CHAPTER 9
Data Aggregation and Group Operations

Categorizing a data set and applying a function to each group, whether an aggregation or transformation, is often a critical component of a data analysis workflow. After loading, merging, and preparing a data set, a familiar task is to compute group statistics or possibly *pivot tables* for reporting or visualization purposes. pandas provides a flexible and high-performance `groupby` facility, enabling you to slice and dice, and summarize data sets in a natural way.

One reason for the popularity of relational databases and SQL (which stands for "structured query language") is the ease with which data can be joined, filtered, transformed, and aggregated. However, query languages like SQL are rather limited in the kinds of group operations that can be performed. As you will see, with the expressiveness and power of Python and pandas, we can perform much more complex grouped operations by utilizing any function that accepts a pandas object or NumPy array. In this chapter, you will learn how to:

- Split a pandas object into pieces using one or more keys (in the form of functions, arrays, or DataFrame column names)
- Computing group summary statistics, like count, mean, or standard deviation, or a user-defined function
- Apply a varying set of functions to each column of a DataFrame
- Apply within-group transformations or other manipulations, like normalization, linear regression, rank, or subset selection
- Compute pivot tables and cross-tabulations
- Perform quantile analysis and other data-derived group analyses

Aggregation of time series data, a special use case of `groupby`, is referred to as *resampling* in this book and will receive separate treatment in Chapter 10.

GroupBy Mechanics

Hadley Wickham, an author of many popular packages for the R programming language, coined the term *split-apply-combine* for talking about group operations, and I think that's a good description of the process. In the first stage of the process, data contained in a pandas object, whether a Series, DataFrame, or otherwise, is *split* into groups based on one or more *keys* that you provide. The splitting is performed on a particular axis of an object. For example, a DataFrame can be grouped on its rows (`axis=0`) or its columns (`axis=1`). Once this is done, a function is *applied* to each group, producing a new value. Finally, the results of all those function applications are *combined* into a result object. The form of the resulting object will usually depend on what's being done to the data. See Figure 9-1 for a mockup of a simple group aggregation.

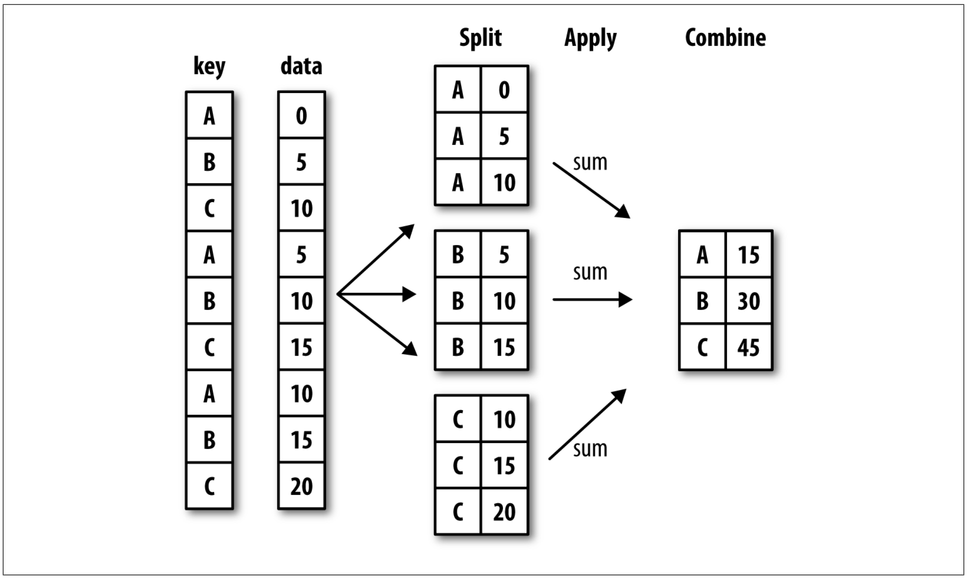


Figure 9-1. Illustration of a group aggregation

Each grouping key can take many forms, and the keys do not have to be all of the same type:

- A list or array of values that is the same length as the axis being grouped
- A value indicating a column name in a DataFrame

- A dict or Series giving a correspondence between the values on the axis being grouped and the group names
- A function to be invoked on the axis index or the individual labels in the index

Note that the latter three methods are all just shortcuts for producing an array of values to be used to split up the object. Don't worry if this all seems very abstract. Throughout this chapter, I will give many examples of all of these methods. To get started, here is a very simple small tabular dataset as a DataFrame:

```
In [13]: df = DataFrame({'key1' : ['a', 'a', 'b', 'b', 'a'],
   ....:                 'key2' : ['one', 'two', 'one', 'two', 'one'],
   ....:                 'data1' : np.random.randn(5),
   ....:                 'data2' : np.random.randn(5)})

In [14]: df
Out[14]:
      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
```

Suppose you wanted to compute the mean of the `data1` column using the groups labels from `key1`. There are a number of ways to do this. One is to access `data1` and call `groupby` with the column (a Series) at `key1`:

```
In [15]: grouped = df['data1'].groupby(df['key1'])

In [16]: grouped
Out[16]: <pandas.core.groupby.SeriesGroupBy at 0x2d78b10>
```

This `grouped` variable is now a *GroupBy* object. It has not actually computed anything yet except for some intermediate data about the group key `df['key1']`. The idea is that this object has all of the information needed to then apply some operation to each of the groups. For example, to compute group means we can call the GroupBy's `mean` method:

```
In [17]: grouped.mean()
Out[17]:
key1
a        0.746672
b       -0.537585
```

Later, I'll explain more about what's going on when you call `.mean()`. The important thing here is that the data (a Series) has been aggregated according to the group key, producing a new Series that is now indexed by the unique values in the `key1` column. The result index has the name `'key1'` because the DataFrame column `df['key1']` did.

If instead we had passed multiple arrays as a list, we get something different:

```
In [18]: means = df['data1'].groupby([df['key1'], df['key2']]).mean()
```

```
In [19]: means
Out[19]:
key1  key2
a     one     0.880536
      two     0.478943
b     one    -0.519439
      two    -0.555730
```

In this case, we grouped the data using two keys, and the resulting Series now has a hierarchical index consisting of the unique pairs of keys observed:

```
In [20]: means.unstack()
Out[20]:
key2       one       two
key1
a     0.880536  0.478943
b    -0.519439 -0.555730
```

In these examples, the group keys are all Series, though they could be any arrays of the right length:

```
In [21]: states = np.array(['Ohio', 'California', 'California', 'Ohio', 'Ohio'])

In [22]: years = np.array([2005, 2005, 2006, 2005, 2006])

In [23]: df['data1'].groupby([states, years]).mean()
Out[23]:
California  2005    0.478943
            2006   -0.519439
Ohio        2005   -0.380219
            2006    1.965781
```

Frequently the grouping information to be found in the same DataFrame as the data you want to work on. In that case, you can pass column names (whether those are strings, numbers, or other Python objects) as the group keys:

```
In [24]: df.groupby('key1').mean()
Out[24]:
         data1     data2
key1
a     0.746672  0.910916
b    -0.537585  0.525384

In [25]: df.groupby(['key1', 'key2']).mean()
Out[25]:
              data1     data2
key1 key2
a    one   0.880536  1.319920
     two   0.478943  0.092908
b    one  -0.519439  0.281746
     two  -0.555730  0.769023
```

You may have noticed in the first case `df.groupby('key1').mean()` that there is no `key2` column in the result. Because `df['key2']` is not numeric data, it is said to be a *nuisance column*, which is therefore excluded from the result. By default, all of the numeric columns are aggregated, though it is possible to filter down to a subset as you'll see soon.

Regardless of the objective in using `groupby`, a generally useful GroupBy method is `size` which return a Series containing group sizes:

```
In [26]: df.groupby(['key1', 'key2']).size()
Out[26]:
key1  key2
a     one     2
      two     1
b     one     1
      two     1
```

As of this writing, any missing values in a group key will be excluded from the result. It's possible (and, in fact, quite likely), that by the time you are reading this there will be an option to include the `NA` group in the result.

