MERGING DATAFRAMES WITH PANDAS

Reading multiple data files

Tools for pandas data import

- pd.read_csv() for CSV files
  - dataframe = pd.read_csv(filepath)
  - dozens of optional input parameters
- Other data import tools:
  - pd.read_excel()
  - pd.read_html()
  - pd.read_json()

Loading separate files

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

In [2]: dataframe0 = pd.read_csv('sales-jan-2015.csv')

In [3]: dataframe1 = pd.read_csv('sales-feb-2015.csv')
```

Using a loop

```
In [4]: filenames = ['sales-jan-2015.csv', 'sales-feb-2015.csv']

In [5]: dataframes = []

In [6]: for f in filenames:
   ...:     dataframes.append(pd.read_csv(f))
```

Using a comprehension

```
In [7]: filenames = ['sales-jan-2015.csv', 'sales-feb-2015.csv']

In [8]: dataframes = [pd.read_csv(f) for f in filenames]
```

Using glob

```
In [9]: from glob import glob

In [10]: filenames = glob('sales*.csv')

In [11]: dataframes = [pd.read_csv(f) for f in filenames]
```

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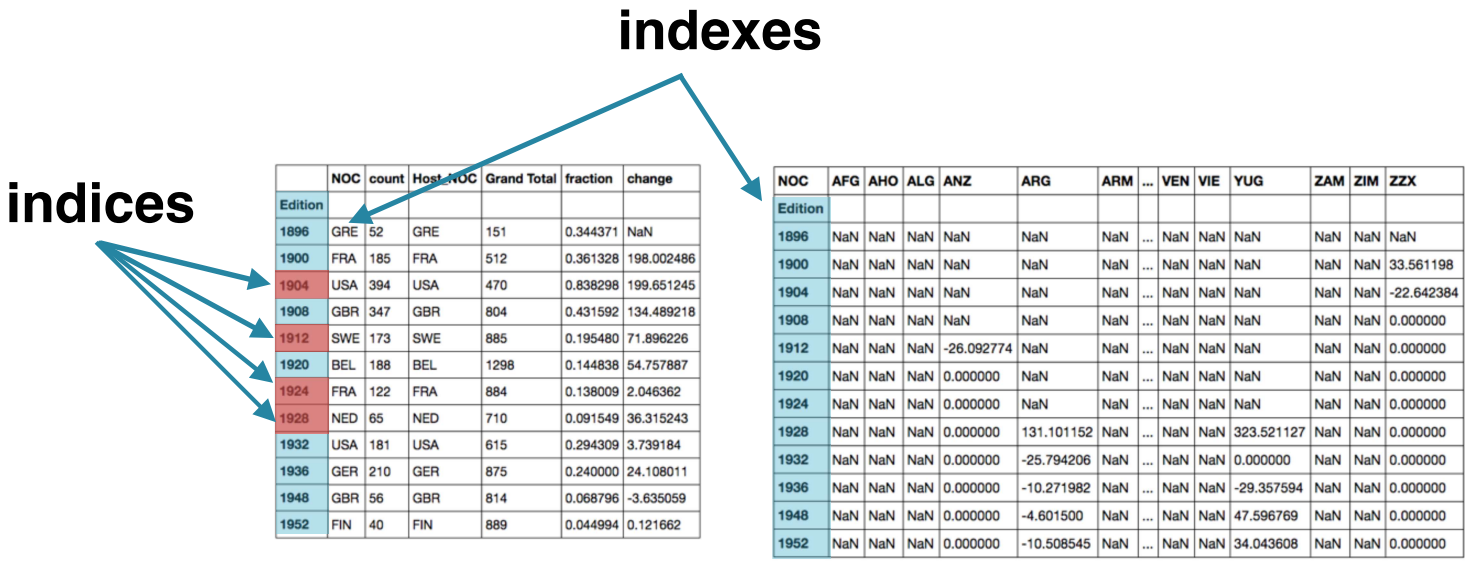
Reindexing DataFrames

"Indexes" vs. "Indices"

- *indices*: many *index labels* within *Index data structures*
- *indexes*: many pandas *Index data structures*



	NOC	count	Host NOC	Grand Total	fraction	change
Edition						
1896	GRE	52	GRE	151	0.344371	NaN
1900	FRA	185	FRA	512	0.361328	198.002486
1904	USA	394	USA	470	0.838298	199.651245
1908	GBR	347	GBR	804	0.431592	134.489218
1912	SWE	173	SWE	885	0.195480	71.896226
