matplotlib.axes.AxesSubplot at 0x1d097c10>
```



CHAPTER

FIFTEEN

# IO TOOLS (TEXT, CSV, HDF5, ...)

## 15.1 CSV & Text files

The two workhorse functions for reading text files (a.k.a. flat files) are `read_csv()` and `read_table()`. They both use the same parsing code to intelligently convert tabular data into a DataFrame object. They can take a number of arguments:

- `filepath_or_buffer`: Either a string path to a file, or any object with a `read` method (such as an open file or `StringIO`).
- `sep` or `delimiter`: A delimiter / separator to split fields on. *read_csv* is capable of inferring the delimiter automatically in some cases by "sniffing." The separator may be specified as a regular expression; for instance you may use '|\s*' to indicate a pipe plus arbitrary whitespace.
- `delim_whitespace`: Parse whitespace-delimited (spaces or tabs) file (much faster than using a regular expression)
- `compression`: decompress `'gzip'` and `'bz2'` formats on the fly.
- `dialect`: string or `csv.Dialect` instance to expose more ways to specify the file format
- `dtype`: A data type name or a dict of column name to data type. If not specified, data types will be inferred.
- `header`: row number to use as the column names, and the start of the data. Defaults to 0 if no `names` passed, otherwise `None`. Explicitly pass `header=0` to be able to replace existing names.
- `skiprows`: A collection of numbers for rows in the file to skip. Can also be an integer to skip the first `n` rows
- `index_col`: column number, column name, or list of column numbers/names, to use as the `index` (row labels) of the resulting DataFrame. By default, it will number the rows without using any column, unless there is one more data column than there are headers, in which case the first column is taken as the index.
- `names`: List of column names to use as column names. To replace header existing in file, explicitly pass `header=0`.
- `na_values`: optional list of strings to recognize as NaN (missing values), either in addition to or in lieu of the default set.
- `true_values`: list of strings to recognize as `True`
- `false_values`: list of strings to recognize as `False`
- `keep_default_na`: whether to include the default set of missing values in addition to the ones specified in `na_values`
- `parse_dates`: if True then index will be parsed as dates (False by default). You can specify more complicated options to parse a subset of columns or a combination of columns into a single date column (list of ints or names, list of lists, or dict) [1, 2, 3] -> try parsing columns 1, 2, 3 each as a separate date column [[1, 3]] -> combine

columns 1 and 3 and parse as a single date column {'foo' : [1, 3]} -> parse columns 1, 3 as date and call result 'foo'

- `keep_date_col`: if True, then date component columns passed into `parse_dates` will be retained in the output (False by default).
- `date_parser`: function to use to parse strings into datetime objects. If `parse_dates` is True, it defaults to the very robust `dateutil.parser`. Specifying this implicitly sets `parse_dates` as True. You can also use functions from community supported date converters from date_converters.py
- `dayfirst`: if True then uses the DD/MM international/European date format (This is False by default)
- `thousands`: sepcifies the thousands separator. If not None, then parser will try to look for it in the output and parse relevant data to integers. Because it has to essentially scan through the data again, this causes a significant performance hit so only use if necessary.
- `comment`: denotes the start of a comment and ignores the rest of the line. Currently line commenting is not supported.
- `nrows`: Number of rows to read out of the file. Useful to only read a small portion of a large file
- `iterator`: If True, return a `TextParser` to enable reading a file into memory piece by piece
- `chunksize`: An number of rows to be used to "chunk" a file into pieces. Will cause an `TextParser` object to be returned. More on this below in the section on *iterating and chunking*
- `skip_footer`: number of lines to skip at bottom of file (default 0)
- `converters`: a dictionary of functions for converting values in certain columns, where keys are either integers or column labels
- `encoding`: a string representing the encoding to use for decoding unicode data, e.g. `'utf-8`` or `'latin-1'`.
- `verbose`: show number of NA values inserted in non-numeric columns
- `squeeze`: if True then output with only one column is turned into Series

Consider a typical CSV file containing, in this case, some time series data:

```
In [830]: print open('foo.csv').read()
date,A,B,C
20090101,a,1,2
20090102,b,3,4
20090103,c,4,5
```

The default for *read_csv* is to create a DataFrame with simple numbered rows:

```
In [831]: pd.read_csv('foo.csv')
Out[831]:
       date  A  B  C
0  20090101  a  1  2
1  20090102  b  3  4
2  20090103  c  4  5
```

In the case of indexed data, you can pass the column number or column name you wish to use as the index:

```
In [832]: pd.read_csv('foo.csv', index_col=0)
Out[832]:
          A  B  C
date
20090101  a  1  2
20090102  b  3  4
20090103  c  4  5
```

```
In [833]: pd.read_csv('foo.csv', index_col='date')
Out[833]:
          A  B  C
date
20090101  a  1  2
20090102  b  3  4
20090103  c  4  5
```

You can also use a list of columns to create a hierarchical index:

```
In [834]: pd.read_csv('foo.csv', index_col=[0, 'A'])
Out[834]:
            B  C
date     A
20090101 a  1  2
20090102 b  3  4
20090103 c  4  5
```

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 [835]: 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 [836]: dia = csv.excel()

In [837]: dia.quoting = csv.QUOTE_NONE

In [838]: pd.read_csv(StringIO(data), dialect=dia)
Out[838]:
       label1 label2 label3
index1     "a      c      e
index2      b      d      f
```

All of the dialect options can be specified separately by keyword arguments:

```
In [839]: data = 'a,b,c~1,2,3~4,5,6'

In [840]: pd.read_csv(StringIO(data), lineterminator='~')
Out[840]:
   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 [841]: data = 'a, b, c\n1, 2, 3\n4, 5, 6'

In [842]: print data
a, b, c
1, 2, 3
4, 5, 6
```

```
In [843]: pd.read_csv(StringIO(data), skipinitialspace=True)
Out[843]:
   a  b  c
0  1  2  3
1  4  5  6
```

The parsers make every attempt to "do the right thing" and not be very fragile. Type inference is a pretty big deal. So if a column can be coerced to integer dtype without altering the contents, it will do so. Any non-numeric columns will come through as object dtype as with the rest of pandas objects.

### 15.1.1 Specifying column data types

Starting with v0.10, you can indicate the data type for the whole DataFrame or individual columns:

```
In [844]: data = 'a,b,c\n1,2,3\n4,5,6\n7,8,9'

In [845]: print data
a,b,c
1,2,3
4,5,6
7,8,9

In [846]: df = pd.read_csv(StringIO(data), dtype=object)

In [847]: df
Out[847]:
   a  b  c
0  1  2  3
1  4  5  6
2  7  8  9

In [848]: df['a'][0]
Out[848]: '1'

In [849]: df = pd.read_csv(StringIO(data), dtype={'b': object, 'c': np.float64})

In [850]: df.dtypes
Out[850]:
a       int64
b      object
c     float64
dtype: object
```

### 15.1.2 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 [851]: from StringIO import StringIO

In [852]: data = 'a,b,c\n1,2,3\n4,5,6\n7,8,9'

In [853]: print data
a,b,c
1,2,3
4,5,6
```

```
7,8,9

In [854]: pd.read_csv(StringIO(data))
Out[854]:
   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 [855]: print data
a,b,c
1,2,3
4,5,6
7,8,9

In [856]: pd.read_csv(StringIO(data), names=['foo', 'bar', 'baz'], header=0)
Out[856]:
   foo  bar  baz
0    1    2    3
1    4    5    6
2    7    8    9

In [857]: pd.read_csv(StringIO(data), names=['foo', 'bar', 'baz'], header=None)
Out[857]:
  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 [858]: data = 'skip this skip it\na,b,c\n1,2,3\n4,5,6\n7,8,9'

In [859]: pd.read_csv(StringIO(data), header=1)
Out[859]:
   a  b  c
0  1  2  3
1  4  5  6
2  7  8  9
```

### 15.1.3 Filtering columns (usecols)

The `usecols` argument allows you to select any subset of the columns in a file, either using the column names or position numbers:

```
In [860]: data = 'a,b,c,d\n1,2,3,foo\n4,5,6,bar\n7,8,9,baz'

In [861]: pd.read_csv(StringIO(data))
Out[861]:
   a  b  c    d
0  1  2  3  foo
1  4  5  6  bar
2  7  8  9  baz
```

```
In [862]: pd.read_csv(StringIO(data), usecols=['b', 'd'])
Out[862]:
   b    d
0  2  foo
1  5  bar
2  8  baz

In [863]: pd.read_csv(StringIO(data), usecols=[0, 2, 3])
Out[863]:
   a  c    d
0  1  3  foo
1  4  6  bar
2  7  9  baz
```

### 15.1.4 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 [864]: data = 'word,length\nTr\xe4umen,7\nGr\xfc\xdfe,5'

In [865]: df = pd.read_csv(StringIO(data), encoding='latin-1')

In [866]: df
Out[866]:
      word  length
0  Träumen       7
1    Grüße       5

In [867]: df['word'][1]
Out[867]: u'Gr\xfc\xdfe'
```

Some formats which encode all characters as multiple bytes, like UTF-16, won't parse correctly at all without specifying the encoding.

### 15.1.5 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 [868]: data = 'a,b,c\n4,apple,bat,5.7\n8,orange,cow,10'

In [869]: pd.read_csv(StringIO(data))
Out[869]:
        a    b     c
4   apple  bat   5.7
8  orange  cow  10.0

In [870]: data = 'index,a,b,c\n4,apple,bat,5.7\n8,orange,cow,10'

In [871]: pd.read_csv(StringIO(data), index_col=0)
Out[871]:
            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 [872]: data = 'a,b,c\n4,apple,bat,\n8,orange,cow,'

In [873]: print data
a,b,c
4,apple,bat,
8,orange,cow,

In [874]: pd.read_csv(StringIO(data))
Out[874]:
        a    b   c
4   apple  bat NaN
8  orange  cow NaN

In [875]: pd.read_csv(StringIO(data), index_col=False)
Out[875]:
   a       b    c
0  4   apple  bat
1  8  orange  cow
```

### 15.1.6 Specifying Date Columns

To better facilitate working with datetime data, `read_csv()` and `read_table()` 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 [876]: df = pd.read_csv('foo.csv', index_col=0, parse_dates=True)

In [877]: df
Out[877]:
            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 [878]: df.index
Out[878]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2009-01-01 00:00:00, ..., 2009-01-03 00:00:00]
Length: 3, Freq: None, Timezone: 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 [879]: 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 [880]: df = pd.read_csv('tmp.csv', header=None, parse_dates=[[1, 2], [1, 3]])

In [881]: df
Out[881]:
                  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 [882]: df = pd.read_csv('tmp.csv', header=None, parse_dates=[[1, 2], [1, 3]],
   .....:                  keep_date_col=True)
   .....:

In [883]: df
Out[883]:
                  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 [884]: date_spec = {'nominal': [1, 2], 'actual': [1, 3]}

In [885]: df = pd.read_csv('tmp.csv', header=None, parse_dates=date_spec)

In [886]: df
Out[886]:
              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 [887]: date_spec = {'nominal': [1, 2], 'actual': [1, 3]}

In [888]: df = pd.read_csv('tmp.csv', header=None, parse_dates=date_spec,
   .....:                  index_col=0) #index is the nominal column
   .....:

In [889]: df
Out[889]:
                                 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**: When passing a dict as the *parse_dates* argument, the order of the columns prepended is not guaranteed, because *dict* objects do not impose an ordering on their keys. On Python 2.7+ you may use *collections.OrderedDict* instead of a regular *dict* if this matters to you. Because of this, when using a dict for 'parse_dates' in conjunction with the *index_col* argument, it's best to specify *index_col* as a column label rather then as an index on the resulting frame.

### 15.1.7 Date Parsing Functions

Finally, the parser allows you can specify a custom `date_parser` function to take full advantage of the flexiblity of the date parsing API:

```
In [890]: import pandas.io.date_converters as conv

In [891]: df = pd.read_csv('tmp.csv', header=None, parse_dates=date_spec,
   .....:                  date_parser=conv.parse_date_time)
   .....:

In [892]: df
Out[892]:
              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
```

You can explore the date parsing functionality in `date_converters.py` and add your own. We would love to turn this module into a community supported set of date/time parsers. To get you started, `date_converters.py` contains functions to parse dual date and time columns, year/month/day columns, and year/month/day/hour/minute/second columns. It also contains a `generic_parser` function so you can curry it with a function that deals with a single date rather than the entire array.

### 15.1.8 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 [893]: print open('tmp.csv').read()
date,value,cat
1/6/2000,5,a
2/6/2000,10,b
3/6/2000,15,c

In [894]: pd.read_csv('tmp.csv', parse_dates=[0])
Out[894]:
                 date  value cat
0 2000-01-06 00:00:00      5   a
1 2000-02-06 00:00:00     10   b
2 2000-03-06 00:00:00     15   c

In [895]: pd.read_csv('tmp.csv', dayfirst=True, parse_dates=[0])
Out[895]:
                 date  value cat
0 2000-06-01 00:00:00      5   a
1 2000-06-02 00:00:00     10   b
2 2000-06-03 00:00:00     15   c
```

### 15.1.9 Thousand Separators

For large integers that have been written with a thousands separator, you can set the `thousands` keyword to `True` so that integers will be parsed correctly:

By default, integers with a thousands separator will be parsed as strings

```
In [896]: print open('tmp.csv').read()
ID|level|category
Patient1|123,000|x
Patient2|23,000|y
Patient3|1,234,018|z

In [897]: df = pd.read_csv('tmp.csv', sep='|')

In [898]: df
Out[898]:
         ID      level category
0  Patient1    123,000        x
1  Patient2     23,000        y
2  Patient3  1,234,018        z

In [899]: df.level.dtype
Out[899]: dtype('object')
```

The `thousands` keyword allows integers to be parsed correctly

```
In [900]: print open('tmp.csv').read()
ID|level|category
Patient1|123,000|x
Patient2|23,000|y
Patient3|1,234,018|z

In [901]: df = pd.read_csv('tmp.csv', sep='|', thousands=',')

In [902]: df
Out[902]:
```

```
         ID    level  category
0  Patient1   123000         x
1  Patient2    23000         y
2  Patient3  1234018         z

In [903]: df.level.dtype
Out[903]: dtype('int64')
```

### 15.1.10 Comments

Sometimes comments or meta data may be included in a file:

```
In [904]: 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 parse includes the comments in the output:

```
In [905]: df = pd.read_csv('tmp.csv')

In [906]: df
Out[906]:
         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 [907]: df = pd.read_csv('tmp.csv', comment='#')

In [908]: df
Out[908]:
         ID    level category
0  Patient1   123000       x
1  Patient2    23000       y
2  Patient3  1234018       z
```

### 15.1.11 Returning Series

Using the `squeeze` keyword, the parser will return output with a single column as a `Series`:

```
In [909]: print open('tmp.csv').read()
level
Patient1,123000
Patient2,23000
Patient3,1234018

In [910]: output =  pd.read_csv('tmp.csv', squeeze=True)

In [911]: output
Out[911]:
Patient1     123000
Patient2      23000
```

```
Patient3    1234018
Name: level, dtype: int64

In [912]: type(output)
Out[912]: pandas.core.series.Series
```

### 15.1.12 Boolean values

The common values `True`, `False`, `TRUE`, and `FALSE` are all recognized as boolean. Sometime you would want to recognize some other values as being boolean. To do this use the `true_values` and `false_values` options:

```
In [913]: data= 'a,b,c\n1,Yes,2\n3,No,4'

In [914]: print data
a,b,c
1,Yes,2
3,No,4

In [915]: pd.read_csv(StringIO(data))
Out[915]:
   a    b  c
0  1  Yes  2
1  3   No  4

In [916]: pd.read_csv(StringIO(data), true_values=['Yes'], false_values=['No'])
Out[916]:
   a      b  c
0  1   True  2
1  3  False  4
```

### 15.1.13 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 will cause an error by default:

```
In [27]: data = 'a,b,c\n1,2,3\n4,5,6,7\n8,9,10'

In [28]: pd.read_csv(StringIO(data))
---------------------------------------------------------------------------
CParserError                              Traceback (most recent call last)
CParserError: 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
```

### 15.1.14 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 [917]: data = 'a,b\n"hello, \\"Bob\\", nice to see you",5'

In [918]: print data
a,b
"hello, \"Bob\", nice to see you",5

In [919]: pd.read_csv(StringIO(data), escapechar='\\')
Out[919]:
                               a  b
0  hello, "Bob", nice to see you  5
```

### 15.1.15 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:

- `colspecs`: a list of pairs (tuples), giving the extents of the fixed-width fields of each line as half-open intervals [from, to[
- `widths`: a list of field widths, which can be used instead of `colspecs` if the intervals are contiguous

Consider a typical fixed-width data file:

```
In [920]: 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 [921]: colspecs = [(0, 6), (8, 20), (21, 33), (34, 43)]

In [922]: df = pd.read_fwf('bar.csv', colspecs=colspecs, header=None, index_col=0)

In [923]: df
Out[923]:
                 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 [924]: widths = [6, 14, 13, 10]
```

```
In [925]: df = pd.read_fwf('bar.csv', widths=widths, header=None)

In [926]: df
Out[926]:
        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.

### 15.1.16 Files with an "implicit" index column

Consider a file with one less entry in the header than the number of data column:

```
In [927]: 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 [928]: pd.read_csv('foo.csv')
Out[928]:
          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 [929]: df = pd.read_csv('foo.csv', parse_dates=True)

In [930]: df.index
Out[930]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2009-01-01 00:00:00, ..., 2009-01-03 00:00:00]
Length: 3, Freq: None, Timezone: None
```

### 15.1.17 Reading DataFrame objects with `MultiIndex`

Suppose you have data indexed by two columns:

```
In [931]: 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 and read_table can take a list of column numbers to turn multiple columns into a MultiIndex:

```
In [932]: df = pd.read_csv("data/mindex_ex.csv", index_col=[0,1])

In [933]: df
Out[933]:
             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 [934]: df.ix[1978]
Out[934]:
       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
```

### 15.1.18 Automatically "sniffing" the delimiter

read_csv is capable of inferring delimited (not necessarily comma-separated) files. YMMV, as pandas uses the csv.Sniffer class of the csv module.

```
In [935]: print open('tmp2.sv').read()
:0:1:2:3
0:0.469112299907:-0.282863344329:-1.50905850317:-1.13563237102
1:1.21211202502:-0.173214649053:0.119208711297:-1.04423596628
2:-0.861848963348:-2.10456921889:-0.494929274069:1.07180380704
3:0.721555162244:-0.70677113363:-1.03957498511:0.271859885543
4:-0.424972329789:0.567020349794:0.276232019278:-1.08740069129
5:-0.673689708088:0.113648409689:-1.47842655244:0.524987667115
6:0.40470521868:0.57704598592:-1.71500201611:-1.03926848351
```

```
7:-0.370646858236:-1.15789225064:-1.34431181273:0.844885141425
8:1.07576978372:-0.10904997528:1.64356307036:-1.46938795954
9:0.357020564133:-0.67460010373:-1.77690371697:-0.968913812447

In [936]: pd.read_csv('tmp2.sv')
Out[936]:
                                             :0:1:2:3
0  0:0.469112299907:-0.282863344329:-1.5090585031...
1  1:1.21211202502:-0.173214649053:0.119208711297...
2  2:-0.861848963348:-2.10456921889:-0.4949292740...
3  3:0.721555162244:-0.70677113363:-1.03957498511...
4  4:-0.424972329789:0.567020349794:0.27623201927...
5  5:-0.673689708088:0.113648409689:-1.4784265524...
6  6:0.40470521868:0.57704598592:-1.71500201611:-...
7  7:-0.370646858236:-1.15789225064:-1.3443118127...
8  8:1.07576978372:-0.10904997528:1.64356307036:-...
9  9:0.357020564133:-0.67460010373:-1.77690371697...
```

### 15.1.19 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 [937]: print open('tmp.sv').read()
|0|1|2|3
0|0.469112299907|-0.282863344329|-1.50905850317|-1.13563237102
1|1.21211202502|-0.173214649053|0.119208711297|-1.04423596628
2|-0.861848963348|-2.10456921889|-0.494929274069|1.07180380704
3|0.721555162244|-0.70677113363|-1.03957498511|0.271859885543
4|-0.424972329789|0.567020349794|0.276232019278|-1.08740069129
5|-0.673689708088|0.113648409689|-1.47842655244|0.524987667115
6|0.40470521868|0.57704598592|-1.71500201611|-1.03926848351
7|-0.370646858236|-1.15789225064|-1.34431181273|0.844885141425
8|1.07576978372|-0.10904997528|1.64356307036|-1.46938795954
9|0.357020564133|-0.67460010373|-1.77690371697|-0.968913812447

In [938]: table = pd.read_table('tmp.sv', sep='|')

In [939]: table
Out[939]:
   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 specifiying a `chunksize` to `read_csv` or `read_table`, the return value will be an iterable object of type `TextParser`:

```
In [940]: reader = pd.read_table('tmp.sv', sep='|', chunksize=4)
```

```
In [941]: reader
Out[941]: <pandas.io.parsers.TextFileReader at 0xcd11ad0>

In [942]: for chunk in reader:
   .....:     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
0          4 -0.424972  0.567020  0.276232 -1.087401
1          5 -0.673690  0.113648 -1.478427  0.524988
2          6  0.404705  0.577046 -1.715002 -1.039268
3          7 -0.370647 -1.157892 -1.344312  0.844885
   Unnamed: 0         0        1         2         3
0          8  1.075770 -0.10905  1.643563 -1.469388
1          9  0.357021 -0.67460 -1.776904 -0.968914
```

Specifying `iterator=True` will also return the `TextParser` object:

```
In [943]: reader = pd.read_table('tmp.sv', sep='|', iterator=True)

In [944]: reader.get_chunk(5)
Out[944]:
   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
```

### 15.1.20 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`: A string path to the file to write `nanRep`: A string representation of a missing value (default '')
- `cols`: 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'
- `sep` : Field delimiter for the output file (default ",")
- `encoding`: a string representing the encoding to use if the contents are non-ascii, for python versions prior to 3

### 15.1.21 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.

### 15.1.22 Writing to HTML format

DataFrame object has 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.

## 15.2 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_table` method described in the next section. 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(delim_whitespace=True)
```

```
In [945]: clipdf
Out[945]:
   A  B  C
x  1  4  p
y  2  5  q
z  3  6  r
```

## 15.3 Excel files

The `ExcelFile` class can read an Excel 2003 file using the `xlrd` Python module and use the same parsing code as the above to convert tabular data into a DataFrame. To use it, create the `ExcelFile` object:

```
xls = ExcelFile('path_to_file.xls')
```

Then use the `parse` instance method with a sheetname, then use the same additional arguments as the parsers above:

```
xls.parse('Sheet1', index_col=None, na_values=['NA'])
```

To read sheets from an Excel 2007 file, you can pass a filename with a `.xlsx` extension, in which case the `openpyxl` module will be used to read the file.

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. *ExcelFile.parse* takes a *parse_cols* keyword to allow you to specify a subset of columns to parse.

If *parse_cols* is an integer, then it is assumed to indicate the last column to be parsed.

```
xls.parse('Sheet1', parse_cols=2, index_col=None, na_values=['NA'])
```

If *parse_cols* is a list of integers, then it is assumed to be the file column indices to be parsed.

```
xls.parse('Sheet1', parse_cols=[0, 2, 3], index_col=None, na_values=['NA'])
```

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 `openpyxl`. The Panel class also has a `to_excel` instance method, which writes each DataFrame in the Panel to a separate sheet.

In order to write separate DataFrames to separate sheets in a single Excel file, one can use the ExcelWriter class, as in the following example:

```
writer = ExcelWriter('path_to_file.xlsx')
df1.to_excel(writer, sheet_name='sheet1')
df2.to_excel(writer, sheet_name='sheet2')
writer.save()
```

## 15.4 HDF5 (PyTables)

`HDFStore` is a dict-like object which reads and writes pandas to the high performance HDF5 format using the excellent PyTables library.

```
In [946]: store = HDFStore('store.h5')

In [947]: print store
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
Empty
```

Objects can be written to the file just like adding key-value pairs to a dict:

```
In [948]: index = date_range('1/1/2000', periods=8)

In [949]: s = Series(randn(5), index=['a', 'b', 'c', 'd', 'e'])

In [950]: df = DataFrame(randn(8, 3), index=index,
   .....:                columns=['A', 'B', 'C'])
   .....:

In [951]: wp = Panel(randn(2, 5, 4), items=['Item1', 'Item2'],
   .....:            major_axis=date_range('1/1/2000', periods=5),
   .....:            minor_axis=['A', 'B', 'C', 'D'])
   .....:

# store.put('s', s) is an equivalent method
In [952]: store['s'] = s

In [953]: store['df'] = df

In [954]: store['wp'] = wp

# the type of stored data
In [955]: store.root.wp._v_attrs.pandas_type
Out[955]: 'wide'

In [956]: store
Out[956]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/df              frame         (shape->[8,3])
/s               series        (shape->[5])
/wp              wide          (shape->[2,5,4])
```

In a current or later Python session, you can retrieve stored objects:

```
# store.get('df') is an equivalent method
In [957]: store['df']
Out[957]:
                   A         B         C
2000-01-01 -0.362543 -0.006154 -0.923061
2000-01-02  0.895717  0.805244 -1.206412
2000-01-03  2.565646  1.431256  1.340309
2000-01-04 -1.170299 -0.226169  0.410835
2000-01-05  0.813850  0.132003 -0.827317
2000-01-06 -0.076467 -1.187678  1.130127
2000-01-07 -1.436737 -1.413681  1.607920
2000-01-08  1.024180  0.569605  0.875906
```

Deletion of the object specified by the key

```
# store.remove('wp') is an equivalent method
In [958]: del store['wp']

In [959]: store
Out[959]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/df              frame         (shape->[8,3])
/s               series        (shape->[5])
```

Closing a Store

```
# closing a store
In [960]: store.close()

# Working with, and automatically closing the store with the context manager.
In [961]: with get_store('store.h5') as store:
   .....:     store.keys()
   .....:
```

These 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.

### 15.4.1 Storing in 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 & query type operations are supported.

```
In [962]: store = HDFStore('store.h5')

In [963]: df1 = df[0:4]

In [964]: df2 = df[4:]

# append data (creates a table automatically)
In [965]: store.append('df', df1)

In [966]: store.append('df', df2)

In [967]: store
Out[967]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/df            frame_table  (typ->appendable,nrows->8,ncols->3,indexers->[index])

# select the entire object
In [968]: store.select('df')
Out[968]:
                   A         B         C
2000-01-01 -0.362543 -0.006154 -0.923061
2000-01-02  0.895717  0.805244 -1.206412
2000-01-03  2.565646  1.431256  1.340309
2000-01-04 -1.170299 -0.226169  0.410835
2000-01-05  0.813850  0.132003 -0.827317
2000-01-06 -0.076467 -1.187678  1.130127
2000-01-07 -1.436737 -1.413681  1.607920
2000-01-08  1.024180  0.569605  0.875906

# the type of stored data
In [969]: store.root.df._v_attrs.pandas_type
Out[969]: 'frame_table'
```

### 15.4.2 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 with out the leading '/' and are ALWAYS absolute (e.g. 'foo' refers to '/foo'). Removal operations can remove everying in the sub-store and BELOW, so be *careful*.

