10 minutes to pandas

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

Customarily, we import as follows:

```
>>>
In [1]: import numpy as np

In [2]: import pandas as pd
```

Object creation

See the Intro to data structures section.

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

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

In [4]: s
Out[4]:
0    1.0
1    3.0
2    5.0
3    NaN
4    6.0
5    8.0
dtype: float64
```

Creating a `DataFrame` by passing a NumPy array, with a datetime index using `date_range()` and labeled columns:

```
>>>
In [5]: dates = pd.date_range("20130101", periods=6)

In [6]: dates
Out[6]:
DatetimeIndex(['2013-01-01', '2013-01-02', '2013-01-03', '2013-01-04',
               '2013-01-05', '2013-01-06'],
              dtype='datetime64[ns]', freq='D')

In [7]: df = pd.DataFrame(np.random.randn(6, 4), index=dates,
columns=list("ABCD"))

In [8]: df
Out[8]:
                   A         B         C         D
2013-01-01  0.469112 -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 dictionary of objects that can be converted into a series-like structure:

```
>>>

In [9]: df2 = pd.DataFrame(
   ...:     {
   ...:         "A": 1.0,
   ...:         "B": pd.Timestamp("20130102"),
   ...:         "C": pd.Series(1, index=list(range(4)), dtype="float32"),
   ...:         "D": np.array([3] * 4, dtype="int32"),
   ...:         "E": pd.Categorical(["test", "train", "test", "train"]),
   ...:         "F": "foo",
   ...:     }
   ...: )
   ...:

In [10]: df2
Out[10]:
     A          B    C  D      E    F
0  1.0 2013-01-02  1.0  3   test  foo
1  1.0 2013-01-02  1.0  3  train  foo
2  1.0 2013-01-02  1.0  3   test  foo
3  1.0 2013-01-02  1.0  3  train  foo
```

The columns of the resulting **DataFrame** have different dtypes:

```
>>>

In [11]: df2.dtypes
Out[11]:
A          float64
B    datetime64[ns]
C          float32
D            int32
E         category
F           object
dtype: object
```

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

```
>>>

In [12]: df2.<TAB>  # noqa: E225, E999
df2.A                  df2.bool
df2.abs                df2.boxplot
df2.add                df2.C
df2.add_prefix         df2.clip
df2.add_suffix         df2.columns
df2.align              df2.copy
df2.all                df2.count
df2.any                df2.combine
```

```
df2.append              df2.D
df2.apply               df2.describe
df2.applymap            df2.diff
df2.B                   df2.duplicated
```
As you can see, the columns `A`, `B`, `C`, and `D` are automatically tab completed. `E` and `F` are there as well; the rest of the attributes have been truncated for brevity.

Viewing data

See the Basics section.

Use **`DataFrame.head()`** and **`DataFrame.tail()`** to view the top and bottom rows of the frame respectively:

```
>>>

In [13]: df.head()
Out[13]:
                   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 [14]: df.tail(3)
Out[14]:
                   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 **`DataFrame.index`** or **`DataFrame.columns`**:

```
>>>

In [15]: df.index
Out[15]:
DatetimeIndex(['2013-01-01', '2013-01-02', '2013-01-03', '2013-01-04',
               '2013-01-05', '2013-01-06'],
              dtype='datetime64[ns]', freq='D')

In [16]: df.columns
Out[16]: Index(['A', 'B', 'C', 'D'], dtype='object')
```
`DataFrame.to_numpy()` gives a NumPy representation of the underlying data. Note that this can be an expensive operation when your **`DataFrame`** has columns with different data types, which comes down to a fundamental difference between pandas and NumPy: **NumPy arrays have one dtype for the entire array, while pandas DataFrames have one dtype per column**. When you call **`DataFrame.to_numpy()`**, pandas will find the NumPy dtype that can hold *all* of the dtypes in the DataFrame. This may end up being `object`, which requires casting every value to a Python object.

For `df`, our **`DataFrame`** of all floating-point values, and **`DataFrame.to_numpy()`** is fast and doesn’t require copying data:

```
>>>

In [17]: df.to_numpy()
Out[17]:
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 ]])
```

For `df2`, the `DataFrame` with multiple dtypes, `DataFrame.to_numpy()` is relatively expensive:

```
>>>

In [18]: df2.to_numpy()
Out[18]:
array([[1.0, Timestamp('2013-01-02 00:00:00'), 1.0, 3, 'test', 'foo'],
       [1.0, Timestamp('2013-01-02 00:00:00'), 1.0, 3, 'train', 'foo'],
       [1.0, Timestamp('2013-01-02 00:00:00'), 1.0, 3, 'test', 'foo'],
       [1.0, Timestamp('2013-01-02 00:00:00'), 1.0, 3, 'train', 'foo']],
      dtype=object)
```

Note

`DataFrame.to_numpy()` does *not* include the index or column labels in the output.

`describe()` shows a quick statistic summary of your data:

```
>>>

In [19]: df.describe()
Out[19]:
              A         B         C         D
count  6.000000  6.000000  6.000000  6.000000
mean   0.073711 -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
```

`DataFrame.sort_index()` sorts 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
```

`DataFrame.sort_values()` sorts 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, `DataFrame.at()`, `DataFrame.iat()`, `DataFrame.loc()` and `DataFrame.iloc()`.

See the indexing documentation Indexing and Selecting Data and MultiIndex / Advanced Indexing.

Getting

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

```
>>>
In [23]: df["A"]
Out[23]:
2013-01-01    0.469112
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 `[]` (`__getitem__`), 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 using `DataFrame.loc()` or `DataFrame.at()`.

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    1.212112
B   -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]: 0.4691122999071863
```

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

```
>>>

In [31]: df.at[dates[0], "A"]
Out[31]: 0.4691122999071863
```

Selection by position

See more in Selection by Position using **`DataFrame.iloc()`** or **`DataFrame.iat()`**.

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 (equivalent 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
```

Selecting values from a DataFrame where a boolean condition is met:

```
>>>

In [40]: df[df > 0]
Out[40]:
                   A         B         C         D
2013-01-01  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  5.0  NaN
2013-01-02  1.212112 -0.173215  0.119209  5.0  1.0
2013-01-03 -0.861849 -2.104569 -0.494929  5.0  2.0
2013-01-04  0.721555 -0.706771 -1.039575  5.0  3.0
2013-01-05 -0.424972  0.567020  0.276232  5.0  4.0
2013-01-06 -0.673690  0.113648 -1.478427  5.0  5.0
```

A `where` operation with setting:

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

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

In [54]: df2
Out[54]:
                   A         B         C    D    F
2013-01-01  0.000000  0.000000 -1.509059 -5.0  NaN
2013-01-02 -1.212112 -0.173215 -0.119209 -5.0 -1.0
2013-01-03 -0.861849 -2.104569 -0.494929 -5.0 -2.0
2013-01-04 -0.721555 -0.706771 -1.039575 -5.0 -3.0
2013-01-05 -0.424972 -0.567020 -0.276232 -5.0 -4.0
2013-01-06 -0.673690 -0.113648 -1.478427 -5.0 -5.0
```

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  5.0  NaN  1.0
2013-01-02  1.212112 -0.173215  0.119209  5.0  1.0  1.0
2013-01-03 -0.861849 -2.104569 -0.494929  5.0  2.0  NaN
2013-01-04  0.721555 -0.706771 -1.039575  5.0  3.0  NaN
```

`DataFrame.dropna()` drops 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  5.0  1.0  1.0
```

`DataFrame.fillna()` fills 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  5.0  5.0  1.0
2013-01-02  1.212112 -0.173215  0.119209  5.0  1.0  1.0
2013-01-03 -0.861849 -2.104569 -0.494929  5.0  2.0  5.0
2013-01-04  0.721555 -0.706771 -1.039575  5.0  3.0  5.0
```

`isna()` gets the boolean mask where values are `nan`:

```
>>>

In [60]: pd.isna(df1)
Out[60]:
                A      B      C      D      F      E
2013-01-01  False  False  False  False   True  False
2013-01-02  False  False  False  False  False  False
2013-01-03  False  False  False  False  False   True
2013-01-04  False  False  False  False  False   True
```

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    1.0
2013-01-04    3.0
2013-01-05    5.0
2013-01-06    NaN
Freq: D, dtype: float64

In [65]: df.sub(s, axis="index")
Out[65]:
                   A         B         C    D    F
2013-01-01       NaN       NaN       NaN  NaN  NaN
2013-01-02       NaN       NaN       NaN  NaN  NaN
2013-01-03 -1.861849 -3.104569 -1.494929  4.0  1.0
2013-01-04 -2.278445 -3.706771 -4.039575  2.0  0.0
2013-01-05 -5.424972 -4.432980 -4.723768  0.0 -1.0
2013-01-06       NaN       NaN       NaN  NaN  NaN
```

Apply

`DataFrame.apply()` applies a user defined function 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   5.0   NaN
2013-01-02  1.212112 -0.173215 -1.389850  10.0   1.0
2013-01-03  0.350263 -2.277784 -1.884779  15.0   3.0
2013-01-04  1.071818 -2.984555 -2.924354  20.0   6.0
2013-01-05  0.646846 -2.417535 -2.648122  25.0  10.0
2013-01-06 -0.026844 -2.303886 -4.126549  30.0  15.0

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: int64

In [70]: s.value_counts()
Out[70]:
4    5
2    2
6    2
1    1
Name: count, 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 and DataFrame objects with various kinds of set logic for the indexes and relational algebra functionality in the case of join / merge-type operations.

See the Merging section.

Concatenating pandas objects together along an axis 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
```

Note

Adding a column to a `DataFrame` is relatively fast. However, adding a row requires a copy, and may be expensive. We recommend passing a pre-built list of records to the `DataFrame` constructor instead of building a `DataFrame` by iteratively appending records to it.

Join

`merge()` enables SQL style join types along specific columns. See the Database style joining section.

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

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

In [79]: left
Out[79]:
   key  lval
0  foo     1
1  foo     2

In [80]: right
Out[80]:
   key  rval
0  foo     4
1  foo     5

In [81]: pd.merge(left, right, on="key")
Out[81]:
   key  lval  rval
0  foo     1     4
1  foo     1     5
2  foo     2     4
3  foo     2     5
```

Another example that can be given is:

```
>>>
In [82]: left = pd.DataFrame({"key": ["foo", "bar"], "lval": [1, 2]})

In [83]: right = pd.DataFrame({"key": ["foo", "bar"], "rval": [4, 5]})

In [84]: left
Out[84]:
   key  lval
0  foo     1
1  bar     2

In [85]: right
Out[85]:
   key  rval
0  foo     4
1  bar     5

In [86]: pd.merge(left, right, on="key")
Out[86]:
   key  lval  rval
0  foo     1     4
1  bar     2     5
```

Grouping

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

- **Splitting** the data into groups based on some criteria
- **Applying** a function to each group independently
- **Combining** the results into a data structure

See the Grouping section.

```
>>>

In [87]: df = pd.DataFrame(
   ....:     {
   ....:         "A": ["foo", "bar", "foo", "bar", "foo", "bar", "foo",
"foo"],
   ....:         "B": ["one", "one", "two", "three", "two", "two", "one",
"three"],
   ....:         "C": np.random.randn(8),
   ....:         "D": np.random.randn(8),
   ....:     }
   ....: )
   ....:

In [88]: df
Out[88]:
     A      B         C         D
0  foo    one  1.346061 -1.577585
1  bar    one  1.511763  0.396823
2  foo    two  1.627081 -0.105381
3  bar  three -0.990582 -0.532532
4  foo    two -0.441652  1.453749
5  bar    two  1.211526  1.208843
6  foo    one  0.268520 -0.080952
7  foo  three  0.024580 -0.264610
```