Iterating Over Groups

The GroupBy object supports iteration, generating a sequence of 2-tuples containing the group name along with the chunk of data. Consider the following small example data set:

```
In [27]: 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
```

In the case of multiple keys, the first element in the tuple will be a tuple of key values:

```
In [28]: 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
```

Of course, you can choose to do whatever you want with the pieces of data. A recipe you may find useful is computing a dict of the data pieces as a one-liner:

```
In [29]: pieces = dict(list(df.groupby('key1')))

In [30]: pieces['b']
Out[30]:
      data1     data2 key1 key2
2 -0.519439  0.281746    b  one
3 -0.555730  0.769023    b  two
```

By default `groupby` groups on `axis=0`, but you can group on any of the other axes. For example, we could group the columns of our example `df` here by `dtype` like so:

```
In [31]: df.dtypes
Out[31]:
data1    float64
data2    float64
key1      object
key2      object

In [32]: grouped = df.groupby(df.dtypes, axis=1)

In [33]: dict(list(grouped))
Out[33]:
{dtype('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,
 dtype('object'):   key1 key2
0    a  one
1    a  two
2    b  one
3    b  two
4    a  one}
```

Selecting a Column or Subset of Columns

Indexing a GroupBy object created from a DataFrame with a column name or array of column names has the effect of *selecting those columns* for aggregation. This means that:

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

are syntactic sugar for:

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

Especially for large data sets, it may be desirable to aggregate only a few columns. For example, in the above data set, to compute means for just the `data2` column and get the result as a DataFrame, we could write:

```
In [34]: df.groupby(['key1', 'key2'])[['data2']].mean()
Out[34]:
              data2
key1 key2
a    one   1.319920
     two   0.092908
b    one   0.281746
     two   0.769023
```

The object returned by this indexing operation is a grouped DataFrame if a list or array is passed and a grouped Series is just a single column name that is passed as a scalar:

```
In [35]: s_grouped = df.groupby(['key1', 'key2'])['data2']

In [36]: s_grouped
Out[36]: <pandas.core.groupby.SeriesGroupBy at 0x2e215d0>

In [37]: s_grouped.mean()
Out[37]:
key1  key2
a     one     1.319920
      two     0.092908
b     one     0.281746
      two     0.769023
Name: data2
```

Grouping with Dicts and Series

Grouping information may exist in a form other than an array. Let's consider another example DataFrame:

```
In [38]: people = DataFrame(np.random.randn(5, 5),
   ....:                    columns=['a', 'b', 'c', 'd', 'e'],
   ....:                    index=['Joe', 'Steve', 'Wes', 'Jim', 'Travis'])

In [39]: people.ix[2:3, ['b', 'c']] = np.nan # Add a few NA values

In [40]: people
Out[40]:
               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
```

Now, suppose I have a group correspondence for the columns and want to sum together the columns by group:

```
In [41]: mapping = {'a': 'red', 'b': 'red', 'c': 'blue',
   ....:            'd': 'blue', 'e': 'red', 'f' : 'orange'}
```

Now, you could easily construct an array from this dict to pass to `groupby`, but instead we can just pass the dict:

```
In [42]: by_column = people.groupby(mapping, axis=1)

In [43]: by_column.sum()
Out[43]:
            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
```

The same functionality holds for Series, which can be viewed as a fixed size mapping. When I used Series as group keys in the above examples, pandas does, in fact, inspect each Series to ensure that its index is aligned with the axis it's grouping:

```
In [44]: map_series = Series(mapping)

In [45]: map_series
Out[45]:
a       red
b       red
c      blue
d      blue
e       red
f    orange

In [46]: people.groupby(map_series, axis=1).count()
Out[46]:
        blue  red
Joe        2    3
Steve      2    3
Wes        1    2
Jim        2    3
Travis     2    3
```

Grouping with Functions

Using Python functions in what can be fairly creative ways is a more abstract way of defining a group mapping compared with a dict or Series. Any function passed as a group key will be called once per index value, with the return values being used as the group names. More concretely, consider the example DataFrame from the previous section, which has people's first names as index values. Suppose you wanted to group by the length of the names; you could compute an array of string lengths, but instead you can just pass the `len` function:

```
In [47]: people.groupby(len).sum()
Out[47]:
          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
```

Mixing functions with arrays, dicts, or Series is not a problem as everything gets converted to arrays internally:

```
In [48]: key_list = ['one', 'one', 'one', 'two', 'two']

In [49]: people.groupby([len, key_list]).min()
Out[49]:
              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
```

Grouping by Index Levels

A final convenience for hierarchically-indexed data sets is the ability to aggregate using one of the levels of an axis index. To do this, pass the level number or name using the `level` keyword:

```
In [50]: columns = pd.MultiIndex.from_arrays([['US', 'US', 'US', 'JP', 'JP'],
   ....:                                     [1, 3, 5, 1, 3]], names=['cty', 'tenor'])

In [51]: hier_df = DataFrame(np.random.randn(4, 5), columns=columns)

In [52]: hier_df
Out[52]:
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

In [53]: hier_df.groupby(level='cty', axis=1).count()
Out[53]:
cty  JP  US
0     2   3
1     2   3
2     2   3
3     2   3
```

Data Aggregation

By aggregation, I am generally referring to any data transformation that produces scalar values from arrays. In the examples above I have used several of them, such as `mean`, `count`, `min` and `sum`. You may wonder what is going on when you invoke `mean()` on a GroupBy object. Many common aggregations, such as those found in Table 9-1, have optimized implementations that compute the statistics on the dataset *in place*. However, you are not limited to only this set of methods. You can use aggregations of your own devising and additionally call any method that is also defined on the grouped object. For example, as you recall `quantile` computes sample quantiles of a Series or a DataFrame's columns [1]:

```
In [54]: df
Out[54]:
      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 [55]: grouped = df.groupby('key1')

In [56]: grouped['data1'].quantile(0.9)
Out[56]:
key1
a       1.668413
b      -0.523068
```

While `quantile` is not explicitly implemented for GroupBy, it is a Series method and thus available for use. Internally, GroupBy efficiently slices up the Series, calls `piece.quantile(0.9)` for each piece, then assembles those results together into the result object.

To use your own aggregation functions, pass any function that aggregates an array to the `aggregate` or `agg` method:

```
In [57]: def peak_to_peak(arr):
   ....:     return arr.max() - arr.min()

In [58]: grouped.agg(peak_to_peak)
Out[58]:
         data1     data2
key1
a     2.170488  1.300498
b     0.036292  0.487276
```

You'll notice that some methods like `describe` also work, even though they are not aggregations, strictly speaking:

```
In [59]: grouped.describe()
Out[59]:
               data1     data2
key1
a    count  3.000000  3.000000
     mean   0.746672  0.910916
     std    1.109736  0.712217
     min   -0.204708  0.092908
     25%    0.137118  0.669671
     50%    0.478943  1.246435
```

1. Note that `quantile` performs linear interpolation if there is no value at exactly the passed percentile.

```
       75%    1.222362  1.319920
       max    1.965781  1.393406
b      count  2.000000  2.000000
       mean  -0.537585  0.525384
       std    0.025662  0.344556
       min   -0.555730  0.281746
       25%   -0.546657  0.403565
       50%   -0.537585  0.525384
       75%   -0.528512  0.647203
       max   -0.519439  0.769023
```

I will explain in more detail what has happened here in the next major section on group-wise operations and transformations.

> You may notice that custom aggregation functions are much slower than the optimized functions found in Table 9-1. This is because there is significant overhead (function calls, data rearrangement) in constructing the intermediate group data chunks.

Table 9-1. Optimized groupby methods

Function name	Description
`count`	Number of non-NA values in the group
`sum`	Sum of non-NA values
`mean`	Mean of non-NA values
`median`	Arithmetic median of non-NA values
`std, var`	Unbiased (n - 1 denominator) standard deviation and variance
`min, max`	Minimum and maximum of non-NA values
`prod`	Product of non-NA values
`first, last`	First and last non-NA values

To illustrate some more advanced aggregation features, I'll use a less trivial dataset, a dataset on restaurant tipping. I obtained it from the R `reshape2` package; it was originally found in Bryant & Smith's 1995 text on business statistics (and found in the book's GitHub repository). After loading it with `read_csv`, I add a tipping percentage column `tip_pct`.

```
In [60]: tips = pd.read_csv('ch08/tips.csv')

# Add tip percentage of total bill
In [61]: tips['tip_pct'] = tips['tip'] / tips['total_bill']

In [62]: tips[:6]
Out[62]:
   total_bill   tip     sex smoker  day    time  size   tip_pct
0       16.99  1.01  Female     No  Sun  Dinner     2  0.059447
1       10.34  1.66    Male     No  Sun  Dinner     3  0.160542
```

```
2       21.01  3.50    Male     No  Sun  Dinner     3  0.166587
3       23.68  3.31    Male     No  Sun  Dinner     2  0.139780
4       24.59  3.61  Female     No  Sun  Dinner     4  0.146808
5       25.29  4.71    Male     No  Sun  Dinner     4  0.186240
```

Column-wise and Multiple Function Application

As you've seen above, aggregating a Series or all of the columns of a DataFrame is a matter of using `aggregate` with the desired function or calling a method like `mean` or `std`. However, you may want to aggregate using a different function depending on the column or multiple functions at once. Fortunately, this is straightforward to do, which I'll illustrate through a number of examples. First, I'll group the `tips` by `sex` and `smoker`:

```
In [63]: grouped = tips.groupby(['sex', 'smoker'])
```

Note that for descriptive statistics like those in Table 9-1, you can pass the name of the function as a string:

```
In [64]: grouped_pct = grouped['tip_pct']

In [65]: grouped_pct.agg('mean')
Out[65]:
sex     smoker
Female  No        0.156921
        Yes       0.182150
Male    No        0.160669
        Yes       0.152771
Name: tip_pct
```

If you pass a list of functions or function names instead, you get back a DataFrame with column names taken from the functions:

```
In [66]: grouped_pct.agg(['mean', 'std', peak_to_peak])
Out[66]:
                   mean       std  peak_to_peak
sex    smoker
Female No      0.156921  0.036421      0.195876
       Yes     0.182150  0.071595      0.360233
Male   No      0.160669  0.041849      0.220186
       Yes     0.152771  0.090588      0.674707
```