```
In [970]: store.put('foo/bar/bah', df)

In [971]: store.append('food/orange', df)

In [972]: store.append('food/apple',  df)

In [973]: store
Out[973]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/df                     frame_table  (typ->appendable,nrows->8,ncols->3,indexers->[index])
/food/apple             frame_table  (typ->appendable,nrows->8,ncols->3,indexers->[index])
/food/orange            frame_table  (typ->appendable,nrows->8,ncols->3,indexers->[index])
/foo/bar/bah            frame        (shape->[8,3])

# a list of keys are returned
In [974]: store.keys()
Out[974]: ['/df', '/food/apple', '/food/orange', '/foo/bar/bah']

# remove all nodes under this level
In [975]: store.remove('food')

In [976]: store
Out[976]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/df                     frame_table  (typ->appendable,nrows->8,ncols->3,indexers->[index])
/foo/bar/bah            frame        (shape->[8,3])
```

### 15.4.3 Storing Mixed Types in a Table

Storing mixed-dtype data is supported. Strings are store as a fixed-width using the maximum size of the appended column. Subsequent appends will truncate strings at this length. 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 [977]: df_mixed             = df.copy()

In [978]: df_mixed['string']   = 'string'

In [979]: df_mixed['int']      = 1

In [980]: df_mixed['bool']     = True

In [981]: df_mixed['datetime64'] = Timestamp('20010102')

In [982]: df_mixed.ix[3:5,['A','B','string','datetime64']] = np.nan

In [983]: store.append('df_mixed', df_mixed, min_itemsize = { 'values' : 50 })
```

```
In [984]: df_mixed1 = store.select('df_mixed')

In [985]: df_mixed1
Out[985]:
                   A         B         C  string  int  bool          datetime64
2000-01-01 -0.362543 -0.006154 -0.923061  string    1  True 2001-01-02 00:00:00
2000-01-02  0.895717  0.805244 -1.206412  string    1  True 2001-01-02 00:00:00
2000-01-03  2.565646  1.431256  1.340309  string    1  True 2001-01-02 00:00:00
2000-01-04       NaN       NaN  0.410835     NaN    1  True                 NaT
2000-01-05       NaN       NaN -0.827317     NaN    1  True                 NaT
2000-01-06 -0.076467 -1.187678  1.130127  string    1  True 2001-01-02 00:00:00
2000-01-07 -1.436737 -1.413681  1.607920  string    1  True 2001-01-02 00:00:00
2000-01-08  1.024180  0.569605  0.875906  string    1  True 2001-01-02 00:00:00

In [986]: df_mixed1.get_dtype_counts()
Out[986]:
bool              1
datetime64[ns]    1
float64           3
int64             1
object            1
dtype: int64

# we have provided a minimum string column size
In [987]: store.root.df_mixed.table
Out[987]:
/df_mixed/table (Table(8,)) ''
  description := {
  "index": Int64Col(shape=(), dflt=0, pos=0),
  "values_block_0": Float64Col(shape=(3,), dflt=0.0, pos=1),
  "values_block_1": StringCol(itemsize=50, shape=(1,), dflt='', pos=2),
  "values_block_2": Int64Col(shape=(1,), dflt=0, pos=3),
  "values_block_3": BoolCol(shape=(1,), dflt=False, pos=4),
  "values_block_4": Int64Col(shape=(1,), dflt=0, pos=5)}
  byteorder := 'little'
  chunkshape := (661,)
  autoIndex := True
  colindexes := {
    "index": Index(6, medium, shuffle, zlib(1)).is_CSI=False}
```

### 15.4.4 Storing Multi-Index DataFrames

Storing multi-index dataframes as tables is very similar to storing/selecting from homogenous index DataFrames.

```
In [988]: index = 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 [989]: df_mi = DataFrame(np.random.randn(10, 3), index=index,
   .....:                   columns=['A', 'B', 'C'])
   .....:

In [990]: df_mi
```

```
Out[990]:
                  A         B         C
foo bar
foo one    0.896171 -0.487602 -0.082240
    two   -2.182937  0.380396  0.084844
    three  0.432390  1.519970 -0.493662
bar one    0.600178  0.274230  0.132885
    two   -0.023688  2.410179  1.450520
baz two    0.206053 -0.251905 -2.213588
    three  1.063327  1.266143  0.299368
qux one   -0.863838  0.408204 -1.048089
    two   -0.025747 -0.988387  0.094055
    three  1.262731  1.289997  0.082423

In [991]: store.append('df_mi',df_mi)

In [992]: store.select('df_mi')
Out[992]:
                  A         B         C
foo bar
foo one    0.896171 -0.487602 -0.082240
    two   -2.182937  0.380396  0.084844
    three  0.432390  1.519970 -0.493662
bar one    0.600178  0.274230  0.132885
    two   -0.023688  2.410179  1.450520
baz two    0.206053 -0.251905 -2.213588
    three  1.063327  1.266143  0.299368
qux one   -0.863838  0.408204 -1.048089
    two   -0.025747 -0.988387  0.094055
    three  1.262731  1.289997  0.082423

# the levels are automatically included as data columns
In [993]: store.select('df_mi', Term('foo=bar'))
Out[993]:
                A         B         C
foo bar
bar one  0.600178  0.274230  0.132885
    two -0.023688  2.410179  1.450520
```

### 15.4.5 Querying a Table

`select` and `delete` operations have an optional criteria 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.

- 'index' and 'columns' are supported indexers of a DataFrame
- 'major_axis', 'minor_axis', and 'items' are supported indexers of the Panel

Valid terms can be created from `dict, list, tuple, or string`. Objects can be embeded as values. Allowed operations are: `<, <=, >, >=, =`. `=` will be inferred as an implicit set operation (e.g. if 2 or more values are provided). The following are all valid terms.

- `dict(field = 'index', op = '>', value = '20121114')`
- `('index', '>', '20121114')`
- `'index > 20121114'`

- `('index', '>', datetime(2012,11,14))`
- `('index', ['20121114','20121115'])`
- `('major_axis', '=', Timestamp('2012/11/14'))`
- `('minor_axis', ['A','B'])`

Queries are built up using a list of `Terms` (currently only **anding** of terms is supported). An example query for a panel might be specified as follows. `['major_axis>20000102', ('minor_axis', '=', ['A','B']) ]`. This is roughly translated to: *major_axis must be greater than the date 20000102 and the minor_axis must be A or B*

```
In [994]: store.append('wp',wp)

In [995]: store
Out[995]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/df                    frame_table  (typ->appendable,nrows->8,ncols->3,indexers->[index])
/df_mi                 frame_table  (typ->appendable_multi,nrows->10,ncols->5,indexers->[index],dc->
/df_mixed              frame_table  (typ->appendable,nrows->8,ncols->7,indexers->[index])
/wp                    wide_table   (typ->appendable,nrows->20,ncols->2,indexers->[major_axis,minor_
/foo/bar/bah           frame        (shape->[8,3])

In [996]: store.select('wp',[ Term('major_axis>20000102'), Term('minor_axis', '=', ['A','B']) ])
Out[996]:
<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
```

The `columns` keyword can be supplied to select to filter a list of the return columns, this is equivalent to passing a `Term('columns',list_of_columns_to_filter)`

```
In [997]: store.select('df', columns = ['A','B'])
Out[997]:
                   A         B
2000-01-01 -0.362543 -0.006154
2000-01-02  0.895717  0.805244
2000-01-03  2.565646  1.431256
2000-01-04 -1.170299 -0.226169
2000-01-05  0.813850  0.132003
2000-01-06 -0.076467 -1.187678
2000-01-07 -1.436737 -1.413681
2000-01-08  1.024180  0.569605
```

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.

```
# this is effectively what the storage of a Panel looks like
In [998]: wp.to_frame()
Out[998]:
                     Item1     Item2
major      minor
2000-01-01 A     -2.211372  0.687738
           B      0.974466  0.176444
           C     -2.006747  0.403310
           D     -0.410001 -0.154951
2000-01-02 A     -0.078638  0.301624
```

```
            B       0.545952 -2.179861
            C      -1.219217 -1.369849
            D      -1.226825 -0.954208
2000-01-03 A       0.769804  1.462696
            B      -1.281247 -1.743161
            C      -0.727707 -0.826591
            D      -0.121306 -0.345352
2000-01-04 A      -0.097883  1.314232
            B       0.695775  0.690579
            C       0.341734  0.995761
            D       0.959726  2.396780
2000-01-05 A      -1.110336  0.014871
            B      -0.619976  3.357427
            C       0.149748 -0.317441
            D      -0.732339 -1.236269
```

```
# limiting the search
In [999]: store.select('wp',[ Term('major_axis>20000102'), Term('minor_axis', '=', ['A','B']) ], star
Out[999]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 1 (major_axis) x 2 (minor_axis)
Items axis: Item1 to Item2
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-03 00:00:00
Minor_axis axis: A to B
```

### 15.4.6 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`. **Indexes are automagically created (starting 0.10.1)** 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 [1000]: i = store.root.df.table.cols.index.index

In [1001]: i.optlevel, i.kind
Out[1001]: (6, 'medium')

# change an index by passing new parameters
In [1002]: store.create_table_index('df', optlevel = 9, kind = 'full')

In [1003]: i = store.root.df.table.cols.index.index

In [1004]: i.optlevel, i.kind
Out[1004]: (9, 'full')
```

### 15.4.7 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 [1005]: df_dc = df.copy()

In [1006]: df_dc['string'] = 'foo'

In [1007]: df_dc.ix[4:6,'string'] = np.nan

In [1008]: df_dc.ix[7:9,'string'] = 'bar'

In [1009]: df_dc['string2'] = 'cool'

In [1010]: df_dc
Out[1010]:
                   A         B         C string string2
2000-01-01 -0.362543 -0.006154 -0.923061    foo    cool
2000-01-02  0.895717  0.805244 -1.206412    foo    cool
2000-01-03  2.565646  1.431256  1.340309    foo    cool
2000-01-04 -1.170299 -0.226169  0.410835    foo    cool
2000-01-05  0.813850  0.132003 -0.827317    NaN    cool
2000-01-06 -0.076467 -1.187678  1.130127    NaN    cool
2000-01-07 -1.436737 -1.413681  1.607920    foo    cool
2000-01-08  1.024180  0.569605  0.875906    bar    cool

# on-disk operations
In [1011]: store.append('df_dc', df_dc, data_columns = ['B','C','string','string2'])

In [1012]: store.select('df_dc',[ Term('B>0') ])
Out[1012]:
                   A         B         C string string2
2000-01-02  0.895717  0.805244 -1.206412    foo    cool
2000-01-03  2.565646  1.431256  1.340309    foo    cool
2000-01-05  0.813850  0.132003 -0.827317    NaN    cool
2000-01-08  1.024180  0.569605  0.875906    bar    cool

# getting creative
In [1013]: store.select('df_dc',[ 'B > 0', 'C > 0', 'string == foo' ])
Out[1013]:
                   A         B         C string string2
2000-01-03  2.565646  1.431256  1.340309    foo    cool

# this is in-memory version of this type of selection
In [1014]: df_dc[(df_dc.B > 0) & (df_dc.C > 0) & (df_dc.string == 'foo')]
Out[1014]:
                   A         B         C string string2
2000-01-03  2.565646  1.431256  1.340309    foo    cool

# we have automagically created this index and that the B/C/string/string2 columns are stored separat
In [1015]: store.root.df_dc.table
Out[1015]:
/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='', pos=4),
  "string2": StringCol(itemsize=4, shape=(), dflt='', pos=5)}
  byteorder := 'little'
  chunkshape := (1680,)
```

```
  autoIndex := True
  colindexes := {
    "index": Index(6, medium, shuffle, zlib(1)).is_CSI=False,
    "C": Index(6, medium, shuffle, zlib(1)).is_CSI=False,
    "B": Index(6, medium, shuffle, zlib(1)).is_CSI=False,
    "string2": Index(6, medium, shuffle, zlib(1)).is_CSI=False,
    "string": Index(6, medium, shuffle, zlib(1)).is_CSI=False}
```

There is some performance degredation 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!)

### 15.4.8 Advanced Queries

#### Unique

To retrieve the *unique* values of an indexable or data column, use the method `unique`. This will, for example, enable you to get the index very quickly. Note `nan` are excluded from the result set.

```
In [1016]: store.unique('df_dc','index')
Out[1016]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2000-01-01 00:00:00, ..., 2000-01-08 00:00:00]
Length: 8, Freq: None, Timezone: None

In [1017]: store.unique('df_dc','string')
Out[1017]: Index([bar, foo], dtype=object)
```

#### Replicating or

`not` and `or` conditions are unsupported at this time; however, `or` operations are easy to replicate, by repeately applying the criteria to the table, and then `concat` the results.

```
In [1018]: crit1 = [ Term('B>0'), Term('C>0'), Term('string=foo') ]

In [1019]: crit2 = [ Term('B<0'), Term('C>0'), Term('string=foo') ]

In [1020]: concat([ store.select('df_dc',c) for c in [ crit1, crit2 ] ])
Out[1020]:
                   A         B         C string string2
2000-01-03  2.565646  1.431256  1.340309    foo    cool
2000-01-04 -1.170299 -0.226169  0.410835    foo    cool
2000-01-07 -1.436737 -1.413681  1.607920    foo    cool
```

#### Storer Object

If you want to inspect the stored object, retrieve via `get_storer`. You could use this progamatically to say get the number of rows in an object.

```
In [1021]: store.get_storer('df_dc').nrows
Out[1021]: 8
```

### 15.4.9 Multiple Table Queries

New in 0.10.1 are the methods `append_to_multple` and `select_as_multiple`, that 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 that are indexed the same the selector table. You can then perform a very fast query on the selector table, yet get lots of data back. This method works similar to having a very wide-table, but is more efficient in terms of queries.

Note, **THE USER IS RESPONSIBLE FOR SYNCHRONIZING THE TABLES**. This means, append to the tables in the same order; `append_to_multiple` splits a single object to multiple tables, given a specification (as a dictionary). This dictionary is a mapping of the table names to the 'columns' you want included in that table. Pass a *None* for a single table (optional) to let it have the remaining columns. The argument `selector` defines which table is the selector table.

```
In [1022]: df_mt = DataFrame(randn(8, 6), index=date_range('1/1/2000', periods=8),
   ......:                               columns=['A', 'B', 'C', 'D', 'E', 'F'])
   ......:

In [1023]: df_mt['foo'] = 'bar'

# you can also create the tables individually
In [1024]: store.append_to_multiple({ 'df1_mt' : ['A','B'], 'df2_mt' : None }, df_mt, selector = 'df1

In [1025]: store
Out[1025]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/df                    frame_table  (typ->appendable,nrows->8,ncols->3,indexers->[index])
/df1_mt                frame_table  (typ->appendable,nrows->8,ncols->2,indexers->[index],dc->[A,B])
/df2_mt                frame_table  (typ->appendable,nrows->8,ncols->5,indexers->[index])
/df_dc                 frame_table  (typ->appendable,nrows->8,ncols->5,indexers->[index],dc->[B,C,st
/df_mi                 frame_table  (typ->appendable_multi,nrows->10,ncols->5,indexers->[index],dc->
/df_mixed              frame_table  (typ->appendable,nrows->8,ncols->7,indexers->[index])
/wp                    wide_table   (typ->appendable,nrows->20,ncols->2,indexers->[major_axis,minor_
/foo/bar/bah           frame        (shape->[8,3])

# indiviual tables were created
In [1026]: store.select('df1_mt')
Out[1026]:
                   A         B
2000-01-01 -0.055758  0.536580
2000-01-02 -0.281461  0.030711
2000-01-03 -0.064034 -1.282782
2000-01-04  0.583787  0.221471
2000-01-05 -0.845696 -1.340896
2000-01-06  0.888782  0.228440
2000-01-07 -1.066969 -0.303421
2000-01-08  1.574159  1.588931

In [1027]: store.select('df2_mt')
Out[1027]:
                   C         D         E         F  foo
2000-01-01 -0.489682  0.369374 -0.034571 -2.484478  bar
2000-01-02  0.109121  1.126203 -0.977349  1.474071  bar
2000-01-03  0.781836 -1.071357  0.441153  2.353925  bar
2000-01-04 -0.744471  0.758527  1.729689 -0.964980  bar
2000-01-05  1.846883 -1.328865  1.682706 -1.717693  bar
2000-01-06  0.901805  1.171216  0.520260 -1.197071  bar
2000-01-07 -0.858447  0.306996 -0.028665  0.384316  bar
2000-01-08  0.476720  0.473424 -0.242861 -0.014805  bar

# as a multiple
In [1028]: store.select_as_multiple(['df1_mt','df2_mt'], where = [ 'A>0','B>0' ], selector = 'df1_mt'
Out[1028]:
```

```
                   A         B         C         D         E         F  foo
2000-01-04  0.583787  0.221471 -0.744471  0.758527  1.729689 -0.964980  bar
2000-01-06  0.888782  0.228440  0.901805  1.171216  0.520260 -1.197071  bar
2000-01-08  1.574159  1.588931  0.476720  0.473424 -0.242861 -0.014805  bar
```

### 15.4.10 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. This is especially true in higher dimensional objects (`Panel` and `Panel4D`). To get optimal deletion speed, it pays 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.

```
# returns the number of rows deleted
In [1029]: store.remove('wp', 'major_axis>20000102' )
Out[1029]: 12

In [1030]: store.select('wp')
Out[1030]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 2 (major_axis) x 4 (minor_axis)
Items axis: Item1 to Item2
Major_axis axis: 2000-01-01 00:00:00 to 2000-01-02 00:00:00
Minor_axis axis: A to D
```

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 *clean* the file, use `ptrepack` (see below).

### 15.4.11 Compression

`PyTables` allows the stored data to be compressed. Tthis applies to all kinds of stores, not just tables.

- Pass `complevel=int` for a compression level (1-9, with 0 being no compression, and the default)

- Pass `complib=lib` where lib is any of `zlib, bzip2, lzo, blosc` for whichever compression library you prefer.

`HDFStore` will use the file based compression scheme if no overriding `complib` or `complevel` options are provided. `blosc` offers very fast compression, and is my most used. Note that `lzo` and `bzip2` may not be installed (by Python) by default.

Compression for all objects within the file

- `store_compressed = HDFStore('store_compressed.h5', complevel=9, complib='blosc')`

Or on-the-fly compression (this only applies to tables). You can turn off file compression for a specific table by passing `complevel=0`

- `store.append('df', df, complib='zlib', complevel=5)`

**ptrepack**

`PyTables` offer better write performance when compressed after writing them, 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. Aalternatively, one can simply remove the file and write again, or use the `copy` method.

### 15.4.12 Notes & Caveats

- Once a `table` is created its items (Panel) / columns (DataFrame) are fixed; only exactly the same columns can be appended
- You can not append/select/delete to a non-table (table creation is determined on the first append, or by passing `table=True` in a put operation)
- `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 issue <https://github.com/pydata/pandas/issues/2397> for more information.
- `PyTables` only supports fixed-width string columns in `tables`. The sizes of a string based indexing column (e.g. *columns* or *minor_axis*) are determined as the maximum size of the elements in that axis or by passing the parameter `min_itemsize` on the first table creation (`min_itemsize` can be an integer or a dict of column name to an integer). If subsequent appends introduce elements in the indexing axis that are larger than the supported indexer, an Exception will be raised (otherwise you could have a silent truncation of these indexers, leading to loss of information). Just to be clear, this fixed-width restriction applies to **indexables** (the indexing columns) and **string values** in a mixed_type table.

```
In [1031]: store.append('wp_big_strings', wp, min_itemsize = { 'minor_axis' : 30 })

In [1032]: wp = wp.rename_axis(lambda x: x + '_big_strings', axis=2)

In [1033]: store.append('wp_big_strings', wp)

In [1034]: store.select('wp_big_strings')
Out[1034]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 5 (major_axis) x 8 (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_big_strings

# we have provided a minimum minor_axis indexable size
In [1035]: store.root.wp_big_strings.table
Out[1035]:
/wp_big_strings/table (Table(40,)) ''
  description := {
  "major_axis": Int64Col(shape=(), dflt=0, pos=0),
  "minor_axis": StringCol(itemsize=30, shape=(), dflt='', pos=1),
  "values_block_0": Float64Col(shape=(2,), dflt=0.0, pos=2)}
  byteorder := 'little'
  chunkshape := (1213,)
  autoIndex := True
  colindexes := {
    "major_axis": Index(6, medium, shuffle, zlib(1)).is_CSI=False,
    "minor_axis": Index(6, medium, shuffle, zlib(1)).is_CSI=False}
```

### 15.4.13 External Compatibility

`HDFStore` write storer objects in specific formats suitable for producing loss-less roundtrips 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. Create a table format store like this:

```
In [1036]: store_export = HDFStore('export.h5')

In [1037]: store_export.append('df_dc',df_dc,data_columns=df_dc.columns)

In [1038]: store_export
Out[1038]:
<class 'pandas.io.pytables.HDFStore'>
File path: export.h5
/df_dc            frame_table  (typ->appendable,nrows->8,ncols->5,indexers->[index],dc->[A,B,C,s
```

### 15.4.14 Backwards Compatibility

0.10.1 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. `HDFStore` will issue a warning if you try to use a prior-version format file. You must read in the entire file and write it out using the new format, using the method `copy` to take advantage of the updates. The group attribute `pandas_version` contains the version information. `copy` takes a number of options, please see the docstring.

```
# a legacy store
In [1039]: legacy_store = HDFStore(legacy_file_path,'r')

In [1040]: legacy_store
Out[1040]:
<class 'pandas.io.pytables.HDFStore'>
File path: /home/wesm/code/pandas/doc/source/_static/legacy_0.10.h5
/a                      series       (shape->[30])
/b                      frame        (shape->[30,4])
/df1_mixed              frame_table [0.10.0] (typ->appendable,nrows->30,ncols->11,indexers->[index
/p1_mixed               wide_table  [0.10.0] (typ->appendable,nrows->120,ncols->9,indexers->[major
/p4d_mixed              ndim_table  [0.10.0] (typ->appendable,nrows->360,ncols->9,indexers->[items
```

```
/foo/bar                wide          (shape->[3,30,4])

# copy (and return the new handle)
In [1041]: new_store = legacy_store.copy('store_new.h5')

In [1042]: new_store
Out[1042]:
<class 'pandas.io.pytables.HDFStore'>
File path: store_new.h5
/a                      series        (shape->[30])
/b                      frame         (shape->[30,4])
/df1_mixed              frame_table   (typ->appendable,nrows->30,ncols->11,indexers->[index])
/p1_mixed               wide_table    (typ->appendable,nrows->120,ncols->9,indexers->[major_axis,mi
/p4d_mixed              wide_table    (typ->appendable,nrows->360,ncols->9,indexers->[items,major_a
/foo/bar                wide          (shape->[3,30,4])

In [1043]: new_store.close()
```

### 15.4.15 Performance

- `Tables` come with a writing performance penalty as compared to regular 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=an integer` to `append`, to change the writing chunksize (default is 50000). This will signficantly lower your memory usage on writing.
- You can pass `expectedrows=an integer` to the first `append`, to set the TOTAL number of expectedrows that `PyTables` will expected. 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 <http://stackoverflow.com/questions/14355151/how-to-make-pandas-hdfstore-put-operation-faster/14370190#14370190> for more information and some solutions.

### 15.4.16 Experimental

HDFStore supports `Panel4D` storage.

```
In [1044]: p4d = Panel4D({ 'l1' : wp })

In [1045]: p4d
Out[1045]:
<class 'pandas.core.panelnd.Panel4D'>
Dimensions: 1 (labels) x 2 (items) x 5 (major_axis) x 4 (minor_axis)
Labels axis: l1 to l1
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_big_strings to D_big_strings

In [1046]: store.append('p4d', p4d)

In [1047]: store
Out[1047]:
```

```
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/df                       frame_table   (typ->appendable,nrows->8,ncols->3,indexers->[index])
/df1_mt                   frame_table   (typ->appendable,nrows->8,ncols->2,indexers->[index],dc->[A,B
/df2_mt                   frame_table   (typ->appendable,nrows->8,ncols->5,indexers->[index])
/df_dc                    frame_table   (typ->appendable,nrows->8,ncols->5,indexers->[index],dc->[B,C
/df_mi                    frame_table   (typ->appendable_multi,nrows->10,ncols->5,indexers->[index],d
/df_mixed                 frame_table   (typ->appendable,nrows->8,ncols->7,indexers->[index])
/p4d                      wide_table    (typ->appendable,nrows->40,ncols->1,indexers->[items,major_ax
/wp                       wide_table    (typ->appendable,nrows->8,ncols->2,indexers->[major_axis,mino
/wp_big_strings           wide_table    (typ->appendable,nrows->40,ncols->2,indexers->[major_axis,min
/foo/bar/bah              frame         (shape->[8,3])
```

These, by default, index the three axes `items, major_axis, minor_axis`. On an `AppendableTable` it is possible to setup with the first append a different indexing scheme, depending on how you want to store your data. Pass the `axes` keyword with a list of dimension (currently must by exactly 1 less than the total dimensions of the object). This cannot be changed after table creation.

```
In [1048]: store.append('p4d2', p4d, axes = ['labels','major_axis','minor_axis'])

In [1049]: store
Out[1049]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/df                       frame_table   (typ->appendable,nrows->8,ncols->3,indexers->[index])
/df1_mt                   frame_table   (typ->appendable,nrows->8,ncols->2,indexers->[index],dc->[A,B
/df2_mt                   frame_table   (typ->appendable,nrows->8,ncols->5,indexers->[index])
/df_dc                    frame_table   (typ->appendable,nrows->8,ncols->5,indexers->[index],dc->[B,C
/df_mi                    frame_table   (typ->appendable_multi,nrows->10,ncols->5,indexers->[index],d
/df_mixed                 frame_table   (typ->appendable,nrows->8,ncols->7,indexers->[index])
/p4d                      wide_table    (typ->appendable,nrows->40,ncols->1,indexers->[items,major_ax
/p4d2                     wide_table    (typ->appendable,nrows->20,ncols->2,indexers->[labels,major_a
/wp                       wide_table    (typ->appendable,nrows->8,ncols->2,indexers->[major_axis,mino
/wp_big_strings           wide_table    (typ->appendable,nrows->40,ncols->2,indexers->[major_axis,min
/foo/bar/bah              frame         (shape->[8,3])

In [1050]: store.select('p4d2', [ Term('labels=l1'), Term('items=Item1'), Term('minor_axis=A_big_str
Out[1050]:
<class 'pandas.core.panelnd.Panel4D'>
Dimensions: 1 (labels) x 1 (items) x 5 (major_axis) x 1 (minor_axis)
Labels axis: l1 to l1
Items axis: Item1 to Item1
Major_axis axis: 2000-01-01 00:00:00 to 2000-01-05 00:00:00
Minor_axis axis: A_big_strings to A_big_strings
```

## 15.5 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. There wrappers only support the Python database adapters which respect the Python DB-API.

Suppose you want to query some data with different types from a table such as:

| 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 |

Functions from `pandas.io.sql` can extract some data into a DataFrame. In the following example, we use SQlite SQL database engine. You can use a temporary SQLite database where data are stored in "memory". Just do:

```
import sqlite3
from pandas.io import sql
# Create your connection.
cnx = sqlite3.connect(':memory:')
```

Let `data` be the name of your SQL table. With a query and your database connection, just use the `read_frame()` function to get the query results into a DataFrame:

```
In [1051]: sql.read_frame("SELECT * FROM data;", cnx)
Out[1051]:
   id                 date Col_1  Col_2  Col_3
0  26  2010-10-18 00:00:00     X  27.50      1
1  42  2010-10-19 00:00:00     Y -12.50      0
2  63  2010-10-20 00:00:00     Z   5.73      1
```

You can also specify the name of the column as the DataFrame index:

```
In [1052]: sql.read_frame("SELECT * FROM data;", cnx, index_col='id')
Out[1052]:
                   date Col_1  Col_2  Col_3
id
26  2010-10-18 00:00:00     X  27.50      1
42  2010-10-19 00:00:00     Y -12.50      0
63  2010-10-20 00:00:00     Z   5.73      1

In [1053]: sql.read_frame("SELECT * FROM data;", cnx, index_col='date')
Out[1053]:
                     id Col_1  Col_2  Col_3
date
2010-10-18 00:00:00  26     X  27.50      1
2010-10-19 00:00:00  42     Y -12.50      0
2010-10-20 00:00:00  63     Z   5.73      1
```

Of course, you can specify more "complex" query.

```
In [1054]: sql.read_frame("SELECT id, Col_1, Col_2 FROM data WHERE id = 42;", cnx)
Out[1054]:
   id Col_1  Col_2
0  42     Y  -12.5
```

There are a few other available functions:

- `tquery` returns list of tuples corresponding to each row.
- `uquery` does the same thing as tquery, but instead of returning results, it returns the number of related rows.
- `write_frame` writes records stored in a DataFrame into the SQL table.
- `has_table` checks if a given SQLite table exists.

**Note:** For now, writing your DataFrame into a database works only with **SQLite**. Moreover, the **index** will currently be **dropped**.

