

# 10 Minutes to pandas

This is a short introduction to pandas, geared mainly for new users. You can see more complex recipes in the [Cookbook](#)

Customarily, we import as follows:

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

In [2]: import numpy as np

In [3]: import matplotlib.pyplot as plt
```

## Object Creation

See the [Data Structure Intro section](#)

Creating a **Series** by passing a list of values, letting pandas create a default integer index:

```
In [4]: s = pd.Series([1,3,5,np.nan,6,8])

In [5]: s
Out[5]:
0      1
1      3
2      5
3     NaN
4      6
5      8
dtype: float64
```

Creating a **DataFrame** by passing a numpy array, with a datetime index and labeled columns:

```
In [6]: dates = pd.date_range('20130101', periods=6)

In [7]: dates
Out[7]:
DatetimeIndex(['2013-01-01', '2013-01-02', '2013-01-03', '2013-01-04',
               '2013-01-05', '2013-01-06'],
              dtype='datetime64[ns]', freq='D')

In [8]: df = pd.DataFrame(np.random.randn(6,4), index=dates, columns=list('ABCD'))

In [9]: df
Out[9]:
              A          B          C          D
2013-01-01  0.469112 -0.282863 -1.509059 -1.135632
2013-01-02  1.212112 -0.173215  0.119209 -1.044236
```

```

2013-01-03 -0.861849 -2.104569 -0.494929 1.071804
2013-01-04 0.721555 -0.706771 -1.039575 0.271860
2013-01-05 -0.424972 0.567020 0.276232 -1.087401
2013-01-06 -0.673690 0.113648 -1.478427 0.524988

```

Creating a DataFrame by passing a dict of objects that can be converted to series-like.

```

In [10]: df2 = pd.DataFrame({ 'A' : 1.,
    ....:                     'B' : pd.Timestamp('20130102'),
    ....:                     'C' : pd.Series(1,index=list(range(4)),dtype='float',
    ....:                     'D' : np.array([3] * 4,dtype='int32'),
    ....:                     'E' : pd.Categorical(["test","train","test","train"])
    ....:                     'F' : 'foo' })

```

```

In [11]: df2

```

```

Out[11]:
   A      B      C  D      E      F
0  1  2013-01-02  1  3   test   foo
1  1  2013-01-02  1  3  train   foo
2  1  2013-01-02  1  3   test   foo
3  1  2013-01-02  1  3  train   foo

```

Having specific *dtypes*

```

In [12]: df2.dtypes

```

```

Out[12]:
A      float64
B  datetime64[ns]
C      float32
D      int32
E      category
F      object
dtype: object

```

If you're using IPython, tab completion for column names (as well as public attributes) is automatically enabled. Here's a subset of the attributes that will be completed:

```

In [13]: df2.<TAB>
df2.A      df2.boxplot
df2.abs     df2.C
df2.add     df2.clip
df2.add_prefix df2.clip_lower
df2.add_suffix df2.clip_upper
df2.align   df2.columns
df2.all     df2.combine
df2.any     df2.combineAdd
df2.append  df2.combine_first
df2.apply   df2.combineMult
df2.applymap df2.compound
df2.as_blocks df2.consolidate
df2.asfreq  df2.convert_objects
df2.as_matrix df2.copy

```

df2.astype	df2.corr
df2.at	df2.corrwith
df2.at_time	df2.count
df2.axes	df2.cov
df2.B	df2.cummax
df2.between_time	df2.cummin
df2.bfill	df2.cumprod
df2.blocks	df2.cumsum
df2.bool	df2.D

As you can see, the columns A, B, C, and D are automatically tab completed. E is there as well; the rest of the attributes have been truncated for brevity.

## Viewing Data

See the [Basics section](#)

See the top & bottom rows of the frame

```
In [14]: df.head()
Out[14]:
```

	A	B	C	D
2013-01-01	0.469112	-0.282863	-1.509059	-1.135632
2013-01-02	1.212112	-0.173215	0.119209	-1.044236
2013-01-03	-0.861849	-2.104569	-0.494929	1.071804
2013-01-04	0.721555	-0.706771	-1.039575	0.271860
2013-01-05	-0.424972	0.567020	0.276232	-1.087401

```
In [15]: df.tail(3)
Out[15]:
```

	A	B	C	D
2013-01-04	0.721555	-0.706771	-1.039575	0.271860
2013-01-05	-0.424972	0.567020	0.276232	-1.087401
2013-01-06	-0.673690	0.113648	-1.478427	0.524988

Display the index, columns, and the underlying numpy data

```
In [16]: df.index
Out[16]:
DatetimeIndex(['2013-01-01', '2013-01-02', '2013-01-03', '2013-01-04',
               '2013-01-05', '2013-01-06'],
              dtype='datetime64[ns]', freq='D')

In [17]: df.columns
Out[17]: Index([u'A', u'B', u'C', u'D'], dtype='object')

In [18]: df.values
Out[18]:
array([[ 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  ]])
```

Describe shows a quick statistic summary of your data

```
In [19]: df.describe()
Out[19]:
```

	A	B	C	D
count	6.000000	6.000000	6.000000	6.000000
mean	0.073711	-0.431125	-0.687758	-0.233103
std	0.843157	0.922818	0.779887	0.973118
min	-0.861849	-2.104569	-1.509059	-1.135632
25%	-0.611510	-0.600794	-1.368714	-1.076610
50%	0.022070	-0.228039	-0.767252	-0.386188
75%	0.658444	0.041933	-0.034326	0.461706
max	1.212112	0.567020	0.276232	1.071804

Transposing your data

