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Data Aggregation and Group Operations

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Reference

- **Chapter 10: Data Aggregation and Group Operations**

- Wes McKinney, **Python for Data Analysis**: Data Wrangling with Pandas, NumPy, and IPython, O'Reilly Media, 2nd Edition, 2018.
  - Material: https://github.com/wesm/pypop-book

Data Aggregation and Group Operations

- **Categorizing** a dataset and **applying a function to each group**, whether an aggregation or transformation, is often a critical component of a data analysis workflow.
  - Split a pandas object **into pieces** using one or more keys
  - Calculate **group summary** statistics
  - Apply **within-group transformations** or other manipulations
  - Compute **pivot tables** and cross-tabulations

Outline

- 10.1 GroupBy Mechanics
- 10.2 Data Aggregation
- 10.3 Apply: General split-apply-combine
- 10.4 Pivot Tables and Cross-Tabulation

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- 10.1 GroupBy Mechanics
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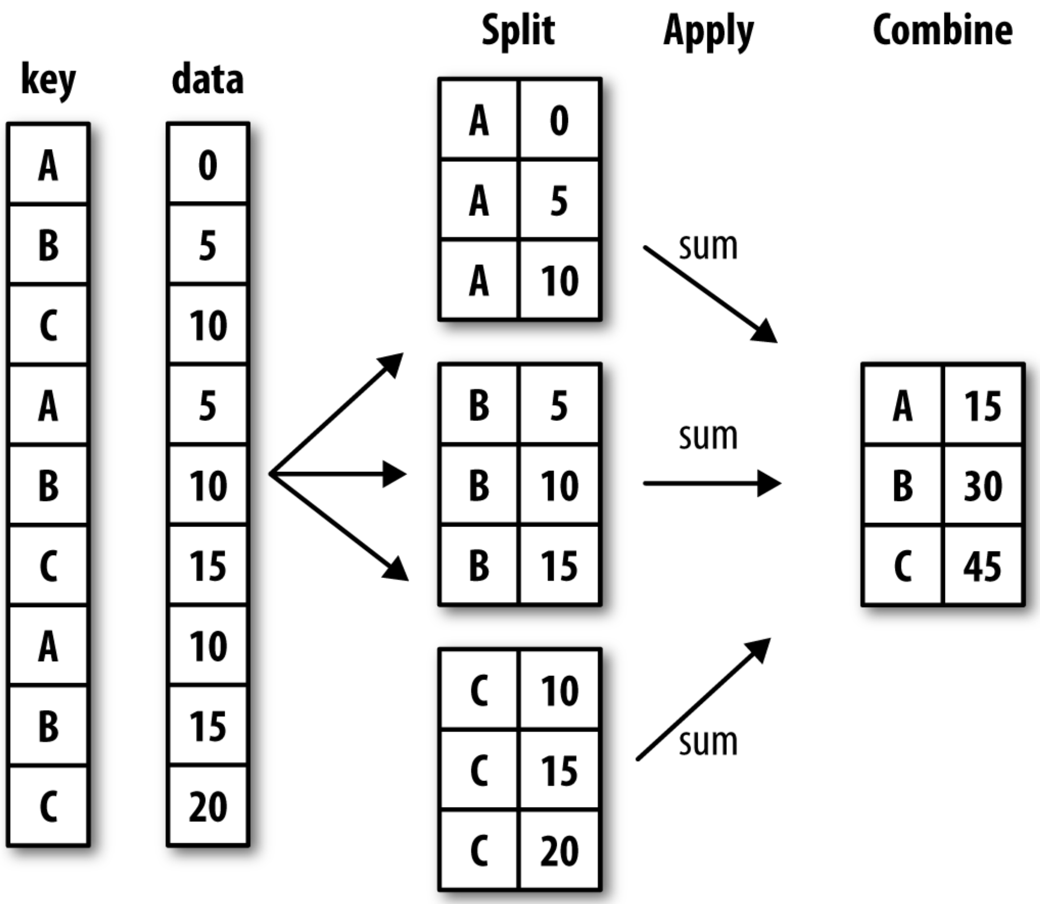
- Iterating Over Groups
- Selecting a Column or Subset of Columns
- Grouping with Dicts and Series
- Grouping with Functions

10.1 GroupBy Mechanics

- Group operations involve **split-apply-combine** sub-operations.
- **Grouping key**
  - **A list** or array of values of same length as the values 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**



10.1 GroupBy Mechanics

- **Example**: Group by a column
- Compute the **mean** of the **data1** using the labels from **key1**.
- The **groupby** method gives an object that can apply some operation to each of the groups.

```
df
  key1 key2     data1     data2
0    a  one  1.303569  1.411498
1    a  two  0.792029 -1.116429
2    b  one -0.422705  0.589257
3    b  two -0.654579 -0.533492
4    a  one  0.567334 -1.029506
```

```
grouped = df['data1'].groupby(
                    df['key1'])
grouped
<pandas.core.groupby.SeriesGrou
pBy object at 0x7faa315[?]7390>

grouped.mean()
key1
a     0.746672
b    -0.537585
grouped.size()
key1
a     3
b     2
```

The values and the keys can be default, one, or multiple columns.

