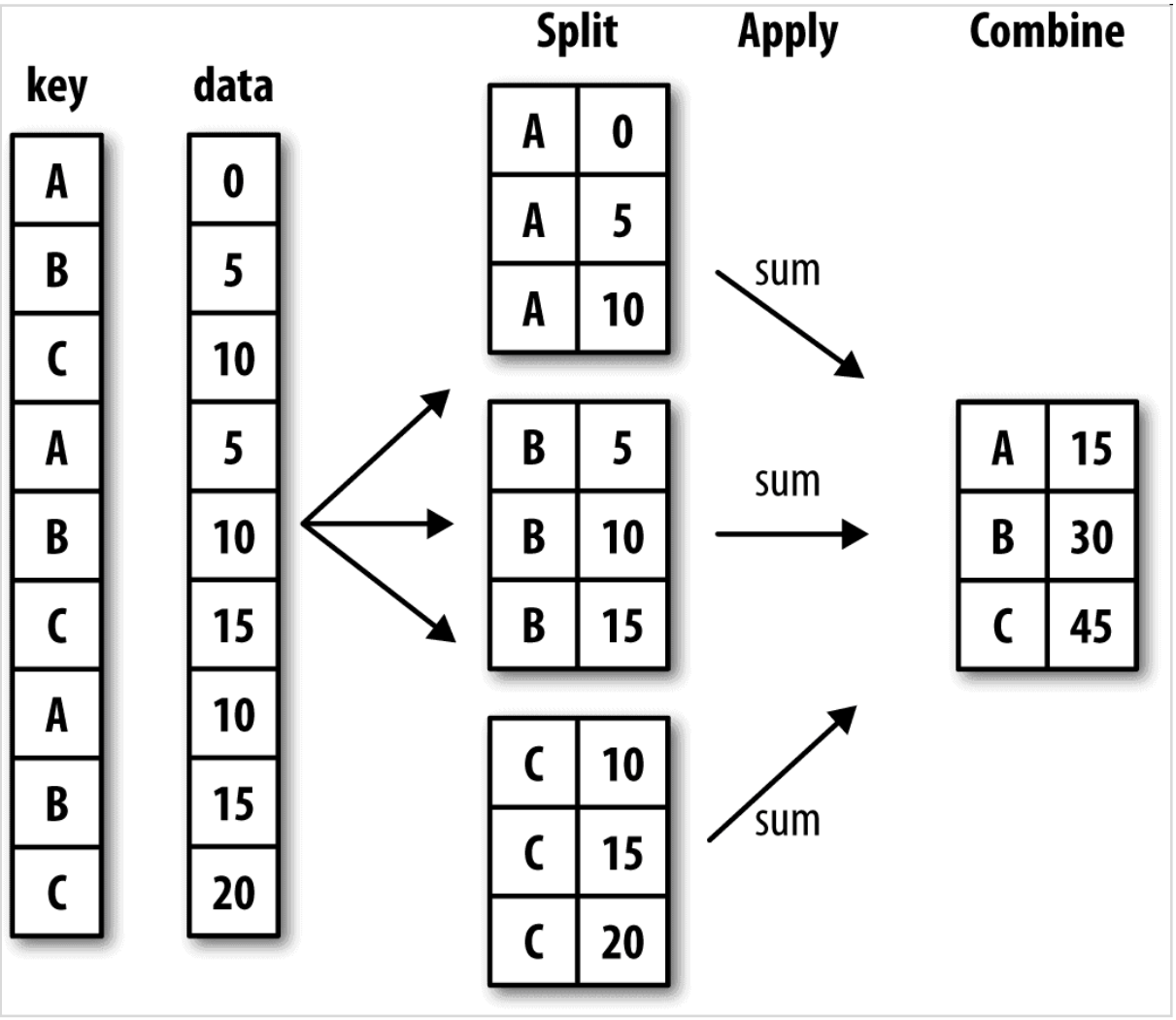
数据分析 8 数据聚合与分组运算

在将数据集加载、融合、准备好之后，通常就是计算分组统计或生成透视表， pandas提供了一个灵活高效的groupby功能，它使你能以一种自然的方式对数据集进行切片、切块、摘要等操作。