CHAPTER

SIXTEEN

# SPARSE DATA STRUCTURES

We have implemented "sparse" versions of Series, DataFrame, and Panel. These are not sparse in the typical "mostly 0". You can view these objects as being "compressed" where any data matching a specific value (NaN/missing by default, though any value can be chosen) is omitted. A special `SparseIndex` object tracks where data has been "sparsified". This will make much more sense in an example. All of the standard pandas data structures have a `to_sparse` method:

```
In [1276]: ts = Series(randn(10))

In [1277]: ts[2:-2] = np.nan

In [1278]: sts = ts.to_sparse()

In [1279]: sts
Out[1279]:
0    0.469112
1   -0.282863
2         NaN
3         NaN
4         NaN
5         NaN
6         NaN
7         NaN
8   -0.861849
9   -2.104569
dtype: float64
BlockIndex
Block locations: array([0, 8], dtype=int32)
Block lengths: array([2, 2], dtype=int32)
```

The `to_sparse` method takes a `kind` argument (for the sparse index, see below) and a `fill_value`. So if we had a mostly zero Series, we could convert it to sparse with `fill_value=0`:

```
In [1280]: ts.fillna(0).to_sparse(fill_value=0)
Out[1280]:
0    0.469112
1   -0.282863
2    0.000000
3    0.000000
4    0.000000
5    0.000000
6    0.000000
7    0.000000
8   -0.861849
9   -2.104569
```

```
dtype: float64
BlockIndex
Block locations: array([0, 8], dtype=int32)
Block lengths: array([2, 2], dtype=int32)
```

The sparse objects exist for memory efficiency reasons. Suppose you had a large, mostly NA DataFrame:

```
In [1281]: df = DataFrame(randn(10000, 4))

In [1282]: df.ix[:9998] = np.nan

In [1283]: sdf = df.to_sparse()

In [1284]: sdf
Out[1284]:
<class 'pandas.sparse.frame.SparseDataFrame'>
Int64Index: 10000 entries, 0 to 9999
Data columns:
0    1  non-null values
1    1  non-null values
2    1  non-null values
3    1  non-null values
dtypes: float64(4)

In [1285]: sdf.density
Out[1285]: 0.0001
```

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. Functionally, their behavior should be nearly identical to their dense counterparts.

Any sparse object can be converted back to the standard dense form by calling `to_dense`:

```
In [1286]: sts.to_dense()
Out[1286]:
0    0.469112
1   -0.282863
2         NaN
3         NaN
4         NaN
5         NaN
6         NaN
7         NaN
8   -0.861849
9   -2.104569
dtype: float64
```

## 16.1 SparseArray

`SparseArray` is the base layer for all of the sparse indexed data structures. It is a 1-dimensional ndarray-like object storing only values distinct from the `fill_value`:

```
In [1287]: arr = np.random.randn(10)

In [1288]: arr[2:5] = np.nan; arr[7:8] = np.nan

In [1289]: sparr = SparseArray(arr)
```

```
In [1290]: sparr
Out[1290]:
SparseArray([-1.9557, -1.6589,     nan,     nan,     nan,  1.1589,  0.1453,
            nan,  0.606 ,  1.3342])
IntIndex
Indices: array([0, 1, 5, 6, 8, 9], dtype=int32)
```

Like the indexed objects (SparseSeries, SparseDataFrame, SparsePanel), a `SparseArray` can be converted back to a regular ndarray by calling `to_dense`:

```
In [1291]: sparr.to_dense()
Out[1291]:
array([-1.9557, -1.6589,     nan,     nan,     nan,  1.1589,  0.1453,
            nan,  0.606 ,  1.3342])
```

## 16.2 SparseList

`SparseList` is a list-like data structure for managing a dynamic collection of SparseArrays. To create one, simply call the `SparseList` constructor with a `fill_value` (defaulting to `NaN`):

```
In [1292]: spl = SparseList()

In [1293]: spl
Out[1293]:
<pandas.sparse.list.SparseList object at 0xea14590>
```

The two important methods are `append` and `to_array`. `append` can accept scalar values or any 1-dimensional sequence:

```
In [1294]: spl.append(np.array([1., nan, nan, 2., 3.]))

In [1295]: spl.append(5)

In [1296]: spl.append(sparr)

In [1297]: spl
Out[1297]:
<pandas.sparse.list.SparseList object at 0xea14590>
SparseArray([ 1., nan, nan,  2.,  3.])
IntIndex
Indices: array([0, 3, 4], dtype=int32)
SparseArray([ 5.])
IntIndex
Indices: array([0], dtype=int32)
SparseArray([-1.9557, -1.6589,     nan,     nan,     nan,  1.1589,  0.1453,
            nan,  0.606 ,  1.3342])
IntIndex
Indices: array([0, 1, 5, 6, 8, 9], dtype=int32)
```

As you can see, all of the contents are stored internally as a list of memory-efficient `SparseArray` objects. Once you've accumulated all of the data, you can call `to_array` to get a single `SparseArray` with all the data:

```
In [1298]: spl.to_array()
Out[1298]:
SparseArray([ 1.    ,     nan,     nan,  2.    ,  3.    ,  5.    , -1.9557,
       -1.6589,     nan,     nan,     nan,  1.1589,  0.1453,     nan,
```

```
        0.606 ,  1.3342])
IntIndex
Indices: array([ 0,  3,  4,  5,  6,  7, 11, 12, 14, 15], dtype=int32)
```

## 16.3 SparseIndex objects

Two kinds of `SparseIndex` are implemented, `block` and `integer`. We recommend using `block` as it's more memory efficient. The `integer` format keeps an arrays of all of the locations where the data are not equal to the fill value. The `block` format tracks only the locations and sizes of blocks of data.

CHAPTER

SEVENTEEN

# CAVEATS AND GOTCHAS

## 17.1 NaN, Integer NA values and NA type promotions

### 17.1.1 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
- 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 isnull and notnull 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.

### 17.1.2 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 [488]: s = Series([1, 2, 3, 4, 5], index=list('abcde'))

In [489]: s
Out[489]:
a    1
b    2
c    3
d    4
e    5
dtype: int64

In [490]: s.dtype
Out[490]: dtype('int64')

In [491]: s2 = s.reindex(['a', 'b', 'c', 'f', 'u'])

In [492]: s2
Out[492]:
a     1
```

```
b     2
c     3
f   NaN
u   NaN
dtype: float64

In [493]: s2.dtype
Out[493]: dtype('float64')
```

This trade-off is made largely for memory and performance reasons, and also so that the resulting Series continues to be "numeric". One possibility is to use `dtype=object` arrays instead.

### 17.1.3 `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. These are summarized by 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, in practice I have found very few cases where this is an issue in practice. Some explanation for the motivation here in the next section.

### 17.1.4 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 langauge 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.

## 17.2 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 `.ix`. The following code will generate exceptions:

```
s = Series(range(5))
s[-1]
df = DataFrame(np.random.randn(5, 4))
df
df.ix[-2:]
```

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).

## 17.3 Label-based slicing conventions

### 17.3.1 Non-monotonic indexes require exact matches

### 17.3.2 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 [494]: s = Series(randn(6), index=list('abcdef'))

In [495]: s
Out[495]:
a    1.337122
b   -1.531095
c    1.331458
d   -0.571329
e   -0.026671
f   -1.085663
dtype: float64
```

Suppose we wished to slice from `c` to `e`, using integers this would be

```
In [496]: s[2:5]
Out[496]:
c    1.331458
d   -0.571329
e   -0.026671
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.ix['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 design to make label-based slicing include both endpoints:

```
In [497]: s.ix['c':'e']
Out[497]:
c    1.331458
d   -0.571329
e   -0.026671
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.

## 17.4 Miscellaneous indexing gotchas

### 17.4.1 Reindex versus ix gotchas

Many users will find themselves using the `ix` indexing capabilities as a concise means of selecting data from a pandas object:

```
In [498]: df = DataFrame(randn(6, 4), columns=['one', 'two', 'three', 'four'],
   .....:                index=list('abcdef'))
   .....:

In [499]: df
Out[499]:
        one       two     three      four
a -1.114738 -0.058216 -0.486768  1.685148
b  0.112572 -1.495309  0.898435 -0.148217
c -1.596070  0.159653  0.262136  0.036220
d  0.184735 -0.255069 -0.271020  1.288393
e  0.294633 -1.165787  0.846974 -0.685597
f  0.609099 -0.303961  0.625555 -0.059268

In [500]: df.ix[['b', 'c', 'e']]
Out[500]:
        one       two     three      four
b  0.112572 -1.495309  0.898435 -0.148217
c -1.596070  0.159653  0.262136  0.036220
e  0.294633 -1.165787  0.846974 -0.685597
```

This is, of course, completely equivalent *in this case* to using th `reindex` method:

```
In [501]: df.reindex(['b', 'c', 'e'])
Out[501]:
        one       two     three      four
b  0.112572 -1.495309  0.898435 -0.148217
c -1.596070  0.159653  0.262136  0.036220
e  0.294633 -1.165787  0.846974 -0.685597
```

Some might conclude that `ix` and `reindex` are 100% equivalent based on this. This is indeed true **except in the case of integer indexing**. For example, the above operation could alternately have been expressed as:

```
In [502]: df.ix[[1, 2, 4]]
Out[502]:
        one       two     three      four
b  0.112572 -1.495309  0.898435 -0.148217
c -1.596070  0.159653  0.262136  0.036220
e  0.294633 -1.165787  0.846974 -0.685597
```

If you pass `[1, 2, 4]` to `reindex` you will get another thing entirely:

```
In [503]: df.reindex([1, 2, 4])
Out[503]:
   one  two  three  four
1  NaN  NaN    NaN   NaN
2  NaN  NaN    NaN   NaN
4  NaN  NaN    NaN   NaN
```

So it's important to remember that `reindex` is **strict label indexing only**. This can lead to some potentially surprising results in pathological cases where an index contains, say, both integers and strings:

```
In [504]: s = Series([1, 2, 3], index=['a', 0, 1])

In [505]: s
Out[505]:
a    1
0    2
1    3
dtype: int64

In [506]: s.ix[[0, 1]]
Out[506]:
0    2
1    3
dtype: int64

In [507]: s.reindex([0, 1])
Out[507]:
0    2
1    3
dtype: int64
```

Because the index in this case does not contain solely integers, `ix` falls back on integer indexing. By contrast, `reindex` only looks for the values passed in the index, thus finding the integers `0` and `1`. While it would be possible to insert some logic to check whether a passed sequence is all contained in the index, that logic would exact a very high cost in large data sets.

### 17.4.2 Reindex potentially changes underlying Series dtype

The use of `reindex_like` can potentially change the dtype of a `Series`.

```
series = pandas.Series([1, 2, 3])
x = pandas.Series([True])
x.dtype
x = pandas.Series([True]).reindex_like(series)
x.dtype
```

This is because `reindex_like` 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.

## 17.5 Timestamp limitations

### 17.5.1 Minimum and maximum timestamps

Since pandas represents timestamps in nanosecond resolution, the timespan that can be represented using a 64-bit integer is limited to approximately 584 years:

```
In [508]: begin = Timestamp(-9223285636854775809L)

In [509]: begin
Out[509]: <Timestamp: 1677-09-22 00:12:43.145224191>

In [510]: end = Timestamp(np.iinfo(np.int64).max)

In [511]: end
Out[511]: <Timestamp: 2262-04-11 23:47:16.854775807>
```

If you need to represent time series data outside the nanosecond timespan, use PeriodIndex:

```
In [512]: span = period_range('1215-01-01', '1381-01-01', freq='D')

In [513]: span
Out[513]:
<class 'pandas.tseries.period.PeriodIndex'>
freq: D
[1215-01-01, ..., 1381-01-01]
length: 60632
```

## 17.6 Parsing Dates from Text Files

When parsing multiple text file columns into a single date column, the new date column is prepended to the data and then *index_col* specification is indexed off of the new set of columns rather than the original ones:

```
In [514]: 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 [515]: date_spec = {'nominal': [1, 2], 'actual': [1, 3]}

In [516]: df = read_csv('tmp.csv', header=None,
   .....:                 parse_dates=date_spec,
   .....:                 keep_date_col=True,
   .....:                 index_col=0)
   .....:

# index_col=0 refers to the combined column "nominal" and not the original
# first column of 'KORD' strings
In [517]: df
Out[517]:
                                 actual     0         1          2          3     4
nominal
```

```
1999-01-27 19:00:00 1999-01-27 18:56:00  KORD  19990127   19:00:00   18:56:00  0.81
1999-01-27 20:00:00 1999-01-27 19:56:00  KORD  19990127   20:00:00   19:56:00  0.01
1999-01-27 21:00:00 1999-01-27 20:56:00  KORD  19990127   21:00:00   20:56:00 -0.59
1999-01-27 21:00:00 1999-01-27 21:18:00  KORD  19990127   21:00:00   21:18:00 -0.99
1999-01-27 22:00:00 1999-01-27 21:56:00  KORD  19990127   22:00:00   21:56:00 -0.59
1999-01-27 23:00:00 1999-01-27 22:56:00  KORD  19990127   23:00:00   22:56:00 -0.59
```

## 17.7 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.

CHAPTER

EIGHTEEN

# RPY2 / R INTERFACE

**Note:** This is all highly experimental. I would like to get more people involved with building a nice RPy2 interface for pandas

If your computer has R and rpy2 (> 2.2) installed (which will be left to the reader), you will be able to leverage the below functionality. On Windows, doing this is quite an ordeal at the moment, but users on Unix-like systems should find it quite easy. rpy2 evolves in time, and is currently reaching its release 2.3, while the current interface is designed for the 2.2.x series. We recommend to use 2.2.x over other series unless you are prepared to fix parts of the code, yet the rpy2-2.3.0 introduces improvements such as a better R-Python bridge memory management layer so I might be a good idea to bite the bullet and submit patches for the few minor differences that need to be fixed.

```
# if installing for the first time
hg clone http://bitbucket.org/lgautier/rpy2

cd rpy2
hg pull
hg update version_2.2.x
sudo python setup.py install
```

**Note:** To use R packages with this interface, you will need to install them inside R yourself. At the moment it cannot install them for you.

Once you have done installed R and rpy2, you should be able to import `pandas.rpy.common` without a hitch.

## 18.1 Transferring R data sets into Python

The **load_data** function retrieves an R data set and converts it to the appropriate pandas object (most likely a DataFrame):

```
In [1214]: import pandas.rpy.common as com

In [1215]: infert = com.load_data('infert')

In [1216]: infert.head()
Out[1216]:
  education  age  parity  induced  case  spontaneous  stratum  pooled.stratum
1    0-5yrs   26       6        1     1            2        1               3
2    0-5yrs   42       1        1     1            0        2               1
3    0-5yrs   39       6        2     1            0        3               4
```

```
4     0-5yrs    34        4         2      1             0         4              2
5    6-11yrs    35        3         1      1             1         5             32
```

## 18.2 Converting DataFrames into R objects

New in version 0.8. Starting from pandas 0.8, there is **experimental** support to convert DataFrames into the equivalent R object (that is, **data.frame**):

```
In [1217]: from pandas import DataFrame

In [1218]: df = DataFrame({'A': [1, 2, 3], 'B': [4, 5, 6], 'C':[7,8,9]},
   ......:                index=["one", "two", "three"])
   ......:

In [1219]: r_dataframe = com.convert_to_r_dataframe(df)

In [1220]: print type(r_dataframe)
<class 'rpy2.robjects.vectors.DataFrame'>

In [1221]: print r_dataframe
      A B C
one   1 4 7
two   2 5 8
three 3 6 9
```

The DataFrame's index is stored as the `rownames` attribute of the data.frame instance.

You can also use **convert_to_r_matrix** to obtain a `Matrix` instance, but bear in mind that it will only work with homogeneously-typed DataFrames (as R matrices bear no information on the data type):

```
In [1222]: r_matrix = com.convert_to_r_matrix(df)

In [1223]: print type(r_matrix)
<class 'rpy2.robjects.vectors.Matrix'>

In [1224]: print r_matrix
      A B C
one   1 4 7
two   2 5 8
three 3 6 9
```

## 18.3 Calling R functions with pandas objects

## 18.4 High-level interface to R estimators

CHAPTER

NINETEEN

# RELATED PYTHON LIBRARIES

## 19.1 la (larry)

Keith Goodman's excellent labeled array package is very similar to pandas in many regards, though with some key differences. The main philosophical design difference is to be a wrapper around a single NumPy `ndarray` object while adding axis labeling and label-based operations and indexing. Because of this, creating a size-mutable object with heterogeneous columns (e.g. DataFrame) is not possible with the `la` package.

- Provide a single n-dimensional object with labeled axes with functionally analogous data alignment semantics to pandas objects
- Advanced / label-based indexing similar to that provided in pandas but setting is not supported
- Stays much closer to NumPy arrays than pandas– `larry` objects must be homogeneously typed
- GroupBy support is relatively limited, but a few functions are available: `group_mean`, `group_median`, and `group_ranking`
- It has a collection of analytical functions suited to quantitative portfolio construction for financial applications
- It has a collection of moving window statistics implemented in Bottleneck

## 19.2 statsmodels

The main statistics and econometrics library for Python. pandas has become a dependency of this library.

## 19.3 scikits.timeseries

scikits.timeseries provides a data structure for fixed frequency time series data based on the numpy.MaskedArray class. For time series data, it provides some of the same functionality to the pandas Series class. It has many more functions for time series-specific manipulation. Also, it has support for many more frequencies, though less customizable by the user (so 5-minutely data is easier to do with pandas for example).

We are aiming to merge these libraries together in the near future.

Progress:

- It has a collection of moving window statistics implemented in Bottleneck
- Outstanding issues

Summarising, Pandas offers superior functionality due to its combination with the `pandas.DataFrame`.

An introduction for former users of `scikits.timeseries` is provided in the *migration guide*.

CHAPTER

TWENTY

# 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 it's many 3rd party libraries as they relate to pandas. In offering 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 or harder to use (you may have to be the judge of this given side-by-side code comparisons)

As I do not have an encyclopedic knowledge of R packages, feel free to suggest additional CRAN packages to add to this list. This is also here to offer a big of a translation guide for users of these R packages.

## 20.1 data.frame

## 20.2 zoo

## 20.3 xts

## 20.4 plyr

## 20.5 reshape / reshape2

CHAPTER

TWENTYONE

# API REFERENCE

## 21.1 General functions

### 21.1.1 Data manipulations

| | |
|---|---|
| pivot_table(data[, values, rows, cols, ...]) | Create a spreadsheet-style pivot table as a DataFrame. The levels in the |

#### pandas.tools.pivot.pivot_table

pandas.tools.pivot.**pivot_table**(*data*, *values=None*, *rows=None*, *cols=None*, *aggfunc='mean'*, *fill_value=None*, *margins=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

**rows** : list of column names or arrays to group on

Keys to group on the x-axis of the pivot table

**cols** : list of column names or arrays to group on

Keys to group on the y-axis of the pivot table

**aggfunc** : function, default numpy.mean, or list of functions

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)

**fill_value** : scalar, default None

Value to replace missing values with

**margins** : boolean, default False

Add all row / columns (e.g. for subtotal / grand totals)

**Returns** **table** : DataFrame

### Examples

```
>>> df
   A   B   C      D
0  foo one small  1
1  foo one large  2
2  foo one large  2
3  foo two small  3
4  foo two small  3
5  bar one large  4
6  bar one small  5
7  bar two small  6
8  bar two large  7

>>> table = pivot_table(df, values='D', rows=['A', 'B'],
...                     cols=['C'], aggfunc=np.sum)
>>> table
          small  large
foo  one  1      4
     two  6      NaN
bar  one  5      4
     two  6      7
```

| | |
|---|---|
| merge(left, right[, how, on, left_on, ...]) | Merge DataFrame objects by performing a database-style join operation by |
| concat(objs[, axis, join, join_axes, ...]) | Concatenate pandas objects along a particular axis with optional set logic along the other a |

## pandas.tools.merge.merge

pandas.tools.merge.**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*)

Merge DataFrame objects by performing a database-style join operation by 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.

**Parameters** **left** : DataFrame

**right** : DataFrame

**how** : {'left', 'right', 'outer', 'inner'}, default 'inner'

- 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)

**on** : label or list

Field names to join on. Must be found in both DataFrames. If on is None and not merging on indexes, then it merges on the intersection of the columns by default.

**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_index** : boolean, 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** : boolean, default False

Use the index from the right DataFrame as the join key. Same caveats as left_index

**sort** : boolean, default False

Sort the join keys lexicographically in the result DataFrame

**suffixes** : 2-length sequence (tuple, list, ...)

Suffix to apply to overlapping column names in the left and right side, respectively

**copy** : boolean, default True

If False, do not copy data unnecessarily

**Returns** **merged** : DataFrame

### Examples

```
>>> A              >>> B
    lkey value         rkey value
0   foo  1         0   foo  5
1   bar  2         1   bar  6
2   baz  3         2   qux  7
3   foo  4         3   bar  8
```

```
>>> merge(A, B, left_on='lkey', right_on='rkey', how='outer')
   lkey  value_x  rkey  value_y
0  bar   2        bar   6
1  bar   2        bar   8
2  baz   3        NaN   NaN
3  foo   1        foo   5
4  foo   4        foo   5
5  NaN   NaN      qux   7
```

## pandas.tools.merge.concat

pandas.tools.merge.**concat**(*objs*, *axis=0*, *join='outer'*, *join_axes=None*, *ignore_index=False*, *keys=None*, *levels=None*, *names=None*, *verify_integrity=False*)

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** : list or dict of Series, DataFrame, or Panel 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 an Exception 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)

**join_axes** : list of Index objects

Specific indexes to use for the other n - 1 axes instead of performing inner/outer set logic

**verify_integrity** : boolean, default False

Check whether the new concatenated axis contains duplicates. This can be very expensive relative to the actual data concatenation

**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

**ignore_index** : boolean, 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 the index values on the other axes are still respected in the join.

**Returns** **concatenated** : type of objects

#### Notes

The keys, levels, and names arguments are all optional

### 21.1.2 Pickling

| | |
|---|---|
| `load`(path) | Load pickled pandas object (or any other pickled object) from the specified |
| `save`(obj, path) | Pickle (serialize) object to input file path |

#### pandas.core.common.load

`pandas.core.common.`**`load`**(*path*)

Load pickled pandas object (or any other pickled object) from the specified file path

**Parameters** **path** : string

File path

**Returns** **unpickled** : type of object stored in file

#### pandas.core.common.save

pandas.core.common.**save**(*obj*, *path*)
Pickle (serialize) object to input file path

**Parameters** **obj** : any object

**path** : string

File path

### 21.1.3 File IO

| | |
|---|---|
| read_table(filepath_or_buffer[, sep, ...]) | Read general delimited file into DataFrame |
| read_csv(filepath_or_buffer[, sep, dialect, ...]) | Read CSV (comma-separated) file into DataFrame |
| ExcelFile.parse(sheetname[, header, ...]) | Read Excel table into DataFrame |

#### pandas.io.parsers.read_table

pandas.io.parsers.**read_table**(*filepath_or_buffer*, *sep='\t'*, *dialect=None*, *compression=None*, *doublequote=True*, *escapechar=None*, *quotechar='"'*, *quoting=0*, *skipinitialspace=False*, *lineterminator=None*, *header='infer'*, *index_col=None*, *names=None*, *prefix=None*, *skiprows=None*, *skipfooter=None*, *skip_footer=0*, *na_values=None*, *true_values=None*, *false_values=None*, *delimiter=None*, *converters=None*, *dtype=None*, *usecols=None*, *engine='c'*, *delim_whitespace=False*, *as_recarray=False*, *na_filter=True*, *compact_ints=False*, *use_unsigned=False*, *low_memory=True*, *buffer_lines=None*, *warn_bad_lines=True*, *error_bad_lines=True*, *keep_default_na=True*, *thousands=None*, *comment=None*, *decimal='.'*, *parse_dates=False*, *keep_date_col=False*, *dayfirst=False*, *date_parser=None*, *memory_map=False*, *nrows=None*, *iterator=False*, *chunksize=None*, *verbose=False*, *encoding=None*, *squeeze=False*)
Read general delimited file into DataFrame

Also supports optionally iterating or breaking of the file into chunks.

**Parameters** **filepath_or_buffer** : string or file handle / StringIO. The string could be

a URL. Valid URL schemes include http, ftp, and file. For file URLs, a host is expected. For instance, a local file could be file ://localhost/path/to/table.csv

**sep** : string, default t (tab-stop)

Delimiter to use. Regular expressions are accepted.

**lineterminator** : string (length 1), default None

Character to break file into lines. Only valid with C parser

**quotechar** : string

**quoting** : string

**skipinitialspace** : boolean, default False

Skip spaces after delimiter

**escapechar** : string

**dtype** : Type name or dict of column -> type

Data type for data or columns. E.g. {'a': np.float64, 'b': np.int32}

**compression** : {'gzip', 'bz2', None}, default None

For on-the-fly decompression of on-disk data

**dialect** : string or csv.Dialect instance, default None

If None defaults to Excel dialect. Ignored if sep longer than 1 char See csv.Dialect documentation for more details

**header** : int, default 0 if names parameter not specified, otherwise None

Row to use for the column labels of the parsed DataFrame. Specify None if there is no header row.

**skiprows** : list-like or integer

Row numbers to skip (0-indexed) or number of rows to skip (int) at the start of the file

**index_col** : int or sequence or False, default None

Column to use as the row labels of the DataFrame. If a sequence is given, a MultiIndex is used. If you have a malformed file with delimiters at the end of each line, you might consider index_col=False to force pandas to _not_ use the first column as the index (row names)

**names** : array-like

List of column names to use. If file contains no header row, then you should explicitly pass header=None

**prefix** : string or None (default)

Prefix to add to column numbers when no header, e.g 'X' for X0, X1, ...

**na_values** : list-like or dict, default None

Additional strings to recognize as NA/NaN. If dict passed, specific per-column NA values

**true_values** : list

Values to consider as True

**false_values** : list

Values to consider as False

**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

**parse_dates** : boolean, list of ints or names, list of lists, or dict

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. {'foo' : [1, 3]} -> parse columns 1, 3 as date and call result 'foo'

**keep_date_col** : boolean, default False

If True and parse_dates specifies combining multiple columns then keep the original columns.

**date_parser** : function

Function to use for converting dates to strings. Defaults to dateutil.parser

**dayfirst** : boolean, default False

DD/MM format dates, international and European format

**thousands** : str, default None

Thousands separator

**comment** : str, default None

Indicates remainder of line should not be parsed Does not support line commenting (will return empty line)

**decimal** : str, default '.'

Character to recognize as decimal point. E.g. use ',' for European data

**nrows** : int, default None

Number of rows of file to read. Useful for reading pieces of large files

**iterator** : boolean, default False

Return TextParser object

**chunksize** : int, default None

Return TextParser object for iteration

**skipfooter** : int, default 0

Number of line at bottom of file to skip

**converters** : dict. optional

Dict of functions for converting values in certain columns. Keys can either be integers or column labels

**verbose** : boolean, default False

Indicate number of NA values placed in non-numeric columns

**delimiter** : string, default None

Alternative argument name for sep. Regular expressions are accepted.

**encoding** : string, default None

Encoding to use for UTF when reading/writing (ex. 'utf-8')

**squeeze** : boolean, default False

If the parsed data only contains one column then return a Series

**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

**Returns** **result** : DataFrame or TextParser

### pandas.io.parsers.read_csv

pandas.io.parsers.**read_csv**(*filepath_or_buffer*, *sep=', '*, *dialect=None*, *compression=None*, *doublequote=True*, *escapechar=None*, *quotechar='"'*, *quoting=0*, *skipinitialspace=False*, *lineterminator=None*, *header='infer'*, *index_col=None*, *names=None*, *prefix=None*, *skiprows=None*, *skipfooter=None*, *skip_footer=0*, *na_values=None*, *true_values=None*, *false_values=None*, *delimiter=None*, *converters=None*, *dtype=None*, *usecols=None*, *engine='c'*, *delim_whitespace=False*, *as_recarray=False*, *na_filter=True*, *compact_ints=False*, *use_unsigned=False*, *low_memory=True*, *buffer_lines=None*, *warn_bad_lines=True*, *error_bad_lines=True*, *keep_default_na=True*, *thousands=None*, *comment=None*, *decimal='.'*, *parse_dates=False*, *keep_date_col=False*, *dayfirst=False*, *date_parser=None*, *memory_map=False*, *nrows=None*, *iterator=False*, *chunksize=None*, *verbose=False*, *encoding=None*, *squeeze=False*)

Read CSV (comma-separated) file into DataFrame

Also supports optionally iterating or breaking of the file into chunks.

**Parameters** **filepath_or_buffer** : string or file handle / StringIO. The string could be

a URL. Valid URL schemes include http, ftp, and file. For file URLs, a host is expected. For instance, a local file could be file ://localhost/path/to/table.csv

**sep** : string, default ','

Delimiter to use. If sep is None, will try to automatically determine this. Regular expressions are accepted.