```
In [20]: df.T
Out[20]:
```

	2013-01-01	2013-01-02	2013-01-03	2013-01-04	2013-01-05	2013-01-06
A	0.469112	1.212112	-0.861849	0.721555	-0.424972	-0.673690
B	-0.282863	-0.173215	-2.104569	-0.706771	0.567020	0.113648
C	-1.509059	0.119209	-0.494929	-1.039575	0.276232	-1.478427
D	-1.135632	-1.044236	1.071804	0.271860	-1.087401	0.524988

Sorting by an axis

```
In [21]: df.sort_index(axis=1, ascending=False)
Out[21]:
```

	D	C	B	A
2013-01-01	-1.135632	-1.509059	-0.282863	0.469112
2013-01-02	-1.044236	0.119209	-0.173215	1.212112
2013-01-03	1.071804	-0.494929	-2.104569	-0.861849
2013-01-04	0.271860	-1.039575	-0.706771	0.721555
2013-01-05	-1.087401	0.276232	0.567020	-0.424972
2013-01-06	0.524988	-1.478427	0.113648	-0.673690

Sorting by values

```
In [22]: df.sort_values(by='B')
Out[22]:
```

	A	B	C	D
2013-01-03	-0.861849	-2.104569	-0.494929	1.071804
2013-01-04	0.721555	-0.706771	-1.039575	0.271860
2013-01-01	0.469112	-0.282863	-1.509059	-1.135632
2013-01-02	1.212112	-0.173215	0.119209	-1.044236
2013-01-06	-0.673690	0.113648	-1.478427	0.524988
2013-01-05	-0.424972	0.567020	0.276232	-1.087401

# Selection

**Note:** While standard Python / Numpy expressions for selecting and setting are intuitive and come in handy for interactive work, for production code, we recommend the optimized pandas data access methods, `.at`, `.iat`, `.loc`, `.iloc` and `.ix`.

See the indexing documentation [Indexing and Selecting Data](#) and [MultiIndex / Advanced Indexing](#)

## Getting

Selecting a single column, which yields a `series`, equivalent to `df.A`

```
In [23]: df['A']
Out[23]:
2013-01-01    0.469112
2013-01-02    1.212112
2013-01-03   -0.861849
2013-01-04    0.721555
2013-01-05   -0.424972
2013-01-06   -0.673690
Freq: D, Name: A, dtype: float64
```

Selecting via `[ ]`, which slices the rows.

```
In [24]: df[0:3]
Out[24]:
```

	A	B	C	D
2013-01-01	0.469112	-0.282863	-1.509059	-1.135632
2013-01-02	1.212112	-0.173215	0.119209	-1.044236
2013-01-03	-0.861849	-2.104569	-0.494929	1.071804

```
In [25]: df['20130102':'20130104']
Out[25]:
```

	A	B	C	D
2013-01-02	1.212112	-0.173215	0.119209	-1.044236
2013-01-03	-0.861849	-2.104569	-0.494929	1.071804
2013-01-04	0.721555	-0.706771	-1.039575	0.271860

## Selection by Label

See more in [Selection by Label](#)

For getting a cross section using a label

```
In [26]: df.loc[dates[0]]
Out[26]:
A    0.469112
```

```
B    -0.282863
C    -1.509059
D    -1.135632
Name: 2013-01-01 00:00:00, dtype: float64
```

## Selecting on a multi-axis by label

```
In [27]: df.loc[:, ['A', 'B']]
Out[27]:
```

	A	B
2013-01-01	0.469112	-0.282863
2013-01-02	1.212112	-0.173215
2013-01-03	-0.861849	-2.104569
2013-01-04	0.721555	-0.706771
2013-01-05	-0.424972	0.567020
2013-01-06	-0.673690	0.113648

## Showing label slicing, both endpoints are *included*

```
In [28]: df.loc['20130102':'20130104', ['A', 'B']]
Out[28]:
```

	A	B
2013-01-02	1.212112	-0.173215
2013-01-03	-0.861849	-2.104569
2013-01-04	0.721555	-0.706771

## Reduction in the dimensions of the returned object

```
In [29]: df.loc['20130102', ['A', 'B']]
Out[29]:
```

	A	B
2013-01-02	1.212112	-0.173215

Name: 2013-01-02 00:00:00, dtype: float64

## For getting a scalar value

```
In [30]: df.loc[dates[0], 'A']
Out[30]: 0.46911229990718628
```

## For getting fast access to a scalar (equiv to the prior method)

```
In [31]: df.at[dates[0], 'A']
Out[31]: 0.46911229990718628
```

## Selection by Position

See more in [Selection by Position](#)

Select via the position of the passed integers

```
In [32]: df.iloc[3]
Out[32]:
A    0.721555
B   -0.706771
C   -1.039575
D    0.271860
Name: 2013-01-04 00:00:00, dtype: float64
```

By integer slices, acting similar to numpy/python

```
In [33]: df.iloc[3:5,0:2]
Out[33]:
```

	A	B
2013-01-04	0.721555	-0.706771
2013-01-05	-0.424972	0.567020

By lists of integer position locations, similar to the numpy/python style

```
In [34]: df.iloc[[1,2,4],[0,2]]
Out[34]:
```

	A	C
2013-01-02	1.212112	0.119209
2013-01-03	-0.861849	-0.494929
2013-01-05	-0.424972	0.276232

For slicing rows explicitly

```
In [35]: df.iloc[1:3,:]
Out[35]:
```

	A	B	C	D
2013-01-02	1.212112	-0.173215	0.119209	-1.044236
2013-01-03	-0.861849	-2.104569	-0.494929	1.071804

For slicing columns explicitly

```
In [36]: df.iloc[:,1:3]
Out[36]:
```

	B	C
2013-01-01	-0.282863	-1.509059
2013-01-02	-0.173215	0.119209
2013-01-03	-2.104569	-0.494929
2013-01-04	-0.706771	-1.039575
2013-01-05	0.567020	0.276232
2013-01-06	0.113648	-1.478427

For getting a value explicitly

```
In [37]: df.iloc[1,1]
Out[37]: -0.17321464905330858
```

For getting fast access to a scalar (equiv to the prior method)

```
In [38]: df.iat[1,1]
Out[38]: -0.17321464905330858
```

## Boolean Indexing

Using a single column's values to select data.