GroupBy机制

分组运算"split-apply-combine"（拆分－应用－合并）。第一个阶段，pandas对象（无论是Series、DataFrame还是其他的）中的数据会根据你所提供的一个或多个键被拆分（split）为多组。拆分操作是在对象的特定轴上执行的。例如，DataFrame可以在其行（axis=0）或列（axis=1）上进行分组。然后，将一个函数应用（apply）到各个分组并产生一个新值。最后，所有这些函数的执行结果会被合并（combine）到最终的结果对象中。




```
In [10]: df = pd.DataFrame({'key1' : ['a', 'a', 'b', 'b', 'a'],
   ....:                    'key2' : ['one', 'two', 'one', 'two', 'one'],
```

```
   ....:                    'data1' : np.random.randn(5),
   ....:                    'data2' : np.random.randn(5)})

In [11]: df
Out[11]:
      data1     data2 key1 key2
0 -0.204708  1.393406    a  one
1  0.478943  0.092908    a  two
2 -0.519439  0.281746    b  one
3 -0.555730  0.769023    b  two
4  1.965781  1.246435    a  one
```

```
In [12]: grouped = df['data1'].groupby(df['key1'])

In [13]: grouped
Out[13]: <pandas.core.groupby.SeriesGroupBy object at 0x7faa31537390>
```

变量grouped是一个GroupBy对象。它实际上还没有进行任何计算，只是含有一些有关分组键df['key1']的中间数据而已

```
In [14]: grouped.mean()
Out[14]:
key1
a    0.746672
b   -0.537585
Name: data1, dtype: float64
```

数据（Series）根据分组键进行了聚合，产生了一个新的Series，其索引为key1列中的唯一值。

一次传入多个数组的列表

```
In [15]: means = df['data1'].groupby([df['key1'], df['key2']]).mean()

In [16]: means
```

```
Out[16]:
key1  key2
a     one     0.880536
      two     0.478943
b     one    -0.519439
      two    -0.555730
Name: data1, dtype: float64
```

```
In [17]: means.unstack()
Out[17]:
key2       one       two
key1
a     0.880536  0.478943
b    -0.519439 -0.555730
```

GroupBy的size方法，它可以返回一个含有分组大小的Series

```
In [23]: df.groupby(['key1', 'key2']).size()
Out[23]:
key1  key2
a     one     2
      two     1
b     one     1
      two     1
dtype: int64
```

对分组进行迭代

GroupBy对象支持迭代，可以产生一组二元元组（由分组名和数据块组成）

```
In [24]: for name, group in df.groupby('key1'):
   ....:     print(name)
   ....:     print(group)
   ....:
a
```

```
      data1     data2 key1 key2
0 -0.204708  1.393406    a  one
1  0.478943  0.092908    a  two
4  1.965781  1.246435    a  one
b
      data1     data2 key1 key2
2 -0.519439  0.281746    b  one
3 -0.555730  0.769023    b  two
```

对于多重键的情况，元组的第一个元素将会是由键值组成的元组

```
In [25]: for (k1, k2), group in df.groupby(['key1', 'key2']):
   ....:     print((k1, k2))
   ....:     print(group)
   ....:
('a', 'one')
      data1     data2 key1 key2
0 -0.204708  1.393406    a  one
4  1.965781  1.246435    a  one
('a', 'two')
      data1     data2 key1 key2
1  0.478943  0.092908    a  two
('b', 'one')
      data1     data2 key1 key2
2 -0.519439  0.281746    b  one
('b', 'two')
     data1     data2 key1 key2
3 -0.55573  0.769023    b  two
```

可以将这些数据片段做成一个字典

```
In [26]: pieces = dict(list(df.groupby('key1')))

In [27]: pieces['b']
Out[27]:
      data1     data2 key1 key2
2 -0.519439  0.281746    b  one
```

```
3 -0.555730  0.769023    b  two
```

可以根据dtype对列进行分组

```
In [28]: df.dtypes
Out[28]:
data1    float64
data2    float64
key1      object
key2      object
dtype: object

In [29]: grouped = df.groupby(df.dtypes, axis=1)
```

```
In [30]: for dtype, group in grouped:
   ....:     print(dtype)
   ....:     print(group)
   ....:
float64
      data1     data2
0 -0.204708  1.393406
1  0.478943  0.092908
2 -0.519439  0.281746
3 -0.555730  0.769023
4  1.965781  1.246435
object
  key1 key2
0    a  one
1    a  two
2    b  one
3    b  two
4    a  one
```

选取一列或列的子集

```
df.groupby('key1')['data1']
df.groupby('key1')[['data2']]
```

```
for name, data in df.groupby('key1')['data1']:
    print(name)
    print(data)
```

对于大数据集，很可能只需要对部分列进行聚合，只需计算data2列的平均值并以DataFrame形式得到结果

```
In [31]: df.groupby(['key1', 'key2'])[['data2']].mean()
Out[31]:
              data2
key1 key2
a    one   1.319920
     two   0.092908
b    one   0.281746
     two   0.769023
```