Iterating Over Groups

- The **GroupBy** object **supports iteration**.
- Or the pieces can be put in a **`dict`**.

```
pieces = dict(list(df.groupby(
                    'key1')))
pieces['b']
      data1     data2 key1 key2
2 -0.519439  0.281746    b  one
3 -0.555730  0.769023    b  two
```

```
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
…
```

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 column **subsetting** for aggregation.

- Can get a **Series** when a single column name is passed.

```
df.groupby(['key1', 'key2'])
                  [['data2']].mean()
                data2
key1 key2
a    one     0.190996
     two    -1.116429
b    one     0.589257
     two    -0.533492
```

Hierarchical index

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

Grouping with Dicts and Series

- Grouping information may exist in a **dictionary** or a **series**.
- **Example**: Group by mapping:

```
mapping = {'a': 'red', 'b': 'red',
    'c': 'blue', 'd': 'blue', 'e':
    'red', 'f' : 'orange'}
```

```
by_column = people.groupby(mapping,
                           axis=1)
```

```
by_column.sum()
             blue       red
Joe      1.148819  2.478529
Steve   -3.498286  0.783905
Wes     -0.505604  0.442407
Jim      1.265539 -2.598872
Travis   0.691711  1.255747
```

```
people
               a         b         c         d         e
Joe    -1.403637  2.135849  1.131019  0.017800  1.746317
Steve   0.313654  0.694288 -2.342447 -1.155839 -0.224036
Wes     1.863238       NaN       NaN -0.505604 -1.420831
Jim    -0.539711 -0.887612  1.136920  0.128619 -1.171549
Travis -0.919159  1.603411 -0.469481  1.161192  0.571495
```

Grouping with Functions

- Any **function** passed as a group key will be **called once per index value**.
- **Example**: Group by length of index.

```
people.groupby(len).sum()
          a         b         c         d         e
3 -0.080110  1.248237  2.267939 -0.359185 -0.846063
5  0.313654  0.694288 -2.342447 -1.155839 -0.224036
6 -0.919159  1.603411 -0.469481  1.161192  0.571495
```

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10.2 Data Aggregation

Fast

- Aggregations refer to any data transformation that produces **scalar values from arrays**.
- You can use your **own** aggregation **function**.

```
def peak_to_peak(arr):
    return arr.max() - arr.min()
grouped.agg(peak_to_peak)
```

- Some **other methods** also work.

Table 10-1. 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

```
grouped.describe()
```

Column-Wise and Multiple Function Application

- Pandas allows you to aggregate using a **different function** depending on the column, or **multiple functions** at once.

Example:
```
grouped.agg({'tip' : np.max,
             'size' : 'sum'})
```

```
tips = pd.read_csv(
                    'examples/tips.csv')
tips['tip_pct'] = tips['tip'] /
                    tips['total_bill']
grouped = tips.groupby(['day',
                        'smoker'])
functions = ['count', 'mean',
             'max']
result = grouped['tip_pct',
         'total_bill'].agg(functions)
```

```
result
          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
```

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10.3 Apply: General split-apply-combine

- The **most general-purpose** GroupBy method is `apply`.
- `apply` applies the function to each group.
- `agg` aggregates each column for each group, so you end up with one value per column per group.
- **Example**: Filling missing values with group-specific values

```
data
Ohio          0.922264
New York     -2.153545
Vermont            NaN
Florida      -0.375842
Oregon        0.329939
Nevada             NaN
California    1.105913
Idaho              NaN
```

East

West

Example: Filling Missing Values with Group-Specific Values

```
group_key = ['East'] * 4 +
            ['West'] * 4

data.groupby(group_key).mean()
East -0.535707
West  0.717926

fill_mean = lambda g:
                g.fillna(g.mean())
```

```
data.groupby(group_key).apply(
                        fill_mean)
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
```

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Pivot Tables

- DataFrame has **pivot_table** that performs groupby operations and adds partial totals (**margins**).

```
tips.pivot_table('tip_pct',
     index=['time', 'smoker'],
     columns='day', aggfunc='mean',
     margins=True)
```

```
day                Fri       Sat       Sun      Thur       All
time   smoker
Dinner No     0.139622  0.158048  0.160113  0.159744  0.158653
       Yes    0.165347  0.147906  0.187250       NaN  0.160828
Lunch  No     0.187735       NaN       NaN  0.160311  0.160920
       Yes    0.188937       NaN       NaN  0.163863  0.170404
All           0.169913  0.153152  0.166897  0.161276  0.160803
```

Cross-Tabulation

- A **cross-tabulation** (`crosstab`) is a special case of a pivot table that computes **group frequencies**.

```
pd.crosstab([tips.time, tips.day],
            tips.smoker,
            margins=True)
```

```
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
```

Summary

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