```
In [39]: df[df.A > 0]
Out[39]:
```

	A	B	C	D
2013-01-01	0.469112	-0.282863	-1.509059	-1.135632
2013-01-02	1.212112	-0.173215	0.119209	-1.044236
2013-01-04	0.721555	-0.706771	-1.039575	0.271860

A where operation for getting.

```
In [40]: df[df > 0]
Out[40]:
```

	A	B	C	D
2013-01-01	0.469112	NaN	NaN	NaN
2013-01-02	1.212112	NaN	0.119209	NaN
2013-01-03	NaN	NaN	NaN	1.071804
2013-01-04	0.721555	NaN	NaN	0.271860
2013-01-05	NaN	0.567020	0.276232	NaN
2013-01-06	NaN	0.113648	NaN	0.524988

Using the `isin()` method for filtering:

```
In [41]: df2 = df.copy()
In [42]: df2['E'] = ['one', 'one', 'two', 'three', 'four', 'three']
In [43]: df2
Out[43]:
```

	A	B	C	D	E
2013-01-01	0.469112	-0.282863	-1.509059	-1.135632	one
2013-01-02	1.212112	-0.173215	0.119209	-1.044236	one
2013-01-03	-0.861849	-2.104569	-0.494929	1.071804	two
2013-01-04	0.721555	-0.706771	-1.039575	0.271860	three
2013-01-05	-0.424972	0.567020	0.276232	-1.087401	four
2013-01-06	-0.673690	0.113648	-1.478427	0.524988	three



```
In [44]: df2[df2['E'].isin(['two', 'four'])]
Out[44]:
```

	A	B	C	D	E
2013-01-03	-0.861849	-2.104569	-0.494929	1.071804	two
2013-01-05	-0.424972	0.567020	0.276232	-1.087401	four

## Setting

Setting a new column automatically aligns the data by the indexes

```
In [45]: s1 = pd.Series([1,2,3,4,5,6], index=pd.date_range('20130102', periods=6))

In [46]: s1
Out[46]:
```

2013-01-02	1
2013-01-03	2
2013-01-04	3
2013-01-05	4
2013-01-06	5
2013-01-07	6

```
Freq: D, dtype: int64

In [47]: df['F'] = s1
```

Setting values by label

```
In [48]: df.at[dates[0], 'A'] = 0
```

Setting values by position

```
In [49]: df.iat[0,1] = 0
```

Setting by assigning with a numpy array

```
In [50]: df.loc[:, 'D'] = np.array([5] * len(df))
```

The result of the prior setting operations

```
In [51]: df
Out[51]:
```

	A	B	C	D	F
2013-01-01	0.000000	0.000000	-1.509059	5	NaN
2013-01-02	1.212112	-0.173215	0.119209	5	1
2013-01-03	-0.861849	-2.104569	-0.494929	5	2
2013-01-04	0.721555	-0.706771	-1.039575	5	3
2013-01-05	-0.424972	0.567020	0.276232	5	4

```
2013-01-06 -0.673690  0.113648 -1.478427  5    5
```

A where operation with setting.

```
In [52]: df2 = df.copy()
```

```
In [53]: df2[df2 > 0] = -df2
```

```
In [54]: df2
```

```
Out[54]:
```

	A	B	C	D	F
2013-01-01	0.000000	0.000000	-1.509059	-5	NaN
2013-01-02	-1.212112	-0.173215	-0.119209	-5	-1
2013-01-03	-0.861849	-2.104569	-0.494929	-5	-2
2013-01-04	-0.721555	-0.706771	-1.039575	-5	-3
2013-01-05	-0.424972	-0.567020	-0.276232	-5	-4
2013-01-06	-0.673690	-0.113648	-1.478427	-5	-5

## Missing Data

pandas primarily uses the value `np.nan` to represent missing data. It is by default not included in computations. See the [Missing Data section](#)

Reindexing allows you to change/add/delete the index on a specified axis. This returns a copy of the data.

```
In [55]: df1 = df.reindex(index=dates[0:4], columns=list(df.columns) + ['E'])
```

```
In [56]: df1.loc[dates[0]:dates[1], 'E'] = 1
```

```
In [57]: df1
```

```
Out[57]:
```

	A	B	C	D	F	E
2013-01-01	0.000000	0.000000	-1.509059	5	NaN	1
2013-01-02	1.212112	-0.173215	0.119209	5	1	1
2013-01-03	-0.861849	-2.104569	-0.494929	5	2	NaN
2013-01-04	0.721555	-0.706771	-1.039575	5	3	NaN

To drop any rows that have missing data.