通过字典或Series进行分组

```
In [35]: people = pd.DataFrame(np.random.randn(5, 5),
   ....:                       columns=['a', 'b', 'c', 'd', 'e'],
   ....:                       index=['Joe', 'Steve', 'Wes', 'Jim', 'Travis'])

In [36]: people.iloc[2:3, [1, 2]] = np.nan # Add a few NA values

In [37]: people
Out[37]:
               a         b         c         d         e
Joe     1.007189 -1.296221  0.274992  0.228913  1.352917
Steve   0.886429 -2.001637 -0.371843  1.669025 -0.438570
Wes    -0.539741       NaN       NaN -1.021228 -0.577087
```

```
Jim     0.124121  0.302614  0.523772  0.000940  1.343810
Travis -0.713544 -0.831154 -2.370232 -1.860761 -0.860757
```

```
In [38]: mapping = {'a': 'red', 'b': 'red', 'c': 'blue',
   ....:            'd': 'blue', 'e': 'red', 'f' : 'orange'}
```

```
In [39]: by_column = people.groupby(mapping, axis=1)

In [40]: by_column.sum()
Out[40]:
            blue       red
Joe     0.503905  1.063885
Steve   1.297183 -1.553778
Wes    -1.021228 -1.116829
Jim     0.524712  1.770545
Travis -4.230992 -2.405455
```

Series也有同样的功能

```
In [41]: map_series = pd.Series(mapping)

In [42]: map_series
Out[42]:
a       red
b       red
c      blue
d      blue
e       red
f    orange
dtype: object

In [43]: people.groupby(map_series, axis=1).count()
Out[43]:
        blue  red
```

```
Joe       2    3
Steve     2    3
Wes       1    2
Jim       2    3
Travis    2    3
```

通过函数进行分组

使用Python函数是一种更原生的方法定义分组映射。任何被当做分组键的函数都会在各个索引值上被调用一次，其返回值就会被用作分组名称。

计算一个字符串长度的数组，更简单的方法是传入len函数

```
In [44]: people.groupby(len).sum()
Out[44]:
          a         b         c         d         e
3  0.591569 -0.993608  0.798764 -0.791374  2.119639
5  0.886429 -2.001637 -0.371843  1.669025 -0.438570
6 -0.713544 -0.831154 -2.370232 -1.860761 -0.860757
```

```
In [45]: key_list = ['one', 'one', 'one', 'two', 'two']

In [46]: people.groupby([len, key_list]).min()
Out[46]:
              a         b         c         d         e
3 one -0.539741 -1.296221  0.274992 -1.021228 -0.577087
  two  0.124121  0.302614  0.523772  0.000940  1.343810
5 one  0.886429 -2.001637 -0.371843  1.669025 -0.438570
6 two -0.713544 -0.831154 -2.370232 -1.860761 -0.860757
```

根据索引级别分组

层次化索引数据集最方便的地方就在于它能够根据轴索引的一个级别进行聚合

```
```

```
In [47]: columns = pd.MultiIndex.from_arrays([['US', 'US', 'US', 'JP', 'JP'],
   ....:                                      [1, 3, 5, 1, 3]],
   ....:                                      names=['cty', 'tenor'])

In [48]: hier_df = pd.DataFrame(np.random.randn(4, 5), columns=columns)

In [49]: hier_df
Out[49]:
cty          US                            JP
tenor         1         3         5         1         3
0      0.560145 -1.265934  0.119827 -1.063512  0.332883
1     -2.359419 -0.199543 -1.541996 -0.970736 -1.307030
2      0.286350  0.377984 -0.753887  0.331286  1.349742
3      0.069877  0.246674 -0.011862  1.004812  1.327195
```

要根据级别分组，使用level关键字传递级别序号或名字

```
In [50]: hier_df.groupby(level='cty', axis=1).count()
Out[50]:
cty  JP  US
0     2   3
1     2   3
2     2   3
3     2   3
```

数据聚合

聚合指的是任何能够从数组产生标量值的数据转换过程，比如mean、count、min以及sum等。

函数名	说明
count	分组中非NA值的数量
sum	非NA值的和
mean	非NA值的平均值
median	非NA值的算术中位数
std、var	无偏（分母为n - 1）标准差和方差
min、max	非NA值的最小值和最大值
prod	非NA值的积
first、last	第一个和最后一个非NA值

使用你自己的聚合函数，只需将其传入aggregate或agg方法即可

```
In [54]: def peak_to_peak(arr):
   ....:     return arr.max() - arr.min()
In [55]: grouped.agg(peak_to_peak)
Out[55]:
         data1     data2
key1
a     2.170488  1.300498
b     0.036292  0.487276
```