You don't need to accept the names that GroupBy gives to the columns; notably `lambda` functions have the name `'<lambda>'` which make them hard to identify (you can see for yourself by looking at a function's `__name__` attribute). As such, if you pass a list of `(name, function)` tuples, the first element of each tuple will be used as the DataFrame column names (you can think of a list of 2-tuples as an ordered mapping):

```
In [67]: grouped_pct.agg([('foo', 'mean'), ('bar', np.std)])
Out[67]:
                    foo       bar
sex    smoker
Female No      0.156921  0.036421
       Yes     0.182150  0.071595
```

```
Male   No      0.160669  0.041849
       Yes     0.152771  0.090588
```

With a DataFrame, you have more options as you can specify a list of functions to apply to all of the columns or different functions per column. To start, suppose we wanted to compute the same three statistics for the tip_pct and total_bill columns:

```
In [68]: functions = ['count', 'mean', 'max']

In [69]: result = grouped['tip_pct', 'total_bill'].agg(functions)

In [70]: result
Out[70]:
               tip_pct                     total_bill
                 count      mean       max      count       mean    max
sex    smoker
Female No           54  0.156921  0.252672         54  18.105185  35.83
       Yes          33  0.182150  0.416667         33  17.977879  44.30
Male   No           97  0.160669  0.291990         97  19.791237  48.33
       Yes          60  0.152771  0.710345         60  22.284500  50.81
```

As you can see, the resulting DataFrame has hierarchical columns, the same as you would get aggregating each column separately and using concat to glue the results together using the column names as the keys argument:

```
In [71]: result['tip_pct']
Out[71]:
               count      mean       max
sex    smoker
Female No         54  0.156921  0.252672
       Yes        33  0.182150  0.416667
Male   No         97  0.160669  0.291990
       Yes        60  0.152771  0.710345
```

As above, a list of tuples with custom names can be passed:

```
In [72]: ftuples = [('Durchschnitt', 'mean'), ('Abweichung', np.var)]

In [73]: grouped['tip_pct', 'total_bill'].agg(ftuples)
Out[73]:
                    tip_pct               total_bill
               Durchschnitt  Abweichung  Durchschnitt  Abweichung
sex    smoker
Female No          0.156921    0.001327     18.105185   53.092422
       Yes         0.182150    0.005126     17.977879   84.451517
Male   No          0.160669    0.001751     19.791237   76.152961
       Yes         0.152771    0.008206     22.284500   98.244673
```

Now, suppose you wanted to apply potentially different functions to one or more of the columns. The trick is to pass a dict to agg that contains a mapping of column names to any of the function specifications listed so far:

```
In [74]: grouped.agg({'tip' : np.max, 'size' : 'sum'})
Out[74]:
               size   tip
sex    smoker
```

```
Female No       140   5.2
       Yes       74   6.5
Male   No       263   9.0
       Yes      150  10.0

In [75]: grouped.agg({'tip_pct' : ['min', 'max', 'mean', 'std'],
   ....:              'size' : 'sum'})
Out[75]:
                tip_pct                                       size
                    min       max      mean       std   sum
sex    smoker
Female No      0.056797  0.252672  0.156921  0.036421   140
       Yes     0.056433  0.416667  0.182150  0.071595    74
Male   No      0.071804  0.291990  0.160669  0.041849   263
       Yes     0.035638  0.710345  0.152771  0.090588   150
```

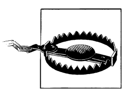
A DataFrame will have hierarchical columns only if multiple functions are applied to at least one column.

Returning Aggregated Data in "unindexed" Form

In all of the examples up until now, the aggregated data comes back with an index, potentially hierarchical, composed from the unique group key combinations observed. Since this isn't always desirable, you can disable this behavior in most cases by passing `as_index=False` to `groupby`:

```
In [76]: tips.groupby(['sex', 'smoker'], as_index=False).mean()
Out[76]:
      sex smoker  total_bill       tip      size   tip_pct
0  Female     No   18.105185  2.773519  2.592593  0.156921
1  Female    Yes   17.977879  2.931515  2.242424  0.182150
2    Male     No   19.791237  3.113402  2.711340  0.160669
3    Male    Yes   22.284500  3.051167  2.500000  0.152771
```

Of course, it's always possible to obtain the result in this format by calling `reset_index` on the result.



Using `groupby` in this way is generally less flexible; results with hierarchical columns, for example, are not currently implemented as the form of the result would have to be somewhat arbitrary.

Group-wise Operations and Transformations

Aggregation is only one kind of group operation. It is a special case in the more general class of data transformations; that is, it accepts functions that reduce a one-dimensional array to a scalar value. In this section, I will introduce you to the `transform` and `apply` methods, which will enable you to do many other kinds of group operations.

Suppose, instead, we wanted to add a column to a DataFrame containing group means for each index. One way to do this is to aggregate, then merge:

```
In [77]: df
Out[77]:
      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 [78]: k1_means = df.groupby('key1').mean().add_prefix('mean_')

In [79]: k1_means
Out[79]:
      mean_data1  mean_data2
key1
a       0.746672    0.910916
b      -0.537585    0.525384

In [80]: pd.merge(df, k1_means, left_on='key1', right_index=True)
Out[80]:
      data1     data2 key1 key2  mean_data1  mean_data2
0 -0.204708  1.393406    a  one    0.746672    0.910916
1  0.478943  0.092908    a  two    0.746672    0.910916
4  1.965781  1.246435    a  one    0.746672    0.910916
2 -0.519439  0.281746    b  one   -0.537585    0.525384
3 -0.555730  0.769023    b  two   -0.537585    0.525384
```

This works, but is somewhat inflexible. You can think of the operation as transforming the two data columns using the `np.mean` function. Let's look back at the `people` DataFrame from earlier in the chapter and use the `transform` method on GroupBy:

```
In [81]: key = ['one', 'two', 'one', 'two', 'one']

In [82]: people.groupby(key).mean()
Out[82]:
            a         b         c         d         e
one -0.082032 -1.063687 -1.047620 -0.884358 -0.028309
two  0.505275 -0.849512  0.075965  0.834983  0.452620

In [83]: people.groupby(key).transform(np.mean)
Out[83]:
               a         b         c         d         e
Joe    -0.082032 -1.063687 -1.047620 -0.884358 -0.028309
Steve   0.505275 -0.849512  0.075965  0.834983  0.452620
Wes    -0.082032 -1.063687 -1.047620 -0.884358 -0.028309
Jim     0.505275 -0.849512  0.075965  0.834983  0.452620
Travis -0.082032 -1.063687 -1.047620 -0.884358 -0.028309
```

As you may guess, `transform` applies a function to each group, then places the results in the appropriate locations. If each group produces a scalar value, it will be propagated (broadcasted). Suppose instead you wanted to subtract the mean value from each group. To do this, create a demeaning function and pass it to `transform`:

```
In [84]: def demean(arr):
   ....:     return arr - arr.mean()
```

```
In [85]: demeaned = people.groupby(key).transform(demean)

In [86]: demeaned
Out[86]:
               a         b         c         d         e
Joe     1.089221 -0.232534  1.322612  1.113271  1.381226
Steve   0.381154 -1.152125 -0.447807  0.834043 -0.891190
Wes    -0.457709       NaN       NaN -0.136869 -0.548778
Jim    -0.381154  1.152125  0.447807 -0.834043  0.891190
Travis -0.631512  0.232534 -1.322612 -0.976402 -0.832448
```

You can check that `demeaned` now has zero group means:

```
In [87]: demeaned.groupby(key).mean()
Out[87]:
      a  b  c  d  e
one   0 -0  0  0  0
two  -0  0  0  0  0
```

As you'll see in the next section, group demeaning can be achieved using `apply` also.

Apply: General split-apply-combine

Like `aggregate`, `transform` is a more specialized function having rigid requirements: the passed function must either produce a scalar value to be broadcasted (like `np.mean`) or a transformed array of the same size. The most general purpose GroupBy method is `apply`, which is the subject of the rest of this section. As in Figure 9-1, `apply` splits the object being manipulated into pieces, invokes the passed function on each piece, then attempts to concatenate the pieces together.