Grouping and then applying the `sum()` function to the resulting groups:

```
>>>

In [89]: df.groupby("A")[["C", "D"]].sum()
Out[89]:
            C         D
A
bar  1.732707  1.073134
foo  2.824590 -0.574779
```

Grouping by multiple columns forms a hierarchical index, and again we can apply the `sum()` function:

```
>>>

In [90]: df.groupby(["A", "B"]).sum()
Out[90]:
                  C         D
A   B
bar one    1.511763  0.396823
```

```
    three -0.990582 -0.532532
    two    1.211526  1.208843
foo one    1.614581 -1.658537
    three  0.024580 -0.264610
    two    1.185429  1.348368
```

Reshaping

See the sections on Hierarchical Indexing and Reshaping.

Stack

```
>>>

In [91]: tuples = list(
   ....:     zip(
   ....:         ["bar", "bar", "baz", "baz", "foo", "foo", "qux", "qux"],
   ....:         ["one", "two", "one", "two", "one", "two", "one", "two"],
   ....:     )
   ....: )
   ....:

In [92]: index = pd.MultiIndex.from_tuples(tuples, names=["first",
"second"])

In [93]: df = pd.DataFrame(np.random.randn(8, 2), index=index,
columns=["A", "B"])

In [94]: df2 = df[:4]

In [95]: df2
Out[95]:
                     A         B
first second
bar   one    -0.727965 -0.589346
      two     0.339969 -0.693205
baz   one    -0.339355  0.593616
      two     0.884345  1.591431
```

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

```
>>>

In [96]: stacked = df2.stack()

In [97]: stacked
Out[97]:
first  second
bar    one     A   -0.727965
               B   -0.589346
       two     A    0.339969
               B   -0.693205
baz    one     A   -0.339355
               B    0.593616
       two     A    0.884345
               B    1.591431
dtype: float64
```

With a "stacked" DataFrame or Series (having a **`MultiIndex`** as the `index`), the inverse operation of **`stack()`** is **`unstack()`**, which by default unstacks the **last level**:

```
>>>

In [98]: stacked.unstack()
Out[98]:
                     A         B
first second
bar   one    -0.727965 -0.589346
      two     0.339969 -0.693205
baz   one    -0.339355  0.593616
      two     0.884345  1.591431

In [99]: stacked.unstack(1)
Out[99]:
second        one       two
first
bar   A -0.727965  0.339969
      B -0.589346 -0.693205
baz   A -0.339355  0.884345
      B  0.593616  1.591431

In [100]: stacked.unstack(0)
Out[100]:
first          bar       baz
second
one     A -0.727965 -0.339355
        B -0.589346  0.593616
two     A  0.339969  0.884345
        B -0.693205  1.591431
```

Pivot tables

See the section on Pivot Tables.

```
>>>

In [101]: df = pd.DataFrame(
   .....:     {
   .....:         "A": ["one", "one", "two", "three"] * 3,
   .....:         "B": ["A", "B", "C"] * 4,
   .....:         "C": ["foo", "foo", "foo", "bar", "bar", "bar"] * 2,
   .....:         "D": np.random.randn(12),
   .....:         "E": np.random.randn(12),
   .....:     }
   .....: )
   .....:

In [102]: df
Out[102]:
        A  B    C         D         E
0     one  A  foo -1.202872  0.047609
1     one  B  foo -1.814470 -0.136473
2     two  C  foo  1.018601 -0.561757
3   three  A  bar -0.595447 -1.623033
4     one  B  bar  1.395433  0.029399
```

```
5     one  C  bar -0.392670 -0.542108
6     two  A  foo  0.007207  0.282696
7   three  B  foo  1.928123 -0.087302
8     one  C  foo -0.055224 -1.575170
9     one  A  bar  2.395985  1.771208
10    two  B  bar  1.552825  0.816482
11  three  C  bar  0.166599  1.100230
```