**lineterminator** : string (length 1), default None

Character to break file into lines. Only valid with C parser

**quotechar** : string

**quoting** : string

**skipinitialspace** : boolean, default False

Skip spaces after delimiter

**escapechar** : string

**dtype** : Type name or dict of column -> type

Data type for data or columns. E.g. {'a': np.float64, 'b': np.int32}

**compression** : {'gzip', 'bz2', None}, default None

For on-the-fly decompression of on-disk data

**dialect** : string or csv.Dialect instance, default None

If None defaults to Excel dialect. Ignored if sep longer than 1 char See csv.Dialect documentation for more details

**header** : int, default 0 if names parameter not specified, otherwise None

Row to use for the column labels of the parsed DataFrame. Specify None if there is no header row.

**skiprows** : list-like or integer

Row numbers to skip (0-indexed) or number of rows to skip (int) at the start of the file

**index_col** : int or sequence or False, default None

Column to use as the row labels of the DataFrame. If a sequence is given, a MultiIndex is used. If you have a malformed file with delimiters at the end of each line, you might consider index_col=False to force pandas to _not_ use the first column as the index (row names)

**names** : array-like

List of column names to use. If file contains no header row, then you should explicitly pass header=None

**prefix** : string or None (default)

Prefix to add to column numbers when no header, e.g 'X' for X0, X1, ...

**na_values** : list-like or dict, default None

Additional strings to recognize as NA/NaN. If dict passed, specific per-column NA values

**true_values** : list

Values to consider as True

**false_values** : list

Values to consider as False

**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

**parse_dates** : boolean, list of ints or names, list of lists, or dict

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. {'foo' : [1, 3]} -> parse columns 1, 3 as date and call result 'foo'

**keep_date_col** : boolean, default False

If True and parse_dates specifies combining multiple columns then keep the original columns.

**date_parser** : function

Function to use for converting dates to strings. Defaults to dateutil.parser

**dayfirst** : boolean, default False

DD/MM format dates, international and European format

**thousands** : str, default None

Thousands separator

**comment** : str, default None

Indicates remainder of line should not be parsed Does not support line commenting (will return empty line)

**decimal** : str, default '.'

Character to recognize as decimal point. E.g. use ',' for European data

**nrows** : int, default None

Number of rows of file to read. Useful for reading pieces of large files

**iterator** : boolean, default False

Return TextParser object

**chunksize** : int, default None

Return TextParser object for iteration

**skipfooter** : int, default 0

Number of line at bottom of file to skip

**converters** : dict. optional

Dict of functions for converting values in certain columns. Keys can either be integers or column labels

**verbose** : boolean, default False

Indicate number of NA values placed in non-numeric columns

**delimiter** : string, default None

Alternative argument name for sep. Regular expressions are accepted.

**encoding** : string, default None

Encoding to use for UTF when reading/writing (ex. 'utf-8')

**squeeze** : boolean, default False

If the parsed data only contains one column then return a Series

**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

**Returns** **result** : DataFrame or TextParser

### pandas.io.parsers.ExcelFile.parse

ExcelFile.**parse**(*sheetname*, *header=0*, *skiprows=None*, *skip_footer=0*, *index_col=None*, *parse_cols=None*, *parse_dates=False*, *date_parser=None*, *na_values=None*, *thousands=None*, *chunksize=None*, ***kwds*)

Read Excel table into DataFrame

**Parameters** **sheetname** : string

Name of Excel sheet

**header** : int, default 0

Row to use for the column labels of the parsed DataFrame

**skiprows** : list-like

Rows to skip at the beginning (0-indexed)

**skip_footer** : int, default 0

Rows at the end to skip (0-indexed)

**index_col** : int, default None

Column to use as the row labels of the DataFrame. Pass None if there is no such column

**parse_cols** : int or list, default None

If None then parse all columns, If int then indicates last column to be parsed If list of ints then indicates list of column numbers to be parsed If string then indicates comma separated list of column names and

column ranges (e.g. "A:E" or "A,C,E:F")

**na_values** : list-like, default None

List of additional strings to recognize as NA/NaN

**Returns parsed** : DataFrame

### 21.1.4 HDFStore: PyTables (HDF5)

| | |
|---|---|
| `HDFStore.put`(key, value[, table, append]) | Store object in HDFStore |
| `HDFStore.get`(key) | Retrieve pandas object stored in file |

#### pandas.io.pytables.HDFStore.put

`HDFStore.put` (*key*, *value*, *table=None*, *append=False*, ***kwargs*)

Store object in HDFStore

**Parameters key** : object

**value** : {Series, DataFrame, Panel}

**table** : boolean, default False

Write as a PyTables Table structure which may perform worse but allow more flexible operations like searching / selecting subsets of the data

**append** : boolean, default False

For table data structures, append the input data to the existing table

#### pandas.io.pytables.HDFStore.get

`HDFStore.get` (*key*)

Retrieve pandas object stored in file

**Parameters key** : object

**Returns obj** : type of object stored in file

### 21.1.5 Standard moving window functions

| | |
|---|---|
| `rolling_count`(arg, window[, freq, center, ...]) | Rolling count of number of non-NaN observations inside provided window. |
| `rolling_sum`(arg, window[, min_periods, ...]) | Moving sum |
| `rolling_mean`(arg, window[, min_periods, ...]) | Moving mean |
| `rolling_median`(arg, window[, min_periods, ...]) | O(N log(window)) implementation using skip list |
| `rolling_var`(arg, window[, min_periods, ...]) | Unbiased moving variance |

Continued on next page

Table 21.6 – continued from previous page

| | |
|---|---|
| rolling_std(arg, window[, min_periods, ...]) | Unbiased moving standard deviation |
| rolling_corr(arg1, arg2, window[, ...]) | Moving sample correlation |
| rolling_cov(arg1, arg2, window[, ...]) | Unbiased moving covariance |
| rolling_skew(arg, window[, min_periods, ...]) | Unbiased moving skewness |
| rolling_kurt(arg, window[, min_periods, ...]) | Unbiased moving kurtosis |
| rolling_apply(arg, window, func[, ...]) | Generic moving function application |
| rolling_quantile(arg, window, quantile[, ...]) | Moving quantile |

### pandas.stats.moments.rolling_count

pandas.stats.moments.**rolling_count**(*arg*, *window*, *freq=None*, *center=False*, *time_rule=None*)

Rolling count of number of non-NaN observations inside provided window.

**Parameters** **arg** : DataFrame or numpy ndarray-like

**window** : Number of observations used for calculating statistic

**freq** : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic

**center** : boolean, default False

Whether the label should correspond with center of window

**Returns** **rolling_count** : type of caller

### pandas.stats.moments.rolling_sum

pandas.stats.moments.**rolling_sum**(*arg*, *window*, *min_periods=None*, *freq=None*, *center=False*, *time_rule=None*, ***kwargs*)

Moving sum

**Parameters** **arg** : Series, DataFrame

**window** : Number of observations used for calculating statistic

**min_periods** : int

Minimum number of observations in window required to have a value

**freq** : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic time_rule is a legacy alias for freq

**Returns** **y** : type of input argument

### pandas.stats.moments.rolling_mean

pandas.stats.moments.**rolling_mean**(*arg*, *window*, *min_periods=None*, *freq=None*, *center=False*, *time_rule=None*, ***kwargs*)

Moving mean

**Parameters** **arg** : Series, DataFrame

**window** : Number of observations used for calculating statistic

**min_periods** : int

Minimum number of observations in window required to have a value

**freq** : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic time_rule is a legacy alias for freq

**Returns** **y** : type of input argument

### pandas.stats.moments.rolling_median

pandas.stats.moments.**rolling_median**(*arg*, *window*, *min_periods=None*, *freq=None*, *center=False*, *time_rule=None*, ***kwargs*)

O(N log(window)) implementation using skip list

Moving median

**Parameters** **arg** : Series, DataFrame

**window** : Number of observations used for calculating statistic

**min_periods** : int

Minimum number of observations in window required to have a value

**freq** : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic time_rule is a legacy alias for freq

**Returns** **y** : type of input argument

### pandas.stats.moments.rolling_var

pandas.stats.moments.**rolling_var**(*arg*, *window*, *min_periods=None*, *freq=None*, *center=False*, *time_rule=None*, ***kwargs*)

Unbiased moving variance

**Parameters** **arg** : Series, DataFrame

**window** : Number of observations used for calculating statistic

**min_periods** : int

Minimum number of observations in window required to have a value

**freq** : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic time_rule is a legacy alias for freq

**Returns** **y** : type of input argument

### pandas.stats.moments.rolling_std

pandas.stats.moments.**rolling_std**(*arg*, *window*, *min_periods=None*, *freq=None*, *center=False*, *time_rule=None*, ***kwargs*)

Unbiased moving standard deviation

**Parameters** **arg** : Series, DataFrame

**window** : Number of observations used for calculating statistic

**min_periods** : int

Minimum number of observations in window required to have a value

**freq** : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic time_rule is a legacy alias for freq

**Returns** **y** : type of input argument

### pandas.stats.moments.rolling_corr

pandas.stats.moments.**rolling_corr**(*arg1*, *arg2*, *window*, *min_periods=None*, *freq=None*, *center=False*, *time_rule=None*)

Moving sample correlation

**Parameters** **arg1** : Series, DataFrame, or ndarray

**arg2** : Series, DataFrame, or ndarray

**window** : Number of observations used for calculating statistic

**min_periods** : int

Minimum number of observations in window required to have a value

**freq** : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic time_rule is a legacy alias for freq

**Returns** **y** : type depends on inputs

DataFrame / DataFrame -> DataFrame (matches on columns) DataFrame / Series -> Computes result for each column Series / Series -> Series

### pandas.stats.moments.rolling_cov

pandas.stats.moments.**rolling_cov**(*arg1*, *arg2*, *window*, *min_periods=None*, *freq=None*, *center=False*, *time_rule=None*)

Unbiased moving covariance

**Parameters** **arg1** : Series, DataFrame, or ndarray

**arg2** : Series, DataFrame, or ndarray

**window** : Number of observations used for calculating statistic

**min_periods** : int

Minimum number of observations in window required to have a value

**freq** : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic time_rule is a legacy alias for freq

**Returns** **y** : type depends on inputs

DataFrame / DataFrame -> DataFrame (matches on columns) DataFrame / Series -> Computes result for each column Series / Series -> Series

### pandas.stats.moments.rolling_skew

pandas.stats.moments.**rolling_skew**(*arg*, *window*, *min_periods=None*, *freq=None*, *center=False*, *time_rule=None*, ***kwargs*)

Unbiased moving skewness

**Parameters** **arg** : Series, DataFrame

**window** : Number of observations used for calculating statistic

**min_periods** : int

Minimum number of observations in window required to have a value

**freq** : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic time_rule is a legacy alias for freq

**Returns** **y** : type of input argument

### pandas.stats.moments.rolling_kurt

pandas.stats.moments.**rolling_kurt**(*arg*, *window*, *min_periods=None*, *freq=None*, *center=False*, *time_rule=None*, ***kwargs*)

Unbiased moving kurtosis

**Parameters** **arg** : Series, DataFrame

**window** : Number of observations used for calculating statistic

**min_periods** : int

Minimum number of observations in window required to have a value

**freq** : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic time_rule is a legacy alias for freq

**Returns** **y** : type of input argument

### pandas.stats.moments.rolling_apply

pandas.stats.moments.**rolling_apply**(*arg*, *window*, *func*, *min_periods=None*, *freq=None*, *center=False*, *time_rule=None*)

Generic moving function application

**Parameters** **arg** : Series, DataFrame

**window** : Number of observations used for calculating statistic

**func** : function

Must produce a single value from an ndarray input

**min_periods** : int

Minimum number of observations in window required to have a value

**freq** : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic

**center** : boolean, default False

Whether the label should correspond with center of window

**Returns** **y** : type of input argument

### pandas.stats.moments.rolling_quantile

pandas.stats.moments.**rolling_quantile**(*arg*, *window*, *quantile*, *min_periods=None*, *freq=None*, *center=False*, *time_rule=None*)

Moving quantile

**Parameters** **arg** : Series, DataFrame

**window** : Number of observations used for calculating statistic

**quantile** : 0 <= quantile <= 1

**min_periods** : int

Minimum number of observations in window required to have a value

**freq** : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic

**center** : boolean, default False

Whether the label should correspond with center of window

**Returns** **y** : type of input argument

## 21.1.6 Standard expanding window functions

| | |
|---|---|
| expanding_count(arg[, freq, center, time_rule]) | Expanding count of number of non-NaN observations. |
| expanding_sum(arg[, min_periods, freq, ...]) | Expanding sum |
| expanding_mean(arg[, min_periods, freq, ...]) | Expanding mean |
| expanding_median(arg[, min_periods, freq, ...]) | O(N log(window)) implementation using skip list |
| expanding_var(arg[, min_periods, freq, ...]) | Unbiased expanding variance |
| expanding_std(arg[, min_periods, freq, ...]) | Unbiased expanding standard deviation |
| expanding_corr(arg1, arg2[, min_periods, ...]) | Expanding sample correlation |
| expanding_cov(arg1, arg2[, min_periods, ...]) | Unbiased expanding covariance |
| expanding_skew(arg[, min_periods, freq, ...]) | Unbiased expanding skewness |
| expanding_kurt(arg[, min_periods, freq, ...]) | Unbiased expanding kurtosis |
| expanding_apply(arg, func[, min_periods, ...]) | Generic expanding function application |
| expanding_quantile(arg, quantile[, ...]) | Expanding quantile |

### pandas.stats.moments.expanding_count

pandas.stats.moments.**expanding_count**(*arg*, *freq=None*, *center=False*, *time_rule=None*)

Expanding count of number of non-NaN observations.

**Parameters** **arg** : DataFrame or numpy ndarray-like

**freq** : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic

**center** : boolean, default False

Whether the label should correspond with center of window

**Returns** **expanding_count** : type of caller

### pandas.stats.moments.expanding_sum

pandas.stats.moments.**expanding_sum**(*arg*, *min_periods=1*, *freq=None*, *center=False*, *time_rule=None*, ***kwargs*)

Expanding sum

**Parameters** **arg** : Series, DataFrame

**min_periods** : int

Minimum number of observations in window required to have a value

**freq** : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic

**Returns** **y** : type of input argument

### pandas.stats.moments.expanding_mean

pandas.stats.moments.**expanding_mean**(*arg*, *min_periods=1*, *freq=None*, *center=False*, *time_rule=None*, ***kwargs*)

Expanding mean

**Parameters** **arg** : Series, DataFrame

**min_periods** : int

Minimum number of observations in window required to have a value

**freq** : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic

**Returns** **y** : type of input argument

### pandas.stats.moments.expanding_median

pandas.stats.moments.**expanding_median**(*arg*, *min_periods=1*, *freq=None*, *center=False*, *time_rule=None*, ***kwargs*)

O(N log(window)) implementation using skip list

Expanding median

**Parameters** **arg** : Series, DataFrame

**min_periods** : int

Minimum number of observations in window required to have a value

**freq** : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic

**Returns** **y** : type of input argument

### pandas.stats.moments.expanding_var

pandas.stats.moments.**expanding_var**(*arg*, *min_periods=1*, *freq=None*, *center=False*, *time_rule=None*, ***kwargs*)

Unbiased expanding variance

**Parameters** **arg** : Series, DataFrame

**min_periods** : int

Minimum number of observations in window required to have a value

**freq** : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic

**Returns** **y** : type of input argument

### pandas.stats.moments.expanding_std

pandas.stats.moments.**expanding_std**(*arg*, *min_periods=1*, *freq=None*, *center=False*, *time_rule=None*, ***kwargs*)

Unbiased expanding standard deviation

**Parameters** **arg** : Series, DataFrame

**min_periods** : int

Minimum number of observations in window required to have a value

**freq** : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic

**Returns** **y** : type of input argument

### pandas.stats.moments.expanding_corr

pandas.stats.moments.**expanding_corr**(*arg1*, *arg2*, *min_periods=1*, *freq=None*, *center=False*, *time_rule=None*)

Expanding sample correlation

**Parameters** **arg1** : Series, DataFrame, or ndarray

**arg2** : Series, DataFrame, or ndarray

**min_periods** : int

Minimum number of observations in window required to have a value

**freq** : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic

**Returns** **y** : type depends on inputs

DataFrame / DataFrame -> DataFrame (matches on columns) DataFrame / Series -> Computes result for each column Series / Series -> Series

### pandas.stats.moments.expanding_cov

pandas.stats.moments.**expanding_cov**(*arg1*, *arg2*, *min_periods=1*, *freq=None*, *center=False*, *time_rule=None*)

Unbiased expanding covariance

**Parameters** **arg1** : Series, DataFrame, or ndarray

**arg2** : Series, DataFrame, or ndarray

**min_periods** : int

Minimum number of observations in window required to have a value

**freq** : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic

**Returns** **y** : type depends on inputs

DataFrame / DataFrame -> DataFrame (matches on columns) DataFrame / Series -> Computes result for each column Series / Series -> Series

### pandas.stats.moments.expanding_skew

pandas.stats.moments.**expanding_skew**(*arg*, *min_periods=1*, *freq=None*, *center=False*, *time_rule=None*, ***kwargs*)

Unbiased expanding skewness

**Parameters** **arg** : Series, DataFrame

**min_periods** : int

Minimum number of observations in window required to have a value

**freq** : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic

**Returns** **y** : type of input argument

### pandas.stats.moments.expanding_kurt

pandas.stats.moments.**expanding_kurt**(*arg*, *min_periods=1*, *freq=None*, *center=False*, *time_rule=None*, ***kwargs*)

Unbiased expanding kurtosis

**Parameters** **arg** : Series, DataFrame

**min_periods** : int

Minimum number of observations in window required to have a value

**freq** : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic

**Returns** **y** : type of input argument

### pandas.stats.moments.expanding_apply

pandas.stats.moments.**expanding_apply**(*arg*, *func*, *min_periods=1*, *freq=None*, *center=False*, *time_rule=None*)

Generic expanding function application

**Parameters** **arg** : Series, DataFrame

**func** : function

Must produce a single value from an ndarray input

**min_periods** : int

Minimum number of observations in window required to have a value

**freq** : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic

**center** : boolean, default False

Whether the label should correspond with center of window

**Returns** **y** : type of input argument

### pandas.stats.moments.expanding_quantile

`pandas.stats.moments.expanding_quantile`(*arg*, *quantile*, *min_periods=1*, *freq=None*, *center=False*, *time_rule=None*)

Expanding quantile

**Parameters** **arg** : Series, DataFrame

**quantile** : 0 <= quantile <= 1

**min_periods** : int

Minimum number of observations in window required to have a value

**freq** : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic

**center** : boolean, default False

Whether the label should correspond with center of window

**Returns** **y** : type of input argument

## 21.1.7 Exponentially-weighted moving window functions

| | |
|---|---|
| `ewma`(arg[, com, span, min_periods, freq, ...]) | Exponentially-weighted moving average |
| `ewmstd`(arg[, com, span, min_periods, bias, ...]) | Exponentially-weighted moving std |
| `ewmvar`(arg[, com, span, min_periods, bias, ...]) | Exponentially-weighted moving variance |
| `ewmcorr`(arg1, arg2[, com, span, ...]) | Exponentially-weighted moving correlation |
| `ewmcov`(arg1, arg2[, com, span, min_periods, ...]) | Exponentially-weighted moving covariance |

### pandas.stats.moments.ewma

`pandas.stats.moments.ewma`(*arg*, *com=None*, *span=None*, *min_periods=0*, *freq=None*, *time_rule=None*, *adjust=True*)

Exponentially-weighted moving average

**Parameters** **arg** : Series, DataFrame

**com** : float. optional

Center of mass: alpha = com / (1 + com),

**span** : float, optional

Specify decay in terms of span, alpha = 2 / (span + 1)

**min_periods** : int, default 0

Number of observations in sample to require (only affects beginning)

**freq** : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic time_rule is a legacy alias for freq

**adjust** : boolean, default True

Divide by decaying adjustment factor in beginning periods to account for imbalance in relative weightings (viewing EWMA as a moving average)

**Returns** **y** : type of input argument

### Notes

Either center of mass or span must be specified

EWMA is sometimes specified using a "span" parameter s, we have have that the decay parameter alpha is related to the span as $\alpha = 1 - 2/(s + 1) = c/(1 + c)$

where c is the center of mass. Given a span, the associated center of mass is $c = (s - 1)/2$

So a "20-day EWMA" would have center 9.5.

## pandas.stats.moments.ewmstd

`pandas.stats.moments.ewmstd(arg, com=None, span=None, min_periods=0, bias=False, time_rule=None)`

Exponentially-weighted moving std

**Parameters** **arg** : Series, DataFrame

**com** : float. optional

Center of mass: alpha = com / (1 + com),

**span** : float, optional

Specify decay in terms of span, alpha = 2 / (span + 1)

**min_periods** : int, default 0

Number of observations in sample to require (only affects beginning)

**freq** : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic time_rule is a legacy alias for freq

**adjust** : boolean, default True

Divide by decaying adjustment factor in beginning periods to account for imbalance in relative weightings (viewing EWMA as a moving average)

**bias** : boolean, default False

Use a standard estimation bias correction

**Returns** **y** : type of input argument

### Notes

Either center of mass or span must be specified

EWMA is sometimes specified using a "span" parameter s, we have have that the decay parameter alpha is related to the span as $\alpha = 1 - 2/(s + 1) = c/(1 + c)$

where c is the center of mass. Given a span, the associated center of mass is $c = (s - 1)/2$

So a “20-day EWMA” would have center 9.5.

### pandas.stats.moments.ewmvar

`pandas.stats.moments.ewmvar(arg, com=None, span=None, min_periods=0, bias=False, freq=None, time_rule=None)`

Exponentially-weighted moving variance

**Parameters** **arg** : Series, DataFrame

**com** : float. optional

Center of mass: alpha = com / (1 + com),

**span** : float, optional

Specify decay in terms of span, alpha = 2 / (span + 1)

**min_periods** : int, default 0

Number of observations in sample to require (only affects beginning)

**freq** : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic time_rule is a legacy alias for freq

**adjust** : boolean, default True

Divide by decaying adjustment factor in beginning periods to account for imbalance in relative weightings (viewing EWMA as a moving average)

**bias** : boolean, default False

Use a standard estimation bias correction

**Returns** **y** : type of input argument

#### Notes

Either center of mass or span must be specified

EWMA is sometimes specified using a “span” parameter s, we have have that the decay parameter alpha is related to the span as $\alpha = 1 - 2/(s + 1) = c/(1 + c)$

where c is the center of mass. Given a span, the associated center of mass is $c = (s - 1)/2$

So a “20-day EWMA” would have center 9.5.

### pandas.stats.moments.ewmcorr

`pandas.stats.moments.ewmcorr(arg1, arg2, com=None, span=None, min_periods=0, freq=None, time_rule=None)`

Exponentially-weighted moving correlation

**Parameters** **arg1** : Series, DataFrame, or ndarray

**arg2** : Series, DataFrame, or ndarray

**com** : float. optional

Center of mass: alpha = com / (1 + com),

**span** : float, optional

Specify decay in terms of span, alpha = 2 / (span + 1)

**min_periods** : int, default 0

Number of observations in sample to require (only affects beginning)

**freq** : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic time_rule is a legacy alias for freq

**adjust** : boolean, default True

Divide by decaying adjustment factor in beginning periods to account for imbalance in relative weightings (viewing EWMA as a moving average)

**Returns** **y** : type of input argument

#### Notes

Either center of mass or span must be specified

EWMA is sometimes specified using a "span" parameter s, we have have that the decay parameter alpha is related to the span as $\alpha = 1 - 2/(s + 1) = c/(1 + c)$

where c is the center of mass. Given a span, the associated center of mass is $c = (s - 1)/2$

So a "20-day EWMA" would have center 9.5.

### pandas.stats.moments.ewmcov

`pandas.stats.moments.`**`ewmcov`**(*arg1*, *arg2*, *com=None*, *span=None*, *min_periods=0*, *bias=False*, *freq=None*, *time_rule=None*)

Exponentially-weighted moving covariance

**Parameters** **arg1** : Series, DataFrame, or ndarray

**arg2** : Series, DataFrame, or ndarray

**com** : float. optional

Center of mass: alpha = com / (1 + com),

**span** : float, optional

Specify decay in terms of span, alpha = 2 / (span + 1)

**min_periods** : int, default 0

Number of observations in sample to require (only affects beginning)

**freq** : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic time_rule is a legacy alias for freq

**adjust** : boolean, default True

Divide by decaying adjustment factor in beginning periods to account for imbalance in relative weightings (viewing EWMA as a moving average)

**Returns** **y** : type of input argument

#### Notes

Either center of mass or span must be specified

EWMA is sometimes specified using a "span" parameter s, we have have that the decay parameter alpha is related to the span as $\alpha = 1 - 2/(s+1) = c/(1+c)$

where c is the center of mass. Given a span, the associated center of mass is $c = (s-1)/2$

So a "20-day EWMA" would have center 9.5.

## 21.2 Series

### 21.2.1 Attributes and underlying data

**Axes**

- **index**: axis labels

| | |
|---|---|
| `Series.values` | Return Series as ndarray |
| `Series.dtype` | Data-type of the array's elements. |
| `Series.isnull`(obj) | Detect missing values (NaN in numeric arrays, None/NaN in object arrays) |
| `Series.notnull`(obj) | Replacement for numpy.isfinite / -numpy.isnan which is suitable for use on object arrays. |

#### pandas.Series.values

`Series.`**`values`**

Return Series as ndarray

**Returns arr** : numpy.ndarray

#### pandas.Series.dtype

`Series.`**`dtype`**

Data-type of the array's elements.

**Parameters None** :

**Returns d** : numpy dtype object

**See Also:**

`numpy.dtype`

#### Examples

```
>>> x
array([[0, 1],
       [2, 3]])
>>> x.dtype
dtype('int32')
>>> type(x.dtype)
<type 'numpy.dtype'>
```

### pandas.Series.isnull

`Series.isnull(obj)`
Detect missing values (NaN in numeric arrays, None/NaN in object arrays)

**Parameters** **arr: ndarray or object value** :

**Returns** **boolean ndarray or boolean** :

### pandas.Series.notnull

`Series.notnull(obj)`
Replacement for numpy.isfinite / -numpy.isnan which is suitable for use on object arrays.

**Parameters** **arr: ndarray or object value** :

**Returns** **boolean ndarray or boolean** :

## 21.2.2 Conversion / Constructors

| | |
|---|---|
| `Series.__init__`([data, index, dtype, name, copy]) | One-dimensional ndarray with axis labels (including time series). |
| `Series.astype`(dtype) | See numpy.ndarray.astype |
| `Series.copy`([order]) | Return new Series with copy of underlying values |

### pandas.Series.__init__

`Series.__init__(data=None, index=None, dtype=None, name=None, copy=False)`
One-dimensional ndarray with axis labels (including time series). Labels need not be unique but must be any 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, dict, or scalar value

Contains data stored in Series

**index** : array-like or Index (1d)

Values must be unique and hashable, same length as data. Index object (or other iterable of same length as data) Will default to np.arange(len(data)) if not provided. If both a dict and index sequence are used, the index will override the keys found in the dict.