Returning to the tipping data set above, suppose you wanted to select the top five `tip_pct` values by group. First, it's straightforward to write a function that selects the rows with the largest values in a particular column:

```
In [88]: def top(df, n=5, column='tip_pct'):
   ....:     return df.sort_index(by=column)[-n:]

In [89]: top(tips, n=6)
Out[89]:
     total_bill   tip     sex smoker  day    time  size   tip_pct
109       14.31  4.00  Female    Yes  Sat  Dinner     2  0.279525
183       23.17  6.50    Male    Yes  Sun  Dinner     4  0.280535
232       11.61  3.39    Male     No  Sat  Dinner     2  0.291990
67         3.07  1.00  Female    Yes  Sat  Dinner     1  0.325733
178        9.60  4.00  Female    Yes  Sun  Dinner     2  0.416667
172        7.25  5.15    Male    Yes  Sun  Dinner     2  0.710345
```

Now, if we group by `smoker`, say, and call `apply` with this function, we get the following:

```
In [90]: tips.groupby('smoker').apply(top)
Out[90]:
            total_bill   tip     sex smoker  day    time  size   tip_pct
smoker
```

```
No     88          24.71  5.85    Male     No  Thur   Lunch     2  0.236746
       185         20.69  5.00    Male     No   Sun  Dinner     5  0.241663
       51          10.29  2.60  Female     No   Sun  Dinner     2  0.252672
       149          7.51  2.00    Male     No  Thur   Lunch     2  0.266312
       232         11.61  3.39    Male     No   Sat  Dinner     2  0.291990
Yes    109         14.31  4.00  Female    Yes   Sat  Dinner     2  0.279525
       183         23.17  6.50    Male    Yes   Sun  Dinner     4  0.280535
       67           3.07  1.00  Female    Yes   Sat  Dinner     1  0.325733
       178          9.60  4.00  Female    Yes   Sun  Dinner     2  0.416667
       172          7.25  5.15    Male    Yes   Sun  Dinner     2  0.710345
```

What has happened here? The `top` function is called on each piece of the DataFrame, then the results are glued together using `pandas.concat`, labeling the pieces with the group names. The result therefore has a hierarchical index whose inner level contains index values from the original DataFrame.

If you pass a function to `apply` that takes other arguments or keywords, you can pass these after the function:

```
In [91]: tips.groupby(['smoker', 'day']).apply(top, n=1, column='total_bill')
Out[91]:
                 total_bill    tip     sex smoker   day    time  size   tip_pct
smoker day
No     Fri  94        22.75   3.25  Female     No   Fri  Dinner     2  0.142857
       Sat  212       48.33   9.00    Male     No   Sat  Dinner     4  0.186220
       Sun  156       48.17   5.00    Male     No   Sun  Dinner     6  0.103799
       Thur 142       41.19   5.00    Male     No  Thur   Lunch     5  0.121389
Yes    Fri  95        40.17   4.73    Male    Yes   Fri  Dinner     4  0.117750
       Sat  170       50.81  10.00    Male    Yes   Sat  Dinner     3  0.196812
       Sun  182       45.35   3.50    Male    Yes   Sun  Dinner     3  0.077178
       Thur 197       43.11   5.00  Female    Yes  Thur   Lunch     4  0.115982
```

Beyond these basic usage mechanics, getting the most out of `apply` is largely a matter of creativity. What occurs inside the function passed is up to you; it only needs to return a pandas object or a scalar value. The rest of this chapter will mainly consist of examples showing you how to solve various problems using `groupby`.

You may recall above I called `describe` on a GroupBy object:

```
In [92]: result = tips.groupby('smoker')['tip_pct'].describe()

In [93]: result
Out[93]:
smoker
No      count    151.000000
        mean       0.159328
        std        0.039910
        min        0.056797
        25%        0.136906
        50%        0.155625
        75%        0.185014
        max        0.291990
```

```
Yes     count     93.000000
        mean       0.163196
        std        0.085119
        min        0.035638
        25%        0.106771
        50%        0.153846
        75%        0.195059
        max        0.710345

In [94]: result.unstack('smoker')
Out[94]:
smoker          No        Yes
count   151.000000  93.000000
mean      0.159328   0.163196
std       0.039910   0.085119
min       0.056797   0.035638
25%       0.136906   0.106771
50%       0.155625   0.153846
75%       0.185014   0.195059
max       0.291990   0.710345
```

Inside GroupBy, when you invoke a method like `describe`, it is actually just a shortcut for:

```
f = lambda x: x.describe()
grouped.apply(f)
```

Suppressing the group keys

In the examples above, you see that the resulting object has a hierarchical index formed from the group keys along with the indexes of each piece of the original object. This can be disabled by passing `group_keys=False` to `groupby`:

```
In [95]: tips.groupby('smoker', group_keys=False).apply(top)
Out[95]:
     total_bill   tip     sex smoker   day    time  size   tip_pct
88        24.71  5.85    Male     No  Thur   Lunch     2  0.236746
185       20.69  5.00    Male     No   Sun  Dinner     5  0.241663
51        10.29  2.60  Female     No   Sun  Dinner     2  0.252672
149        7.51  2.00    Male     No  Thur   Lunch     2  0.266312
232       11.61  3.39    Male     No   Sat  Dinner     2  0.291990
109       14.31  4.00  Female    Yes   Sat  Dinner     2  0.279525
183       23.17  6.50    Male    Yes   Sun  Dinner     4  0.280535
67         3.07  1.00  Female    Yes   Sat  Dinner     1  0.325733
178        9.60  4.00  Female    Yes   Sun  Dinner     2  0.416667
172        7.25  5.15    Male    Yes   Sun  Dinner     2  0.710345
```

Quantile and Bucket Analysis

As you may recall from Chapter 7, pandas has some tools, in particular `cut` and `qcut`, for slicing data up into buckets with bins of your choosing or by sample quantiles. Combining these functions with `groupby`, it becomes very simple to perform bucket or quantile analysis on a data set. Consider a simple random data set and an equal-length bucket categorization using `cut`:

```
In [96]: frame = DataFrame({'data1': np.random.randn(1000),
   ....:                    'data2': np.random.randn(1000)})

In [97]: factor = pd.cut(frame.data1, 4)

In [98]: factor[:10]
Out[98]:
Categorical:
array([(-1.23, 0.489], (-2.956, -1.23], (-1.23, 0.489], (0.489, 2.208],
       (-1.23, 0.489], (0.489, 2.208], (-1.23, 0.489], (-1.23, 0.489],
       (0.489, 2.208], (0.489, 2.208]], dtype=object)
Levels (4): Index([(-2.956, -1.23], (-1.23, 0.489], (0.489, 2.208],
                   (2.208, 3.928]], dtype=object)
```

The `Factor` object returned by `cut` can be passed directly to `groupby`. So we could compute a set of statistics for the `data2` column like so:

```
In [99]: def get_stats(group):
   ....:     return {'min': group.min(), 'max': group.max(),
   ....:             'count': group.count(), 'mean': group.mean()}

In [100]: grouped = frame.data2.groupby(factor)

In [101]: grouped.apply(get_stats).unstack()
Out[101]:
                 count       max      mean       min
data1
(-1.23, 0.489]     598  3.260383 -0.002051 -2.989741
(-2.956, -1.23]     95  1.670835 -0.039521 -3.399312
(0.489, 2.208]     297  2.954439  0.081822 -3.745356
(2.208, 3.928]      10  1.765640  0.024750 -1.929776
```

These were equal-length buckets; to compute equal-size buckets based on sample quantiles, use `qcut`. I'll pass `labels=False` to just get quantile numbers.

```
# Return quantile numbers
In [102]: grouping = pd.qcut(frame.data1, 10, labels=False)

In [103]: grouped = frame.data2.groupby(grouping)

In [104]: grouped.apply(get_stats).unstack()
Out[104]:
   count       max      mean       min
0    100  1.670835 -0.049902 -3.399312
1    100  2.628441  0.030989 -1.950098
2    100  2.527939 -0.067179 -2.925113
3    100  3.260383  0.065713 -2.315555
4    100  2.074345 -0.111653 -2.047939
5    100  2.184810  0.052130 -2.989741
6    100  2.458842 -0.021489 -2.223506
7    100  2.954439 -0.026459 -3.056990
8    100  2.735527  0.103406 -3.745356
9    100  2.377020  0.220122 -2.064111
```

Example: Filling Missing Values with Group-specific Values

When cleaning up missing data, in some cases you will filter out data observations using `dropna`, but in others you may want to impute (fill in) the NA values using a fixed value or some value derived from the data. `fillna` is the right tool to use; for example here I fill in NA values with the mean:

```
In [105]: s = Series(np.random.randn(6))

In [106]: s[::2] = np.nan

In [107]: s
Out[107]:
0         NaN
1   -0.125921
2         NaN
3   -0.884475
4         NaN
5    0.227290

In [108]: s.fillna(s.mean())
Out[108]:
0   -0.261035
1   -0.125921
2   -0.261035
3   -0.884475
4   -0.261035
5    0.227290
```

Suppose you need the fill value to vary by group. As you may guess, you need only group the data and use `apply` with a function that calls `fillna` on each data chunk. Here is some sample data on some US states divided into eastern and western states:

```
In [109]: states = ['Ohio', 'New York', 'Vermont', 'Florida',
   .....:           'Oregon', 'Nevada', 'California', 'Idaho']

In [110]: group_key = ['East'] * 4 + ['West'] * 4

In [111]: data = Series(np.random.randn(8), index=states)

In [112]: data[['Vermont', 'Nevada', 'Idaho']] = np.nan

In [113]: data
Out[113]:
Ohio          0.922264
New York     -2.153545
Vermont            NaN
Florida      -0.375842
Oregon        0.329939
Nevada             NaN
California    1.105913
Idaho              NaN

In [114]: data.groupby(group_key).mean()
Out[114]:
```

```
East   -0.535707
West    0.717926
```