1920	BEL	188	BEL	1298	0.144838	54.757887
1924	FRA	122	FRA	884	0.138009	2.046362
1928	NED	65	NED	710	0.091549	36.315243
1932	USA	181	USA	615	0.294309	3.739184
1936	GER	210	GER	875	0.240000	24.108011
1948	GBR	56	GBR	814	0.068796	-3.635059
1952	FIN	40	FIN	889	0.044994	0.121662

NOC	AFG	AHO	ALG	ANZ	ARG	ARM	...	VEN	VIE	YUG	ZAM	ZIM	ZZX
Edition													
1896	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	NaN
1900	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	33.561198
1904	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	-22.642384
1908	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	0.000000
1912	NaN	NaN	NaN	-26.092774	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	0.000000
1920	NaN	NaN	NaN	0.000000	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	0.000000
1924	NaN	NaN	NaN	0.000000	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	0.000000
1928	NaN	NaN	NaN	0.000000	131.101152	NaN	...	NaN	NaN	323.521127	NaN	NaN	0.000000
1932	NaN	NaN	NaN	0.000000	-25.794206	NaN	...	NaN	NaN	0.000000	NaN	NaN	0.000000
1936	NaN	NaN	NaN	0.000000	-10.271982	NaN	...	NaN	NaN	-29.357594	NaN	NaN	0.000000
1948	NaN	NaN	NaN	0.000000	-4.601500	NaN	...	NaN	NaN	47.596769	NaN	NaN	0.000000
1952	NaN	NaN	NaN	0.000000	-10.508545	NaN	...	NaN	NaN	34.043608	NaN	NaN	0.000000

Importing weather data

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

In [2]: w_mean = pd.read_csv('quarterly_mean_temp.csv', index_col='Month')

In [3]: w_max = pd.read_csv('quarterly_max_temp.csv', index_col='Month')
```