**dtype** : numpy.dtype or None

If None, dtype will be inferred copy : boolean, default False Copy input data

**copy** : boolean, default False

### pandas.Series.astype

`Series.astype(dtype)`
See numpy.ndarray.astype

### pandas.Series.copy

`Series.copy(order='C')`

Return new Series with copy of underlying values

**Returns** **cp** : Series

## 21.2.3 Indexing, iteration

| | |
|---|---|
| `Series.get`(label[, default]) | Returns value occupying requested label, default to specified missing value if not present. |
| `Series.ix` | |
| `Series.__iter__`() | |
| `Series.iteritems`() | Lazily iterate over (index, value) tuples |

### pandas.Series.get

`Series.get(label, default=None)`

Returns value occupying requested label, default to specified missing value if not present. Analogous to dict.get

**Parameters** **label** : object

Label value looking for

**default** : object, optional

Value to return if label not in index

**Returns** **y** : scalar

### pandas.Series.ix

`Series.ix`

### pandas.Series.__iter__

`Series.__iter__()`

### pandas.Series.iteritems

`Series.iteritems()`

Lazily iterate over (index, value) tuples

## 21.2.4 Binary operator functions

| | |
|---|---|
| `Series.add`(other[, level, fill_value]) | Binary operator add with support to substitute a fill_value for missing data |
| `Series.div`(other[, level, fill_value]) | Binary operator divide with support to substitute a fill_value for missing data |
| `Series.mul`(other[, level, fill_value]) | Binary operator multiply with support to substitute a fill_value for missing data |
| `Series.sub`(other[, level, fill_value]) | Binary operator subtract with support to substitute a fill_value for missing data |
| `Series.combine`(other, func[, fill_value]) | Perform elementwise binary operation on two Series using given function |

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Table 21.12 – continued from previous page

| | |
|---|---|
| `Series.combine_first`(other) | Combine Series values, choosing the calling Series's values |
| `Series.round`([decimals, out]) | Return *a* with each element rounded to the given number of decimals. |

### pandas.Series.add

`Series.add`(*other*, *level=None*, *fill_value=None*)

Binary operator add with support to substitute a fill_value for missing data in one of the inputs

**Parameters** **other: Series or scalar value** :

**fill_value** : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

**level** : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns** **result** : Series

### pandas.Series.div

`Series.div`(*other*, *level=None*, *fill_value=None*)

Binary operator divide with support to substitute a fill_value for missing data in one of the inputs

**Parameters** **other: Series or scalar value** :

**fill_value** : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

**level** : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns** **result** : Series

### pandas.Series.mul

`Series.mul`(*other*, *level=None*, *fill_value=None*)

Binary operator multiply with support to substitute a fill_value for missing data in one of the inputs

**Parameters** **other: Series or scalar value** :

**fill_value** : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

**level** : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns** **result** : Series

### pandas.Series.sub

`Series.sub(other, level=None, fill_value=None)`

Binary operator subtract with support to substitute a fill_value for missing data in one of the inputs

**Parameters** **other: Series or scalar value** :

**fill_value** : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

**level** : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns** **result** : Series

### pandas.Series.combine

`Series.combine(other, func, fill_value=nan)`

Perform elementwise binary operation on two Series using given function with optional fill value when an index is missing from one Series or the other

**Parameters** **other** : Series or scalar value

**func** : function

**fill_value** : scalar value

**Returns** **result** : Series

### pandas.Series.combine_first

`Series.combine_first(other)`

Combine Series values, choosing the calling Series's values first. Result index will be the union of the two indexes

**Parameters** **other** : Series

**Returns** **y** : Series

### pandas.Series.round

`Series.round(decimals=0, out=None)`

Return *a* with each element rounded to the given number of decimals.

Refer to *numpy.around* for full documentation.

**See Also:**

**numpy.around** equivalent function

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Table 21.13 – continued from previous page

### 21.2.5 Function application, GroupBy

| | |
|---|---|
| `Series.apply`(func[, convert_dtype, args]) | Invoke function on values of Series. Can be ufunc (a NumPy function |
| `Series.map`(arg[, na_action]) | Map values of Series using input correspondence (which can be |
| `Series.groupby`([by, axis, level, as_index, ...]) | Group series using mapper (dict or key function, apply given function |

#### 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

**convert_dtype** : boolean, default True

Try to find better dtype for elementwise function results. If False, leave as dtype=object

**Returns** **y** : Series or DataFrame if func returns a Series

**See Also:**

**`Series.map`** For element-wise operations

#### pandas.Series.map

`Series.map(arg, na_action=None)`

Map values of Series using input correspondence (which can be a dict, Series, or function)

**Parameters** **arg** : function, dict, or Series

**na_action** : {None, 'ignore'}

If 'ignore', propagate NA values

**Returns** **y** : Series

same index as caller

##### Examples

```
>>> x
one   1
two   2
three 3
```

```
>>> y
1  foo
2  bar
3  baz
```

```
>>> x.map(y)
one   foo
two   bar
three baz
```

### pandas.Series.groupby

`Series.groupby`(*by=None*, *axis=0*, *level=None*, *as_index=True*, *sort=True*, *group_keys=True*)

Group series using mapper (dict or key function, apply given function to group, return result as series) or by a series of columns

**Parameters** **by** : mapping function / list of functions, dict, Series, or tuple /

list of column names. Called on each element of the object index to determine the groups. If a dict or Series is passed, the Series or dict VALUES will be used to determine the groups

**axis** : int, default 0

**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** : boolean, 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** : boolean, default True

Sort group keys. Get better performance by turning this off

**group_keys** : boolean, default True

When calling apply, add group keys to index to identify pieces

**Returns** **GroupBy object** :

#### Examples

# DataFrame result >>> data.groupby(func, axis=0).mean()

# DataFrame result >>> data.groupby(['col1', 'col2'])['col3'].mean()

# DataFrame with hierarchical index >>> data.groupby(['col1', 'col2']).mean()

## 21.2.6 Computations / Descriptive Stats

| | |
|---|---|
| `Series.abs`() | Return an object with absolute value taken. |
| `Series.any`([axis, out]) | Returns True if any of the elements of *a* evaluate to True. |
| `Series.autocorr`() | Lag-1 autocorrelation |
| `Series.between`(left, right[, inclusive]) | Return boolean Series equivalent to left <= series <= right. NA values |
| `Series.clip`([lower, upper, out]) | Trim values at input threshold(s) |
| `Series.clip_lower`(threshold) | Return copy of series with values below given value truncated |
| `Series.clip_upper`(threshold) | Return copy of series with values above given value truncated |
| `Series.corr`(other[, method, min_periods]) | Compute correlation with *other* Series, excluding missing values |

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**Table 21.14 – continued from previous page**

| | |
|---|---|
| `Series.count`([level]) | Return number of non-NA/null observations in the Series |
| `Series.cov`(other[, min_periods]) | Compute covariance with Series, excluding missing values |
| `Series.cummax`([axis, dtype, out, skipna]) | Cumulative max of values. |
| `Series.cummin`([axis, dtype, out, skipna]) | Cumulative min of values. |
| `Series.cumprod`([axis, dtype, out, skipna]) | Cumulative product of values. |
| `Series.cumsum`([axis, dtype, out, skipna]) | Cumulative sum of values. |
| `Series.describe`([percentile_width]) | Generate various summary statistics of Series, excluding NaN |
| `Series.diff`([periods]) | 1st discrete difference of object |
| `Series.kurt`([skipna, level]) | Return unbiased kurtosis of values |
| `Series.mad`([skipna, level]) | Return mean absolute deviation of values |
| `Series.max`([axis, out, skipna, level]) | Return maximum of values |
| `Series.mean`([axis, dtype, out, skipna, level]) | Return mean of values |
| `Series.median`([axis, dtype, out, skipna, level]) | Return median of values |
| `Series.min`([axis, out, skipna, level]) | Return minimum of values |
| `Series.nunique`() | Return count of unique elements in the Series |
| `Series.pct_change`([periods, fill_method, ...]) | Percent change over given number of periods |
| `Series.prod`([axis, dtype, out, skipna, level]) | Return product of values |
| `Series.quantile`([q]) | Return value at the given quantile, a la scoreatpercentile in |
| `Series.rank`([method, na_option, ascending]) | Compute data ranks (1 through n). |
| `Series.skew`([skipna, level]) | Return unbiased skewness of values |
| `Series.std`([axis, dtype, out, ddof, skipna, ...]) | Return standard deviation of values |
| `Series.sum`([axis, dtype, out, skipna, level]) | Return sum of values |
| `Series.unique`() | Return array of unique values in the Series. Significantly faster than |
| `Series.var`([axis, dtype, out, ddof, skipna, ...]) | Return variance of values |
| `Series.value_counts`([normalize]) | Returns Series containing counts of unique values. The resulting Series |

### pandas.Series.abs

`Series.abs()`

Return an object with absolute value taken. Only applicable to objects that are all numeric

**Returns abs: type of caller** :

### pandas.Series.any

`Series.any`(*axis=None*, *out=None*)

Returns True if any of the elements of *a* evaluate to True.

Refer to *numpy.any* for full documentation.

**See Also:**

**`numpy.any`** equivalent function

### pandas.Series.autocorr

`Series.autocorr()`

Lag-1 autocorrelation

**Returns autocorr** : float

### pandas.Series.between

`Series.between(left, right, inclusive=True)`

Return boolean Series equivalent to left <= series <= right. NA values will be treated as False

**Parameters** **left** : scalar

Left boundary

**right** : scalar

Right boundary

**Returns** **is_between** : Series

### pandas.Series.clip

`Series.clip(lower=None, upper=None, out=None)`

Trim values at input threshold(s)

**Parameters** **lower** : float, default None

**upper** : float, default None

**Returns** **clipped** : Series

### pandas.Series.clip_lower

`Series.clip_lower(threshold)`

Return copy of series with values below given value truncated

**Returns** **clipped** : Series

**See Also:**

`clip`

### pandas.Series.clip_upper

`Series.clip_upper(threshold)`

Return copy of series with values above given value truncated

**Returns** **clipped** : Series

**See Also:**

`clip`

### pandas.Series.corr

`Series.corr(other, method='pearson', min_periods=None)`

Compute correlation with *other* Series, excluding missing values

**Parameters** **other** : Series

**method** : {'pearson', 'kendall', 'spearman'}

pearson : standard correlation coefficient kendall : Kendall Tau correlation coefficient spearman : Spearman rank correlation

**min_periods** : int, optional

Minimum number of observations needed to have a valid result

**Returns** **correlation** : float

### pandas.Series.count

`Series.count(level=None)`

Return number of non-NA/null observations in the Series

**Parameters** **level** : int, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a smaller Series

**Returns** **nobs** : int or Series (if level specified)

### pandas.Series.cov

`Series.cov(other, min_periods=None)`

Compute covariance with Series, excluding missing values

**Parameters** **other** : Series

**min_periods** : int, optional

Minimum number of observations needed to have a valid result

**Returns** **covariance** : float

**Normalized by N-1 (unbiased estimator).** :

### pandas.Series.cummax

`Series.cummax(axis=0, dtype=None, out=None, skipna=True)`

Cumulative max of values. Preserves locations of NaN values

Extra parameters are to preserve ndarray interface.

**Parameters** **skipna** : boolean, default True

Exclude NA/null values

**Returns** **cummax** : Series

### pandas.Series.cummin

`Series.cummin(axis=0, dtype=None, out=None, skipna=True)`

Cumulative min of values. Preserves locations of NaN values

Extra parameters are to preserve ndarray interface.

**Parameters** **skipna** : boolean, default True

Exclude NA/null values

**Returns** **cummin** : Series

### pandas.Series.cumprod

`Series.cumprod(axis=0, dtype=None, out=None, skipna=True)`

Cumulative product of values. Preserves locations of NaN values

Extra parameters are to preserve ndarray interface.

**Parameters** **skipna** : boolean, default True

Exclude NA/null values

**Returns** **cumprod** : Series

### pandas.Series.cumsum

`Series.cumsum(axis=0, dtype=None, out=None, skipna=True)`

Cumulative sum of values. Preserves locations of NaN values

Extra parameters are to preserve ndarray interface.

**Parameters** **skipna** : boolean, default True

Exclude NA/null values

**Returns** **cumsum** : Series

### pandas.Series.describe

`Series.describe(percentile_width=50)`

Generate various summary statistics of Series, excluding NaN values. These include: count, mean, std, min, max, and lower%/50%/upper% percentiles

**Parameters** **percentile_width** : float, optional

width of the desired uncertainty interval, default is 50, which corresponds to lower=25, upper=75

**Returns** **desc** : Series

### pandas.Series.diff

`Series.diff(periods=1)`

1st discrete difference of object

**Parameters** **periods** : int, default 1

Periods to shift for forming difference

**Returns** **diffed** : Series

### pandas.Series.kurt

`Series.kurt(skipna=True, level=None)`

Return unbiased kurtosis of values NA/null values are excluded

**Parameters** **skipna** : boolean, default True

Exclude NA/null values

**level** : int, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a smaller Series

**Returns** **kurt** : float (or Series if level specified)

### pandas.Series.mad

`Series.mad`(*skipna=True*, *level=None*)

Return mean absolute deviation of values NA/null values are excluded

**Parameters** **skipna** : boolean, default True

Exclude NA/null values

**level** : int, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a smaller Series

**Returns** **mad** : float (or Series if level specified)

### pandas.Series.max

`Series.max`(*axis=None*, *out=None*, *skipna=True*, *level=None*)

Return maximum of values NA/null values are excluded

**Parameters** **skipna** : boolean, default True

Exclude NA/null values

**level** : int, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a smaller Series

**Returns** **max** : float (or Series if level specified)

### pandas.Series.mean

`Series.mean`(*axis=0*, *dtype=None*, *out=None*, *skipna=True*, *level=None*)

Return mean of values NA/null values are excluded

**Parameters** **skipna** : boolean, default True

Exclude NA/null values

**level** : int, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a smaller Series

**Extra parameters are to preserve ndarrayinterface.** :

**Returns** **mean** : float (or Series if level specified)

### pandas.Series.median

`Series.median(axis=0, dtype=None, out=None, skipna=True, level=None)`
Return median of values NA/null values are excluded

**Parameters** **skipna** : boolean, default True

Exclude NA/null values

**level** : int, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a smaller Series

**Returns** **median** : float (or Series if level specified)

### pandas.Series.min

`Series.min(axis=None, out=None, skipna=True, level=None)`
Return minimum of values NA/null values are excluded

**Parameters** **skipna** : boolean, default True

Exclude NA/null values

**level** : int, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a smaller Series

**Returns** **min** : float (or Series if level specified)

### pandas.Series.nunique

`Series.nunique()`
Return count of unique elements in the Series

**Returns** **nunique** : int

### pandas.Series.pct_change

`Series.pct_change(periods=1, fill_method='pad', limit=None, freq=None, **kwds)`
Percent change over given number of periods

**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 offset alias string, optional

Increment to use from time series API (e.g. 'M' or BDay())

**Returns** **chg** : Series or DataFrame

### pandas.Series.prod

`Series.prod(axis=0, dtype=None, out=None, skipna=True, level=None)`

Return product of values NA/null values are excluded

**Parameters** **skipna** : boolean, default True

Exclude NA/null values

**level** : int, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a smaller Series

**Returns** **prod** : float (or Series if level specified)

### pandas.Series.quantile

`Series.quantile(q=0.5)`

Return value at the given quantile, a la scoreatpercentile in scipy.stats

**Parameters** **q** : quantile

0 <= q <= 1

**Returns** **quantile** : float

### pandas.Series.rank

`Series.rank(method='average', na_option='keep', ascending=True)`

Compute data ranks (1 through n). Equal values are assigned a rank that is the average of the ranks of those values

**Parameters** **method** : {'average', 'min', 'max', 'first'}

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

**na_option** : {'keep'}

keep: leave NA values where they are

**ascending** : boolean, default True

False for ranks by high (1) to low (N)

**Returns** **ranks** : Series

### pandas.Series.skew

`Series.skew(skipna=True, level=None)`

Return unbiased skewness of values NA/null values are excluded

**Parameters** **skipna** : boolean, default True

Exclude NA/null values

**level** : int, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a smaller Series

**Returns** **skew** : float (or Series if level specified)

### pandas.Series.std

`Series.std(axis=None, dtype=None, out=None, ddof=1, skipna=True, level=None)`

Return standard deviation of values NA/null values are excluded

**Parameters** **skipna** : boolean, default True

Exclude NA/null values

**level** : int, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a smaller Series

**Returns** **stdev** : float (or Series if level specified)

Normalized by N-1 (unbiased estimator).

### pandas.Series.sum

`Series.sum(axis=0, dtype=None, out=None, skipna=True, level=None)`

Return sum of values NA/null values are excluded

**Parameters** **skipna** : boolean, default True

Exclude NA/null values

**level** : int, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a smaller Series

**Extra parameters are to preserve ndarrayinterface.** :

**Returns** **sum** : float (or Series if level specified)

### pandas.Series.unique

`Series.unique()`

Return array of unique values in the Series. Significantly faster than numpy.unique

**Returns** **uniques** : ndarray

### pandas.Series.var

`Series.var(axis=None, dtype=None, out=None, ddof=1, skipna=True, level=None)`

Return variance of values NA/null values are excluded

**Parameters** **skipna** : boolean, default True

Exclude NA/null values

**level** : int, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a smaller Series

**Returns** **var** : float (or Series if level specified)

Normalized by N-1 (unbiased estimator).

### pandas.Series.value_counts

Series.**value_counts**(*normalize=False*)

Returns Series containing counts of unique values. The resulting Series will be in descending order so that the first element is the most frequently-occurring element. Excludes NA values

**Parameters** **normalize: boolean, default False** :

If True then the Series returned will contain the relative frequencies of the unique values.

**Returns** **counts** : Series

## 21.2.7 Reindexing / Selection / Label manipulation

| | |
|---|---|
| Series.align(other[, join, level, copy, ...]) | Align two Series object with the specified join method |
| Series.drop(labels[, axis, level]) | Return new object with labels in requested axis removed |
| Series.first(offset) | Convenience method for subsetting initial periods of time series data |
| Series.head([n]) | Returns first n rows of Series |
| Series.idxmax([axis, out, skipna]) | Index of first occurrence of maximum of values. |
| Series.idxmin([axis, out, skipna]) | Index of first occurrence of minimum of values. |
| Series.isin(values) | Return boolean vector showing whether each element in the Series is |
| Series.last(offset) | Convenience method for subsetting final periods of time series data |
| Series.reindex([index, method, level, ...]) | Conform Series to new index with optional filling logic, placing |
| Series.reindex_like(other[, method, limit, ...]) | Reindex Series to match index of another Series, optionally with |
| Series.rename(mapper[, inplace]) | Alter Series index using dict or function |
| Series.reset_index([level, drop, name, inplace]) | Analogous to the DataFrame.reset_index function, see docstring there. |
| Series.select(crit[, axis]) | Return data corresponding to axis labels matching criteria |
| Series.take(indices[, axis]) | Analogous to ndarray.take, return Series corresponding to requested |
| Series.tail([n]) | Returns last n rows of Series |
| Series.truncate([before, after, copy]) | Function truncate a sorted DataFrame / Series before and/or after |

### pandas.Series.align

Series.**align**(*other*, *join='outer'*, *level=None*, *copy=True*, *fill_value=None*, *method=None*, *limit=None*)

Align two Series object with the specified join method

**Parameters** **other** : Series

**join** : {'outer', 'inner', 'left', 'right'}, default 'outer'

**level** : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

**copy** : boolean, default True

Always return new objects. If copy=False and no reindexing is required, the same object will be returned (for better performance)

**fill_value** : object, default None

**method** : str, default 'pad'

**limit** : int, default None

fill_value, method, inplace, limit are passed to fillna

**Returns** **(left, right)** : (Series, Series)

Aligned Series

### pandas.Series.drop

`Series.drop(labels, axis=0, level=None)`
Return new object with labels in requested axis removed

**Parameters** **labels** : array-like

**axis** : int

**level** : int or name, default None

For MultiIndex

**Returns** **dropped** : type of caller

### pandas.Series.first

`Series.first(offset)`
Convenience method for subsetting initial periods of time series data based on a date offset

**Parameters** **offset** : string, DateOffset, dateutil.relativedelta

**Returns** **subset** : type of caller

#### Examples

ts.last('10D') -> First 10 days

### pandas.Series.head

`Series.head(n=5)`
Returns first n rows of Series

### pandas.Series.idxmax

`Series.idxmax(axis=None, out=None, skipna=True)`
Index of first occurrence of maximum of values.

**Parameters** **skipna** : boolean, default True

Exclude NA/null values

**Returns** **idxmax** : Index of minimum of values

### pandas.Series.idxmin

`Series.idxmin(axis=None, out=None, skipna=True)`

Index of first occurrence of minimum of values.

**Parameters** **skipna** : boolean, default True

Exclude NA/null values

**Returns** **idxmin** : Index of minimum of values

### pandas.Series.isin

`Series.isin(values)`

Return boolean vector showing whether each element in the Series is exactly contained in the passed sequence of values

**Parameters** **values** : sequence

**Returns** **isin** : Series (boolean dtype)

### pandas.Series.last

`Series.last(offset)`

Convenience method for subsetting final periods of time series data based on a date offset

**Parameters** **offset** : string, DateOffset, dateutil.relativedelta

**Returns** **subset** : type of caller

#### Examples

ts.last('5M') -> Last 5 months

### pandas.Series.reindex

`Series.reindex(index=None, method=None, level=None, fill_value=nan, limit=None, copy=True)`

Conform Series to new index with optional filling logic, placing 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 or Index

New labels / index to conform to. Preferably an Index object to avoid duplicating data

**method** : {'backfill', 'bfill', 'pad', 'ffill', 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

**copy** : boolean, 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 NaN

Value to use for missing values. Defaults to NaN, but can be any "compatible" value

**limit** : int, default None

Maximum size gap to forward or backward fill

**Returns reindexed** : Series

### pandas.Series.reindex_like

`Series.reindex_like(other, method=None, limit=None, fill_value=nan)`

Reindex Series to match index of another Series, optionally with filling logic

**Parameters other** : Series

**method** : string or None

See Series.reindex docstring

**limit** : int, default None

Maximum size gap to forward or backward fill

**Returns reindexed** : Series

#### Notes

Like calling s.reindex(other.index, method=...)

### pandas.Series.rename

`Series.rename(mapper, inplace=False)`

Alter Series index using dict or function

**Parameters mapper** : dict-like or function

Transformation to apply to each index

**Returns renamed** : Series (new object)

#### Notes

Function / dict values must be unique (1-to-1)

#### Examples

```
>>> x
foo 1
bar 2
baz 3

>>> x.rename(str.upper)
FOO 1
BAR 2
BAZ 3
```

```
>>> x.rename({'foo' : 'a', 'bar' : 'b', 'baz' : 'c'})
a 1
b 2
c 3
```

### pandas.Series.reset_index

`Series.reset_index(level=None, drop=False, name=None, inplace=False)`
Analogous to the DataFrame.reset_index function, see docstring there.

**Parameters** **level** : int, str, tuple, or list, default None

Only remove the given levels from the index. Removes all levels by default

**drop** : boolean, default False

Do not try to insert index into dataframe columns

**name** : object, default None

The name of the column corresponding to the Series values

**inplace** : boolean, default False

Modify the Series in place (do not create a new object)

**Returns** **resetted** : DataFrame, or Series if drop == True

### pandas.Series.select

`Series.select(crit, axis=0)`
Return data corresponding to axis labels matching criteria

**Parameters** **crit** : function

To be called on each index (label). Should return True or False

**axis** : int

**Returns** **selection** : type of caller

### pandas.Series.take

`Series.take(indices, axis=0)`
Analogous to ndarray.take, return Series corresponding to requested indices

**Parameters** **indices** : list / array of ints

**Returns** **taken** : Series

### pandas.Series.tail

`Series.tail(n=5)`
Returns last n rows of Series

### pandas.Series.truncate

`Series.truncate(before=None, after=None, copy=True)`

Function truncate a sorted DataFrame / Series before and/or after some particular dates.

**Parameters** **before** : date

Truncate before date

**after** : date

Truncate after date

**Returns** **truncated** : type of caller

## 21.2.8 Missing data handling

| | |
|---|---|
| Series.dropna() | Return Series without null values |
| Series.fillna([value, method, inplace, limit]) | Fill NA/NaN values using the specified method |
| Series.interpolate([method]) | Interpolate missing values (after the first valid value) |

### pandas.Series.dropna

`Series.dropna()`

Return Series without null values

**Returns** **valid** : Series

### pandas.Series.fillna

`Series.fillna(value=None, method=None, inplace=False, limit=None)`

Fill NA/NaN values using the specified method

**Parameters** **value** : any kind (should be same type as array)

Value to use to fill holes (e.g. 0)

**method** : {'backfill', 'bfill', 'pad', 'ffill', None}, default 'pad'

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

**inplace** : boolean, default False

If True, fill the Series in place. Note: this will modify any other views on this Series, for example a column in a DataFrame. Returns a reference to the filled object, which is self if inplace=True

**limit** : int, default None

Maximum size gap to forward or backward fill

**Returns** **filled** : Series

**See Also:**

reindex, asfreq

#### pandas.Series.interpolate

`Series.interpolate(method='linear')`
Interpolate missing values (after the first valid value)

**Parameters** **method** : {'linear', 'time', 'values'}

Interpolation method. 'time' interpolation works on daily and higher resolution data to interpolate given length of interval 'values' using the actual index numeric values

**Returns** **interpolated** : Series

### 21.2.9 Reshaping, sorting

| | |
|---|---|
| `Series.argsort`([axis, kind, order]) | Overrides ndarray.argsort. |
| `Series.order`([na_last, ascending, kind]) | Sorts Series object, by value, maintaining index-value link |
| `Series.reorder_levels`(order) | Rearrange index levels using input order. |
| `Series.sort`([axis, kind, order]) | Sort values and index labels by value, in place. |
| `Series.sort_index`([ascending]) | Sort object by labels (along an axis) |
| `Series.sortlevel`([level, ascending]) | Sort Series with MultiIndex by chosen level. Data will be |
| `Series.swaplevel`(i, j[, copy]) | Swap levels i and j in a MultiIndex |
| `Series.unstack`([level]) | Unstack, a.k.a. |

#### pandas.Series.argsort

`Series.argsort(axis=0, kind='quicksort', order=None)`
Overrides ndarray.argsort. Argsorts the value, omitting NA/null values, and places the result in the same locations as the non-NA values

**Parameters** **axis** : int (can only be zero)

**kind** : {'mergesort', 'quicksort', 'heapsort'}, default 'quicksort'

Choice of sorting algorithm. See np.sort for more information. 'mergesort' is the only stable algorithm

**order** : ignored

**Returns** **argsorted** : Series, with -1 indicated where nan values are present

#### pandas.Series.order

`Series.order(na_last=True, ascending=True, kind='mergesort')`
Sorts Series object, by value, maintaining index-value link

**Parameters** **na_last** : boolean (optional, default=True)

Put NaN's at beginning or end

**ascending** : boolean, default True

Sort ascending. Passing False sorts descending

**kind** : {'mergesort', 'quicksort', 'heapsort'}, default 'mergesort'

Choice of sorting algorithm. See np.sort for more information. 'mergesort' is the only stable algorithm

**Returns** **y** : Series

### 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 not by key)

**axis: where to reorder levels** :

**Returns** **type of caller (new object)** :

### pandas.Series.sort

`Series.`**`sort`**(*axis=0*, *kind='quicksort'*, *order=None*)

Sort values and index labels by value, in place. For compatibility with ndarray API. No return value

**Parameters** **axis** : int (can only be zero)

**kind** : {'mergesort', 'quicksort', 'heapsort'}, default 'quicksort'

Choice of sorting algorithm. See np.sort for more information. 'mergesort' is the only stable algorithm

**order** : ignored

### pandas.Series.sort_index

`Series.`**`sort_index`**(*ascending=True*)

Sort object by labels (along an axis)

**Parameters** **ascending** : boolean or list, default True

Sort ascending vs. descending. Specify list for multiple sort orders

**Returns** **sorted_obj** : Series

#### Examples

```
>>> result1 = s.sort_index(ascending=False)
>>> result2 = s.sort_index(ascending=[1, 0])
```

### pandas.Series.sortlevel

`Series.`**`sortlevel`**(*level=0*, *ascending=True*)

Sort Series with MultiIndex by chosen level. Data will be lexicographically sorted by the chosen level followed by the other levels (in order)

**Parameters** **level** : int

**ascending** : bool, default True

**Returns** **sorted** : Series

### pandas.Series.swaplevel

`Series.swaplevel(i, j, copy=True)`
Swap levels i and j in a MultiIndex

**Parameters** **i, j** : int, string (can be mixed)

Level of index to be swapped. Can pass level name as string.

