十分钟搞定 pandas

转载：http://www.cnblogs.com/chaosimple/p/4153083.html

本文是对 pandas 官方网站上《10 Minutes to pandas》的一个简单的翻译，原文在这里。这篇文章是对 pandas 的一个简单的介绍，详细的介绍请参考：*Cookbook* 。习惯上，我们会按下面格式引入所需要的包：

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

In [2]: import numpy as np

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

一、 创建对象

可以通过 Data Structure Intro Setion 来查看有关该节内容的详细信息。

1、可以通过传递一个 list 对象来创建一个 Series，pandas 会默认创建整型索引

```
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
```

2、通过传递一个 numpy array，时间索引以及列标签来创建一个 DataFrame

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

In [7]: dates
Out[7]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2013-01-01, ..., 2013-01-06]
Length: 6, Freq: D, Timezone: None

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
```

3、通过传递一个能够被转换成类似序列结构的字典对象来创建一个 DataFrame

```
In [10]: df2 = pd.DataFrame({ 'A' : 1.,
   ....:                      '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 [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
```

4、查看不同列的数据类型

```
In [12]: df2.dtypes
Out[12]:
A           float64
B    datetime64[ns]
C           float32
D             int32
E          category
F            object
dtype: object
```

5、如果你使用的是 IPython，使用 Tab 自动补全功能会自动识别所有的属性以及自定义的列，下图中是所有能够被自动识别的属性的一个子集

```
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
```

二、 查看数据

详情请参阅：Basics Section

1、 查看 frame 中头部和尾部的行

```
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
```

2、 显示索引、列和底层的 numpy 数据

```
In [16]: df.index
Out[16]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2013-01-01, ..., 2013-01-06]
Length: 6, Freq: D, Timezone: None

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 ]])
```

3、 describe()函数对于数据的快速统计汇总

```
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
```

4、 对数据的转置

```
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
```

5、 按轴进行排序

```
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
```

6、 按值进行排序

```
In [22]: df.sort(columns='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
```

三、 选择

虽然标准的 Python/Numpy 的选择和设置表达式都能够直接派上用场，但是作为工程使用的代码，我们推荐使用经过优化的 pandas 数据访问方式：.at, .iat, .loc, .iloc 和 .ix 详情请参阅 Indexing and Selecing Data 和 MultiIndex / Advanced Indexing。

获取

1、 选择一个单独的列，这将会返回一个 Series，等同于 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
```

2、 通过[]进行选择，这将会对行进行切片

```
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
```

通过标签选择

1、 使用标签来获取一个交叉的区域

```
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
```

2、 通过标签来在多个轴上进行选择

```
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
```

3、 标签切片

```
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
```

4、 对于返回的对象进行维度缩减

```
In [29]: df.loc['20130102',['A','B']]
Out[29]:
A    1.212112
B   -0.173215
Name: 2013-01-02 00:00:00, dtype: float64
```

5、 获取一个标量

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

6、 快速访问一个标量（与上一个方法等价）

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

通过位置选择

1、 通过传递数值进行位置选择（选择的是行）

```
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
```

2、 通过数值进行切片，与 numpy/python 中的情况类似

```
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
```

3、 通过指定一个位置的列表，与 numpy/python 中的情况类似

```
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
```

4、 对行进行切片

```
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
```

5、 对列进行切片

```
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
```

6、 获取特定的值

```
In [37]: df.iloc[1,1]
Out[37]: -0.17321464905330861
```

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

```
In [38]: df.iat[1,1]
Out[38]: -0.17321464905330861
```

布尔索引

1、 使用一个单独列的值来选择数据

```
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
```

2、 使用 where 操作来选择数据

```
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
```

3、 使用 isin()方法来过滤

```
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
```

设置

1、 设置一个新的列

```
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
```

2、 通过标签设置新的值

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

3、 通过位置设置新的值

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

4、 通过一个 numpy 数组设置一组新值

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

上述操作结果如下：

```
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
```

5、 通过 where 操作来设置新的值

```
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
```

四、 缺失值处理

在 pandas 中，使用 np.nan 来代替缺失值，这些值将默认不会包含在计算中，详情请参阅：Missing Data Section。

1、 reindex()方法可以对指定轴上的索引进行改变/增加/删除操作，这将返回原始数据的一个拷贝：

```
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
```

2、 去掉包含缺失值的行

```
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
```

3、 对缺失值进行填充

```
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
```

4、 对数据进行布尔填充

```
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
```

五、 相关操作

详情请参与 Basic Section On Binary Ops

统计（相关操作通常情况下不包括缺失值）

1、 执行描述性统计

```
In [61]: df.mean()
Out[61]:
A   -0.004474
B   -0.383981
C   -0.687758
D    5.000000
F    3.000000
dtype: float64
```