Examining the data

```
In [4]: print(w_mean)
       Mean TemperatureF
Month
Apr            61.956044
Jan            32.133333
Jul            68.934783
Oct            43.434783

In [5]: print(w_max)
       Max TemperatureF
Month
Jan                  68
Apr                  89
Jul                  91
Oct                  84
```

The DataFrame indexes

```
In [6]: print(w_mean.index)
Index(['Apr', 'Jan', 'Jul', 'Oct'], dtype='object', name='Month')

In [7]: print(w_max.index)
Index(['Jan', 'Apr', 'Jul', 'Oct'], dtype='object', name='Month')

In [8]: print(type(w_mean.index))
<class 'pandas.indexes.base.Index'>
```

Using .reindex()

```
In [9]: ordered = ['Jan', 'Apr', 'Jul', 'Oct']

In [10]: w_mean2 = w_mean.reindex(ordered)

In [11]: print(w_mean2)
       Mean TemperatureF
Month
Jan            32.133333
Apr            61.956044
Jul            68.934783
Oct            43.434783
```

Using .sort_index()

```
In [12]: w_mean2.sort_index()
Out[12]:
       Mean TemperatureF
Month
Apr            61.956044
Jan            32.133333
Jul            68.934783
Oct            43.434783
```

Reindex from a DataFrame Index

```
In [13]: w_mean.reindex(w_max.index)
Out[13]:
       Mean TemperatureF
Month
Jan            32.133333
Apr            61.956044
Jul            68.934783
Oct            43.434783
```

Reindexing with missing labels

```
In [14]: w_mean3 = w_mean.reindex(['Jan', 'Apr', 'Dec'])

In [15]: print(w_mean3)
       Mean TemperatureF
Month
Jan             32.133333
Apr             61.956044
Dec                   NaN
```

Reindex from a DataFrame Index

```
In [16]: w_max.reindex(w_mean3.index)
Out[16]:
       Max TemperatureF
Month
Jan                68.0
Apr                89.0
Dec                 NaN

In [17]: w_max.reindex(w_mean3.index).dropna()
Out[17]:
       Max TemperatureF
Month
Jan                68.0
Apr                89.0
```

Order matters

```
In [18]: w_max.reindex(w_mean.index)
Out[18]:
       Max TemperatureF
Month
Apr                  89
Jan                  68
Jul                  91
Oct                  84

In [19]: w_mean.reindex(w_max.index)
Out[19]:
       Mean TemperatureF
Month
Jan            32.133333
Apr            61.956044
Jul            68.934783
Oct            43.434783
```

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Arithmetic with Series & DataFrames

Loading weather data

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

In [2]: weather = pd.read_csv('pittsburgh2013.csv',
   ...:                       index_col='Date', parse_dates=True)

In [3]: weather.loc['2013-7-1':'2013-7-7', 'PrecipitationIn']
Out[3]:
Date
2013-07-01    0.18
2013-07-02    0.14
2013-07-03    0.00
2013-07-04    0.25
2013-07-05    0.02
2013-07-06    0.06
2013-07-07    0.10
Name: PrecipitationIn, dtype: float64
```

Scalar multiplication

```
In [4]: weather.loc['2013-07-01':'2013-07-07', 'PrecipitationIn'] * 2.54
Out[4]:
Date
2013-07-01    0.4572
2013-07-02    0.3556
2013-07-03    0.0000
2013-07-04    0.6350
2013-07-05    0.0508
2013-07-06    0.1524
2013-07-07    0.2540
Name: PrecipitationIn, dtype: float64
```

Absolute temperature range

```
In [5]: week1_range = weather.loc['2013-07-01':'2013-07-07',
   ...:                           ['Min TemperatureF', 'Max TemperatureF']]

In [6]: print(week1_range)
            Min TemperatureF  Max TemperatureF
Date
2013-07-01                66                79
2013-07-02                66                84
2013-07-03                71                86
2013-07-04                70                86
2013-07-05                69                86
2013-07-06                70                89
2013-07-07                70                77
```

Average temperature

```
In [7]: week1_mean = weather.loc['2013-07-01':'2013-07-07',
   ...:                          'Mean TemperatureF']

In [8]: print(week1_mean)
Date
2013-07-01    72
2013-07-02    74
2013-07-03    78
2013-07-04    77
2013-07-05    76
2013-07-06    78
2013-07-07    72
Name: Mean TemperatureF, dtype: int64
```

Relative temperature range

```
In [9]: week1_range / week1_mean
RuntimeWarning: Cannot compare type 'Timestamp' with type 'str', sort order is
undefined for incomparable objects
  return this.join(other, how=how, return_indexers=return_indexers)
Out[9]:
            2013-07-01 00:00:00  2013-07-02 00:00:00  2013-07-03 00:00:00  \
Date
2013-07-01                  NaN                  NaN                  NaN
2013-07-02                  NaN                  NaN                  NaN
2013-07-03                  NaN                  NaN                  NaN
2013-07-04                  NaN                  NaN                  NaN
2013-07-05                  NaN                  NaN                  NaN
2013-07-06                  NaN                  NaN                  NaN
2013-07-07                  NaN                  NaN                  NaN