面向列的多函数应用

```
In [57]: tips = pd.read_csv('examples/tips.csv')

# Add tip percentage of total bill
In [58]: tips['tip_pct'] = tips['tip'] / tips['total_bill']

In [59]: tips[:6]
Out[59]:
   total_bill   tip smoker  day    time  size   tip_pct
0       16.99  1.01     No  Sun  Dinner     2  0.059447
1       10.34  1.66     No  Sun  Dinner     3  0.160542
2       21.01  3.50     No  Sun  Dinner     3  0.166587
3       23.68  3.31     No  Sun  Dinner     2  0.139780
```

```
4       24.59  3.61     No  Sun  Dinner     4  0.146808
5       25.29  4.71     No  Sun  Dinner     4  0.186240
```

对不同的列使用不同的聚合函数，或一次应用多个函数

```
In [60]: grouped = tips.groupby(['day', 'smoker'])
In [61]: grouped_pct = grouped['tip_pct']

In [62]: grouped_pct.agg('mean')
Out[62]:
day   smoker
Fri   No        0.151650
      Yes       0.174783
Sat   No        0.158048
      Yes       0.147906
Sun   No        0.160113
      Yes       0.187250
Thur  No        0.160298
      Yes       0.163863
Name: tip_pct, dtype: float64
```

如果传入一组函数或函数名，得到的DataFrame的列就会以相应的函数命名

```
In [63]: grouped_pct.agg(['mean', 'std', peak_to_peak])
Out[63]:
                 mean       std  peak_to_peak
day  smoker
Fri  No      0.151650  0.028123      0.067349
     Yes     0.174783  0.051293      0.159925
Sat  No      0.158048  0.039767      0.235193
     Yes     0.147906  0.061375      0.290095
Sun  No      0.160113  0.042347      0.193226
     Yes     0.187250  0.154134      0.644685
Thur No      0.160298  0.038774      0.193350
     Yes     0.163863  0.039389      0.151240
```

传入的是一个由(name,function)元组组成的列表，则各元组的第一个元素就会被用作DataFrame的列名

```
In [64]: grouped_pct.agg([('foo', 'mean'), ('bar', np.std)])
Out[64]:
                  foo       bar
day  smoker
Fri  No      0.151650  0.028123
     Yes     0.174783  0.051293
Sat  No      0.158048  0.039767
     Yes     0.147906  0.061375
Sun  No      0.160113  0.042347
     Yes     0.187250  0.154134
Thur No      0.160298  0.038774
     Yes     0.163863  0.039389
```

想要对tip_pct和total_bill列计算三个统计信息

```
In [65]: functions = ['count', 'mean', 'max']

In [66]: result = grouped['tip_pct', 'total_bill'].agg(functions)

In [67]: result
Out[67]:
            tip_pct                     total_bill
              count      mean       max      count       mean    max
day  smoker
Fri  No           4  0.151650  0.187735          4  18.420000  22.75
     Yes         15  0.174783  0.263480         15  16.813333  40.17
Sat  No          45  0.158048  0.291990         45  19.661778  48.33
     Yes         42  0.147906  0.325733         42  21.276667  50.81
Sun  No          57  0.160113  0.252672         57  20.506667  48.17
     Yes         19  0.187250  0.710345         19  24.120000  45.35
Thur No          45  0.160298  0.266312         45  17.113111  41.19
     Yes         17  0.163863  0.241255         17  19.190588  43.11
```

```
In [68]: result['tip_pct']
Out[68]:
             count      mean       max
day  smoker
Fri  No          4  0.151650  0.187735
     Yes        15  0.174783  0.263480
Sat  No         45  0.158048  0.291990
     Yes        42  0.147906  0.325733
Sun  No         57  0.160113  0.252672
     Yes        19  0.187250  0.710345
Thur No         45  0.160298  0.266312
     Yes        17  0.163863  0.241255
```

也可以传入带有自定义名称的一组元组

```
In [69]: ftuples = [('Durchschnitt', 'mean'),('Abweichung', np.var)]

In [70]: grouped['tip_pct', 'total_bill'].agg(ftuples)
Out[70]:
                 tip_pct              total_bill
            Durchschnitt Abweichung Durchschnitt  Abweichung
day  smoker
Fri  No         0.151650   0.000791    18.420000   25.596333
     Yes        0.174783   0.002631    16.813333   82.562438
Sat  No         0.158048   0.001581    19.661778   79.908965
     Yes        0.147906   0.003767    21.276667  101.387535
Sun  No         0.160113   0.001793    20.506667   66.099980
     Yes        0.187250   0.023757    24.120000  109.046044
Thur No         0.160298   0.001503    17.113111   59.625081
     Yes        0.163863   0.001551    19.190588   69.808518
```