We can fill the NA values using the group means like so:

```
In [115]: fill_mean = lambda g: g.fillna(g.mean())

In [116]: data.groupby(group_key).apply(fill_mean)
Out[116]:
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
```

In another case, you might have pre-defined fill values in your code that vary by group. Since the groups have a `name` attribute set internally, we can use that:

```
In [117]: fill_values = {'East': 0.5, 'West': -1}

In [118]: fill_func = lambda g: g.fillna(fill_values[g.name])

In [119]: data.groupby(group_key).apply(fill_func)
Out[119]:
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
```

Example: Random Sampling and Permutation

Suppose you wanted to draw a random sample (with or without replacement) from a large dataset for Monte Carlo simulation purposes or some other application. There are a number of ways to perform the "draws"; some are much more efficient than others. One way is to select the first `K` elements of `np.random.permutation(N)`, where `N` is the size of your complete dataset and `K` the desired sample size. As a more fun example, here's a way to construct a deck of English-style playing cards:

```
# Hearts, Spades, Clubs, Diamonds
suits = ['H', 'S', 'C', 'D']
card_val = (range(1, 11) + [10] * 3) * 4
base_names = ['A'] + range(2, 11) + ['J', 'K', 'Q']
cards = []
for suit in ['H', 'S', 'C', 'D']:
    cards.extend(str(num) + suit for num in base_names)

deck = Series(card_val, index=cards)
```

So now we have a Series of length 52 whose index contains card names and values are the ones used in blackjack and other games (to keep things simple, I just let the ace be 1):

```
In [121]: deck[:13]
Out[121]:
AH      1
2H      2
3H      3
4H      4
5H      5
6H      6
7H      7
8H      8
9H      9
10H    10
JH     10
KH     10
QH     10
```

Now, based on what I said above, drawing a hand of 5 cards from the desk could be written as:

```
In [122]: def draw(deck, n=5):
   .....:     return deck.take(np.random.permutation(len(deck))[:n])

In [123]: draw(deck)
Out[123]:
AD     1
8C     8
5H     5
KC    10
2C     2
```

Suppose you wanted two random cards from each suit. Because the suit is the last character of each card name, we can group based on this and use `apply`:

```
In [124]: get_suit = lambda card: card[-1] # last letter is suit

In [125]: deck.groupby(get_suit).apply(draw, n=2)
Out[125]:
C  2C     2
   3C     3
D  KD    10
   8D     8
H  KH    10
   3H     3
S  2S     2
   4S     4

# alternatively
In [126]: deck.groupby(get_suit, group_keys=False).apply(draw, n=2)
Out[126]:
KC    10
JC    10
AD     1
```

```
5D     5
5H     5
6H     6
7S     7
KS    10
```

Example: Group Weighted Average and Correlation

Under the split-apply-combine paradigm of `groupby`, operations between columns in a DataFrame or two Series, such a group weighted average, become a routine affair. As an example, take this dataset containing group keys, values, and some weights:

```
In [127]: df = DataFrame({'category': ['a', 'a', 'a', 'a', 'b', 'b', 'b', 'b'],
   .....:                 'data': np.random.randn(8),
   .....:                 'weights': np.random.rand(8)})

In [128]: df
Out[128]:
  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
```

The group weighted average by `category` would then be:

```
In [129]: grouped = df.groupby('category')

In [130]: get_wavg = lambda g: np.average(g['data'], weights=g['weights'])

In [131]: grouped.apply(get_wavg)
Out[131]:
category
a           0.811643
b          -0.122262
```

As a less trivial example, consider a data set from Yahoo! Finance containing end of day prices for a few stocks and the S&P 500 index (the `SPX` ticker):

```
In [132]: close_px = pd.read_csv('ch09/stock_px.csv', parse_dates=True, index_col=0)

In [133]: close_px
Out[133]:
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 2214 entries, 2003-01-02 00:00:00 to 2011-10-14 00:00:00
Data columns:
AAPL    2214  non-null values
MSFT    2214  non-null values
XOM     2214  non-null values
SPX     2214  non-null values
dtypes: float64(4)
```

```
In [134]: close_px[-4:]
Out[134]:
              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
```

One task of interest might be to compute a DataFrame consisting of the yearly correlations of daily returns (computed from percent changes) with `SPX`. Here is one way to do it:

```
In [135]: rets = close_px.pct_change().dropna()

In [136]: spx_corr = lambda x: x.corrwith(x['SPX'])

In [137]: by_year = rets.groupby(lambda x: x.year)

In [138]: by_year.apply(spx_corr)
Out[138]:
          AAPL      MSFT       XOM  SPX
2003  0.541124  0.745174  0.661265    1
2004  0.374283  0.588531  0.557742    1
2005  0.467540  0.562374  0.631010    1
2006  0.428267  0.406126  0.518514    1
2007  0.508118  0.658770  0.786264    1
2008  0.681434  0.804626  0.828303    1
2009  0.707103  0.654902  0.797921    1
2010  0.710105  0.730118  0.839057    1
2011  0.691931  0.800996  0.859975    1
```

There is, of course, nothing to stop you from computing inter-column correlations:

```
# Annual correlation of Apple with Microsoft
In [139]: by_year.apply(lambda g: g['AAPL'].corr(g['MSFT']))
Out[139]:
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
```


Example: Group-wise Linear Regression

In the same vein as the previous example, you can use `groupby` to perform more complex group-wise statistical analysis, as long as the function returns a pandas object or scalar value. For example, I can define the following `regress` function (using the `statsmodels` econometrics library) which executes an ordinary least squares (OLS) regression on each chunk of data:

```
import statsmodels.api as sm
def regress(data, yvar, xvars):
    Y = data[yvar]
    X = data[xvars]
    X['intercept'] = 1.
    result = sm.OLS(Y, X).fit()
    return result.params
```

Now, to run a yearly linear regression of `AAPL` on `SPX` returns, I execute:

```
In [141]: by_year.apply(regress, 'AAPL', ['SPX'])
Out[141]:
           SPX  intercept
2003  1.195406   0.000710
2004  1.363463   0.004201
2005  1.766415   0.003246
2006  1.645496   0.000080
2007  1.198761   0.003438
2008  0.968016  -0.001110
2009  0.879103   0.002954
2010  1.052608   0.001261
2011  0.806605   0.001514
```

Pivot Tables and Cross-Tabulation

A *pivot table* is a data summarization tool frequently found in spreadsheet programs and other data analysis software. It aggregates a table of data by one or more keys, arranging the data in a rectangle with some of the group keys along the rows and some along the columns. Pivot tables in Python with pandas are made possible using the `groupby` facility described in this chapter combined with reshape operations utilizing hierarchical indexing. DataFrame has a `pivot_table` method, and additionally there is a top-level `pandas.pivot_table` function. In addition to providing a convenience interface to `groupby`, `pivot_table` also can add partial totals, also known as *margins*.

Returning to the tipping data set, suppose I wanted to compute a table of group means (the default `pivot_table` aggregation type) arranged by `sex` and `smoker` on the rows:

```
In [142]: tips.pivot_table(rows=['sex', 'smoker'])
Out[142]:
                   size       tip   tip_pct  total_bill
sex    smoker
Female No      2.592593  2.773519  0.156921   18.105185
       Yes     2.242424  2.931515  0.182150   17.977879
Male   No      2.711340  3.113402  0.160669   19.791237
       Yes     2.500000  3.051167  0.152771   22.284500
```

This could have been easily produced using `groupby`. Now, suppose we want to aggregate only `tip_pct` and `size`, and additionally group by `day`. I'll put `smoker` in the table columns and `day` in the rows:

```
In [143]: tips.pivot_table(['tip_pct', 'size'], rows=['sex', 'day'],
   .....:                  cols='smoker')
Out[143]:
```

```
                 tip_pct               size
smoker                No       Yes       No       Yes
sex    day
Female Fri      0.165296  0.209129  2.500000  2.000000
       Sat      0.147993  0.163817  2.307692  2.200000
       Sun      0.165710  0.237075  3.071429  2.500000
       Thur     0.155971  0.163073  2.480000  2.428571
Male   Fri      0.138005  0.144730  2.000000  2.125000
       Sat      0.162132  0.139067  2.656250  2.629630
       Sun      0.158291  0.173964  2.883721  2.600000
       Thur     0.165706  0.164417  2.500000  2.300000
```

This table could be augmented to include partial totals by passing `margins=True`. This has the effect of adding `All` row and column labels, with corresponding values being the group statistics for all the data within a single tier. In this below example, the `All` values are means without taking into account smoker vs. non-smoker (the `All` columns) or any of the two levels of grouping on the rows (the `All` row):

```
In [144]: tips.pivot_table(['tip_pct', 'size'], rows=['sex', 'day'],
   .....:                  cols='smoker', margins=True)
Out[144]:
                 size                          tip_pct
smoker             No       Yes       All       No       Yes       All
sex    day
Female Fri   2.500000  2.000000  2.111111  0.165296  0.209129  0.199388
       Sat   2.307692  2.200000  2.250000  0.147993  0.163817  0.156470
       Sun   3.071429  2.500000  2.944444  0.165710  0.237075  0.181569
       Thur  2.480000  2.428571  2.468750  0.155971  0.163073  0.157525
Male   Fri   2.000000  2.125000  2.100000  0.138005  0.144730  0.143385
       Sat   2.656250  2.629630  2.644068  0.162132  0.139067  0.151577
       Sun   2.883721  2.600000  2.810345  0.158291  0.173964  0.162344
       Thur  2.500000  2.300000  2.433333  0.165706  0.164417  0.165276
All          2.668874  2.408602  2.569672  0.159328  0.163196  0.160803
```