            2013-07-04 00:00:00  2013-07-05 00:00:00  2013-07-06 00:00:00  \
Date
2013-07-01                  NaN                  NaN                  NaN
... ...
```

Relative temperature range

```
In [10]: week1_range.divide(week1_mean, axis='rows')
Out[10]:
            Min TemperatureF  Max TemperatureF
Date
2013-07-01          0.916667          1.097222
2013-07-02          0.891892          1.135135
2013-07-03          0.910256          1.102564
2013-07-04          0.909091          1.116883
2013-07-05          0.907895          1.131579
2013-07-06          0.897436          1.141026
2013-07-07          0.972222          1.069444
```

Percentage changes

```
In [11]: week1_mean.pct_change() * 100
Out[11]:
Date
2013-07-01          NaN
2013-07-02     2.777778
2013-07-03     5.405405
2013-07-04    -1.282051
2013-07-05    -1.298701
2013-07-06     2.631579
2013-07-07    -7.692308
Name: Mean TemperatureF, dtype: float64
```

Bronze Olympic medals

```
In [12]: bronze = pd.read_csv('bronze_top5.csv', index_col=0)

In [13]: print(bronze)
                 Total
Country
United States   1052.0
Soviet Union     584.0
United Kingdom   505.0
France           475.0
Germany          454.0
```

Silver Olympic medals

```
In [14]: silver = pd.read_csv('silver_top5.csv', index_col=0)

In [15]: print(silver)
                 Total
Country
United States   1195.0
Soviet Union     627.0
United Kingdom   591.0
France           461.0
Italy            394.0
```

Gold Olympic medals

```
In [16]: gold = pd.read_csv('gold_top5.csv', index_col=0)

In [17]: print(gold)
                  Total
Country
United States    2088.0
Soviet Union      838.0
United Kingdom    498.0
Italy             460.0
Germany           407.0
```

Adding bronze, silver

```
In [18]: bronze + silver
Out[18]:
Country
France                936.0
Germany                 NaN
Italy                   NaN
Soviet Union         1211.0
United Kingdom       1096.0
United States        2247.0
Name: Total, dtype: float64
```

Adding bronze, silver

```
In [19]: bronze + silver
Out[19]:
Country
France              936.0
Germany               NaN
Italy                 NaN
Soviet Union       1211.0
United Kingdom     1096.0
United States      2247.0
Name: Total, dtype: float64

In [22]: print(bronze['United States'])
1052.0

In [23]: print(silver['United States'])
1195.0
```

Using the .add() method

```
In [21]: bronze.add(silver)

Out[21]:
Country
France                936.0
Germany                 NaN
Italy                   NaN
Soviet Union         1211.0
United Kingdom       1096.0
United States        2247.0
Name: Total, dtype: float64
```

Using a fill_value

```
In [22]: bronze.add(silver, fill_value=0)
Out[22]:
Country
France              936.0
Germany             454.0
Italy               394.0
Soviet Union       1211.0
United Kingdom     1096.0
United States      2247.0
Name: Total, dtype: float64
```

Adding bronze, silver, gold

```
In [23]: bronze + silver + gold
Out[23]:
Country
France                 NaN
Germany                NaN
Italy                  NaN
Soviet Union        2049.0
United Kingdom      1594.0
United States       4335.0
Name: Total, dtype: float64
```

Chaining .add()