2、 在其他轴上进行相同的操作

```
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
```

3、 对于拥有不同维度，需要对齐的对象进行操作。Pandas 会自动的沿着指定的维度进行广播

```
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

1、 对数据应用函数

```
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
```

直方图

具体请参照：*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
```

字符串方法

Series 对象在其 str 属性中配备了一组字符串处理方法，可以很容易的应用到数组中的每个元素，如下段代码所示。更多详情请参考：*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
```

六、 合并

Pandas 提供了大量的方法能够轻松的对 Series，DataFrame 和 Panel 对象进行各种符合各种逻辑关系的合并操作。具体请参阅：*Merging section*

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

类似于 SQL 类型的合并，具体请参阅：*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

将一行连接到一个 DataFrame 上，具体请参阅 *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
```

七、 分组 groupby

对于”group by”操作，我们通常是指以下一个或多个操作步骤：

- （Splitting）按照一些规则将数据分为不同的组；
- （Applying）对于每组数据分别执行一个函数；
- （Combining）将结果组合到一个数据结构中；

详情请参阅：*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
```

1、 分组并对每个分组执行 sum 函数

```
In [88]: df.groupby('A').sum()
Out[88]:
            C        D
A
bar -2.802588  2.42611
foo  3.146492 -0.63958
```

2、 通过多个列进行分组形成一个层次索引，然后执行函数

```
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
```

统计每个分组的数量

```
In [14]: df.groupby(['A', 'B']).count()
Out[14]:
           C  D
A   B
bar one    1  1
    three  1  1
    two    1  1
foo one    2  2
    three  1  1
    two    2  2
```

深度截图 20170523093706.png

八、 Reshaping

详情请参阅 *Hierarchical Indexing* 和 *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
```

```
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
```

```
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
```

数据透视表

详情请参阅：*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
```

可以从这个数据中轻松的生成数据透视表：

```
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
```

九、 时间序列

Pandas 在对频率转换进行重新采样时拥有简单、强大且高效的功能（如将按秒采样的数据转换为按 5 分钟为单位进行采样的数据）。这种操作在金融领域非常常见。具体参考：*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
```

1、 时区表示：

```
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
```

2、 时区转换：

```
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
```

3、 时间跨度转换：

```
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
```

4、 时期和时间戳之间的转换使得可以使用一些方便的算术函数。

```
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
```

十、 Categorical

从 0.15 版本开始，pandas 可以在 DataFrame 中支持 Categorical 类型的数据，详细介绍参看：*categorical introduction* 和 *API documentation*。

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

1、 将原始的 grade 转换为 Categorical 数据类型

```
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]
```

2、 将 Categorical 类型数据重命名为更有意义的名称

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

3、 对类别进行重新排序，增加缺失的类别

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

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]
```

4、 排序是按照 Categorical 的顺序进行的而不是按照字典顺序进行

```
In [128]: df.sort("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
```

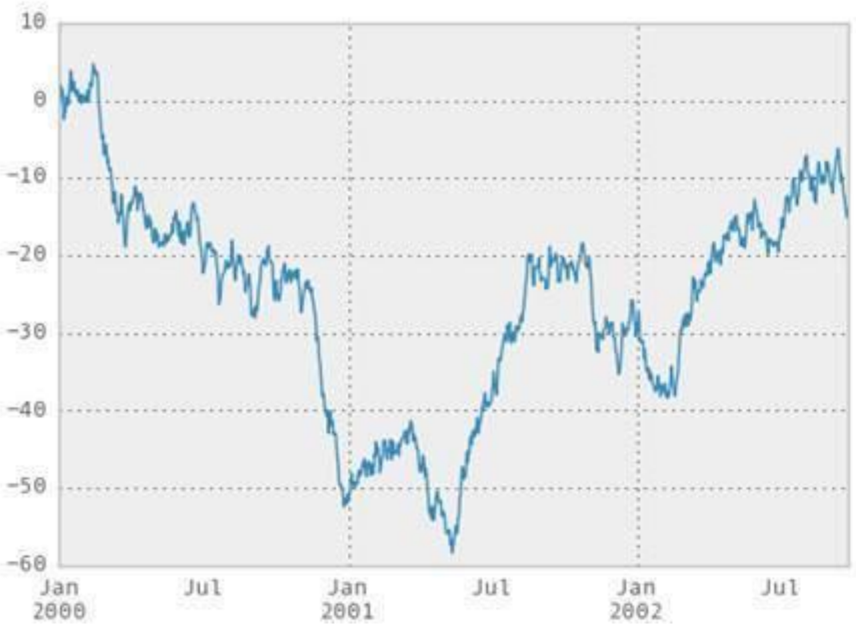
5、 对 Categorical 列进行排序时存在空的类别