To use a different aggregation function, pass it to `aggfunc`. For example, `'count'` or `len` will give you a cross-tabulation (count or frequency) of group sizes:

```
In [145]: tips.pivot_table('tip_pct', rows=['sex', 'smoker'], cols='day',
   .....:                  aggfunc=len, margins=True)
Out[145]:
day            Fri  Sat  Sun  Thur  All
sex    smoker
Female No        2   13   14    25   54
       Yes       7   15    4     7   33
Male   No        2   32   43    20   97
       Yes       8   27   15    10   60
All             19   87   76    62  244
```

If some combinations are empty (or otherwise NA), you may wish to pass a `fill_value`:

```
In [146]: tips.pivot_table('size', rows=['time', 'sex', 'smoker'],
   .....:                  cols='day', aggfunc='sum', fill_value=0)
Out[146]:
day                  Fri  Sat  Sun  Thur
time   sex    smoker
Dinner Female No       2   30   43     2
```

```
            Yes        8   33   10     0
     Male   No         4   85  124     0
            Yes       12   71   39     0
Lunch Female No        3    0    0    60
            Yes        6    0    0    17
     Male   No         0    0    0    50
            Yes        5    0    0    23
```

See Table 9-2 for a summary of `pivot_table` methods.

Table 9-2. pivot_table options

Function name	Description
`values`	Column name or names to aggregate. By default aggregates all numeric columns
`rows`	Column names or other group keys to group on the rows of the resulting pivot table
`cols`	Column names or other group keys to group on the columns of the resulting pivot table
`aggfunc`	Aggregation function or list of functions; `'mean'` by default. Can be any function valid in a groupby context
`fill_value`	Replace missing values in result table
`margins`	Add row/column subtotals and grand total, False by default

Cross-Tabulations: Crosstab

A cross-tabulation (or *crosstab* for short) is a special case of a pivot table that computes group frequencies. Here is a canonical example taken from the Wikipedia page on cross-tabulation:

```
In [150]: data
Out[150]:
   Sample  Gender    Handedness
0       1  Female  Right-handed
1       2    Male   Left-handed
2       3  Female  Right-handed
3       4    Male  Right-handed
4       5    Male   Left-handed
5       6    Male  Right-handed
6       7  Female  Right-handed
7       8  Female   Left-handed
8       9    Male  Right-handed
9      10  Female  Right-handed
```

As part of some survey analysis, we might want to summarize this data by gender and handedness. You could use `pivot_table` to do this, but the `pandas.crosstab` function is very convenient:

```
In [151]: pd.crosstab(data.Gender, data.Handedness, margins=True)
Out[151]:
Handedness  Left-handed  Right-handed  All
Gender
Female                1             4    5
Male                  2             3    5
All                   3             7   10
```

The first two arguments to `crosstab` can each either be an array or Series or a list of arrays. As in the tips data:

```
In [152]: pd.crosstab([tips.time, tips.day], tips.smoker, margins=True)
Out[152]:
smoker        No  Yes  All
time   day
Dinner Fri     3    9   12
       Sat    45   42   87
       Sun    57   19   76
       Thur    1    0    1
Lunch  Fri     1    6    7
       Thur   44   17   61
All          151   93  244
```

Example: 2012 Federal Election Commission Database

The US Federal Election Commission publishes data on contributions to political campaigns. This includes contributor names, occupation and employer, address, and contribution amount. An interesting dataset is from the 2012 US presidential election (*http://www.fec.gov/disclosurep/PDownload.do*). As of this writing (June 2012), the full dataset for all states is a 150 megabyte CSV file `P00000001-ALL.csv`, which can be loaded with `pandas.read_csv`:

```
In [13]: fec = pd.read_csv('ch09/P00000001-ALL.csv')

In [14]: fec
Out[14]:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1001731 entries, 0 to 1001730
Data columns:
cmte_id              1001731  non-null values
cand_id              1001731  non-null values
cand_nm              1001731  non-null values
contbr_nm            1001731  non-null values
contbr_city          1001716  non-null values
contbr_st            1001727  non-null values
contbr_zip           1001620  non-null values
contbr_employer      994314   non-null values
contbr_occupation    994433   non-null values
contb_receipt_amt    1001731  non-null values
contb_receipt_dt     1001731  non-null values
receipt_desc         14166    non-null values
memo_cd              92482    non-null values
memo_text            97770    non-null values
form_tp              1001731  non-null values
file_num             1001731  non-null values
dtypes: float64(1), int64(1), object(14)
```

A sample record in the DataFrame looks like this:

```
In [15]: fec.ix[123456]
Out[15]:
cmte_id                             C00431445
```

```
cand_id                             P80003338
cand_nm                         Obama, Barack
contbr_nm                         ELLMAN, IRA
contbr_city                             TEMPE
contbr_st                                  AZ
contbr_zip                          852816719
contbr_employer     ARIZONA STATE UNIVERSITY
contbr_occupation                   PROFESSOR
contb_receipt_amt                          50
contb_receipt_dt                    01-DEC-11
receipt_desc                              NaN
memo_cd                                   NaN
memo_text                                 NaN
form_tp                                 SA17A
file_num                               772372
Name: 123456
```

You can probably think of many ways to start slicing and dicing this data to extract informative statistics about donors and patterns in the campaign contributions. I'll spend the next several pages showing you a number of different analyses that apply techniques you have learned about so far.

You can see that there are no political party affiliations in the data, so this would be useful to add. You can get a list of all the unique political candidates using `unique` (note that NumPy suppresses the quotes around the strings in the output):

```
In [16]: unique_cands = fec.cand_nm.unique()

In [17]: unique_cands
Out[17]:
array([Bachmann, Michelle, Romney, Mitt, Obama, Barack,
       Roemer, Charles E. 'Buddy' III, Pawlenty, Timothy,
       Johnson, Gary Earl, Paul, Ron, Santorum, Rick, Cain, Herman,
       Gingrich, Newt, McCotter, Thaddeus G, Huntsman, Jon, Perry, Rick], dtype=object)

In [18]: unique_cands[2]
Out[18]: 'Obama, Barack'
```

An easy way to indicate party affiliation is using a dict:[2]

```
parties = {'Bachmann, Michelle': 'Republican',
           'Cain, Herman': 'Republican',
           'Gingrich, Newt': 'Republican',
           'Huntsman, Jon': 'Republican',
           'Johnson, Gary Earl': 'Republican',
           'McCotter, Thaddeus G': 'Republican',
           'Obama, Barack': 'Democrat',
           'Paul, Ron': 'Republican',
           'Pawlenty, Timothy': 'Republican',
           'Perry, Rick': 'Republican',
           "Roemer, Charles E. 'Buddy' III": 'Republican',
```


2. This makes the simplifying assumption that Gary Johnson is a Republican even though he later became the Libertarian party candidate.

```
             'Romney, Mitt': 'Republican',
             'Santorum, Rick': 'Republican'}
```

Now, using this mapping and the map method on Series objects, you can compute an array of political parties from the candidate names:

```
In [20]: fec.cand_nm[123456:123461]
Out[20]:
123456    Obama, Barack
123457    Obama, Barack
123458    Obama, Barack
123459    Obama, Barack
123460    Obama, Barack
Name: cand_nm

In [21]: fec.cand_nm[123456:123461].map(parties)
Out[21]:
123456    Democrat
123457    Democrat
123458    Democrat
123459    Democrat
123460    Democrat
Name: cand_nm

# Add it as a column
In [22]: fec['party'] = fec.cand_nm.map(parties)

In [23]: fec['party'].value_counts()
Out[23]:
Democrat      593746
Republican    407985
```

A couple of data preparation points. First, this data includes both contributions and refunds (negative contribution amount):

```
In [24]: (fec.contb_receipt_amt > 0).value_counts()
Out[24]:
True     991475
False     10256
```

To simplify the analysis, I'll restrict the data set to positive contributions:

```
In [25]: fec = fec[fec.contb_receipt_amt > 0]
```

Since Barack Obama and Mitt Romney are the main two candidates, I'll also prepare a subset that just has contributions to their campaigns:

```
In [26]: fec_mrbo = fec[fec.cand_nm.isin(['Obama, Barack', 'Romney, Mitt'])]
```