对一个列或不同的列应用不同的函数，具体的办法是向agg传入一个从列名映射到函数的字典

```
In [71]: grouped.agg({'tip' : np.max, 'size' : 'sum'})
Out[71]:
               tip  size
day  smoker
```

```
Fri  No       3.50     9
     Yes      4.73    31
Sat  No       9.00   115
     Yes     10.00   104
Sun  No       6.00   167
     Yes      6.50    49
Thur No       6.70   112
     Yes      5.00    40

In [72]: grouped.agg({'tip_pct' : ['min', 'max', 'mean', 'std'],
   ....:              'size' : 'sum'})
Out[72]:
              tip_pct                               size
                  min       max      mean       std  sum
day  smoker
Fri  No      0.120385  0.187735  0.151650  0.028123    9
     Yes     0.103555  0.263480  0.174783  0.051293   31
Sat  No      0.056797  0.291990  0.158048  0.039767  115
     Yes     0.035638  0.325733  0.147906  0.061375  104
Sun  No      0.059447  0.252672  0.160113  0.042347  167
     Yes     0.065660  0.710345  0.187250  0.154134   49
Thur No      0.072961  0.266312  0.160298  0.038774  112
     Yes     0.090014  0.241255  0.163863  0.039389   40
```

以“没有行索引”的形式返回聚合数据

```
In [73]: tips.groupby(['day', 'smoker'], as_index=False).mean()
Out[73]:
    day smoker  total_bill       tip      size   tip_pct
0   Fri     No   18.420000  2.812500  2.250000  0.151650
1   Fri    Yes   16.813333  2.714000  2.066667  0.174783
2   Sat     No   19.661778  3.102889  2.555556  0.158048
3   Sat    Yes   21.276667  2.875476  2.476190  0.147906
4   Sun     No   20.506667  3.167895  2.929825  0.160113
5   Sun    Yes   24.120000  3.516842  2.578947  0.187250
6  Thur     No   17.113111  2.673778  2.488889  0.160298
7  Thur    Yes   19.190588  3.030000  2.352941  0.163863
```

对结果调用reset_index也能得到这种形式的结果。使用as_index=False方法可以避免一些不必要的计算

小费数据集，假设你想要根据分组选出最高的5个tip_pct值。首先，编写一个选取指定列具有最大值的行的函数

```
In [74]: def top(df, n=5, column='tip_pct'):
   ....:     return df.sort_values(by=column)[-n:]

In [75]: top(tips, n=6)
Out[75]:
     total_bill   tip smoker  day    time  size   tip_pct
109       14.31  4.00    Yes  Sat  Dinner     2  0.279525
183       23.17  6.50    Yes  Sun  Dinner     4  0.280535
232       11.61  3.39     No  Sat  Dinner     2  0.291990
67         3.07  1.00    Yes  Sat  Dinner     1  0.325733
178        9.60  4.00    Yes  Sun  Dinner     2  0.416667
172        7.25  5.15    Yes  Sun  Dinner     2  0.710345
```

对smoker分组并用该函数调用apply

```
In [76]: tips.groupby('smoker').apply(top)
Out[76]:
            total_bill   tip smoker   day    time  size   tip_pct
smoker
No     88        24.71  5.85     No  Thur   Lunch     2  0.236746
       185       20.69  5.00     No   Sun  Dinner     5  0.241663
       51        10.29  2.60     No   Sun  Dinner     2  0.252672
       149        7.51  2.00     No  Thur   Lunch     2  0.266312
       232       11.61  3.39     No   Sat  Dinner     2  0.291990
Yes    109       14.31  4.00    Yes   Sat  Dinner     2  0.279525
       183       23.17  6.50    Yes   Sun  Dinner     4  0.280535
       67         3.07  1.00    Yes   Sat  Dinner     1  0.325733
       178        9.60  4.00    Yes   Sun  Dinner     2  0.416667
       172        7.25  5.15    Yes   Sun  Dinner     2  0.710345
```