```
In [58]: df1.dropna(how='any')
```

```
Out[58]:
```

	A	B	C	D	F	E
2013-01-02	1.212112	-0.173215	0.119209	5	1	1

Filling missing data

```
In [59]: df1.fillna(value=5)
```

**Out[59]:**

	A	B	C	D	F	E
2013-01-01	0.000000	0.000000	-1.509059	5	5	1
2013-01-02	1.212112	-0.173215	0.119209	5	1	1
2013-01-03	-0.861849	-2.104569	-0.494929	5	2	5
2013-01-04	0.721555	-0.706771	-1.039575	5	3	5

To get the boolean mask where values are nan

**In [60]:** `pd.isnull(df1)`**Out[60]:**

	A	B	C	D	F	E
2013-01-01	False	False	False	False	True	False
2013-01-02	False	False	False	False	False	False
2013-01-03	False	False	False	False	False	True
2013-01-04	False	False	False	False	False	True

## Operations

See the [Basic section on Binary Ops](#)

## Stats

Operations in general *exclude* missing data.

Performing a descriptive statistic

**In [61]:** `df.mean()`**Out[61]:**

```
A    -0.004474
B    -0.383981
C    -0.687758
D     5.000000
F     3.000000
dtype: float64
```

Same operation on the other axis

**In [62]:** `df.mean(1)`**Out[62]:**

```
2013-01-01    0.872735
2013-01-02    1.431621
2013-01-03    0.707731
2013-01-04    1.395042
2013-01-05    1.883656
2013-01-06    1.592306
Freq: D, dtype: float64
```

Operating with objects that have different dimensionality and need alignment. In addition, pandas automatically broadcasts along the specified dimension.

```
In [63]: s = pd.Series([1,3,5,np.nan,6,8], index=dates).shift(2)
```

```
In [64]: s
```

```
Out[64]:
```

```
2013-01-01    NaN
2013-01-02    NaN
2013-01-03     1
2013-01-04     3
2013-01-05     5
2013-01-06    NaN
Freq: D, dtype: float64
```

```
In [65]: df.sub(s, axis='index')
```

```
Out[65]:
```

	A	B	C	D	F
2013-01-01	NaN	NaN	NaN	NaN	NaN
2013-01-02	NaN	NaN	NaN	NaN	NaN
2013-01-03	-1.861849	-3.104569	-1.494929	4	1
2013-01-04	-2.278445	-3.706771	-4.039575	2	0
2013-01-05	-5.424972	-4.432980	-4.723768	0	-1
2013-01-06	NaN	NaN	NaN	NaN	NaN

## Apply

Applying functions to the data

```
In [66]: df.apply(np.cumsum)
```

```
Out[66]:
```

	A	B	C	D	F
2013-01-01	0.000000	0.000000	-1.509059	5	NaN
2013-01-02	1.212112	-0.173215	-1.389850	10	1
2013-01-03	0.350263	-2.277784	-1.884779	15	3
2013-01-04	1.071818	-2.984555	-2.924354	20	6
2013-01-05	0.646846	-2.417535	-2.648122	25	10
2013-01-06	-0.026844	-2.303886	-4.126549	30	15

```
In [67]: df.apply(lambda x: x.max() - x.min())
```

```
Out[67]:
```

```
A    2.073961
B    2.671590
C    1.785291
D    0.000000
F    4.000000
dtype: float64
```

## Histogramming

See more at [Histogramming and Discretization](#)

```
In [68]: s = pd.Series(np.random.randint(0, 7, size=10))
```

```
In [69]: s
```

```
Out[69]:
```

```
0    4
1    2
2    1
3    2
4    6
5    4
6    4
7    6
8    4
9    4
dtype: int32
```

```
In [70]: s.value_counts()
```

```
Out[70]:
```

```
4    5
6    2
2    2
1    1
dtype: int64
```

## String Methods

Series is equipped with a set of string processing methods in the *str* attribute that make it easy to operate on each element of the array, as in the code snippet below. Note that pattern-matching in *str* generally uses [regular expressions](#) by default (and in some cases always uses them). See more at [Vectorized String Methods](#).

```
In [71]: s = pd.Series(['A', 'B', 'C', 'Aaba', 'Baca', np.nan, 'CABA', 'dog', 'cat'])
```

```
In [72]: s.str.lower()
```

```
Out[72]:
```

```
0    a
1    b
2    c
3  aaba
4  baca
5   NaN
6  caba
7   dog
8   cat
dtype: object
```

## Merge

## Concat

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.

See the [Merging section](#)

Concatenating pandas objects together with `concat()`:

```
In [73]: df = pd.DataFrame(np.random.randn(10, 4))
```

```
In [74]: df
```

```
Out[74]:
```

	0	1	2	3
0	-0.548702	1.467327	-1.015962	-0.483075
1	1.637550	-1.217659	-0.291519	-1.745505
2	-0.263952	0.991460	-0.919069	0.266046
3	-0.709661	1.669052	1.037882	-1.705775
4	-0.919854	-0.042379	1.247642	-0.009920
5	0.290213	0.495767	0.362949	1.548106
6	-1.131345	-0.089329	0.337863	-0.945867
7	-0.932132	1.956030	0.017587	-0.016692
8	-0.575247	0.254161	-1.143704	0.215897
9	1.193555	-0.077118	-0.408530	-0.862495