Donation Statistics by Occupation and Employer

Donations by occupation is another oft-studied statistic. For example, lawyers (attorneys) tend to donate more money to Democrats, while business executives tend to donate more to Republicans. You have no reason to believe me; you can see for yourself in the data. First, the total number of donations by occupation is easy:

```
In [27]: fec.contbr_occupation.value_counts()[:10]
Out[27]:
RETIRED                                   233990
INFORMATION REQUESTED                      35107
ATTORNEY                                   34286
HOMEMAKER                                  29931
PHYSICIAN                                  23432
INFORMATION REQUESTED PER BEST EFFORTS     21138
ENGINEER                                   14334
TEACHER                                    13990
CONSULTANT                                 13273
PROFESSOR                                  12555
```

You will notice by looking at the occupations that many refer to the same basic job type, or there are several variants of the same thing. Here is a code snippet illustrates a technique for cleaning up a few of them by mapping from one occupation to another; note the "trick" of using `dict.get` to allow occupations with no mapping to "pass through":

```
occ_mapping = {
   'INFORMATION REQUESTED PER BEST EFFORTS' : 'NOT PROVIDED',
   'INFORMATION REQUESTED' : 'NOT PROVIDED',
   'INFORMATION REQUESTED (BEST EFFORTS)' : 'NOT PROVIDED',
   'C.E.O.': 'CEO'
}

# If no mapping provided, return x
f = lambda x: occ_mapping.get(x, x)
fec.contbr_occupation = fec.contbr_occupation.map(f)
```

I'll also do the same thing for employers:

```
emp_mapping = {
   'INFORMATION REQUESTED PER BEST EFFORTS' : 'NOT PROVIDED',
   'INFORMATION REQUESTED' : 'NOT PROVIDED',
   'SELF' : 'SELF-EMPLOYED',
   'SELF EMPLOYED' : 'SELF-EMPLOYED',
}

# If no mapping provided, return x
f = lambda x: emp_mapping.get(x, x)
fec.contbr_employer = fec.contbr_employer.map(f)
```

Now, you can use `pivot_table` to aggregate the data by party and occupation, then filter down to the subset that donated at least $2 million overall:

```
In [34]: by_occupation = fec.pivot_table('contb_receipt_amt',
   ....:                                 rows='contbr_occupation',
   ....:                                 cols='party', aggfunc='sum')

In [35]: over_2mm = by_occupation[by_occupation.sum(1) > 2000000]

In [36]: over_2mm
Out[36]:
party                 Democrat       Republican
contbr_occupation
```

```
ATTORNEY            11141982.97   7477194.430000
CEO                  2074974.79   4211040.520000
CONSULTANT           2459912.71   2544725.450000
ENGINEER              951525.55   1818373.700000
EXECUTIVE            1355161.05   4138850.090000
HOMEMAKER            4248875.80  13634275.780000
INVESTOR              884133.00   2431768.920000
LAWYER               3160478.87    391224.320000
MANAGER               762883.22   1444532.370000
NOT PROVIDED         4866973.96  20565473.010000
OWNER                1001567.36   2408286.920000
PHYSICIAN            3735124.94   3594320.240000
PRESIDENT            1878509.95   4720923.760000
PROFESSOR            2165071.08    296702.730000
REAL ESTATE           528902.09   1625902.250000
RETIRED             25305116.38  23561244.489999
SELF-EMPLOYED         672393.40   1640252.540000
```

It can be easier to look at this data graphically as a bar plot (`'barh'` means horizontal bar plot, see Figure 9-2):

```
In [38]: over_2mm.plot(kind='barh')
```

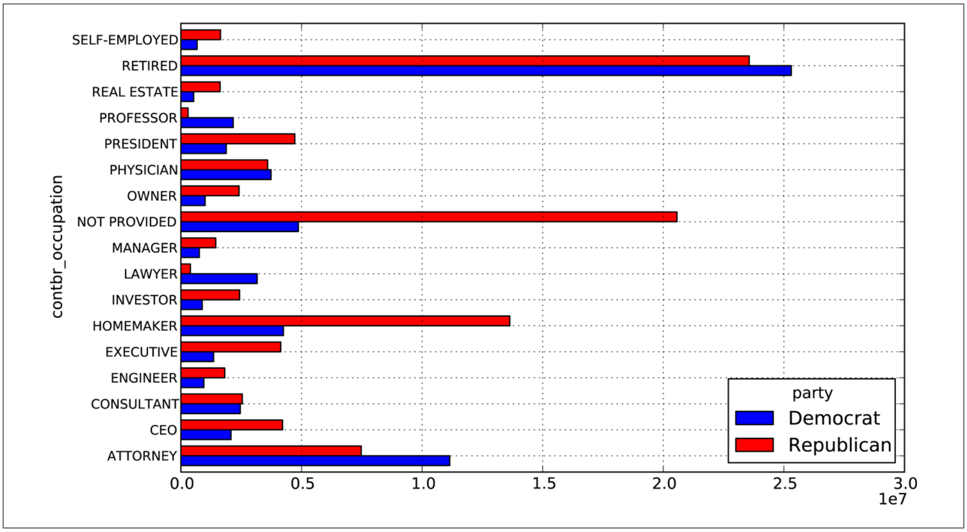


Figure 9-2. Total donations by party for top occupations

You might be interested in the top donor occupations or top companies donating to Obama and Romney. To do this, you can group by candidate name and use a variant of the `top` method from earlier in the chapter:

```
def get_top_amounts(group, key, n=5):
    totals = group.groupby(key)['contb_receipt_amt'].sum()

    # Order totals by key in descending order
    return totals.order(ascending=False)[:n]
```

Then aggregated by occupation and employer:

```
In [40]: grouped = fec_mrbo.groupby('cand_nm')

In [41]: grouped.apply(get_top_amounts, 'contbr_occupation', n=7)
Out[41]:
cand_nm        contbr_occupation
Obama, Barack  RETIRED              25305116.38
               ATTORNEY             11141982.97
               NOT PROVIDED          4866973.96
               HOMEMAKER             4248875.80
               PHYSICIAN             3735124.94
               LAWYER                3160478.87
               CONSULTANT            2459912.71
Romney, Mitt   RETIRED              11508473.59
               NOT PROVIDED         11396894.84
               HOMEMAKER             8147446.22
               ATTORNEY              5364718.82
               PRESIDENT             2491244.89
               EXECUTIVE             2300947.03
               C.E.O.                1968386.11
Name: contb_receipt_amt

In [42]: grouped.apply(get_top_amounts, 'contbr_employer', n=10)
Out[42]:
cand_nm        contbr_employer
Obama, Barack  RETIRED               22694358.85
               SELF-EMPLOYED         18626807.16
               NOT EMPLOYED           8586308.70
               NOT PROVIDED           5053480.37
               HOMEMAKER              2605408.54
               STUDENT                 318831.45
               VOLUNTEER               257104.00
               MICROSOFT               215585.36
               SIDLEY AUSTIN LLP       168254.00
               REFUSED                 149516.07
Romney, Mitt   NOT PROVIDED          12059527.24
               RETIRED               11506225.71
               HOMEMAKER              8147196.22
               SELF-EMPLOYED          7414115.22
               STUDENT                 496490.94
               CREDIT SUISSE           281150.00
               MORGAN STANLEY          267266.00
               GOLDMAN SACH & CO.      238250.00
               BARCLAYS CAPITAL        162750.00
               H.I.G. CAPITAL          139500.00
Name: contb_receipt_amt
```

Bucketing Donation Amounts

A useful way to analyze this data is to use the `cut` function to discretize the contributor amounts into buckets by contribution size:

```
In [43]: bins = np.array([0, 1, 10, 100, 1000, 10000, 100000, 1000000, 10000000])
```

```
In [44]: labels = pd.cut(fec_mrbo.contb_receipt_amt, bins)

In [45]: labels
Out[45]:
Categorical:contb_receipt_amt
array([(10, 100], (100, 1000], (100, 1000], ..., (1, 10], (10, 100],
       (100, 1000]], dtype=object)
Levels (8): array([(0, 1], (1, 10], (10, 100], (100, 1000], (1000, 10000],
       (10000, 100000], (100000, 1000000], (1000000, 10000000]], dtype=object)
```

We can then group the data for Obama and Romney by name and bin label to get a histogram by donation size:

```
In [46]: grouped = fec_mrbo.groupby(['cand_nm', labels])

In [47]: grouped.size().unstack(0)
Out[47]:
cand_nm              Obama, Barack  Romney, Mitt
contb_receipt_amt
(0, 1]                         493            77
(1, 10]                      40070          3681
(10, 100]                   372280         31853
(100, 1000]                 153991         43357
(1000, 10000]                22284         26186
(10000, 100000]                  2             1
(100000, 1000000]                3           NaN
(1000000, 10000000]              4           NaN
```

This data shows that Obama has received a significantly larger number of small donations than Romney. You can also sum the contribution amounts and normalize within buckets to visualize percentage of total donations of each size by candidate:

```
In [48]: bucket_sums = grouped.contb_receipt_amt.sum().unstack(0)

In [49]: bucket_sums
Out[49]:
cand_nm              Obama, Barack  Romney, Mitt
contb_receipt_amt
(0, 1]                      318.24         77.00
(1, 10]                  337267.62      29819.66
(10, 100]              20288981.41    1987783.76
(100, 1000]            54798531.46   22363381.69
(1000, 10000]          51753705.67   63942145.42
(10000, 100000]           59100.00      12700.00
(100000, 1000000]       1490683.08           NaN
(1000000, 10000000]     7148839.76           NaN

In [50]: normed_sums = bucket_sums.div(bucket_sums.sum(axis=1), axis=0)

In [51]: normed_sums
Out[51]:
cand_nm              Obama, Barack  Romney, Mitt
contb_receipt_amt
(0, 1]                    0.805182      0.194818
(1, 10]                   0.918767      0.081233
(10, 100]                 0.910769      0.089231
```

```
(100, 1000]             0.710176      0.289824
(1000, 10000]           0.447326      0.552674
(10000, 100000]         0.823120      0.176880
(100000, 1000000]       1.000000           NaN
(1000000, 10000000]     1.000000           NaN

In [52]: normed_sums[:-2].plot(kind='barh', stacked=True)
```

I excluded the two largest bins as these are not donations by individuals. See Figure 9-3 for the resulting figure.