如果传给apply的函数能够接受其他参数或关键字，则可以将这些内容放在函数名后面一并传入

```
In [77]: tips.groupby(['smoker', 'day']).apply(top, n=1, column='total_bill')
Out[77]:
                 total_bill    tip smoker   day    time  size   tip_pct
smoker day
No     Fri  94        22.75   3.25     No   Fri  Dinner     2  0.142857
       Sat  212       48.33   9.00     No   Sat  Dinner     4  0.186220
       Sun  156       48.17   5.00     No   Sun  Dinner     6  0.103799
       Thur 142       41.19   5.00     No  Thur   Lunch     5  0.121389
Yes    Fri  95        40.17   4.73    Yes   Fri  Dinner     4  0.117750
       Sat  170       50.81  10.00    Yes   Sat  Dinner     3  0.196812
       Sun  182       45.35   3.50    Yes   Sun  Dinner     3  0.077178
       Thur 197       43.11   5.00    Yes  Thur   Lunch     4  0.115982
```

禁止分组键

分组键会跟原始对象的索引共同构成结果对象中的层次化索引。将group_keys=False传入groupby即可禁止该效果

```
In [81]: tips.groupby('smoker', group_keys=False).apply(top)
Out[81]:
     total_bill   tip smoker   day    time  size   tip_pct
88        24.71  5.85     No  Thur   Lunch     2  0.236746
185       20.69  5.00     No   Sun  Dinner     5  0.241663
51        10.29  2.60     No   Sun  Dinner     2  0.252672
149        7.51  2.00     No  Thur   Lunch     2  0.266312
232       11.61  3.39     No   Sat  Dinner     2  0.291990
109       14.31  4.00    Yes   Sat  Dinner     2  0.279525
183       23.17  6.50    Yes   Sun  Dinner     4  0.280535
67         3.07  1.00    Yes   Sat  Dinner     1  0.325733
178        9.60  4.00    Yes   Sun  Dinner     2  0.416667
172        7.25  5.15    Yes   Sun  Dinner     2  0.710345
```

分位数和桶分析

将数据拆分成多块的工具（比如cut和qcut）。将这些函数跟groupby结合起来，就能非常轻松地实现对数据集的桶（bucket）或分位数（quantile）分析

```
In [82]: frame = pd.DataFrame({'data1': np.random.randn(1000),
   ....:                       'data2': np.random.randn(1000)})

In [83]: quartiles = pd.cut(frame.data1, 4)

In [84]: quartiles[:10]
Out[84]:
0     (-1.23, 0.489]
1    (-2.956, -1.23]
2     (-1.23, 0.489]
3     (0.489, 2.208]
4     (-1.23, 0.489]
5     (0.489, 2.208]
6     (-1.23, 0.489]
7     (-1.23, 0.489]
8     (0.489, 2.208]
9     (0.489, 2.208]
Name: data1, dtype: category
Categories (4, interval[float64]): [(-2.956, -1.23] < (-1.23, 0.489] < (0.489,
2.
208] < (2.208, 3.928]]
```

```
In [85]: def get_stats(group):
   ....:     return {'min': group.min(), 'max': group.max(),
   ....:             'count': group.count(), 'mean': group.mean()}

In [86]: grouped = frame.data2.groupby(quartiles)

In [87]: grouped.apply(get_stats).unstack()
Out[87]:
                count       max      mean       min
```

```
data1
(-2.956, -1.23]   95.0  1.670835 -0.039521 -3.399312
(-1.23, 0.489]   598.0  3.260383 -0.002051 -2.989741
(0.489, 2.208]   297.0  2.954439  0.081822 -3.745356
(2.208, 3.928]    10.0  1.765640  0.024750 -1.929776
```

这些都是长度相等的桶。要根据样本分位数得到大小相等的桶，使用qcut即可

```
# Return quantile numbers
In [88]: grouping = pd.qcut(frame.data1, 10, labels=False)

In [89]: grouped = frame.data2.groupby(grouping)

In [90]: grouped.apply(get_stats).unstack()
Out[90]:
       count       max      mean       min
data1
0      100.0  1.670835 -0.049902 -3.399312
1      100.0  2.628441  0.030989 -1.950098
2      100.0  2.527939 -0.067179 -2.925113
3      100.0  3.260383  0.065713 -2.315555
4      100.0  2.074345 -0.111653 -2.047939
5      100.0  2.184810  0.052130 -2.989741
6      100.0  2.458842 -0.021489 -2.223506
7      100.0  2.954439 -0.026459 -3.056990
8      100.0  2.735527  0.103406 -3.745356
9      100.0  2.377020  0.220122 -2.064111
```