```
In [129]: df.groupby("grade").size()
Out[129]:
grade
very bad       1
bad          NaN
medium       NaN
good           2
very good      3
dtype: float64
```

十一、 画图

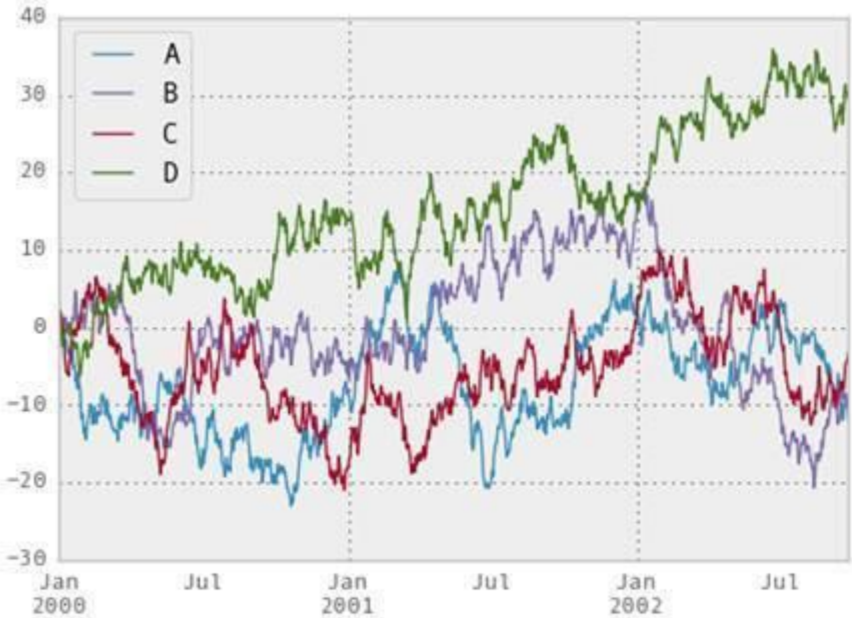
具体文档参看：*Plotting* docs

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

131]: ts = ts.cumsum()

132]: ts.plot()
32]: <matplotlib.axes._subplots.AxesSubplot at 0xaf40e8cc>
```

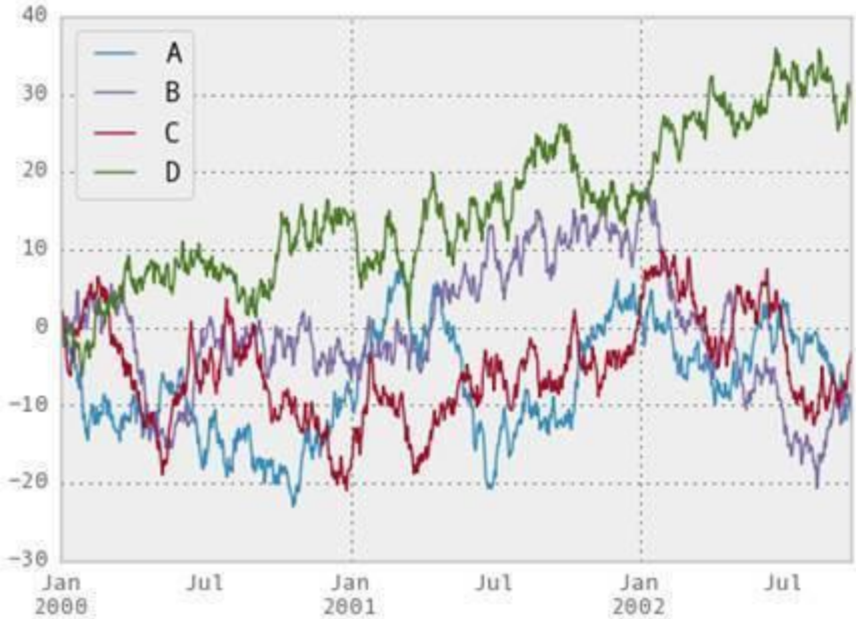


对于 DataFrame 来说，plot 是一种将所有列及其标签进行绘制的简便方法：

```
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 0xaf3512cc>
```



```
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 0xaf3512cc>
```



十二、 导入和保存数据

CSV，参考：*Writing to a csv file*

1、 写入 csv 文件

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

2、 从 csv 文件中读取

```
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

参考：*HDFStores*

1、 写入 HDF5 存储

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

2、 从 HDF5 存储中读取

```
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

参考：*MS Excel*

1、 写入 excel 文件

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

2、 从 excel 文件中读取