```
# break it into pieces
```

```
In [75]: pieces = [df[:3], df[3:7], df[7:]]
```

```
In [76]: pd.concat(pieces)
```

```
Out[76]:
```

	0	1	2	3
0	-0.548702	1.467327	-1.015962	-0.483075
1	1.637550	-1.217659	-0.291519	-1.745505
2	-0.263952	0.991460	-0.919069	0.266046
3	-0.709661	1.669052	1.037882	-1.705775
4	-0.919854	-0.042379	1.247642	-0.009920
5	0.290213	0.495767	0.362949	1.548106
6	-1.131345	-0.089329	0.337863	-0.945867
7	-0.932132	1.956030	0.017587	-0.016692
8	-0.575247	0.254161	-1.143704	0.215897
9	1.193555	-0.077118	-0.408530	-0.862495

## Join

SQL style merges. See the [Database style joining](#)

```
In [77]: left = pd.DataFrame({'key': ['foo', 'foo'], 'lval': [1, 2]})
```

```
In [78]: right = pd.DataFrame({'key': ['foo', 'foo'], 'rval': [4, 5]})
```

```
In [79]: left
```

```
Out[79]:
```

	key	lval
0	foo	1
1	foo	2

```
In [80]: right
Out[80]:
```

	key	rval
0	foo	4
1	foo	5

```
In [81]: pd.merge(left, right, on='key')
Out[81]:
```

	key	lval	rval
0	foo	1	4
1	foo	1	5
2	foo	2	4
3	foo	2	5

## Append

Append rows to a dataframe. See the [Appending](#)

```
In [82]: df = pd.DataFrame(np.random.randn(8, 4), columns=['A', 'B', 'C', 'D'])

In [83]: df
Out[83]:
```

	A	B	C	D
0	1.346061	1.511763	1.627081	-0.990582
1	-0.441652	1.211526	0.268520	0.024580
2	-1.577585	0.396823	-0.105381	-0.532532
3	1.453749	1.208843	-0.080952	-0.264610
4	-0.727965	-0.589346	0.339969	-0.693205
5	-0.339355	0.593616	0.884345	1.591431
6	0.141809	0.220390	0.435589	0.192451
7	-0.096701	0.803351	1.715071	-0.708758

```
In [84]: s = df.iloc[3]

In [85]: df.append(s, ignore_index=True)
Out[85]:
```

	A	B	C	D
0	1.346061	1.511763	1.627081	-0.990582
1	-0.441652	1.211526	0.268520	0.024580
2	-1.577585	0.396823	-0.105381	-0.532532
3	1.453749	1.208843	-0.080952	-0.264610
4	-0.727965	-0.589346	0.339969	-0.693205
5	-0.339355	0.593616	0.884345	1.591431
6	0.141809	0.220390	0.435589	0.192451
7	-0.096701	0.803351	1.715071	-0.708758
8	1.453749	1.208843	-0.080952	-0.264610

## Grouping

By “group by” we are referring to a process involving one or more of the following steps

- **Splitting** the data into groups based on some criteria

- **Applying** a function to each group independently
- **Combining** the results into a data structure

See the [Grouping section](#)

```
In [86]: df = pd.DataFrame({'A' : ['foo', 'bar', 'foo', 'bar',
.....:                             'foo', 'bar', 'foo', 'foo'],
.....:                     'B' : ['one', 'one', 'two', 'three',
.....:                             'two', 'two', 'one', 'three'],
.....:                     'C' : np.random.randn(8),
.....:                     'D' : np.random.randn(8)})
```

```
In [87]: df
Out[87]:
```

	A	B	C	D
0	foo	one	-1.202872	-0.055224
1	bar	one	-1.814470	2.395985
2	foo	two	1.018601	1.552825
3	bar	three	-0.595447	0.166599
4	foo	two	1.395433	0.047609
5	bar	two	-0.392670	-0.136473
6	foo	one	0.007207	-0.561757
7	foo	three	1.928123	-1.623033

Grouping and then applying a function `sum` to the resulting groups.

```
In [88]: df.groupby('A').sum()
Out[88]:
```

		C	D
A			
bar		-2.802588	2.42611
foo		3.146492	-0.63958

Grouping by multiple columns forms a hierarchical index, which we then apply the function.

```
In [89]: df.groupby(['A', 'B']).sum()
Out[89]:
```

			C	D
A	B			
bar	one		-1.814470	2.395985
	three		-0.595447	0.166599
	two		-0.392670	-0.136473
foo	one		-1.195665	-0.616981
	three		1.928123	-1.623033
	two		2.414034	1.600434

## Reshaping

See the sections on [Hierarchical Indexing](#) and [Reshaping](#).



## Stack

```
In [90]: tuples = list(zip(*[['bar', 'bar', 'baz', 'baz',
.....:                      'foo', 'foo', 'qux', 'qux'],
.....:                      ['one', 'two', 'one', 'two',
.....:                      'one', 'two', 'one', 'two']]))
.....:

In [91]: index = pd.MultiIndex.from_tuples(tuples, names=['first', 'second'])

In [92]: df = pd.DataFrame(np.random.randn(8, 2), index=index, columns=['A', 'B'])

In [93]: df2 = df[:4]

In [94]: df2
Out[94]:
```

		A	B
first	second		
bar	one	0.029399	-0.542108
	two	0.282696	-0.087302
baz	one	-1.575170	1.771208
	two	0.816482	1.100230

The **stack()** method “compresses” a level in the DataFrame’s columns.