`pivot_table()` pivots a **`DataFrame`** specifying the `values`, `index` and `columns`

```
>>>
In [103]: pd.pivot_table(df, values="D", index=["A", "B"], columns=["C"])
Out[103]:
C             bar       foo
A     B
one   A  2.395985 -1.202872
      B  1.395433 -1.814470
      C -0.392670 -0.055224
three A -0.595447       NaN
      B       NaN  1.928123
      C  0.166599       NaN
two   A       NaN  0.007207
      B  1.552825       NaN
      C       NaN  1.018601
```

Time series

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

```
>>>
In [104]: rng = pd.date_range("1/1/2012", periods=100, freq="S")

In [105]: ts = pd.Series(np.random.randint(0, 500, len(rng)), index=rng)

In [106]: ts.resample("5Min").sum()
Out[106]:
2012-01-01    24182
Freq: 5T, dtype: int64
```

`Series.tz_localize()` localizes a time series to a time zone:

```
>>>
In [107]: rng = pd.date_range("3/6/2012 00:00", periods=5, freq="D")

In [108]: ts = pd.Series(np.random.randn(len(rng)), rng)

In [109]: ts
Out[109]:
2012-03-06    1.857704
2012-03-07   -1.193545
2012-03-08    0.677510
2012-03-09   -0.153931
```

```
2012-03-10    0.520091
Freq: D, dtype: float64

In [110]: ts_utc = ts.tz_localize("UTC")

In [111]: ts_utc
Out[111]:
2012-03-06 00:00:00+00:00    1.857704
2012-03-07 00:00:00+00:00   -1.193545
2012-03-08 00:00:00+00:00    0.677510
2012-03-09 00:00:00+00:00   -0.153931
2012-03-10 00:00:00+00:00    0.520091
Freq: D, dtype: float64
```

`Series.tz_convert()` converts a timezones aware time series to another time zone:

```
>>>

In [112]: ts_utc.tz_convert("US/Eastern")
Out[112]:
2012-03-05 19:00:00-05:00    1.857704
2012-03-06 19:00:00-05:00   -1.193545
2012-03-07 19:00:00-05:00    0.677510
2012-03-08 19:00:00-05:00   -0.153931
2012-03-09 19:00:00-05:00    0.520091
Freq: D, dtype: float64
```

Converting between time span representations:

```
>>>

In [113]: rng = pd.date_range("1/1/2012", periods=5, freq="M")

In [114]: ts = pd.Series(np.random.randn(len(rng)), index=rng)

In [115]: ts
Out[115]:
2012-01-31   -1.475051
2012-02-29    0.722570
2012-03-31   -0.322646
2012-04-30   -1.601631
2012-05-31    0.778033
Freq: M, dtype: float64

In [116]: ps = ts.to_period()

In [117]: ps
Out[117]:
2012-01   -1.475051
2012-02    0.722570
2012-03   -0.322646
2012-04   -1.601631
2012-05    0.778033
Freq: M, dtype: float64

In [118]: ps.to_timestamp()
Out[118]:
2012-01-01   -1.475051
```

```
2012-02-01    0.722570
2012-03-01   -0.322646
2012-04-01   -1.601631
2012-05-01    0.778033
Freq: MS, dtype: float64
```

Converting between period and timestamp enables some convenient arithmetic functions to be used. In the following example, we convert a quarterly frequency with year ending in November to 9am of the end of the month following the quarter end:

```
>>>

In [119]: prng = pd.period_range("1990Q1", "2000Q4", freq="Q-NOV")

In [120]: ts = pd.Series(np.random.randn(len(prng)), prng)

In [121]: ts.index = (prng.asfreq("M", "e") + 1).asfreq("H", "s") + 9

In [122]: ts.head()
Out[122]:
1990-03-01 09:00   -0.289342
1990-06-01 09:00    0.233141
1990-09-01 09:00   -0.223540
1990-12-01 09:00    0.542054
1991-03-01 09:00   -0.688585
Freq: H, dtype: float64
```

Categoricals

pandas can include categorical data in a **`DataFrame`**. For full docs, see the categorical introduction and the API documentation.

```
>>>

In [123]: df = pd.DataFrame(
   .....:     {"id": [1, 2, 3, 4, 5, 6], "raw_grade": ["a", "b", "b", "a",
"a", "e"]}
   .....: )
   .....:
```