用特定于分组的值填充缺失值

假设需要对不同的分组填充不同的值。一种方法是将数据分组，并使用apply和一个能够对各数据块调用fillna的函数即可。下面是一些有关美国几个州的示例数据，这些州又被分为东部和西部

```
In [95]: states = ['Ohio', 'New York', 'Vermont', 'Florida',
   ....:           'Oregon', 'Nevada', 'California', 'Idaho']
```

```
In [96]: group_key = ['East'] * 4 + ['West'] * 4

In [97]: data = pd.Series(np.random.randn(8), index=states)

In [98]: data
Out[98]:
Ohio          0.922264
New York     -2.153545
Vermont      -0.365757
Florida      -0.375842
Oregon        0.329939
Nevada        0.981994
California    1.105913
Idaho        -1.613716
dtype: float64
```

```
In [99]: data[['Vermont', 'Nevada', 'Idaho']] = np.nan

In [100]: data
Out[100]:
Ohio          0.922264
New York     -2.153545
Vermont            NaN
Florida      -0.375842
Oregon        0.329939
Nevada             NaN
California    1.105913
Idaho              NaN
dtype: float64

In [101]: data.groupby(group_key).mean()
Out[101]:
East   -0.535707
West    0.717926
dtype: float64
```

用分组平均值去填充NA值

```
In [102]: fill_mean = lambda g: g.fillna(g.mean())

In [103]: data.groupby(group_key).apply(fill_mean)
Out[103]:
Ohio          0.922264
New York     -2.153545
Vermont      -0.535707
Florida      -0.375842
Oregon        0.329939
Nevada        0.717926
California    1.105913
Idaho         0.717926
dtype: float64
```

预定义各组的填充值

```
In [104]: fill_values = {'East': 0.5, 'West': -1}

In [105]: fill_func = lambda g: g.fillna(fill_values[g.name])

In [106]: data.groupby(group_key).apply(fill_func)
Out[106]:
Ohio          0.922264
New York     -2.153545
Vermont       0.500000
Florida      -0.375842
Oregon        0.329939
Nevada       -1.000000
California    1.105913
Idaho        -1.000000
dtype: float64
```

示例：分组加权平均数和相关系数

可以进行DataFrame的列与列之间或两个Series之间的运算（比如分组加权平均）

```
In [114]: df = pd.DataFrame({'category': ['a', 'a', 'a', 'a',
   .....:                                  'b', 'b', 'b', 'b'],
   .....:                    'data': np.random.randn(8),
   .....:                    'weights': np.random.rand(8)})

In [115]: df
Out[115]:
  category      data   weights
0        a  1.561587  0.957515
1        a  1.219984  0.347267
2        a -0.482239  0.581362
3        a  0.315667  0.217091
4        b -0.047852  0.894406
5        b -0.454145  0.918564
6        b -0.556774  0.277825
7        b  0.253321  0.955905
```

用category计算分组加权平均数

```
In [116]: grouped = df.groupby('category')

In [117]: get_wavg = lambda g: np.average(g['data'], weights=g['weights'])

In [118]: grouped.apply(get_wavg)
Out[118]:
category
a    0.811643
b   -0.122262
dtype: float64
```

Yahoo!Finance的数据集，其中含有几只股票和标准普尔500指数（符号SPX）的收盘价

```
In [119]: close_px = pd.read_csv('examples/stock_px_2.csv', parse_dates=True,
   .....:                        index_col=0)

In [120]: close_px.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 2214 entries, 2003-01-02 to 2011-10-14
Data columns (total 4 columns):
AAPL    2214 non-null float64
MSFT    2214 non-null float64
XOM     2214 non-null float64
SPX     2214 non-null float64
dtypes: float64(4)
memory usage: 86.5 KB

In [121]: close_px[-4:]
Out[121]:
              AAPL   MSFT    XOM      SPX
2011-10-11  400.29  27.00  76.27  1195.54
2011-10-12  402.19  26.96  77.16  1207.25
2011-10-13  408.43  27.18  76.37  1203.66
2011-10-14  422.00  27.27  78.11  1224.58
```

计算一个由日收益率（通过百分数变化计算）与SPX之间的年度相关系数组成的DataFrame。创建一个函数，用它计算每列和SPX列的成对相关系数

```
In [122]: spx_corr = lambda x: x.corrwith(x['SPX'])
# 计算相邻数字之间的变化率
In [123]: rets = close_px.pct_change().dropna()
```

```
In [124]: get_year = lambda x: x.year

In [125]: by_year = rets.groupby(get_year)

In [126]: by_year.apply(spx_corr)
Out[126]:
          AAPL      MSFT       XOM  SPX
2003  0.541124  0.745174  0.661265  1.0
2004  0.374283  0.588531  0.557742  1.0
2005  0.467540  0.562374  0.631010  1.0
2006  0.428267  0.406126  0.518514  1.0
```

```
2007  0.508118  0.658770  0.786264  1.0
2008  0.681434  0.804626  0.828303  1.0
2009  0.707103  0.654902  0.797921  1.0
2010  0.710105  0.730118  0.839057  1.0
2011  0.691931  0.800996  0.859975  1.0
```