```
In [95]: stacked = df2.stack()

In [96]: stacked
Out[96]:
```

first	second		
bar	one	A	0.029399
		B	-0.542108
	two	A	0.282696
		B	-0.087302
baz	one	A	-1.575170
		B	1.771208
	two	A	0.816482
		B	1.100230

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 [97]: stacked.unstack()
Out[97]:
```

		A	B
first	second		
bar	one	0.029399	-0.542108
	two	0.282696	-0.087302
baz	one	-1.575170	1.771208
	two	0.816482	1.100230

```
In [98]: stacked.unstack(1)
```

```
Out[98]:
second      one      two
first
bar  A  0.029399  0.282696
     B -0.542108 -0.087302
baz   A -1.575170  0.816482
     B  1.771208  1.100230
```

```
In [99]: stacked.unstack(0)
```

```
Out[99]:
first      bar      baz
second
one   A  0.029399 -1.575170
     B -0.542108  1.771208
two   A  0.282696  0.816482
     B -0.087302  1.100230
```

## Pivot Tables

See the section on [Pivot Tables](#).

```
In [100]: df = pd.DataFrame({'A' : ['one', 'one', 'two', 'three'] * 3,
.....:                      'B' : ['A', 'B', 'C'] * 4,
.....:                      'C' : ['foo', 'foo', 'foo', 'bar', 'bar', 'bar'] * 2
.....:                      'D' : np.random.randn(12),
.....:                      'E' : np.random.randn(12)})
```

```
In [101]: df
```

```
Out[101]:
   A  B  C      D      E
0  one A  foo  1.418757 -0.179666
1  one B  foo -1.879024  1.291836
2  two C  foo  0.536826 -0.009614
3 three A  bar  1.006160  0.392149
4  one B  bar -0.029716  0.264599
5  one C  bar -1.146178 -0.057409
6  two A  foo  0.100900 -1.425638
7 three B  foo -1.035018  1.024098
8  one C  foo  0.314665 -0.106062
9  one A  bar -0.773723  1.824375
10 two B  bar -1.170653  0.595974
11 three C  bar  0.648740  1.167115
```

We can produce pivot tables from this data very easily:

```
In [102]: pd.pivot_table(df, values='D', index=['A', 'B'], columns=['C'])
```

```
Out[102]:
C      bar      foo
A  B
one A -0.773723  1.418757
     B -0.029716 -1.879024
     C -1.146178  0.314665
three A  1.006160      NaN
```

```

      B      NaN -1.035018
      C    0.648740      NaN
two   A      NaN  0.100900
      B -1.170653      NaN
      C      NaN  0.536826

```

## Time Series

pandas has simple, powerful, and efficient functionality for performing resampling operations during frequency conversion (e.g., converting secondly data into 5-minutely data). This is extremely common in, but not limited to, financial applications. See the [Time Series section](#)

```

In [103]: rng = pd.date_range('1/1/2012', periods=100, freq='S')

In [104]: ts = pd.Series(np.random.randint(0, 500, len(rng)), index=rng)

In [105]: ts.resample('5Min', how='sum')
Out[105]:
2012-01-01    25083
Freq: 5T, dtype: int32

```

### Time zone representation

```

In [106]: rng = pd.date_range('3/6/2012 00:00', periods=5, freq='D')

In [107]: ts = pd.Series(np.random.randn(len(rng)), rng)

In [108]: ts
Out[108]:
2012-03-06    0.464000
2012-03-07    0.227371
2012-03-08   -0.496922
2012-03-09    0.306389
2012-03-10   -2.290613
Freq: D, dtype: float64

In [109]: ts_utc = ts.tz_localize('UTC')

In [110]: ts_utc
Out[110]:
2012-03-06 00:00:00+00:00    0.464000
2012-03-07 00:00:00+00:00    0.227371
2012-03-08 00:00:00+00:00   -0.496922
2012-03-09 00:00:00+00:00    0.306389
2012-03-10 00:00:00+00:00   -2.290613
Freq: D, dtype: float64

```

### Convert to another time zone

```

In [111]: ts_utc.tz_convert('US/Eastern')
Out[111]:

```

```

2012-03-05 19:00:00-05:00    0.464000
2012-03-06 19:00:00-05:00    0.227371
2012-03-07 19:00:00-05:00   -0.496922
2012-03-08 19:00:00-05:00    0.306389
2012-03-09 19:00:00-05:00   -2.290613
Freq: D, dtype: float64

```

## Converting between time span representations

```
In [112]: rng = pd.date_range('1/1/2012', periods=5, freq='M')
```

```
In [113]: ts = pd.Series(np.random.randn(len(rng)), index=rng)
```

```
In [114]: ts
```

```

Out[114]:
2012-01-31    -1.134623
2012-02-29    -1.561819
2012-03-31    -0.260838
2012-04-30     0.281957
2012-05-31     1.523962
Freq: M, dtype: float64

```

```
In [115]: ps = ts.to_period()
```

```
In [116]: ps
```

```

Out[116]:
2012-01     -1.134623
2012-02     -1.561819
2012-03     -0.260838
2012-04      0.281957
2012-05      1.523962
Freq: M, dtype: float64

```

```
In [117]: ps.to_timestamp()
```

```

Out[117]:
2012-01-01    -1.134623
2012-02-01    -1.561819
2012-03-01    -0.260838
2012-04-01     0.281957
2012-05-01     1.523962
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 [118]: prng = pd.period_range('1990Q1', '2000Q4', freq='Q-NOV')
```

```
In [119]: ts = pd.Series(np.random.randn(len(prng)), prng)
```

```
In [120]: ts.index = (prng.asfreq('M', 'e') + 1).asfreq('H', 's') + 9
```

```
In [121]: ts.head()
```

```

Out[121]:
1990-03-01 09:00    -0.902937

```

```
1990-06-01 09:00    0.068159
1990-09-01 09:00   -0.057873
1990-12-01 09:00   -0.368204
1991-03-01 09:00   -1.144073
Freq: H, dtype: float64
```