Converting the raw grades to a categorical data type:

```
>>>

In [124]: df["grade"] = df["raw_grade"].astype("category")

In [125]: df["grade"]
Out[125]:
0    a
1    b
2    b
3    a
4    a
5    e
Name: grade, dtype: category
Categories (3, object): ['a', 'b', 'e']
```

Rename the categories to more meaningful names:

```
>>>

In [126]: new_categories = ["very good", "good", "very bad"]

In [127]: df["grade"] = df["grade"].cat.rename_categories(new_categories)
```

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

```
>>>

In [128]: df["grade"] = df["grade"].cat.set_categories(
   .....:     ["very bad", "bad", "medium", "good", "very good"]
   .....: )
   .....:

In [129]: df["grade"]
Out[129]:
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 [130]: df.sort_values(by="grade")
Out[130]:
   id raw_grade      grade
5   6         e   very bad
1   2         b       good
2   3         b       good
0   1         a  very good
3   4         a  very good
4   5         a  very good
```

Grouping by a categorical column also shows empty categories:

```
>>>

In [131]: df.groupby("grade").size()
Out[131]:
grade
very bad     1
bad          0
medium       0
good         2
very good    3
dtype: int64
```

Plotting

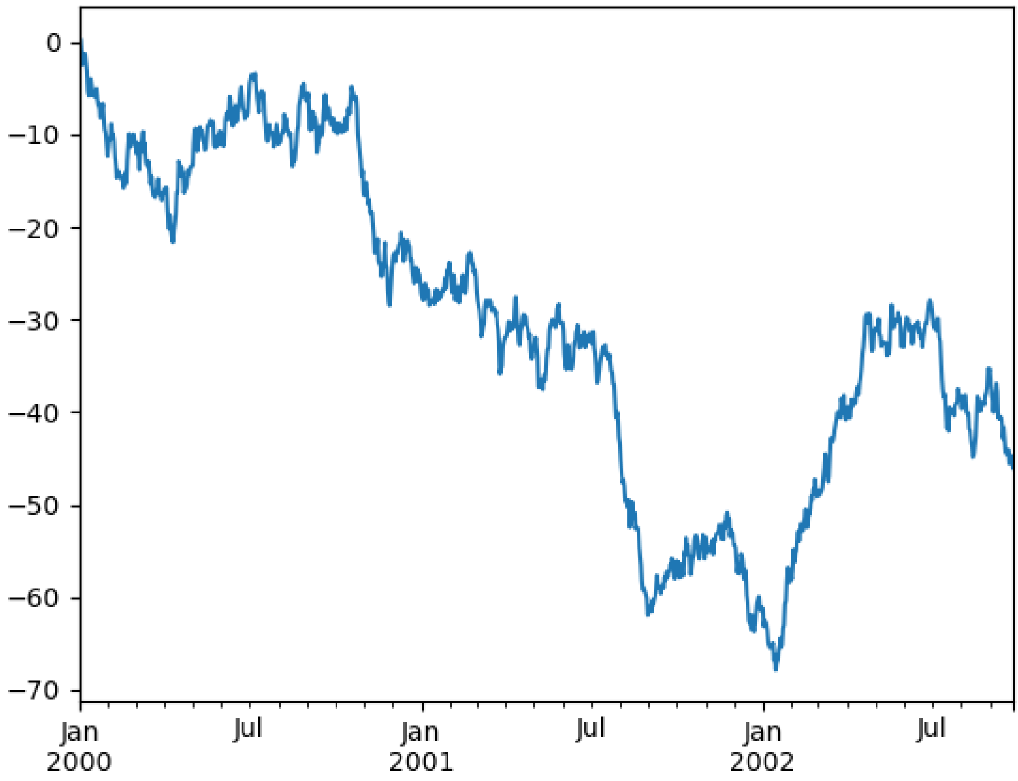
See the Plotting docs.