```
In [24]: bronze.add(silver, fill_value=0).add(gold, fill_value=0)
Out[24]:
Country
France              936.0
Germany             861.0
Italy               854.0
Soviet Union       2049.0
United Kingdom     1594.0
United States      4335.0
Name: Total, dtype: float64
```

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Appending & concatenating Series

append()

- .append(): Series & DataFrame *method*
- Invocation:
  - s1.append(s2)
- Stacks rows of s2 below s1
- Method for Series & DataFrames

concat()

- concat(): pandas module *function*
- Invocation:
  - pd.concat([s1, s2, s3])
- Can stack row-wise or column-wise

concat() & .append()

- Equivalence of concat() & .append():
  - result1 = pd.concat([s1, s2, s3])
  - result2 = s1.append(s2).append(s3)
- result1 == result2 elementwise

Series of US states

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

In [2]: northeast = pd.Series(['CT', 'ME', 'MA', 'NH', 'RI', 'VT',
   ...: 'NJ', 'NY', 'PA'])

In [3]: south = pd.Series(['DE', 'FL', 'GA', 'MD', 'NC', 'SC', 'VA',
   ...: 'DC', 'WV', 'AL', 'KY', 'MS', 'TN', 'AR', 'LA', 'OK', 'TX'])

In [4]: midwest = pd.Series(['IL', 'IN', 'MN', 'MO', 'NE', 'ND',
   ...: 'SD', 'IA', 'KS', 'MI', 'OH', 'WI'])

In [5]: west = pd.Series(['AZ', 'CO', 'ID', 'MT', 'NV', 'NM',
   ...: 'UT', 'WY', 'AK', 'CA', 'HI', 'OR','WA'])
```

Using .append()

```
In [6]: east = northeast.append(south)

In [7]: print(east)
0      CT
1      ME
2      MA
3      NH
4      RI
5      VT
6      NJ
7      NY
8      PA
0      DE
1      FL
2      GA
3      MD
4      NC
5      SC
6      VA
7      DC
8      WV
9      AL
10     KY
11     MS
12     TN
13     AR
14     LA
15     OK
16     TX
dtype: object
```

The appended Index

```
In [8]: print(east.index)
Int64Index([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  0,  1,  2,  3, 4,
             5,  6,  7, 8,  9, 10, 11, 12, 13, 14, 15, 16], dtype='int64')

In [9]: print(east.loc[3])
3    NH
3    MD
dtype: object
```

Using .reset_index()

```
In [10]: new_east = northeast.append(south).reset_index(drop=True)

In [11]: print(new_east.head(11))
0     CT
1     ME
2     MA
3     NH
4     RI
5     VT
6     NJ
7     NY
8     PA
9     DE
10    FL
dtype: object

In [12]: print(new_east.index)
RangeIndex(start=0, stop=26, step=1)
```

Using concat()

```
In [13]: east = pd.concat([northeast, south])

In [14]: print(east.head(11))
0    CT
1    ME
2    MA
3    NH
4    RI
5    VT
6    NJ
7    NY
8    PA
0    DE
1    FL
dtype: object

In [15]: print(east.index)
Int64Index([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  0,  1,  2,  3,  4,
             5,  6,  7, 8,  9, 10, 11, 12, 13, 14, 15, 16], dtype='int64')
```

Using ignore_index

```
In [16]: new_east = pd.concat([northeast, south],
    ...:                      ignore_index=True)

In [17]: print(new_east.head(11))
0     CT
1     ME
2     MA
3     NH
4     RI
5     VT
6     NJ
7     NY
8     PA
9     DE
10    FL
dtype: object

In [18]: print(new_east.index)
RangeIndex(start=0, stop=26, step=1)
```

MERGING DATAFRAMES WITH PANDAS

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MERGING DATAFRAMES WITH PANDAS

Appending & concatenating DataFrames

Loading population data

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

In [2]: pop1 = pd.read_csv('population_01.csv', index_col=0)

In [3]: pop2 = pd.read_csv('population_02.csv', index_col=0)

In [4]: print(type(pop1), pop1.shape)
<class 'pandas.core.frame.DataFrame'> (4, 1)

In [5]: print(type(pop2), pop2.shape)
<class 'pandas.core.frame.DataFrame'> (4, 1)
```

Examining population data

```
In [6]: print(pop1)
                2010 Census Population
Zip Code ZCTA
66407                                479
72732                               4716
50579                               2405
46241                              30670