**Returns** **swapped** : Series

### pandas.Series.unstack

`Series.unstack(level=-1)`
Unstack, a.k.a. pivot, Series with MultiIndex to produce DataFrame

**Parameters** **level** : int, string, or list of these, default last level

Level(s) to unstack, can pass level name

**Returns** **unstacked** : DataFrame

#### Examples

```
>>> s
one  a   1.
one  b   2.
two  a   3.
two  b   4.

>>> s.unstack(level=-1)
     a   b
one  1.  2.
two  3.  4.

>>> s.unstack(level=0)
   one  two
a  1.   2.
b  3.   4.
```

## 21.2.10 Combining / joining / merging

| | |
|---|---|
| `Series.append`(to_append[, verify_integrity]) | Concatenate two or more Series. The indexes must not overlap |
| `Series.replace`(to_replace[, value, method, ...]) | Replace arbitrary values in a Series |
| `Series.update`(other) | Modify Series in place using non-NA values from passed |

### pandas.Series.append

`Series.append(to_append, verify_integrity=False)`
Concatenate two or more Series. The indexes must not overlap

**Parameters** **to_append** : Series or list/tuple of Series

**verify_integrity** : boolean, default False

If True, raise Exception on creating index with duplicates

**Returns** **appended** : Series

### pandas.Series.replace

`Series.replace(to_replace, value=None, method='pad', inplace=False, limit=None)`

Replace arbitrary values in a Series

**Parameters** **to_replace** : list or dict

list of values to be replaced or dict of replacement values

**value** : anything

if to_replace is a list then value is the replacement value

**method** : {'backfill', 'bfill', 'pad', 'ffill', None}, default 'pad'

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

**inplace** : boolean, default False

If True, fill the Series in place. Note: this will modify any other views on this Series, for example a column in a DataFrame. Returns a reference to the filled object, which is self if inplace=True

**limit** : int, default None

Maximum size gap to forward or backward fill

**Returns** **replaced** : Series

**See Also:**

`fillna`, `reindex`, `asfreq`

#### Notes

replace does not distinguish between NaN and None

### pandas.Series.update

`Series.update(other)`

Modify Series in place using non-NA values from passed Series. Aligns on index

**Parameters** **other** : Series

## 21.2.11 Time series-related

| | |
|---|---|
| `Series.asfreq`(freq[, method, how, normalize]) | Convert all TimeSeries inside to specified frequency using DateOffset |
| `Series.asof`(where) | Return last good (non-NaN) value in TimeSeries if value is NaN for |
| `Series.shift`([periods, freq, copy]) | Shift the index of the Series by desired number of periods with an |
| `Series.first_valid_index`() | Return label for first non-NA/null value |
| `Series.last_valid_index`() | Return label for last non-NA/null value |

Continued o

Table 21.19 – continued from previous page

| | |
|---|---|
| Series.weekday | |
| Series.resample(rule[, how, axis, ...]) | Convenience method for frequency conversion and resampling of regular time- |
| Series.tz_convert(tz[, copy]) | Convert TimeSeries to target time zone |
| Series.tz_localize(tz[, copy]) | Localize tz-naive TimeSeries to target time zone |

### pandas.Series.asfreq

Series.**asfreq**(*freq*, *method=None*, *how=None*, *normalize=False*)

Convert all TimeSeries inside to specified frequency using DateOffset objects. Optionally provide fill method to pad/backfill missing values.

**Parameters** **freq** : DateOffset object, or string

**method** : {'backfill', 'bfill', 'pad', 'ffill', 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 methdo

**how** : {'start', 'end'}, default end

For PeriodIndex only, see PeriodIndex.asfreq

**normalize** : bool, default False

Whether to reset output index to midnight

**Returns** **converted** : type of caller

### pandas.Series.asof

Series.**asof**(*where*)

Return last good (non-NaN) value in TimeSeries if value is NaN for requested date.

If there is no good value, NaN is returned.

**Parameters** **where** : date or array of dates

**Returns** **value or NaN** :

#### Notes

Dates are assumed to be sorted

### pandas.Series.shift

Series.**shift**(*periods=1*, *freq=None*, *copy=True*, ***kwds*)

Shift the index of the Series by desired number of periods with an optional time offset

**Parameters** **periods** : int

Number of periods to move, can be positive or negative

**freq** : DateOffset, timedelta, or offset alias string, optional

Increment to use from datetools module or time rule (e.g. 'EOM')

**Returns** **shifted** : Series

### pandas.Series.first_valid_index

`Series.first_valid_index()`

Return label for first non-NA/null value

### pandas.Series.last_valid_index

`Series.last_valid_index()`

Return label for last non-NA/null value

### pandas.Series.weekday

`Series.weekday`

### pandas.Series.resample

`Series.resample(rule, how=None, axis=0, fill_method=None, closed=None, label=None, convention='start', kind=None, loffset=None, limit=None, base=0)`

Convenience method for frequency conversion and resampling of regular time-series data.

**Parameters** **rule** : the offset string or object representing target conversion

**how** : string, method for down- or re-sampling, default to 'mean' for

downsampling

**axis** : int, optional, default 0

**fill_method** : string, fill_method for upsampling, default None

**closed** : {'right', 'left'}, default None

Which side of bin interval is closed

**label** : {'right', 'left'}, default None

Which bin edge label to label bucket with

**convention** : {'start', 'end', 's', 'e'}

**kind: "period"/"timestamp"** :

**loffset: timedelta** :

Adjust the resampled time labels

**limit: int, default None** :

Maximum size gap to when reindexing with fill_method

**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

### pandas.Series.tz_convert

`Series.tz_convert(tz, copy=True)`

Convert TimeSeries to target time zone

**Parameters** **tz** : string or pytz.timezone object

**copy** : boolean, default True

Also make a copy of the underlying data

**Returns** **converted** : TimeSeries

### pandas.Series.tz_localize

`Series.tz_localize(tz, copy=True)`

Localize tz-naive TimeSeries to target time zone

**Parameters** **tz** : string or pytz.timezone object

**copy** : boolean, default True

Also make a copy of the underlying data

**Returns** **localized** : TimeSeries

## 21.2.12 Plotting

| | |
|---|---|
| Series.hist([by, ax, grid, xlabelsize, ...]) | Draw histogram of the input series using matplotlib |
| Series.plot(series[, label, kind, ...]) | Plot the input series with the index on the x-axis using matplotlib |

### pandas.Series.hist

`Series.hist(by=None, ax=None, grid=True, xlabelsize=None, xrot=None, ylabelsize=None, yrot=None, **kwds)`

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** : boolean, 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

**kwds** : keywords

To be passed to the actual plotting function

### Notes

See matplotlib documentation online for more on this

## pandas.Series.plot

`Series.plot` (*series*, *label=None*, *kind='line'*, *use_index=True*, *rot=None*, *xticks=None*, *yticks=None*, *xlim=None*, *ylim=None*, *ax=None*, *style=None*, *grid=None*, *legend=False*, *logx=False*, *logy=False*, *secondary_y=False*, ***kwds*)

Plot the input series with the index on the x-axis using matplotlib

**Parameters** **label** : label argument to provide to plot

**kind** : {'line', 'bar', 'barh', 'kde', 'density'}

bar : vertical bar plot barh : horizontal bar plot kde/density : Kernel Density Estimation plot

**use_index** : boolean, default True

Plot index as axis tick labels

**rot** : int, default None

Rotation for tick labels

**xticks** : sequence

Values to use for the xticks

**yticks** : sequence

Values to use for the yticks

**xlim** : 2-tuple/list

**ylim** : 2-tuple/list

**ax** : matplotlib axis object

If not passed, uses gca()

**style** : string, default matplotlib default

matplotlib line style to use

**grid** : matplot grid

**legend: matplot legende** :

**logx** : boolean, default False

For line plots, use log scaling on x axis

**logy** : boolean, default False

For line plots, use log scaling on y axis

**secondary_y** : boolean or sequence of ints, default False

If True then y-axis will be on the right

**kwds** : keywords

Options to pass to matplotlib plotting method

### Notes

See matplotlib documentation online for more on this subject

## 21.2.13 Serialization / IO / Conversion

| | |
|---|---|
| `Series.from_csv`(path[, sep, parse_dates, ...]) | Read delimited file into Series |
| `Series.load`(path) | |
| `Series.save`(path) | |
| `Series.to_csv`(path[, index, sep, na_rep, ...]) | Write Series to a comma-separated values (csv) file |
| `Series.to_dict`() | Convert Series to {label -> value} dict |
| `Series.to_sparse`([kind, fill_value]) | Convert Series to SparseSeries |
| `Series.to_string`([buf, na_rep, ...]) | Render a string representation of the Series |

### pandas.Series.from_csv

**classmethod** `Series.`**`from_csv`**(*path*, *sep=',*', *parse_dates=True*, *header=None*, *index_col=0*, *encoding=None*)

Read delimited file into Series

**Parameters** **path** : string file path or file handle / StringIO

**sep** : string, default ','

Field delimiter

**parse_dates** : boolean, default True

Parse dates. Different default from read_table

**header** : int, default 0

Row to use at header (skip prior rows)

**index_col** : int or sequence, default 0

Column to use for index. If a sequence is given, a MultiIndex is used. Different default from read_table

**encoding** : string, optional

a string representing the encoding to use if the contents are non-ascii, for python versions prior to 3

**Returns** **y** : Series

### pandas.Series.load

**classmethod** `Series.`**`load`**(*path*)

### pandas.Series.save

`Series.save(path)`

### pandas.Series.to_csv

`Series.to_csv(path, index=True, sep=', ', na_rep='', float_format=None, header=False, index_label=None, mode='w', nanRep=None, encoding=None)`

Write Series to a comma-separated values (csv) file

**Parameters** **path** : string file path or file handle / StringIO

**na_rep** : string, default ''

Missing data representation

**float_format** : string, default None

Format string for floating point numbers

**header** : boolean, default False

Write out series name

**index** : boolean, default True

Write row names (index)

**index_label** : string or sequence, 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 DataFrame uses MultiIndex.

**mode** : Python write mode, default 'w'

**sep** : character, default ","

Field delimiter for the output file.

**encoding** : string, optional

a string representing the encoding to use if the contents are non-ascii, for python versions prior to 3

### pandas.Series.to_dict

`Series.to_dict()`

Convert Series to {label -> value} dict

**Returns** **value_dict** : dict

### pandas.Series.to_sparse

`Series.to_sparse(kind='block', fill_value=None)`

Convert Series to SparseSeries

**Parameters** **kind** : {'block', 'integer'}

**fill_value** : float, defaults to NaN (missing)

**Returns** **sp** : SparseSeries

### pandas.Series.to_string

`Series.to_string(buf=None, na_rep='NaN', float_format=None, nanRep=None, length=False, dtype=False, name=False)`

Render a string representation of the Series

**Parameters** **buf** : StringIO-like, optional

buffer to write to

**na_rep** : string, 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

**length** : boolean, default False

Add the Series length

**dtype** : boolean, default False

Add the Series dtype

**name** : boolean, default False

Add the Series name (which may be None)

**Returns** **formatted** : string (if not buffer passed)

## 21.3 DataFrame

### 21.3.1 Attributes and underlying data

**Axes**

- **index**: row labels
- **columns**: column labels

| | |
|---|---|
| `DataFrame.as_matrix`([columns]) | Convert the frame to its Numpy-array matrix representation. Columns |
| `DataFrame.dtypes` | |
| `DataFrame.get_dtype_counts`() | return the counts of dtypes in this frame |
| `DataFrame.values` | Convert the frame to its Numpy-array matrix representation. Columns |
| `DataFrame.axes` | |
| `DataFrame.ndim` | |
| `DataFrame.shape` | |

#### pandas.DataFrame.as_matrix

`DataFrame.as_matrix(columns=None)`

Convert the frame to its Numpy-array matrix representation. Columns are presented in sorted order unless a specific list of columns is provided.

**NOTE: 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 accomodates all will be chosen use this with care if you are not dealing with the blocks

**e.g. if the dtypes are float16,float32 -> float32** float16,float32,float64 -> float64 int32,uint8 -> int32

**Parameters** **columns** : array-like

Specific column order

**Returns** **values** : ndarray

If the DataFrame is heterogeneous and contains booleans or objects, the result will be of dtype=object

### pandas.DataFrame.dtypes

`DataFrame.dtypes`

### pandas.DataFrame.get_dtype_counts

`DataFrame.get_dtype_counts()`

return the counts of dtypes in this frame

### pandas.DataFrame.values

`DataFrame.values`

Convert the frame to its Numpy-array matrix representation. Columns are presented in sorted order unless a specific list of columns is provided.

**NOTE: 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 accomodates all will be chosen use this with care if you are not dealing with the blocks

**e.g. if the dtypes are float16,float32 -> float32** float16,float32,float64 -> float64 int32,uint8 -> int32

**Parameters** **columns** : array-like

Specific column order

**Returns** **values** : ndarray

If the DataFrame is heterogeneous and contains booleans or objects, the result will be of dtype=object

### pandas.DataFrame.axes

`DataFrame.axes`

### pandas.DataFrame.ndim

`DataFrame.ndim`

### pandas.DataFrame.shape

`DataFrame.shape`

### 21.3.2 Conversion / Constructors

| | |
|---|---|
| DataFrame.__init__([data, index, columns, ...]) | Two-dimensional size-mutable, potentially heterogeneous tabular data str |
| DataFrame.astype(dtype[, copy, raise_on_error]) | Cast object to input numpy.dtype |
| DataFrame.convert_objects([convert_dates, ...]) | Attempt to infer better dtype for object columns |
| DataFrame.copy([deep]) | Make a copy of this object |

#### pandas.DataFrame.__init__

DataFrame.**__init__**(*data=None*, *index=None*, *columns=None*, *dtype=None*, *copy=False*)

Two-dimensional size-mutable, potentially heterogeneous tabular data structure with labeled axes (rows and columns). Arithmetic operations align on both row and column labels. Can be thought of as a dict-like container for Series objects. The primary pandas data structure

**Parameters** **data** : numpy ndarray (structured or homogeneous), dict, or DataFrame

Dict can contain Series, arrays, constants, or list-like objects

**index** : Index or array-like

Index to use for resulting frame. Will default to np.arange(n) if no indexing information part of input data and no index provided

**columns** : Index or array-like

Will default to np.arange(n) if not column labels provided

**dtype** : dtype, default None

Data type to force, otherwise infer

**copy** : boolean, 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

**DataFrame.from_csv** from CSV files

**DataFrame.from_items** from sequence of (key, value) pairs

read_csv

##### Examples

```
>>> d = {'col1': ts1, 'col2': ts2}
>>> df = DataFrame(data=d, index=index)
>>> df2 = DataFrame(np.random.randn(10, 5))
>>> df3 = DataFrame(np.random.randn(10, 5),
...                 columns=['a', 'b', 'c', 'd', 'e'])
```

#### pandas.DataFrame.astype

`DataFrame.`**`astype`**(*dtype*, *copy=True*, *raise_on_error=True*)

Cast object to input numpy.dtype Return a copy when copy = True (be really careful with this!)

**Parameters** **dtype** : numpy.dtype or Python type

**raise_on_error** : raise on invalid input

**Returns** **casted** : type of caller

#### pandas.DataFrame.convert_objects

`DataFrame.`**`convert_objects`**(*convert_dates=True*, *convert_numeric=False*)

Attempt to infer better dtype for object columns Always returns a copy (even if no object columns)

**Parameters** **convert_dates** : if True, attempt to soft convert_dates, if 'coerce', force conversion (and non-convertibles get NaT)

**convert_numeric** : if True attempt to coerce to numerbers (including strings), non-convertibles get NaN

**Returns** **converted** : DataFrame

#### pandas.DataFrame.copy

`DataFrame.`**`copy`**(*deep=True*)

Make a copy of this object

**Parameters** **deep** : boolean, default True

Make a deep copy, i.e. also copy data

**Returns** **copy** : type of caller

### 21.3.3 Indexing, iteration

| | |
|---|---|
| `DataFrame.head`([n]) | Returns first n rows of DataFrame |
| `DataFrame.ix` | |
| `DataFrame.insert`(loc, column, value) | Insert column into DataFrame at specified location. Raises Exception if |
| `DataFrame.__iter__`() | Iterate over columns of the frame. |
| `DataFrame.iteritems`() | Iterator over (column, series) pairs |
| `DataFrame.iterrows`() | Iterate over rows of DataFrame as (index, Series) pairs |
| `DataFrame.itertuples`([index]) | Iterate over rows of DataFrame as tuples, with index value |
| `DataFrame.lookup`(row_labels, col_labels) | Label-based "fancy indexing" function for DataFrame. Given equal-length |
| `DataFrame.pop`(item) | Return column and drop from frame. |
| `DataFrame.tail`([n]) | Returns last n rows of DataFrame |
| `DataFrame.xs`(key[, axis, level, copy]) | Returns a cross-section (row(s) or column(s)) from the DataFrame. |

#### pandas.DataFrame.head

`DataFrame.`**`head`**(*n=5*)

Returns first n rows of DataFrame

### pandas.DataFrame.ix

`DataFrame.ix`

### pandas.DataFrame.insert

`DataFrame.insert(loc, column, value)`
Insert column into DataFrame at specified location. Raises Exception if column is already contained in the DataFrame

**Parameters** **loc** : int

Must have 0 <= loc <= len(columns)

**column** : object

**value** : int, Series, or array-like

### pandas.DataFrame.__iter__

`DataFrame.__iter__()`
Iterate over columns of the frame.

### pandas.DataFrame.iteritems

`DataFrame.iteritems()`
Iterator over (column, series) pairs

### pandas.DataFrame.iterrows

`DataFrame.iterrows()`
Iterate over rows of DataFrame as (index, Series) pairs

### pandas.DataFrame.itertuples

`DataFrame.itertuples(index=True)`
Iterate over rows of DataFrame as tuples, with index value as first element of the tuple

### 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.

**Parameters** **row_labels** : sequence

**col_labels** : sequence

### Notes

Akin to

result = [] for row, col in zip(row_labels, col_labels):

result.append(df.get_value(row, col))

## pandas.DataFrame.pop

`DataFrame.pop(item)`

Return column and drop from frame. Raise KeyError if not found.

**Returns** **column** : Series

## pandas.DataFrame.tail

`DataFrame.tail(n=5)`

Returns last n rows of DataFrame

## pandas.DataFrame.xs

`DataFrame.xs(key, axis=0, level=None, copy=True)`

Returns a cross-section (row(s) or column(s)) from the DataFrame. Defaults to cross-section on the rows (axis=0).

**Parameters** **key** : object

Some label contained in the index, or partially in a MultiIndex

**axis** : int, 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.

**copy** : boolean, default True

Whether to make a copy of the data

**Returns** **xs** : Series or DataFrame

### Examples

```
>>> df
   A  B  C
a  4  5  2
b  4  0  9
c  9  7  3
>>> df.xs('a')
A    4
B    5
C    2
Name: a
```

```
>>> df.xs('C', axis=1)
a    2
b    9
c    3
Name: C
>>> s = df.xs('a', copy=False)
>>> s['A'] = 100
>>> df
     A  B  C
a  100  5  2
b    4  0  9
c    9  7  3

>>> df
                    A  B  C  D
first second third
bar   one    1      4  1  8  9
      two    1      7  5  5  0
baz   one    1      6  6  8  0
      three  2      5  3  5  3
>>> df.xs(('baz', 'three'))
       A  B  C  D
third
2      5  3  5  3
>>> df.xs('one', level=1)
             A  B  C  D
first third
bar   1      4  1  8  9
baz   1      6  6  8  0
>>> df.xs(('baz', 2), level=[0, 'third'])
        A  B  C  D
second
three   5  3  5  3
```

### 21.3.4 Binary operator functions

| | |
|---|---|
| `DataFrame.add`(other[, axis, level, fill_value]) | Binary operator add with support to substitute a fill_value for missing data in |
| `DataFrame.div`(other[, axis, level, fill_value]) | Binary operator divide with support to substitute a fill_value for missing data |
| `DataFrame.mul`(other[, axis, level, fill_value]) | Binary operator multiply with support to substitute a fill_value for missing da |
| `DataFrame.sub`(other[, axis, level, fill_value]) | Binary operator subtract with support to substitute a fill_value for missing dat |
| `DataFrame.radd`(other[, axis, level, fill_value]) | Binary operator radd with support to substitute a fill_value for missing data in |
| `DataFrame.rdiv`(other[, axis, level, fill_value]) | Binary operator rdivide with support to substitute a fill_value for missing data |
| `DataFrame.rmul`(other[, axis, level, fill_value]) | Binary operator rmultiply with support to substitute a fill_value for missing da |
| `DataFrame.rsub`(other[, axis, level, fill_value]) | Binary operator rsubtract with support to substitute a fill_value for missing da |
| `DataFrame.combine`(other, func[, fill_value, ...]) | Add two DataFrame objects and do not propagate NaN values, so if for a |
| `DataFrame.combineAdd`(other) | Add two DataFrame objects and do not propagate |
| `DataFrame.combine_first`(other) | Combine two DataFrame objects and default to non-null values in frame |
| `DataFrame.combineMult`(other) | Multiply two DataFrame objects and do not propagate NaN values, so if |

#### pandas.DataFrame.add

`DataFrame.`**add**(*other*, *axis='columns'*, *level=None*, *fill_value=None*)

Binary operator add with support to substitute a fill_value for missing data in one of the inputs

**Parameters** **other** : Series, DataFrame, or constant

**axis** : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

**fill_value** : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

**level** : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns** **result** : DataFrame

#### Notes

Mismatched indices will be unioned together

### pandas.DataFrame.div

`DataFrame.div`(*other*, *axis='columns'*, *level=None*, *fill_value=None*)

Binary operator divide with support to substitute a fill_value for missing data in one of the inputs

**Parameters** **other** : Series, DataFrame, or constant

**axis** : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

**fill_value** : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

**level** : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns** **result** : DataFrame

#### Notes

Mismatched indices will be unioned together

### pandas.DataFrame.mul

`DataFrame.mul`(*other*, *axis='columns'*, *level=None*, *fill_value=None*)

Binary operator multiply with support to substitute a fill_value for missing data in one of the inputs

**Parameters** **other** : Series, DataFrame, or constant

**axis** : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

**fill_value** : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

**level** : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns** **result** : DataFrame

### Notes

Mismatched indices will be unioned together

## pandas.DataFrame.sub

`DataFrame.`**`sub`**`(`*other*, *axis='columns'*, *level=None*, *fill_value=None*`)`

Binary operator subtract with support to substitute a fill_value for missing data in one of the inputs

**Parameters** **other** : Series, DataFrame, or constant

**axis** : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

**fill_value** : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

**level** : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns** **result** : DataFrame

### Notes

Mismatched indices will be unioned together

## pandas.DataFrame.radd

`DataFrame.`**`radd`**`(`*other*, *axis='columns'*, *level=None*, *fill_value=None*`)`

Binary operator radd with support to substitute a fill_value for missing data in one of the inputs

**Parameters** **other** : Series, DataFrame, or constant

**axis** : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

**fill_value** : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

**level** : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns** **result** : DataFrame

#### Notes

Mismatched indices will be unioned together

### pandas.DataFrame.rdiv

`DataFrame.rdiv(other, axis='columns', level=None, fill_value=None)`

Binary operator rdivide with support to substitute a fill_value for missing data in one of the inputs

**Parameters** **other** : Series, DataFrame, or constant

**axis** : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

**fill_value** : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

**level** : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns** **result** : DataFrame

#### Notes

Mismatched indices will be unioned together

### pandas.DataFrame.rmul

`DataFrame.rmul(other, axis='columns', level=None, fill_value=None)`

Binary operator rmultiply with support to substitute a fill_value for missing data in one of the inputs

**Parameters** **other** : Series, DataFrame, or constant

**axis** : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

**fill_value** : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

**level** : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns** **result** : DataFrame

#### Notes

Mismatched indices will be unioned together

### pandas.DataFrame.rsub

`DataFrame.rsub(other, axis='columns', level=None, fill_value=None)`

Binary operator rsubtract with support to substitute a fill_value for missing data in one of the inputs

**Parameters** **other** : Series, DataFrame, or constant

**axis** : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

**fill_value** : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

**level** : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

**Returns** **result** : DataFrame

#### Notes

Mismatched indices will be unioned together

### pandas.DataFrame.combine

`DataFrame.combine(other, func, fill_value=None, overwrite=True)`

Add two DataFrame objects and do not propagate NaN values, so if for a (column, time) one frame is missing a value, it will default to the other frame's value (which might be NaN as well)

**Parameters** **other** : DataFrame

**func** : function

**fill_value** : scalar value

**overwrite** : boolean, default True

If True then overwrite values for common keys in the calling frame

**Returns** **result** : DataFrame

### pandas.DataFrame.combineAdd

`DataFrame.combineAdd(other)`

Add two DataFrame objects and do not propagate NaN values, so if for a (column, time) one frame is missing a value, it will default to the other frame's value (which might be NaN as well)

**Parameters** **other** : DataFrame

**Returns** **DataFrame** :

### pandas.DataFrame.combine_first

`DataFrame.combine_first(other)`

Combine two DataFrame objects and default to non-null values in frame calling the method. Result index columns will be the union of the respective indexes and columns

**Parameters** **other** : DataFrame

**Returns** **combined** : DataFrame

#### Examples

```
>>> a.combine_first(b)
    a's values prioritized, use values from b to fill holes
```

### pandas.DataFrame.combineMult

DataFrame.**combineMult**(*other*)

Multiply two DataFrame objects and do not propagate NaN values, so if for a (column, time) one frame is missing a value, it will default to the other frame's value (which might be NaN as well)

**Parameters** **other** : DataFrame

**Returns** **DataFrame** :

## 21.3.5 Function application, GroupBy

| | |
|---|---|
| DataFrame.apply(func[, axis, broadcast, ...]) | Applies function along input axis of DataFrame. Objects passed to |
| DataFrame.applymap(func) | Apply a function to a DataFrame that is intended to operate |
| DataFrame.groupby([by, axis, level, ...]) | Group series using mapper (dict or key function, apply given function |

### pandas.DataFrame.apply

DataFrame.**apply**(*func*, *axis=0*, *broadcast=False*, *raw=False*, *args=()*, ***kwds*)

Applies function along input axis of DataFrame. Objects passed to functions are Series objects having index either the DataFrame's index (axis=0) or the columns (axis=1). Return type depends on whether passed function aggregates

**Parameters** **func** : function

Function to apply to each column

**axis** : {0, 1}

0 : apply function to each column 1 : apply function to each row

**broadcast** : bool, default False

For aggregation functions, return object of same size with values propagated

**raw** : boolean, default False

If False, convert each row or column into a Series. If raw=True the passed function will receive ndarray objects instead. If you are just applying a NumPy reduction function this will achieve much better performance

**args** : tuple

Positional arguments to pass to function in addition to the array/series

**Additional keyword arguments will be passed as keywords to the function** :

**Returns** **applied** : Series or DataFrame

**See Also:**

`DataFrame.applymap` For elementwise operations

### Examples

```
>>> df.apply(numpy.sqrt) # returns DataFrame
>>> df.apply(numpy.sum, axis=0) # equiv to df.sum(0)
>>> df.apply(numpy.sum, axis=1) # equiv to df.sum(1)
```

## pandas.DataFrame.applymap

`DataFrame.applymap(`*func*`)`

Apply a function to a DataFrame that is intended to operate elementwise, i.e. like doing map(func, series) for each series in the DataFrame

**Parameters** **func** : function

Python function, returns a single value from a single value

**Returns** **applied** : DataFrame

## pandas.DataFrame.groupby

`DataFrame.groupby(`*by=None*, *axis=0*, *level=None*, *as_index=True*, *sort=True*, *group_keys=True*`)`

Group series using mapper (dict or key function, apply given function to group, return result as series) or by a series of columns

**Parameters** **by** : mapping function / list of functions, dict, Series, or tuple /

list of column names. Called on each element of the object index to determine the groups. If a dict or Series is passed, the Series or dict VALUES will be used to determine the groups

**axis** : int, default 0

**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** : boolean, 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** : boolean, default True

Sort group keys. Get better performance by turning this off

**group_keys** : boolean, default True

When calling apply, add group keys to index to identify pieces

**Returns** **GroupBy object** :

#### Examples

# DataFrame result >>> data.groupby(func, axis=0).mean()

# DataFrame result >>> data.groupby(['col1', 'col2'])['col3'].mean()

# DataFrame with hierarchical index >>> data.groupby(['col1', 'col2']).mean()

## 21.3.6 Computations / Descriptive Stats

| | |
|---|---|
| DataFrame.abs() | Return an object with absolute value taken. |
| DataFrame.any([axis, bool_only, skipna, level]) | Return whether any element is True over requested axis. |
| DataFrame.clip([lower, upper]) | Trim values at input threshold(s) |
| DataFrame.clip_lower(threshold) | Trim values below threshold |
| DataFrame.clip_upper(threshold) | Trim values above threshold |
| DataFrame.corr([method, min_periods]) | Compute pairwise correlation of columns, excluding NA/null values |
| DataFrame.corrwith(other[, axis, drop]) | Compute pairwise correlation between rows or columns of two DataFrame |
| DataFrame.count([axis, level, numeric_only]) | Return Series with number of non-NA/null observations over requested |
| DataFrame.cov([min_periods]) | Compute pairwise covariance of columns, excluding NA/null values |
| DataFrame.cummax([axis, skipna]) | Return DataFrame of cumulative max over requested axis. |
| DataFrame.cummin([axis, skipna]) | Return DataFrame of cumulative min over requested axis. |
| DataFrame.cumprod([axis, skipna]) | Return cumulative product over requested axis as DataFrame |
| DataFrame.cumsum([axis, skipna]) | Return DataFrame of cumulative sums over requested axis. |
| DataFrame.describe([percentile_width]) | Generate various summary statistics of each column, excluding |
| DataFrame.diff([periods]) | 1st discrete difference of object |
| DataFrame.kurt([axis, skipna, level]) | Return unbiased kurtosis over requested axis. |
| DataFrame.mad([axis, skipna, level]) | Return mean absolute deviation over requested axis. |
| DataFrame.max([axis, skipna, level]) | Return maximum over requested axis. |
| DataFrame.mean([axis, skipna, level]) | Return mean over requested axis. |
| DataFrame.median([axis, skipna, level]) | Return median over requested axis. |
| DataFrame.min([axis, skipna, level]) | Return minimum over requested axis. |
| DataFrame.pct_change([periods, fill_method, ...]) | Percent change over given number of periods |
| DataFrame.prod([axis, skipna, level]) | Return product over requested axis. |
| DataFrame.quantile([q, axis, numeric_only]) | Return values at the given quantile over requested axis, a la |
| DataFrame.rank([axis, numeric_only, method, ...]) | Compute numerical data ranks (1 through n) along axis. |
| DataFrame.skew([axis, skipna, level]) | Return unbiased skewness over requested axis. |
| DataFrame.sum([axis, numeric_only, skipna, ...]) | Return sum over requested axis. |
| DataFrame.std([axis, skipna, level, ddof]) | Return standard deviation over requested axis. |
| DataFrame.var([axis, skipna, level, ddof]) | Return variance over requested axis. |

### pandas.DataFrame.abs

`DataFrame.abs()`

Return an object with absolute value taken. Only applicable to objects that are all numeric

**Returns abs: type of caller** :

### pandas.DataFrame.any

`DataFrame.any(axis=0, bool_only=None, skipna=True, level=None)`

Return whether any element is True over requested axis. %(na_action)s

**Parameters** **axis** : {0, 1}

0 for row-wise, 1 for column-wise

**skipna** : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

**level** : int, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

**bool_only** : boolean, default None

Only include boolean data.