We use the standard convention for referencing the matplotlib API:

```
>>>
In [132]: import matplotlib.pyplot as plt

In [133]: plt.close("all")
```

The `plt.close` method is used to close a figure window:

```
>>>
In [134]: ts = pd.Series(np.random.randn(1000),
index=pd.date_range("1/1/2000", periods=1000))

In [135]: ts = ts.cumsum()

In [136]: ts.plot();
```

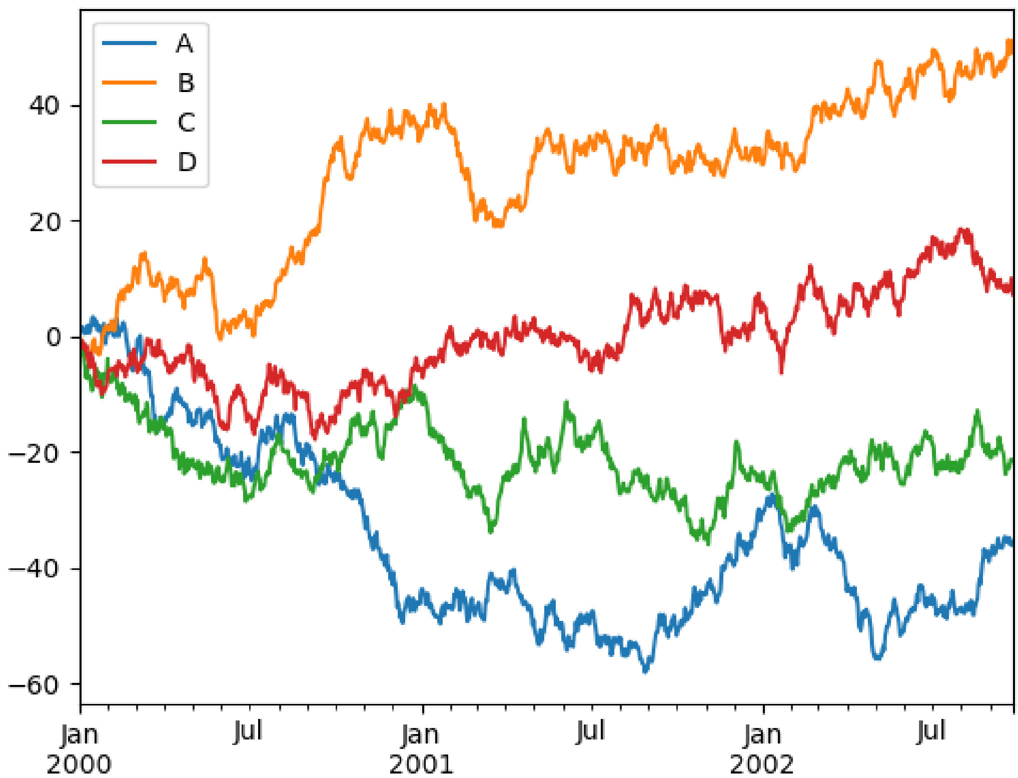


If running under Jupyter Notebook, the plot will appear on **`plot()`**. Otherwise use matplotlib.pyplot.show to show it or matplotlib.pyplot.savefig to write it to a file.

```
>>>
In [137]: plt.show();
```

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

```
>>>
In [138]: df = pd.DataFrame(
   .....:     np.random.randn(1000, 4), index=ts.index, columns=["A", "B",
"C", "D"]
   .....: )
   .....:

In [139]: df = df.cumsum()

In [140]: plt.figure();

In [141]: df.plot();

In [142]: plt.legend(loc='best');
```



Importing and exporting data

CSV

Writing to a csv file: using **`DataFrame.to_csv()`**

```
>>>
In [143]: df.to_csv("foo.csv")
```