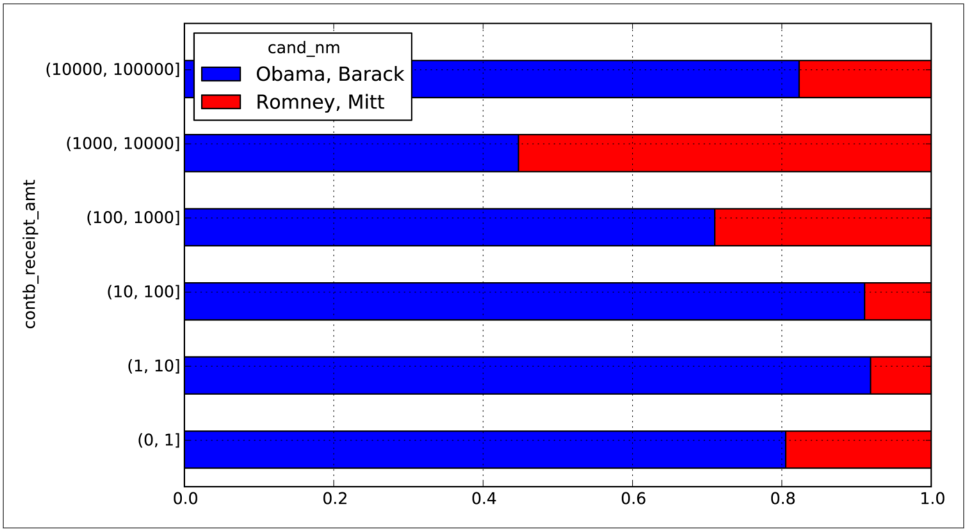


Figure 9-3. Percentage of total donations received by candidates for each donation size

There are of course many refinements and improvements of this analysis. For example, you could aggregate donations by donor name and zip code to adjust for donors who gave many small amounts versus one or more large donations. I encourage you to download it and explore it yourself.

Donation Statistics by State

Aggregating the data by candidate and state is a routine affair:

```
In [53]: grouped = fec_mrbo.groupby(['cand_nm', 'contbr_st'])

In [54]: totals = grouped.contb_receipt_amt.sum().unstack(0).fillna(0)

In [55]: totals = totals[totals.sum(1) > 100000]

In [56]: totals[:10]
Out[56]:
cand_nm    Obama, Barack  Romney, Mitt
contbr_st
```

```
AK              281840.15      86204.24
AL              543123.48     527303.51
AR              359247.28     105556.00
AZ             1506476.98    1888436.23
CA            23824984.24   11237636.60
CO             2132429.49    1506714.12
CT             2068291.26    3499475.45
DC             4373538.80    1025137.50
DE              336669.14      82712.00
FL             7318178.58    8338458.81
```

If you divide each row by the total contribution amount, you get the relative percentage of total donations by state for each candidate:

```
In [57]: percent = totals.div(totals.sum(1), axis=0)

In [58]: percent[:10]
Out[58]:
cand_nm    Obama, Barack  Romney, Mitt
contbr_st
AK              0.765778      0.234222
AL              0.507390      0.492610
AR              0.772902      0.227098
AZ              0.443745      0.556255
CA              0.679498      0.320502
CO              0.585970      0.414030
CT              0.371476      0.628524
DC              0.810113      0.189887
DE              0.802776      0.197224
FL              0.467417      0.532583
```

I thought it would be interesting to look at this data plotted on a map, using ideas from Chapter 8. After locating a shape file for the state boundaries (*http://nationalatlas.gov/atlasftp.html?openChapters=chpbound*) and learning a bit more about matplotlib and its `basemap` toolkit (I was aided by a blog posting from Thomas Lecocq)[3], I ended up with the following code for plotting these relative percentages:

```
from mpl_toolkits.basemap import Basemap, cm
import numpy as np
from matplotlib import rcParams
from matplotlib.collections import LineCollection
import matplotlib.pyplot as plt

from shapelib import ShapeFile
import dbflib

obama = percent['Obama, Barack']

fig = plt.figure(figsize=(12, 12))
ax = fig.add_axes([0.1,0.1,0.8,0.8])

lllat = 21; urlat = 53; lllon = -118; urlon = -62
```

3. *http://www.geophysique.be/2011/01/27/matplotlib-basemap-tutorial-07-shapefiles-unleached/*

```
m = Basemap(ax=ax, projection='stere',
            lon_0=(urlon + lllon) / 2, lat_0=(urlat + lllat) / 2,
            llcrnrlat=lllat, urcrnrlat=urlat, llcrnrlon=lllon,
            urcrnrlon=urlon, resolution='l')
m.drawcoastlines()
m.drawcountries()

shp = ShapeFile('../states/statesp020')
dbf = dbflib.open('../states/statesp020')

for npoly in range(shp.info()[0]):
    # Draw colored polygons on the map
    shpsegs = []
    shp_object = shp.read_object(npoly)
    verts = shp_object.vertices()
    rings = len(verts)
    for ring in range(rings):
        lons, lats = zip(*verts[ring])
        x, y = m(lons, lats)
        shpsegs.append(zip(x,y))
        if ring == 0:
            shapedict = dbf.read_record(npoly)
        name = shapedict['STATE']
    lines = LineCollection(shpsegs,antialiaseds=(1,))

    # state_to_code dict, e.g. 'ALASKA' -> 'AK', omitted
    try:
        per = obama[state_to_code[name.upper()]]
    except KeyError:
        continue

    lines.set_facecolors('k')
    lines.set_alpha(0.75 * per) # Shrink the percentage a bit
    lines.set_edgecolors('k')
    lines.set_linewidth(0.3)
    ax.add_collection(lines)

plt.show()
```

See Figure 9-4 for the result.

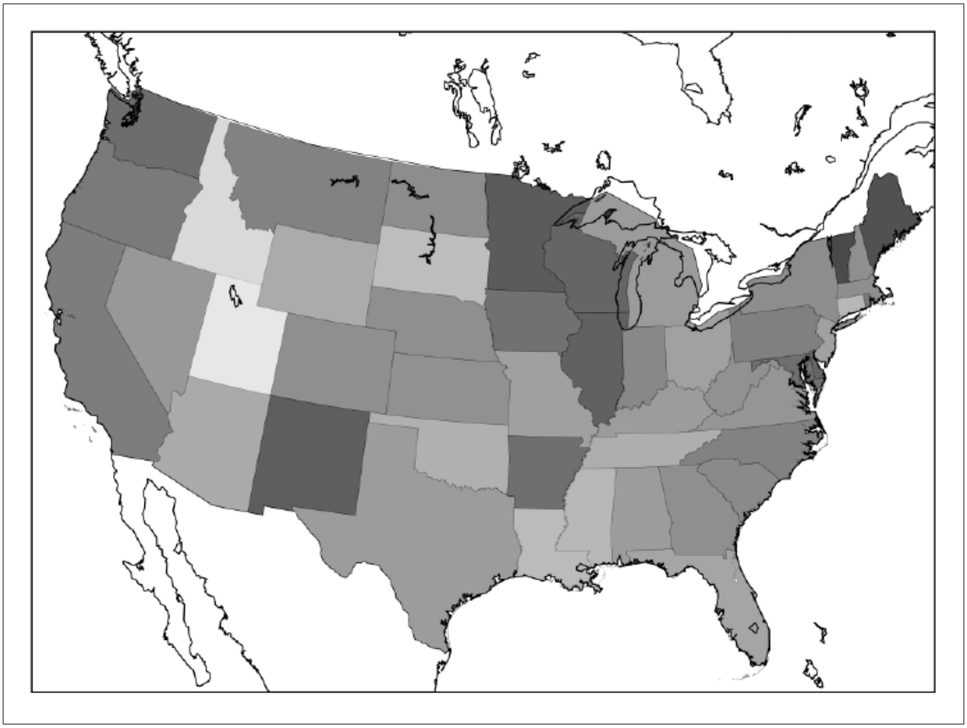


Figure 9-4. US map aggregated donation statistics overlay (darker means more Democratic)