## Categoricals

Since version 0.15, pandas can include categorical data in a `DataFrame`. For full docs, see the [categorical introduction](#) and the [API documentation](#).

```
In [122]: df = pd.DataFrame({"id": [1, 2, 3, 4, 5, 6], "raw_grade": ['a', 'b', 'b', 'a',
```

Convert the raw grades to a categorical data type.

```
In [123]: df["grade"] = df["raw_grade"].astype("category")
```

```
In [124]: df["grade"]
```

```
Out[124]:
```

```
0    a
1    b
2    b
3    a
4    a
5    e
```

```
Name: grade, dtype: category
```

```
Categories (3, object): [a, b, e]
```

Rename the categories to more meaningful names (assigning to `Series.cat.categories` is inplace!)

```
In [125]: df["grade"].cat.categories = ["very good", "good", "very bad"]
```

Reorder the categories and simultaneously add the missing categories (methods under `Series.cat` return a new `Series` per default).

```
In [126]: df["grade"] = df["grade"].cat.set_categories(["very bad", "bad", "medium", "good", "very good"])
```

```
In [127]: df["grade"]
```

```
Out[127]:
```

```
0    very good
1         good
2         good
3    very good
4    very good
5    very bad
```

```
Name: grade, dtype: category
```

```
Categories (5, object): [very bad, bad, medium, good, very good]
```

Sorting is per order in the categories, not lexical order.

```
In [128]: df.sort_values(by="grade")
```

```
Out[128]:
```

	id	raw_grade	grade
5	6	e	very bad
1	2	b	good
2	3	b	good
0	1	a	very good
3	4	a	very good
4	5	a	very good

Grouping by a categorical column shows also empty categories.

```
In [129]: df.groupby("grade").size()
```

```
Out[129]:
```

grade	
very bad	1
bad	0
medium	0
good	2
very good	3

dtype: int64

## Plotting

[Plotting](#) docs.

```
In [130]: ts = pd.Series(np.random.randn(1000), index=pd.date_range('1/1/2000', p
```

```
In [131]: ts = ts.cumsum()
```

```
In [132]: ts.plot()
```

```
Out[132]: <matplotlib.axes._subplots.AxesSubplot at 0xae3696ac>
```