Reading from a csv file: using **`read_csv()`**

```
>>>
```

```
In [144]: pd.read_csv("foo.csv")
Out[144]:
     Unnamed: 0          A          B          C          D
0    2000-01-01   0.350262   0.843315   1.798556   0.782234
1    2000-01-02  -0.586873   0.034907   1.923792  -0.562651
2    2000-01-03  -1.245477  -0.963406   2.269575  -1.612566
3    2000-01-04  -0.252830  -0.498066   3.176886  -1.275581
4    2000-01-05  -1.044057   0.118042   2.768571   0.386039
..          ...        ...        ...        ...        ...
995  2002-09-22 -48.017654  31.474551  69.146374 -47.541670
996  2002-09-23 -47.207912  32.627390  68.505254 -48.828331
997  2002-09-24 -48.907133  31.990402  67.310924 -49.391051
998  2002-09-25 -50.146062  33.716770  67.717434 -49.037577
999  2002-09-26 -49.724318  33.479952  68.108014 -48.822030

[1000 rows x 5 columns]
```

HDF5

Reading and writing to HDFStores.

Writing to a HDF5 Store using `DataFrame.to_hdf()`:

```
>>>

In [145]: df.to_hdf("foo.h5", "df")
```

Reading from a HDF5 Store using `read_hdf()`:

```
>>>

In [146]: pd.read_hdf("foo.h5", "df")
Out[146]:
                    A          B          C          D
2000-01-01   0.350262   0.843315   1.798556   0.782234
2000-01-02  -0.586873   0.034907   1.923792  -0.562651
2000-01-03  -1.245477  -0.963406   2.269575  -1.612566
2000-01-04  -0.252830  -0.498066   3.176886  -1.275581
2000-01-05  -1.044057   0.118042   2.768571   0.386039
...               ...        ...        ...        ...
2002-09-22 -48.017654  31.474551  69.146374 -47.541670
2002-09-23 -47.207912  32.627390  68.505254 -48.828331
2002-09-24 -48.907133  31.990402  67.310924 -49.391051
2002-09-25 -50.146062  33.716770  67.717434 -49.037577
2002-09-26 -49.724318  33.479952  68.108014 -48.822030

[1000 rows x 4 columns]
```

Excel

Reading and writing to Excel.

Writing to an excel file using `DataFrame.to_excel()`:

```
>>>

In [147]: df.to_excel("foo.xlsx", sheet_name="Sheet1")
```

Reading from an excel file using `read_excel()`:

```
>>>

In [148]: pd.read_excel("foo.xlsx", "Sheet1", index_col=None,
na_values=["NA"])
Out[148]:
    Unnamed: 0          A          B          C          D
0   2000-01-01   0.350262   0.843315   1.798556   0.782234
1   2000-01-02  -0.586873   0.034907   1.923792  -0.562651
2   2000-01-03  -1.245477  -0.963406   2.269575  -1.612566
3   2000-01-04  -0.252830  -0.498066   3.176886  -1.275581
4   2000-01-05  -1.044057   0.118042   2.768571   0.386039
..         ...        ...        ...        ...        ...
995 2002-09-22 -48.017654  31.474551  69.146374 -47.541670
996 2002-09-23 -47.207912  32.627390  68.505254 -48.828331
997 2002-09-24 -48.907133  31.990402  67.310924 -49.391051
998 2002-09-25 -50.146062  33.716770  67.717434 -49.037577
999 2002-09-26 -49.724318  33.479952  68.108014 -48.822030

[1000 rows x 5 columns]
```

Gotchas

If you are attempting to perform a boolean operation on a **`Series`** or **`DataFrame`** you might see an exception like:

```
>>>

In [149]: if pd.Series([False, True, False]):
   .....:     print("I was true")
   .....:
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-149-b27eb9c1dfc0> in ?()
----> 1 if pd.Series([False, True, False]):
      2     print("I was true")

~/work/pandas/pandas/pandas/core/generic.py in ?(self)
   1464     @final
   1465     def __nonzero__(self) -> NoReturn:
-> 1466         raise ValueError(
   1467             f"The truth value of a {type(self).__name__} is
ambiguous. "
   1468             "Use a.empty, a.bool(), a.item(), a.any() or a.all()."
   1469         )

ValueError: The truth value of a Series is ambiguous. Use a.empty,
a.bool(), a.item(), a.any() or a.all().
```

See Comparisons and Gotchas for an explanation and what to do.