计算Apple和Microsoft的年相关系数

```
In [127]: by_year.apply(lambda g: g['AAPL'].corr(g['MSFT']))
Out[127]:
2003    0.480868
2004    0.259024
2005    0.300093
2006    0.161735
2007    0.417738
2008    0.611901
2009    0.432738
2010    0.571946
2011    0.581987
dtype: float64
```

透视表和交叉表

小费数据集，假设我想要根据day和smoker计算分组平均数（pivot_table的默认聚合类型），并将day和smoker放到行上

```
In [130]: tips.pivot_table(index=['day', 'smoker'])
Out[130]:
                size       tip   tip_pct  total_bill
day  smoker
Fri  No      2.250000  2.812500  0.151650   18.420000
     Yes     2.066667  2.714000  0.174783   16.813333
Sat  No      2.555556  3.102889  0.158048   19.661778
     Yes     2.476190  2.875476  0.147906   21.276667
Sun  No      2.929825  3.167895  0.160113   20.506667
     Yes     2.578947  3.516842  0.187250   24.120000
Thur No      2.488889  2.673778  0.160298   17.113111
```

```
     Yes     2.352941  3.030000  0.163863   19.190588
```

只想聚合tip_pct和size，而且想根据time进行分组。我将smoker放到列上，把day放到行上

```
In [131]: tips.pivot_table(['tip_pct', 'size'], index=['time', 'day'],
   .....:                  columns='smoker')
Out[131]:
                size             tip_pct
smoker             No       Yes        No       Yes
time   day
Dinner Fri   2.000000  2.222222  0.139622  0.165347
       Sat   2.555556  2.476190  0.158048  0.147906
       Sun   2.929825  2.578947  0.160113  0.187250
       Thur  2.000000       NaN  0.159744       NaN
Lunch  Fri   3.000000  1.833333  0.187735  0.188937
       Thur  2.500000  2.352941  0.160311  0.163863
```

传入margins=True添加分项小计。这将会添加标签为All的行和列，其值对应于单个等级中所有数据的分组统计

```
In [132]: tips.pivot_table(['tip_pct', 'size'], index=['time', 'day'],
   .....:                  columns='smoker', margins=True)
Out[132]:
                size                      tip_pct
smoker             No       Yes       All        No       Yes       All
time   day
Dinner Fri   2.000000  2.222222  2.166667  0.139622  0.165347  0.158916
       Sat   2.555556  2.476190  2.517241  0.158048  0.147906  0.153152
       Sun   2.929825  2.578947  2.842105  0.160113  0.187250  0.166897
       Thur  2.000000       NaN  2.000000  0.159744       NaN  0.159744
Lunch  Fri   3.000000  1.833333  2.000000  0.187735  0.188937  0.188765
       Thur  2.500000  2.352941  2.459016  0.160311  0.163863  0.161301
All          2.668874  2.408602  2.569672  0.159328  0.163196  0.160803
```

```
In [133]: tips.pivot_table('tip_pct', index=['time', 'smoker'], columns='day',
```

```
   .....:                 aggfunc=len, margins=True)
Out[133]:
day             Fri   Sat   Sun  Thur    All
time   smoker
Dinner No       3.0  45.0  57.0   1.0  106.0
       Yes      9.0  42.0  19.0   NaN   70.0
Lunch  No       1.0   NaN   NaN  44.0   45.0
       Yes      6.0   NaN   NaN  17.0   23.0
All            19.0  87.0  76.0  62.0  244.0
```

交叉表：crosstab

交叉表（cross-tabulation，简称crosstab）是一种用于计算分组频率的特殊透视表。

```
In [138]: data
Out[138]:
   Sample Nationality    Handedness
0       1         USA  Right-handed
1       2       Japan   Left-handed
2       3         USA  Right-handed
3       4       Japan  Right-handed
4       5       Japan   Left-handed
5       6       Japan  Right-handed
6       7         USA  Right-handed
7       8         USA   Left-handed
8       9       Japan  Right-handed
9      10         USA  Right-handed
```

根据国籍和用手习惯对这段数据进行统计汇总

```
In [139]: pd.crosstab(data.Nationality, data.Handedness, margins=True)
Out[139]:
Handedness   Left-handed  Right-handed  All
Nationality
Japan                  2             3    5
USA                    1             4    5
```

```
All                    3            7   10
```