**Returns** **any** : Series (or DataFrame if level specified)

### pandas.DataFrame.clip

`DataFrame.`**`clip`**(*lower=None*, *upper=None*)

Trim values at input threshold(s)

**Parameters** **lower** : float, default None

**upper** : float, default None

**Returns** **clipped** : DataFrame

### pandas.DataFrame.clip_lower

`DataFrame.`**`clip_lower`**(*threshold*)

Trim values below threshold

**Returns** **clipped** : DataFrame

### pandas.DataFrame.clip_upper

`DataFrame.`**`clip_upper`**(*threshold*)

Trim values above threshold

**Returns** **clipped** : DataFrame

### pandas.DataFrame.corr

`DataFrame.`**`corr`**(*method='pearson'*, *min_periods=None*)

Compute pairwise correlation of columns, excluding NA/null values

**Parameters** **method** : {'pearson', 'kendall', 'spearman'}

pearson : standard correlation coefficient kendall : Kendall Tau correlation coefficient spearman : Spearman rank correlation

**min_periods** : int, optional

Minimum number of observations required per pair of columns to have a valid result. Currently only available for pearson correlation

**Returns** **y** : DataFrame

### pandas.DataFrame.corrwith

DataFrame.**corrwith**(*other*, *axis=0*, *drop=False*)

Compute pairwise correlation between rows or columns of two DataFrame objects.

**Parameters** **other** : DataFrame

**axis** : {0, 1}

0 to compute column-wise, 1 for row-wise

**drop** : boolean, default False

Drop missing indices from result, default returns union of all

**Returns** **correls** : Series

### pandas.DataFrame.count

DataFrame.**count**(*axis=0*, *level=None*, *numeric_only=False*)

Return Series with number of non-NA/null observations over requested axis. Works with non-floating point data as well (detects NaN and None)

**Parameters** **axis** : {0, 1}

0 for row-wise, 1 for column-wise

**level** : int, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

**numeric_only** : boolean, default False

Include only float, int, boolean data

**Returns** **count** : Series (or DataFrame if level specified)

### pandas.DataFrame.cov

DataFrame.**cov**(*min_periods=None*)

Compute pairwise covariance of columns, excluding NA/null values

**Parameters** **min_periods** : int, optional

Minimum number of observations required per pair of columns to have a valid result.

**Returns** **y** : DataFrame

**y contains the covariance matrix of the DataFrame's time series.** :

**The covariance is normalized by N-1 (unbiased estimator).** :

### pandas.DataFrame.cummax

DataFrame.**cummax**(*axis=None*, *skipna=True*)

Return DataFrame of cumulative max over requested axis.

**Parameters** **axis** : {0, 1}

0 for row-wise, 1 for column-wise

**skipna** : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

**Returns** **y** : DataFrame

### pandas.DataFrame.cummin

`DataFrame.`**`cummin`**(*axis=None*, *skipna=True*)

Return DataFrame of cumulative min over requested axis.

**Parameters** **axis** : {0, 1}

0 for row-wise, 1 for column-wise

**skipna** : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

**Returns** **y** : DataFrame

### pandas.DataFrame.cumprod

`DataFrame.`**`cumprod`**(*axis=None*, *skipna=True*)

Return cumulative product over requested axis as DataFrame

**Parameters** **axis** : {0, 1}

0 for row-wise, 1 for column-wise

**skipna** : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

**Returns** **y** : DataFrame

### pandas.DataFrame.cumsum

`DataFrame.`**`cumsum`**(*axis=None*, *skipna=True*)

Return DataFrame of cumulative sums over requested axis.

**Parameters** **axis** : {0, 1}

0 for row-wise, 1 for column-wise

**skipna** : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

**Returns** **y** : DataFrame

### pandas.DataFrame.describe

`DataFrame.`**`describe`**(*percentile_width=50*)

Generate various summary statistics of each column, excluding NaN values. These include: count, mean, std, min, max, and lower%/50%/upper% percentiles

**Parameters** **percentile_width** : float, optional

width of the desired uncertainty interval, default is 50, which corresponds to lower=25, upper=75

**Returns** **DataFrame of summary statistics** :

### pandas.DataFrame.diff

`DataFrame.diff(periods=1)`

1st discrete difference of object

**Parameters** **periods** : int, default 1

Periods to shift for forming difference

**Returns** **diffed** : DataFrame

### pandas.DataFrame.kurt

`DataFrame.kurt(axis=0, skipna=True, level=None)`

Return unbiased kurtosis over requested axis. NA/null values are excluded

**Parameters** **axis** : {0, 1}

0 for row-wise, 1 for column-wise

**skipna** : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

**level** : int, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

**Returns** **kurt** : Series (or DataFrame if level specified)

### pandas.DataFrame.mad

`DataFrame.mad(axis=0, skipna=True, level=None)`

Return mean absolute deviation over requested axis. NA/null values are excluded

**Parameters** **axis** : {0, 1}

0 for row-wise, 1 for column-wise

**skipna** : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

**level** : int, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

**Returns** **mad** : Series (or DataFrame if level specified)

### pandas.DataFrame.max

`DataFrame.max(axis=0, skipna=True, level=None)`

Return maximum over requested axis. NA/null values are excluded

**Parameters** **axis** : {0, 1}

0 for row-wise, 1 for column-wise

**skipna** : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

**level** : int, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

**Returns** **max** : Series (or DataFrame if level specified)

### pandas.DataFrame.mean

`DataFrame.mean` (*axis=0*, *skipna=True*, *level=None*)

Return mean over requested axis. NA/null values are excluded

**Parameters** **axis** : {0, 1}

0 for row-wise, 1 for column-wise

**skipna** : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

**level** : int, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

**Returns** **mean** : Series (or DataFrame if level specified)

### pandas.DataFrame.median

`DataFrame.median` (*axis=0*, *skipna=True*, *level=None*)

Return median over requested axis. NA/null values are excluded

**Parameters** **axis** : {0, 1}

0 for row-wise, 1 for column-wise

**skipna** : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

**level** : int, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

**Returns** **median** : Series (or DataFrame if level specified)

### pandas.DataFrame.min

`DataFrame.min` (*axis=0*, *skipna=True*, *level=None*)

Return minimum over requested axis. NA/null values are excluded

**Parameters** **axis** : {0, 1}

0 for row-wise, 1 for column-wise

**skipna** : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

**level** : int, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

**Returns** **min** : Series (or DataFrame if level specified)

### pandas.DataFrame.pct_change

`DataFrame.pct_change`(*periods=1*, *fill_method='pad'*, *limit=None*, *freq=None*, ***kwds*)

Percent change over given number of periods

**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 offset alias string, optional

Increment to use from time series API (e.g. 'M' or BDay())

**Returns** **chg** : Series or DataFrame

### pandas.DataFrame.prod

`DataFrame.prod`(*axis=0*, *skipna=True*, *level=None*)

Return product over requested axis. NA/null values are treated as 1

**Parameters** **axis** : {0, 1}

0 for row-wise, 1 for column-wise

**skipna** : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

**level** : int, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

**Returns** **product** : Series (or DataFrame if level specified)

### pandas.DataFrame.quantile

`DataFrame.quantile`(*q=0.5*, *axis=0*, *numeric_only=True*)

Return values at the given quantile over requested axis, a la scoreatpercentile in scipy.stats

**Parameters** **q** : quantile, default 0.5 (50% quantile)

0 <= q <= 1

**axis** : {0, 1}

0 for row-wise, 1 for column-wise

**Returns** **quantiles** : Series

### pandas.DataFrame.rank

DataFrame.**rank**(*axis=0*, *numeric_only=None*, *method='average'*, *na_option='keep'*, *ascending=True*)

Compute numerical data ranks (1 through n) along axis. Equal values are assigned a rank that is the average of the ranks of those values

**Parameters** **axis** : {0, 1}, default 0

Ranks over columns (0) or rows (1)

**numeric_only** : boolean, default None

Include only float, int, boolean data

**method** : {'average', 'min', 'max', 'first'}

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

**na_option** : {'keep', 'top', 'bottom'}

keep: leave NA values where they are top: smallest rank if ascending bottom: smallest rank if descending

**ascending** : boolean, default True

False for ranks by high (1) to low (N)

**Returns** **ranks** : DataFrame

### pandas.DataFrame.skew

DataFrame.**skew**(*axis=0*, *skipna=True*, *level=None*)

Return unbiased skewness over requested axis. NA/null values are excluded

**Parameters** **axis** : {0, 1}

0 for row-wise, 1 for column-wise

**skipna** : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

**level** : int, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

**Returns** **skew** : Series (or DataFrame if level specified)

### pandas.DataFrame.sum

DataFrame.**sum**(*axis=0*, *numeric_only=None*, *skipna=True*, *level=None*)

Return sum over requested axis. NA/null values are excluded

**Parameters** **axis** : {0, 1}

0 for row-wise, 1 for column-wise

**skipna** : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

**level** : int, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

**numeric_only** : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

**Returns** **sum** : Series (or DataFrame if level specified)

### pandas.DataFrame.std

`DataFrame.std(axis=0, skipna=True, level=None, ddof=1)`

Return standard deviation over requested axis. NA/null values are excluded

**Parameters** **axis** : {0, 1}

0 for row-wise, 1 for column-wise

**skipna** : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

**level** : int, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

**Returns** **std** : Series (or DataFrame if level specified)

Normalized by N-1 (unbiased estimator).

### pandas.DataFrame.var

`DataFrame.var(axis=0, skipna=True, level=None, ddof=1)`

Return variance over requested axis. NA/null values are excluded

**Parameters** **axis** : {0, 1}

0 for row-wise, 1 for column-wise

**skipna** : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

**level** : int, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

**Returns** **var** : Series (or DataFrame if level specified)

Normalized by N-1 (unbiased estimator).

Continued on next page

**Table 21.28 – continued from previous page**

### 21.3.7 Reindexing / Selection / Label manipulation

| | |
|---|---|
| DataFrame.add_prefix(prefix) | Concatenate prefix string with panel items names. |
| DataFrame.add_suffix(suffix) | Concatenate suffix string with panel items names |
| DataFrame.align(other[, join, axis, level, ...]) | Align two DataFrame object on their index and columns with the |
| DataFrame.drop(labels[, axis, level]) | Return new object with labels in requested axis removed |
| DataFrame.drop_duplicates([cols, take_last, ...]) | Return DataFrame with duplicate rows removed, optionally only |
| DataFrame.duplicated([cols, take_last]) | Return boolean Series denoting duplicate rows, optionally only |
| DataFrame.filter([items, like, regex]) | Restrict frame's columns to set of items or wildcard |
| DataFrame.first(offset) | Convenience method for subsetting initial periods of time series data |
| DataFrame.head([n]) | Returns first n rows of DataFrame |
| 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) | Convenience method for subsetting final periods of time series data |
| DataFrame.reindex([index, columns, method, ...]) | Conform DataFrame to new index with optional filling logic, placing |
| DataFrame.reindex_axis(labels[, axis, ...]) | Conform DataFrame to new index with optional filling logic, placing |
| DataFrame.reindex_like(other[, method, ...]) | Reindex DataFrame to match indices of another DataFrame, optionally |
| DataFrame.rename([index, columns, copy, inplace]) | Alter index and / or columns using input function or functions. |
| DataFrame.reset_index([level, drop, ...]) | For DataFrame with multi-level index, return new DataFrame with |
| DataFrame.select(crit[, axis]) | Return data corresponding to axis labels matching criteria |
| DataFrame.set_index(keys[, drop, append, ...]) | Set the DataFrame index (row labels) using one or more existing |
| DataFrame.tail([n]) | Returns last n rows of DataFrame |
| DataFrame.take(indices[, axis]) | Analogous to ndarray.take, return DataFrame corresponding to requested |
| DataFrame.truncate([before, after, copy]) | Function truncate a sorted DataFrame / Series before and/or after |

#### pandas.DataFrame.add_prefix

DataFrame.**add_prefix**(*prefix*)

Concatenate prefix string with panel items names.

**Parameters** **prefix** : string

**Returns** **with_prefix** : type of caller

#### pandas.DataFrame.add_suffix

DataFrame.**add_suffix**(*suffix*)

Concatenate suffix string with panel items names

**Parameters** **suffix** : string

**Returns** **with_suffix** : type of caller

#### pandas.DataFrame.align

DataFrame.**align**(*other*, *join='outer'*, *axis=None*, *level=None*, *copy=True*, *fill_value=nan*, *method=None*, *limit=None*, *fill_axis=0*)

Align two DataFrame object on their index and columns with the specified join method for each axis Index

**Parameters** **other** : DataFrame or Series

**join** : {'outer', 'inner', 'left', 'right'}, default 'outer'

**axis** : {0, 1, None}, default None

Align on index (0), columns (1), or both (None)

**level** : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

**copy** : boolean, 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** : str, default None

**limit** : int, default None

**fill_axis** : {0, 1}, default 0

Filling axis, method and limit

**Returns** **(left, right)** : (DataFrame, type of other)

Aligned objects

### pandas.DataFrame.drop

`DataFrame.drop`(*labels*, *axis=0*, *level=None*)

Return new object with labels in requested axis removed

**Parameters** **labels** : array-like

**axis** : int

**level** : int or name, default None

For MultiIndex

**Returns** **dropped** : type of caller

### pandas.DataFrame.drop_duplicates

`DataFrame.drop_duplicates`(*cols=None*, *take_last=False*, *inplace=False*)

Return DataFrame with duplicate rows removed, optionally only considering certain columns

**Parameters** **cols** : column label or sequence of labels, optional

Only consider certain columns for identifying duplicates, by default use all of the columns

**take_last** : boolean, default False

Take the last observed row in a row. Defaults to the first row

**inplace** : boolean, default False

Whether to drop duplicates in place or to return a copy

**Returns** **deduplicated** : DataFrame

### pandas.DataFrame.duplicated

`DataFrame.duplicated(cols=None, take_last=False)`

Return boolean Series denoting duplicate rows, optionally only considering certain columns

**Parameters** **cols** : column label or sequence of labels, optional

Only consider certain columns for identifying duplicates, by default use all of the columns

**take_last** : boolean, default False

Take the last observed row in a row. Defaults to the first row

**Returns** **duplicated** : Series

### pandas.DataFrame.filter

`DataFrame.filter(items=None, like=None, regex=None)`

Restrict frame's columns to set of items or wildcard

**Parameters** **items** : list-like

List of columns to restrict to (must not all be present)

**like** : string

Keep columns where "arg in col == True"

**regex** : string (regular expression)

Keep columns with re.search(regex, col) == True

**Returns** **DataFrame with filtered columns** :

#### Notes

Arguments are mutually exclusive, but this is not checked for

### pandas.DataFrame.first

`DataFrame.first(offset)`

Convenience method for subsetting initial periods of time series data based on a date offset

**Parameters** **offset** : string, DateOffset, dateutil.relativedelta

**Returns** **subset** : type of caller

#### Examples

ts.last('10D') -> First 10 days

### pandas.DataFrame.head

`DataFrame.head(n=5)`

Returns first n rows of DataFrame

### 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, 1}

0 for row-wise, 1 for column-wise

**skipna** : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be first index.

**Returns** **idxmax** : Series

### 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, 1}

0 for row-wise, 1 for column-wise

**skipna** : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

**Returns** **idxmin** : Series

### pandas.DataFrame.last

`DataFrame.last(offset)`

Convenience method for subsetting final periods of time series data based on a date offset

**Parameters** **offset** : string, DateOffset, dateutil.relativedelta

**Returns** **subset** : type of caller

#### Examples

ts.last('5M') -> Last 5 months

### pandas.DataFrame.reindex

`DataFrame.reindex(index=None, columns=None, method=None, level=None, fill_value=nan, limit=None, copy=True)`

Conform DataFrame to new index with optional filling logic, placing 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. Preferably an Index object to avoid duplicating data

**columns** : array-like, optional

Same usage as index argument

**method** : {'backfill', 'bfill', 'pad', 'ffill', None}, default None

Method to use for filling holes in reindexed DataFrame pad / ffill: propagate last valid observation forward to next valid backfill / bfill: use NEXT valid observation to fill gap

**copy** : boolean, 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 size gap to forward or backward fill

**Returns** **reindexed** : same type as calling instance

### Examples

```
>>> df.reindex(index=[date1, date2, date3], columns=['A', 'B', 'C'])
```

## pandas.DataFrame.reindex_axis

`DataFrame.reindex_axis`(*labels*, *axis=0*, *method=None*, *level=None*, *copy=True*, *limit=None*, *fill_value=nan*)

Conform DataFrame to new index with optional filling logic, placing 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. Preferably an Index object to avoid duplicating data

**axis** : {0, 1}

0 -> index (rows) 1 -> columns

**method** : {'backfill', 'bfill', 'pad', 'ffill', None}, default None

Method to use for filling holes in reindexed DataFrame pad / ffill: propagate last valid observation forward to next valid backfill / bfill: use NEXT valid observation to fill gap

**copy** : boolean, 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

**limit** : int, default None

Maximum size gap to forward or backward fill

**Returns** **reindexed** : same type as calling instance

**See Also:**

`DataFrame.reindex`, `DataFrame.reindex_like`

### Examples

```
>>> df.reindex_axis(['A', 'B', 'C'], axis=1)
```

## pandas.DataFrame.reindex_like

`DataFrame.reindex_like(other, method=None, copy=True, limit=None, fill_value=nan)`

Reindex DataFrame to match indices of another DataFrame, optionally with filling logic

**Parameters** **other** : DataFrame

**method** : string or None

**copy** : boolean, default True

**limit** : int, default None

Maximum size gap to forward or backward fill

**Returns** **reindexed** : DataFrame

### Notes

**Like calling s.reindex(index=other.index, columns=other.columns,** method=...)

## pandas.DataFrame.rename

`DataFrame.rename(index=None, columns=None, copy=True, inplace=False)`

Alter index and / or columns using input function or functions. Function / dict values must be unique (1-to-1). Labels not contained in a dict / Series will be left as-is.

**Parameters** **index** : dict-like or function, optional

Transformation to apply to index values

**columns** : dict-like or function, optional

Transformation to apply to column values

**copy** : boolean, default True

Also copy underlying data

**inplace** : boolean, default False

Whether to return a new DataFrame. If True then value of copy is ignored.

**Returns** **renamed** : DataFrame (new object)

**See Also:**

`Series.rename`

### pandas.DataFrame.reset_index

DataFrame.**reset_index**(*level=None, drop=False, inplace=False, col_level=0, col_fill=''*)

For DataFrame with multi-level index, return new DataFrame with labeling information in the columns under the index names, defaulting to 'level_0', 'level_1', etc. if any are None. For a standard index, the index name will be used (if set), otherwise a default 'index' or 'level_0' (if 'index' is already taken) will be used.

**Parameters** **level** : int, str, tuple, or list, default None

Only remove the given levels from the index. Removes all levels by default

**drop** : boolean, default False

Do not try to insert index into dataframe columns. This resets the index to the default integer index.

**inplace** : boolean, 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** **resetted** : DataFrame

### pandas.DataFrame.select

DataFrame.**select**(*crit, axis=0*)

Return data corresponding to axis labels matching criteria

**Parameters** **crit** : function

To be called on each index (label). Should return True or False

**axis** : int

**Returns** **selection** : type of caller

### pandas.DataFrame.set_index

DataFrame.**set_index**(*keys, drop=True, append=False, inplace=False, verify_integrity=False*)

Set the DataFrame index (row labels) using one or more existing columns. By default yields a new object.

**Parameters** **keys** : column label or list of column labels / arrays

**drop** : boolean, default True

Delete columns to be used as the new index

**append** : boolean, default False

Whether to append columns to existing index

**inplace** : boolean, default False

Modify the DataFrame in place (do not create a new object)

**verify_integrity** : boolean, 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** : DataFrame

#### Examples

```
>>> indexed_df = df.set_index(['A', 'B'])
>>> indexed_df2 = df.set_index(['A', [0, 1, 2, 0, 1, 2]])
>>> indexed_df3 = df.set_index([[0, 1, 2, 0, 1, 2]])
```

### pandas.DataFrame.tail

`DataFrame.`**`tail`**`(`*n=5*`)`

Returns last n rows of DataFrame

### pandas.DataFrame.take

`DataFrame.`**`take`**`(`*indices*, *axis=0*`)`

Analogous to ndarray.take, return DataFrame corresponding to requested indices along an axis

**Parameters** **indices** : list / array of ints

**axis** : {0, 1}

**Returns** **taken** : DataFrame

### pandas.DataFrame.truncate

`DataFrame.`**`truncate`**`(`*before=None*, *after=None*, *copy=True*`)`

Function truncate a sorted DataFrame / Series before and/or after some particular dates.

**Parameters** **before** : date

Truncate before date

**after** : date

Truncate after date

**Returns** **truncated** : type of caller

## 21.3.8 Missing data handling

| | |
|---|---|
| `DataFrame.dropna`([axis, how, thresh, subset]) | Return object with labels on given axis omitted where alternately any |
| `DataFrame.fillna`([value, method, axis, ...]) | Fill NA/NaN values using the specified method |

### pandas.DataFrame.dropna

`DataFrame.`**`dropna`**`(`*axis=0*, *how='any'*, *thresh=None*, *subset=None*`)`

Return object with labels on given axis omitted where alternately any or all of the data are missing

**Parameters** **axis** : {0, 1}, or tuple/list thereof

Pass tuple or list to drop on multiple axes

**how** : {'any', 'all'}

any : if any NA values are present, drop that label all : if all values are NA, drop that label

**thresh** : int, default None

int value : require that many non-NA values

**subset** : array-like

Labels along other axis to consider, e.g. if you are dropping rows these would be a list of columns to include

**Returns** **dropped** : DataFrame

### pandas.DataFrame.fillna

`DataFrame.fillna`(*value=None*, *method=None*, *axis=0*, *inplace=False*, *limit=None*)

Fill NA/NaN values using the specified method

**Parameters** **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

**value** : scalar or dict

Value to use to fill holes (e.g. 0), alternately a dict of values specifying which value to use for each column (columns not in the dict will not be filled)

**axis** : {0, 1}, default 0

0: fill column-by-column 1: fill row-by-row

**inplace** : boolean, default False

If True, fill the DataFrame in place. Note: this will modify any other views on this DataFrame, like if you took a no-copy slice of an existing DataFrame, for example a column in a DataFrame. Returns a reference to the filled object, which is self if inplace=True

**limit** : int, default None

Maximum size gap to forward or backward fill

**Returns** **filled** : DataFrame

**See Also:**

`reindex`, `asfreq`

## 21.3.9 Reshaping, sorting, transposing

| | |
|---|---|
| `DataFrame.delevel`(*args, **kwargs) | |
| `DataFrame.pivot`([index, columns, values]) | Reshape data (produce a "pivot" table) based on column values. |
| `DataFrame.reorder_levels`(order[, axis]) | Rearrange index levels using input order. |
| | Continued on next page |

Table 21.30 – continued from previous page

| | |
|---|---|
| DataFrame.sort([columns, column, axis, ...]) | Sort DataFrame either by labels (along either axis) or by the values in |
| DataFrame.sort_index([axis, by, ascending, ...]) | Sort DataFrame either by labels (along either axis) or by the values in |
| DataFrame.sortlevel([level, axis, ...]) | Sort multilevel index by chosen axis and primary level. |
| DataFrame.swaplevel(i, j[, axis]) | Swap levels i and j in a MultiIndex on a particular axis |
| DataFrame.stack([level, dropna]) | Pivot a level of the (possibly hierarchical) column labels, returning a |
| DataFrame.unstack([level]) | Pivot a level of the (necessarily hierarchical) index labels, returning |
| DataFrame.T | Returns a DataFrame with the rows/columns switched. If the DataFrame is |
| DataFrame.to_panel() | Transform long (stacked) format (DataFrame) into wide (3D, Panel) |
| DataFrame.transpose() | Returns a DataFrame with the rows/columns switched. If the DataFrame is |

### pandas.DataFrame.delevel

DataFrame.**delevel**(**args*, ***kwargs*)

### pandas.DataFrame.pivot

DataFrame.**pivot**(*index=None*, *columns=None*, *values=None*)

Reshape data (produce a "pivot" table) based on column values. Uses unique values from index / columns to form axes and return either DataFrame or Panel, depending on whether you request a single value column (DataFrame) or all columns (Panel)

**Parameters** **index** : string or object

Column name to use to make new frame's index

**columns** : string or object

Column name to use to make new frame's columns

**values** : string or object, optional

Column name to use for populating new frame's values

**Returns** **pivoted** : DataFrame

If no values column specified, will have hierarchically indexed columns

#### Notes

For finer-tuned control, see hierarchical indexing documentation along with the related stack/unstack methods

#### Examples

```
>>> df
    foo   bar  baz
0   one   A    1.
1   one   B    2.
2   one   C    3.
3   two   A    4.
4   two   B    5.
5   two   C    6.
```

```
>>> df.pivot('foo', 'bar', 'baz')
     A   B   C
one  1   2   3
two  4   5   6

>>> df.pivot('foo', 'bar')['baz']
     A   B   C
one  1   2   3
two  4   5   6
```

### 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 representing new level order.** :

(reference level by number not by key)

**axis: where to reorder levels** :

**Returns** **type of caller (new object)** :

### pandas.DataFrame.sort

DataFrame.**sort**(*columns=None*, *column=None*, *axis=0*, *ascending=True*, *inplace=False*)

Sort DataFrame either by labels (along either axis) or by the values in column(s)

**Parameters** **columns** : object

Column name(s) in frame. Accepts a column name or a list or tuple for a nested sort.