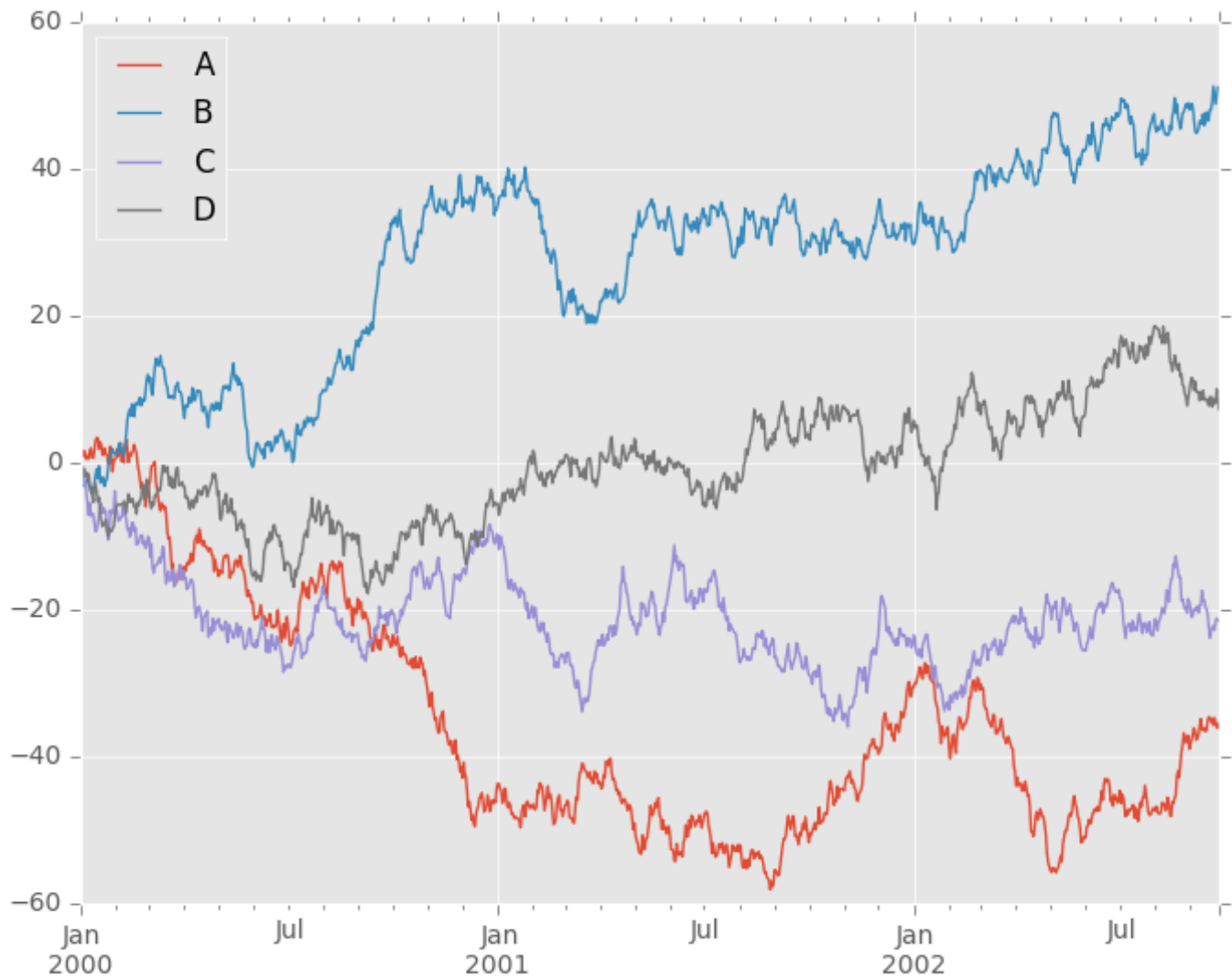


On DataFrame, `plot()` is a convenience to plot all of the columns with labels:

```
In [133]: df = pd.DataFrame(np.random.randn(1000, 4), index=ts.index,
.....:                      columns=['A', 'B', 'C', 'D'])
.....:

In [134]: df = df.cumsum()

In [135]: plt.figure(); df.plot(); plt.legend(loc='best')
Out[135]: <matplotlib.legend.Legend at 0xab53b26c>
```



## Getting Data In/Out

### CSV

#### Writing to a csv file

```
In [136]: df.to_csv('foo.csv')
```

#### Reading from a csv file

```
In [137]: pd.read_csv('foo.csv')
Out[137]:
```

	Unnamed: 0	A	B	C	D
0	2000-01-01	0.266457	-0.399641	-0.219582	1.186860
1	2000-01-02	-1.170732	-0.345873	1.653061	-0.282953
2	2000-01-03	-1.734933	0.530468	2.060811	-0.515536
3	2000-01-04	-1.555121	1.452620	0.239859	-1.156896



```

4      2000-01-05    0.578117    0.511371    0.103552   -2.428202
5      2000-01-06    0.478344    0.449933   -0.741620   -1.962409
6      2000-01-07    1.235339   -0.091757   -1.543861   -1.084753
...
993    2002-09-20  -10.628548   -9.153563   -7.883146   28.313940
994    2002-09-21  -10.390377   -8.727491   -6.399645   30.914107
995    2002-09-22   -8.985362   -8.485624   -4.669462   31.367740
996    2002-09-23   -9.558560   -8.781216   -4.499815   30.518439
997    2002-09-24   -9.902058   -9.340490   -4.386639   30.105593
998    2002-09-25  -10.216020   -9.480682   -3.933802   29.758560
999    2002-09-26  -11.856774  -10.671012   -3.216025   29.369368

[1000 rows x 5 columns]
```

## HDF5

Reading and writing to [HDFStores](#)

Writing to a HDF5 Store

```
In [138]: df.to_hdf('foo.h5', 'df')
```

Reading from a HDF5 Store

```

In [139]: pd.read_hdf('foo.h5', 'df')
Out[139]:
```

	A	B	C	D
2000-01-01	0.266457	-0.399641	-0.219582	1.186860
2000-01-02	-1.170732	-0.345873	1.653061	-0.282953
2000-01-03	-1.734933	0.530468	2.060811	-0.515536
2000-01-04	-1.555121	1.452620	0.239859	-1.156896
2000-01-05	0.578117	0.511371	0.103552	-2.428202
2000-01-06	0.478344	0.449933	-0.741620	-1.962409
2000-01-07	1.235339	-0.091757	-1.543861	-1.084753
...	...	...	...	...
2002-09-20	-10.628548	-9.153563	-7.883146	28.313940
2002-09-21	-10.390377	-8.727491	-6.399645	30.914107
2002-09-22	-8.985362	-8.485624	-4.669462	31.367740
2002-09-23	-9.558560	-8.781216	-4.499815	30.518439
2002-09-24	-9.902058	-9.340490	-4.386639	30.105593
2002-09-25	-10.216020	-9.480682	-3.933802	29.758560
2002-09-26	-11.856774	-10.671012	-3.216025	29.369368

```

[1000 rows x 4 columns]
```

## Excel

Reading and writing to [MS Excel](#)

Writing to an excel file

```
In [140]: df.to_excel('foo.xlsx', sheet_name='Sheet1')
```

## Reading from an excel file

```
In [141]: pd.read_excel('foo.xlsx', 'Sheet1', index_col=None, na_values=['NA'])
Out[141]:
```

	A	B	C	D
2000-01-01	0.266457	-0.399641	-0.219582	1.186860
2000-01-02	-1.170732	-0.345873	1.653061	-0.282953
2000-01-03	-1.734933	0.530468	2.060811	-0.515536
2000-01-04	-1.555121	1.452620	0.239859	-1.156896
2000-01-05	0.578117	0.511371	0.103552	-2.428202
2000-01-06	0.478344	0.449933	-0.741620	-1.962409
2000-01-07	1.235339	-0.091757	-1.543861	-1.084753
...	...	...	...	...
2002-09-20	-10.628548	-9.153563	-7.883146	28.313940
2002-09-21	-10.390377	-8.727491	-6.399645	30.914107
2002-09-22	-8.985362	-8.485624	-4.669462	31.367740
2002-09-23	-9.558560	-8.781216	-4.499815	30.518439
2002-09-24	-9.902058	-9.340490	-4.386639	30.105593
2002-09-25	-10.216020	-9.480682	-3.933802	29.758560
2002-09-26	-11.856774	-10.671012	-3.216025	29.369368

```
[1000 rows x 4 columns]
```

## Gotchas

If you are trying an operation and you see an exception like:

```
>>> if pd.Series([False, True, False]):
    print("I was true")
Traceback
...
ValueError: The truth value of an array is ambiguous. Use a.empty, a.any() or a.all
```

See [Comparisons](#) for an explanation and what to do.

See [Gotchas](#) as well.