**ascending** : boolean or list, default True

Sort ascending vs. descending. Specify list for multiple sort orders

**axis** : {0, 1}

Sort index/rows versus columns

**inplace** : boolean, default False

Sort the DataFrame without creating a new instance

**Returns** **sorted** : DataFrame

#### Examples

```
>>> result = df.sort(['A', 'B'], ascending=[1, 0])
```

### pandas.DataFrame.sort_index

DataFrame.**sort_index**(*axis=0*, *by=None*, *ascending=True*, *inplace=False*)

Sort DataFrame either by labels (along either axis) or by the values in a column

**Parameters** **axis** : {0, 1}

Sort index/rows versus columns

**by** : object

Column name(s) in frame. Accepts a column name or a list or tuple for a nested sort.

**ascending** : boolean or list, default True

Sort ascending vs. descending. Specify list for multiple sort orders

**inplace** : boolean, default False

Sort the DataFrame without creating a new instance

**Returns** **sorted** : DataFrame

#### Examples

```
>>> result = df.sort_index(by=['A', 'B'], ascending=[1, 0])
```

### pandas.DataFrame.sortlevel

DataFrame.**sortlevel**(*level=0*, *axis=0*, *ascending=True*, *inplace=False*)

Sort multilevel index by chosen axis and primary level. Data will be lexicographically sorted by the chosen level followed by the other levels (in order)

**Parameters** **level** : int

**axis** : {0, 1}

**ascending** : bool, default True

**inplace** : boolean, default False

Sort the DataFrame without creating a new instance

**Returns** **sorted** : DataFrame

### pandas.DataFrame.swaplevel

DataFrame.**swaplevel**(*i*, *j*, *axis=0*)

Swap levels i and j in a MultiIndex on a particular axis

**Parameters** **i, j** : int, string (can be mixed)

Level of index to be swapped. Can pass level name as string.

**Returns** **swapped** : type of caller (new object)

### pandas.DataFrame.stack

DataFrame.**stack**(*level=-1*, *dropna=True*)

Pivot a level of the (possibly hierarchical) column labels, returning a DataFrame (or Series in the case of an object with a single level of column labels) having a hierarchical index with a new inner-most level of row labels.

**Parameters** **level** : int, string, or list of these, default last level

Level(s) to stack, can pass level name

**dropna** : boolean, default True

Whether to drop rows in the resulting Frame/Series with no valid values

**Returns** **stacked** : DataFrame or Series

### Examples

```
>>> s
     a    b
one  1.   2.
two  3.   4.

>>> s.stack()
one a     1
    b     2
two a     3
    b     4
```

## pandas.DataFrame.unstack

`DataFrame.`**`unstack`**`(`*level=-1*`)`

Pivot a level of the (necessarily hierarchical) index labels, returning 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, string, or list of these, default last level

Level(s) of index to unstack, can pass level name

**Returns** **unstacked** : DataFrame or Series

### Examples

```
>>> s
one  a   1.
one  b   2.
two  a   3.
two  b   4.

>>> s.unstack(level=-1)
     a   b
one  1.  2.
two  3.  4.

>>> df = s.unstack(level=0)
>>> df
   one  two
a  1.   2.
b  3.   4.

>>> df.unstack()
one  a  1.
     b  3.
two  a  2.
     b  4.
```

### pandas.DataFrame.T

DataFrame.**T**

Returns a DataFrame with the rows/columns switched. If the DataFrame is homogeneously-typed, the data is not copied

### pandas.DataFrame.to_panel

DataFrame.**to_panel**()

Transform long (stacked) format (DataFrame) into wide (3D, Panel) format.

Currently the index of the DataFrame must be a 2-level MultiIndex. This may be generalized later

**Returns** **panel** : Panel

### pandas.DataFrame.transpose

DataFrame.**transpose**()

Returns a DataFrame with the rows/columns switched. If the DataFrame is homogeneously-typed, the data is not copied

## 21.3.10 Combining / joining / merging

| | |
|---|---|
| DataFrame.append(other[, ignore_index, ...]) | Append columns of other to end of this frame's columns and index, returning a |
| DataFrame.join(other[, on, how, lsuffix, ...]) | Join columns with other DataFrame either on index or on a key |
| DataFrame.merge(right[, how, on, left_on, ...]) | Merge DataFrame objects by performing a database-style join operation by |
| DataFrame.replace(to_replace[, value, ...]) | Replace values given in 'to_replace' with 'value' or using 'method' |
| DataFrame.update(other[, join, overwrite, ...]) | Modify DataFrame in place using non-NA values from passed |

### pandas.DataFrame.append

DataFrame.**append**(*other*, *ignore_index=False*, *verify_integrity=False*)

Append columns of other to end of this frame's columns and index, returning a new object. Columns not in this frame are added as new columns.

**Parameters** **other** : DataFrame or list of Series/dict-like objects

**ignore_index** : boolean, default False

If True do not use the index labels. Useful for gluing together record arrays

**verify_integrity** : boolean, default False

If True, raise Exception on creating index with duplicates

**Returns** **appended** : DataFrame

#### Notes

If a list of dict 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

### pandas.DataFrame.join

DataFrame.**join**(*other*, *on=None*, *how='left'*, *lsuffix=''*, *rsuffix=''*, *sort=False*)

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 with name field set, 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** : column name, tuple/list of column names, or array-like

Column(s) to use for joining, otherwise join on index. If multiples columns given, the passed DataFrame must have a MultiIndex. Can pass an array as the join key if not already contained in the calling DataFrame. Like an Excel VLOOKUP operation

**how** : {'left', 'right', 'outer', 'inner'}

How to handle indexes of the two objects. Default: 'left' for joining on index, None otherwise * left: use calling frame's index * right: use input frame's index * outer: form union of indexes * inner: use intersection of indexes

**lsuffix** : string

Suffix to use from left frame's overlapping columns

**rsuffix** : string

Suffix to use from right frame's overlapping columns

**sort** : boolean, default False

Order result DataFrame lexicographically by the join key. If False, preserves the index order of the calling (left) DataFrame

**Returns** **joined** : DataFrame

#### Notes

on, lsuffix, and rsuffix options are not supported when passing a list of DataFrame objects

### 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*)

Merge DataFrame objects by performing a database-style join operation by 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.

**Parameters** **right** : DataFrame

**how** : {'left', 'right', 'outer', 'inner'}, default 'inner'

- 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)

**on** : label or list

Field names to join on. Must be found in both DataFrames. If on is None and not merging on indexes, then it merges on the intersection of the columns by default.

**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_index** : boolean, 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** : boolean, default False

Use the index from the right DataFrame as the join key. Same caveats as left_index

**sort** : boolean, default False

Sort the join keys lexicographically in the result DataFrame

**suffixes** : 2-length sequence (tuple, list, ...)

Suffix to apply to overlapping column names in the left and right side, respectively

**copy** : boolean, default True

If False, do not copy data unnecessarily

**Returns** **merged** : DataFrame

### Examples

```
>>> A              >>> B
    lkey value         rkey value
0   foo  1         0   foo  5
1   bar  2         1   bar  6
2   baz  3         2   qux  7
3   foo  4         3   bar  8
```

```
>>> merge(A, B, left_on='lkey', right_on='rkey', how='outer')
   lkey  value_x  rkey  value_y
0  bar   2        bar   6
1  bar   2        bar   8
2  baz   3        NaN   NaN
3  foo   1        foo   5
4  foo   4        foo   5
5  NaN   NaN      qux   7
```

## pandas.DataFrame.replace

`DataFrame.replace`(*to_replace*, *value=None*, *method='pad'*, *axis=0*, *inplace=False*, *limit=None*)

Replace values given in 'to_replace' with 'value' or using 'method'

**Parameters** **value** : scalar or dict, default None

Value to use to fill holes (e.g. 0), alternately a dict of values specifying which value to use for each column (columns not in the dict will not be filled)

**method** : {'backfill', 'bfill', 'pad', 'ffill', None}, default 'pad'

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, 1}, default 0

0: fill column-by-column 1: fill row-by-row

**inplace** : boolean, default False

If True, fill the DataFrame in place. Note: this will modify any other views on this DataFrame, like if you took a no-copy slice of an existing DataFrame, for example a column in a DataFrame. Returns a reference to the filled object, which is self if inplace=True

**limit** : int, default None

Maximum size gap to forward or backward fill

**Returns** **filled** : DataFrame

**See Also:**

`reindex`, `asfreq`

### pandas.DataFrame.update

`DataFrame.update`(*other*, *join='left'*, *overwrite=True*, *filter_func=None*, *raise_conflict=False*)

Modify DataFrame in place using non-NA values from passed DataFrame. Aligns on indices

**Parameters** **other** : DataFrame, or object coercible into a DataFrame

**join** : {'left', 'right', 'outer', 'inner'}, default 'left'

**overwrite** : boolean, default True

If True then overwrite values for common keys in the calling frame

**filter_func** : callable(1d-array) -> 1d-array<boolean>, default None

Can choose to replace values other than NA. Return True for values that should be updated

**raise_conflict** : bool

If True, will raise an error if the DataFrame and other both contain data in the same place.

## 21.3.11 Time series-related

| | |
|---|---|
| `DataFrame.asfreq`(freq[, method, how, normalize]) | Convert all TimeSeries inside to specified frequency using DateOffset |
| `DataFrame.shift`([periods, freq]) | Shift the index of the DataFrame by desired number of periods with an |
| `DataFrame.first_valid_index`() | Return label for first non-NA/null value |
| `DataFrame.last_valid_index`() | Return label for last non-NA/null value |
| | Continu |

Table 21.32 – continued from previous page

| | |
|---|---|
| `DataFrame.resample`(rule[, how, axis, ...]) | Convenience method for frequency conversion and resampling of regular t |
| `DataFrame.to_period`([freq, axis, copy]) | Convert DataFrame from DatetimeIndex to PeriodIndex with desired |
| `DataFrame.to_timestamp`([freq, how, axis, copy]) | Cast to DatetimeIndex of timestamps, at *beginning* of period |
| `DataFrame.tz_convert`(tz[, axis, copy]) | Convert TimeSeries to target time zone. If it is time zone naive, it |
| `DataFrame.tz_localize`(tz[, axis, copy]) | Localize tz-naive TimeSeries to target time zone |

### pandas.DataFrame.asfreq

`DataFrame.`**`asfreq`**(*freq*, *method=None*, *how=None*, *normalize=False*)

Convert all TimeSeries inside to specified frequency using DateOffset objects. Optionally provide fill method to pad/backfill missing values.

**Parameters** **freq** : DateOffset object, or string

**method** : {'backfill', 'bfill', 'pad', 'ffill', 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 methdo

**how** : {'start', 'end'}, default end

For PeriodIndex only, see PeriodIndex.asfreq

**normalize** : bool, default False

Whether to reset output index to midnight

**Returns** **converted** : type of caller

### pandas.DataFrame.shift

`DataFrame.`**`shift`**(*periods=1*, *freq=None*, ***kwds*)

Shift the index of the DataFrame by desired number of periods with an optional time freq

**Parameters** **periods** : int

Number of periods to move, can be positive or negative

**freq** : DateOffset, timedelta, or time rule string, optional

Increment to use from datetools module or time rule (e.g. 'EOM')

**Returns** **shifted** : DataFrame

#### Notes

If freq is specified then the index values are shifted but the data if not realigned

### pandas.DataFrame.first_valid_index

`DataFrame.`**`first_valid_index`**()

Return label for first non-NA/null value

### pandas.DataFrame.last_valid_index

`DataFrame.last_valid_index()`

Return label for last non-NA/null value

### pandas.DataFrame.resample

`DataFrame.resample(rule, how=None, axis=0, fill_method=None, closed=None, label=None, convention='start', kind=None, loffset=None, limit=None, base=0)`

Convenience method for frequency conversion and resampling of regular time-series data.

**Parameters** **rule** : the offset string or object representing target conversion

**how** : string, method for down- or re-sampling, default to 'mean' for

downsampling

**axis** : int, optional, default 0

**fill_method** : string, fill_method for upsampling, default None

**closed** : {'right', 'left'}, default None

Which side of bin interval is closed

**label** : {'right', 'left'}, default None

Which bin edge label to label bucket with

**convention** : {'start', 'end', 's', 'e'}

**kind: "period"/"timestamp"** :

**loffset: timedelta** :

Adjust the resampled time labels

**limit: int, default None** :

Maximum size gap to when reindexing with fill_method

**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

### pandas.DataFrame.to_period

`DataFrame.to_period(freq=None, axis=0, copy=True)`

Convert DataFrame from DatetimeIndex to PeriodIndex with desired frequency (inferred from index if not passed)

**Parameters** **freq** : string, default

**axis** : {0, 1}, default 0

The axis to convert (the index by default)

**copy** : boolean, default True

If False then underlying input data is not copied

**Returns** **ts** : TimeSeries with PeriodIndex

### 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** : string, default frequency of PeriodIndex

Desired frequency

**how** : {'s', 'e', 'start', 'end'}

Convention for converting period to timestamp; start of period vs. end

**axis** : {0, 1} default 0

The axis to convert (the index by default)

**copy** : boolean, default True

If false then underlying input data is not copied

**Returns** **df** : DataFrame with DatetimeIndex

### pandas.DataFrame.tz_convert

`DataFrame.tz_convert(tz, axis=0, copy=True)`

Convert TimeSeries to target time zone. If it is time zone naive, it will be localized to the passed time zone.

**Parameters** **tz** : string or pytz.timezone object

**copy** : boolean, default True

Also make a copy of the underlying data

### pandas.DataFrame.tz_localize

`DataFrame.tz_localize(tz, axis=0, copy=True)`

Localize tz-naive TimeSeries to target time zone

**Parameters** **tz** : string or pytz.timezone object

**copy** : boolean, default True

Also make a copy of the underlying data

## 21.3.12 Plotting

| | |
|---|---|
| DataFrame.boxplot([column, by, ax, ...]) | Make a box plot from DataFrame column/columns optionally grouped |
| DataFrame.hist(data[, column, by, grid, ...]) | Draw Histogram the DataFrame's series using matplotlib / pylab. |
| DataFrame.plot([frame, x, y, subplots, ...]) | Make line or bar plot of DataFrame's series with the index on the x-axis |

### pandas.DataFrame.boxplot

`DataFrame.boxplot(column=None, by=None, ax=None, fontsize=None, rot=0, grid=True, **kwds)`

Make a box plot from DataFrame column/columns optionally grouped (stratified) by one or more columns

**Parameters** **data** : DataFrame

**column** : column names or list of names, or vector

Can be any valid input to groupby

**by** : string or sequence

Column in the DataFrame to group by

**fontsize** : int or string

**Returns** **ax** : matplotlib.axes.AxesSubplot

### pandas.DataFrame.hist

`DataFrame.hist`(*data*, *column=None*, *by=None*, *grid=True*, *xlabelsize=None*, *xrot=None*, *ylabelsize=None*, *yrot=None*, *ax=None*, *sharex=False*, *sharey=False*, ***kwds*)

Draw Histogram the DataFrame's series using matplotlib / pylab.

**Parameters** **grid** : boolean, 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

**ax** : matplotlib axes object, default None

**sharex** : bool, if True, the X axis will be shared amongst all subplots.

**sharey** : bool, if True, the Y axis will be shared amongst all subplots.

**kwds** : other plotting keyword arguments

To be passed to hist function

### pandas.DataFrame.plot

`DataFrame.plot`(*frame=None*, *x=None*, *y=None*, *subplots=False*, *sharex=True*, *sharey=False*, *use_index=True*, *figsize=None*, *grid=False*, *legend=True*, *rot=None*, *ax=None*, *style=None*, *title=None*, *xlim=None*, *ylim=None*, *logx=False*, *logy=False*, *xticks=None*, *yticks=None*, *kind='line'*, *sort_columns=False*, *fontsize=None*, *secondary_y=False*, ***kwds*)

Make line or bar plot of DataFrame's series with the index on the x-axis using matplotlib / pylab.

**Parameters** **x** : label or position, default None

**y** : label or position, default None

Allows plotting of one column versus another

**subplots** : boolean, default False

Make separate subplots for each time series

**sharex** : boolean, default True

In case subplots=True, share x axis

**sharey** : boolean, default False

In case subplots=True, share y axis

**use_index** : boolean, default True

Use index as ticks for x axis

**stacked** : boolean, default False

If True, create stacked bar plot. Only valid for DataFrame input

**sort_columns: boolean, default False** :

Sort column names to determine plot ordering

**title** : string

Title to use for the plot

**grid** : boolean, default False

Axis grid lines

**legend** : boolean, default True

Place legend on axis subplots

**ax** : matplotlib axis object, default None

**style** : list or dict

matplotlib line style per column

**kind** : {'line', 'bar', 'barh', 'kde', 'density'}

bar : vertical bar plot barh : horizontal bar plot kde/density : Kernel Density Estimation plot

**logx** : boolean, default False

For line plots, use log scaling on x axis

**logy** : boolean, default False

For line plots, use log scaling on y axis

**xticks** : sequence

Values to use for the xticks

**yticks** : sequence

Values to use for the yticks

**xlim** : 2-tuple/list

**ylim** : 2-tuple/list

**rot** : int, default None

Rotation for ticks

**secondary_y** : boolean or sequence, default False

Whether to plot on the secondary y-axis If dict then can select which columns to plot on secondary y-axis

**kwds** : keywords

Options to pass to matplotlib plotting method

**Returns** **ax_or_axes** : matplotlib.AxesSubplot or list of them

### 21.3.13 Serialization / IO / Conversion

| | |
|---|---|
| `DataFrame.from_csv`(path[, header, sep, ...]) | Read delimited file into DataFrame |
| `DataFrame.from_dict`(data[, orient, dtype]) | Construct DataFrame from dict of array-like or dicts |
| `DataFrame.from_items`(items[, columns, orient]) | Convert (key, value) pairs to DataFrame. The keys will be the axis |
| `DataFrame.from_records`(data[, index, ...]) | Convert structured or record ndarray to DataFrame |
| `DataFrame.info`([verbose, buf, max_cols]) | Concise summary of a DataFrame, used in __repr__ when very large. |
| `DataFrame.load`(path) | |
| `DataFrame.save`(path) | |
| `DataFrame.to_csv`(path_or_buf[, sep, na_rep, ...]) | Write DataFrame to a comma-separated values (csv) file |
| `DataFrame.to_dict`([outtype]) | Convert DataFrame to dictionary. |
| `DataFrame.to_excel`(excel_writer[, ...]) | Write DataFrame to a excel sheet |
| `DataFrame.to_html`([buf, columns, col_space, ...]) | to_html-specific options |
| `DataFrame.to_records`([index, convert_datetime64]) | Convert DataFrame to record array. Index will be put in the |
| `DataFrame.to_sparse`([fill_value, kind]) | Convert to SparseDataFrame |
| `DataFrame.to_string`([buf, columns, ...]) | Render a DataFrame to a console-friendly tabular output. |

#### pandas.DataFrame.from_csv

**classmethod** `DataFrame.`**`from_csv`**(*path*, *header=0*, *sep='*, *'*, *index_col=0*, *parse_dates=True*, *encoding=None*)

Read delimited file into DataFrame

**Parameters** **path** : string file path or file handle / StringIO

**header** : int, default 0

Row to use at header (skip prior rows)

**sep** : string, default ','

Field delimiter

**index_col** : int or sequence, default 0

Column to use for index. If a sequence is given, a MultiIndex is used. Different default from read_table

**parse_dates** : boolean, default True

Parse dates. Different default from read_table

**Returns** **y** : DataFrame

#### Notes

Preferable to use read_table for most general purposes but from_csv makes for an easy roundtrip to and from file, especially with a DataFrame of time series data

### pandas.DataFrame.from_dict

**classmethod** `DataFrame.from_dict`(*data*, *orient='columns'*, *dtype=None*)

Construct DataFrame from dict of array-like or dicts

**Parameters** **data** : dict

{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'.

**Returns** **DataFrame** :

### pandas.DataFrame.from_items

**classmethod** `DataFrame.from_items`(*items*, *columns=None*, *orient='columns'*)

Convert (key, value) pairs to DataFrame. The keys will be the axis index (usually the columns, but depends on the specified orientation). The values should be arrays or Series.

**Parameters** **items** : sequence of (key, value) pairs

Values should be arrays or Series.

**columns** : sequence of column labels, optional

Must be passed if orient='index'.

**orient** : {'columns', 'index'}, default 'columns'

The "orientation" of the data. If the keys of the input correspond to column labels, pass 'columns' (default). Otherwise if the keys correspond to the index, pass 'index'.

**Returns** **frame** : DataFrame

### 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

**Parameters** **data** : ndarray (structured dtype), list of tuples, dict, or DataFrame

**index** : string, 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 named 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** : boolean, default False

Attempt to convert values to non-string, non-numeric objects (like decimal.Decimal) to floating point, useful for SQL result sets

**Returns** **df** : DataFrame

### pandas.DataFrame.info

`DataFrame.info`(*verbose=True*, *buf=None*, *max_cols=None*)

Concise summary of a DataFrame, used in __repr__ when very large.

**Parameters** **verbose** : boolean, default True

If False, don't print column count summary

**buf** : writable buffer, defaults to sys.stdout

**max_cols** : int, default None

Determines whether full summary or short summary is printed

### pandas.DataFrame.load

**classmethod** `DataFrame.load`(*path*)

### pandas.DataFrame.save

`DataFrame.save`(*path*)

### pandas.DataFrame.to_csv

`DataFrame.to_csv`(*path_or_buf*, *sep='*, *'*, *na_rep=''*, *float_format=None*, *cols=None*, *header=True*, *index=True*, *index_label=None*, *mode='w'*, *nanRep=None*, *encoding=None*, *quoting=None*, *line_terminator='n'*)

Write DataFrame to a comma-separated values (csv) file

**Parameters** **path_or_buf** : string or file handle / StringIO

File path

**sep** [character, default ","] Field delimiter for the output file.

**na_rep** [string, default ''] Missing data representation

**float_format** [string, default None] Format string for floating point numbers

**cols** [sequence, optional] Columns to write

**header** [boolean or list of string, default True] Write out column names. If a list of string is given it is assumed to be aliases for the column names

**index** [boolean, default True] Write row names (index)

**index_label** [string 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 DataFrame uses MultiIndex. If False do not print fields for index names. Use index_label=False for easier importing in R nanRep : deprecated, use na_rep mode : Python write mode, default 'w' encoding : string, optional

a string representing the encoding to use if the contents are non-ascii, for python versions prior to 3

line_terminator: string, default '

' :

The newline character or character sequence to use in the output file

**quoting** [optional constant from csv module] defaults to csv.QUOTE_MINIMAL

### pandas.DataFrame.to_dict

`DataFrame.to_dict(outtype='dict')`

Convert DataFrame to dictionary.

**Parameters** **outtype** : str {'dict', 'list', 'series'}

Determines the type of the values of the dictionary. The default *dict* is a nested dictionary {column -> {index -> value}}. *list* returns {column -> list(values)}. *series* returns {column -> Series(values)}. Abbreviations are allowed.

**Returns** **result** : dict like {column -> {index -> value}}

### pandas.DataFrame.to_excel

`DataFrame.to_excel(excel_writer, sheet_name='sheet1', na_rep='', float_format=None, cols=None, header=True, index=True, index_label=None, startrow=0, startcol=0)`

Write DataFrame to a excel sheet

**Parameters** **excel_writer** : string or ExcelWriter object

File path or existing ExcelWriter

**sheet_name** : string, default 'sheet1'

Name of sheet which will contain DataFrame

**na_rep** : string, default ''

Missing data representation

**float_format** : string, default None

Format string for floating point numbers

**cols** : sequence, optional

Columns to write

**header** : boolean or list of string, default True

Write out column names. If a list of string is given it is assumed to be aliases for the column names

**index** : boolean, default True

Write row names (index)

**index_label** : string or sequence, 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 DataFrame uses MultiIndex.

**startow** : upper left cell row to dump data frame

**startcol** : upper left cell column to dump data frame

### Notes

If passing an existing ExcelWriter object, then the sheet will be added to the existing workbook. This can be used to save different DataFrames to one workbook >>> writer = ExcelWriter('output.xlsx') >>> df1.to_excel(writer,'sheet1') >>> df2.to_excel(writer,'sheet2') >>> writer.save()

## pandas.DataFrame.to_html

`DataFrame.to_html`(*buf=None*, *columns=None*, *col_space=None*, *colSpace=None*, *header=True*, *index=True*, *na_rep='NaN'*, *formatters=None*, *float_format=None*, *sparsify=None*, *index_names=True*, *justify=None*, *force_unicode=None*, *bold_rows=True*, *classes=None*)

to_html-specific options bold_rows : boolean, 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

Render a DataFrame to an html table.

**Parameters** **frame** : DataFrame

object to render

**buf** : StringIO-like, optional

buffer to write to

**columns** : sequence, optional

the subset of columns to write; default None writes all columns

**col_space** : int, optional

the minimum width of each column

**header** : bool, optional

whether to print column labels, default True

**index** : bool, optional

whether to print index (row) labels, default True

**na_rep** : string, optional

string representation of NAN to use, default 'NaN'

**formatters** : list or dict of one-parameter functions, optional

formatter functions to apply to columns' elements by position or name, default None, if the result is a string , it must be a unicode string. List must be of length equal to the number of columns.

**float_format** : one-parameter function, optional formatter function to apply to columns' elements if they are floats default None

**sparsify** : bool, optional

Set to False for a DataFrame with a hierarchical index to print every multiindex key at each row, default True

**justify** : {'left', 'right'}, default None

Left or right-justify the column labels. If None uses the option from the print configuration (controlled by set_printoptions), 'right' out of the box.

**index_names** : bool, optional

Prints the names of the indexes, default True

**force_unicode** : bool, default False

Always return a unicode result. Deprecated in v0.10.0 as string formatting is now rendered to unicode by default.

**Returns** **formatted** : string (or unicode, depending on data and options)

### pandas.DataFrame.to_records

`DataFrame.`**`to_records`**(*index=True*, *convert_datetime64=True*)

Convert DataFrame to record array. Index will be put in the 'index' field of the record array if requested

**Parameters** **index** : boolean, default True

Include index in resulting record array, stored in 'index' field

**convert_datetime64** : boolean, default True

Whether to convert the index to datetime.datetime if it is a DatetimeIndex

**Returns** **y** : recarray

### pandas.DataFrame.to_sparse

`DataFrame.`**`to_sparse`**(*fill_value=None*, *kind='block'*)

Convert to SparseDataFrame

**Parameters** **fill_value** : float, default NaN

**kind** : {'block', 'integer'}

**Returns** **y** : SparseDataFrame

### pandas.DataFrame.to_string

`DataFrame.`**`to_string`**(*buf=None*, *columns=None*, *col_space=None*, *colSpace=None*, *header=True*, *index=True*, *na_rep='NaN'*, *formatters=None*, *float_format=None*, *sparsify=None*, *nanRep=None*, *index_names=True*, *justify=None*, *force_unicode=None*, *line_width=None*)

Render a DataFrame to a console-friendly tabular output.

**Parameters** **frame** : DataFrame

object to render

**buf** : StringIO-like, optional

buffer to write to

**columns** : sequence, optional

the subset of columns to write; default None writes all columns

**col_space** : int, optional

the minimum width of each column

**header** : bool, optional

whether to print column labels, default True

**index** : bool, optional

whether to print index (row) labels, default True

**na_rep** : string, optional

string representation of NAN to use, default 'NaN'

**formatters** : list or dict of one-parameter functions, optional

formatter functions to apply to columns' elements by position or name, default None, if the result is a string , it must be a unicode string. List must be of length equal to the number of columns.

**float_format** : one-parameter function, optional

formatter function to apply to columns' elements if they are floats default None

**sparsify** : bool, optional

Set to False for a DataFrame with a hierarchical index to print every multiindex key at each row, default True

**justify** : {'left', 'right'}, default None

Left or right-justify the column labels. If None uses the option from the print configuration (controlled by set_printoptions), 'right' out of the box.

**index_names** : bool, optional

Prints the names of the indexes, default True

**force_unicode** : bool, default False

Always return a unicode result. Deprecated in v0.10.0 as string formatting is now rendered to unicode by default.

**Returns** **formatted** : string (or unicode, depending on data and options)

## 21.4 Panel

### 21.4.1 Computations / Descriptive Stats

# PYTHON MODULE INDEX

### p

# PYTHON MODULE INDEX

# INDEX

## Symbols



## A



## B



## C



## D

# E



# F



# G



# H



# I



# J



# K



# L



# M

# N



# O



# P



# Q



# R



# S



# T

## U



## V



## W



## X