In [7]: print(pop2)
                2010 Census Population
Zip Code ZCTA
12776                               2180
76092                              26669
98360                              12221
49464                              27481
```

Appending population DataFrames

```
In [8]:  pop1.append(pop2)
Out[8]:
                2010 Census Population
Zip Code ZCTA
66407                              479
72732                             4716
50579                             2405
46241                            30670
12776                             2180
76092                            26669
98360                            12221
49464                            27481

In [9]: print(pop1.index.name, pop1.columns)
Zip Code ZCTA Index(['2010 Census Population'], dtype='object')

In [10]: print(pop2.index.name, pop2.columns)
Zip Code ZCTA Index(['2010 Census Population'], dtype='object')
```

Population & unemployment data

```
In [11]: population = pd.read_csv('population_00.csv',
    ...:                          index_col=0)

In [12]: unemployment = pd.read_csv('unemployment_00.csv',
                                    index_col=0)

In [13]: print(population)
               2010 Census Population
Zip Code ZCTA
57538                             322
59916                             130
37660                           40038
2860                            45199

In [14]: print(unemployment)
       unemployment  participants
Zip
2860           0.11         34447
46167          0.02          4800
1097           0.33            42
80808          0.07          4310
```

Appending population & unemployment

```
In [15]: population.append(unemployment)
Out[15]:
       2010 Census Population  participants  unemployment
57538                   322.0           NaN           NaN
59916                   130.0           NaN           NaN
37660                 40038.0           NaN           NaN
2860                  45199.0           NaN           NaN
2860                      NaN       34447.0          0.11
46167                     NaN        4800.0          0.02
1097                      NaN          42.0          0.33
80808                     NaN        4310.0          0.07
```

Repeated index labels

```
In [15]: population.append(unemployment)
Out[15]:
       2010 Census Population  participants  unemployment
57538                   322.0           NaN           NaN
59916                   130.0           NaN           NaN
37660                 40038.0           NaN           NaN
2860                  45199.0           NaN           NaN
2860                      NaN       34447.0          0.11
46167                     NaN        4800.0          0.02
1097                      NaN          42.0          0.33
80808                     NaN        4310.0          0.07
```

Concatenating rows

```
In [16]: pd.concat([population, unemployment], axis=0)
Out[16]:
       2010 Census Population  participants  unemployment
57538                   322.0           NaN           NaN
59916                   130.0           NaN           NaN
37660                 40038.0           NaN           NaN
2860                  45199.0           NaN           NaN
2860                      NaN       34447.0          0.11
46167                     NaN        4800.0          0.02
1097                      NaN          42.0          0.33
80808                     NaN        4310.0          0.07
```

Concatenating columns

```
In [17]: pd.concat([population, unemployment], axis=1)
Out[17]:
       2010 Census Population  unemployment  participants
1097                      NaN          0.33          42.0
2860                  45199.0          0.11       34447.0
37660                 40038.0           NaN           NaN
46167                     NaN          0.02        4800.0
57538                   322.0           NaN           NaN
59916                   130.0           NaN           NaN
80808                     NaN          0.07        4310.0
```

MERGING DATAFRAMES WITH PANDAS

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MERGING DATAFRAMES WITH PANDAS

Concatenation, keys, & MultiIndexes

Loading rainfall data

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

In [2]: file1 = 'q1_rainfall_2013.csv'

In [3]: rain2013 = pd.read_csv(file1, index_col='Month', parse_dates=True)

In [4]: file2 = 'q1_rainfall_2014.csv'

In [5]: rain2014 = pd.read_csv(file2, index_col='Month', parse_dates=True)
```

Examining rainfall data

```
In [6]: print(rain2013)
       Precipitation
Month
Jan            0.096129
Feb            0.067143
Mar            0.061613

In [7]: print(rain2014)
       Precipitation
Month
Jan            0.050323
Feb            0.082143
Mar            0.070968
```

Concatenating rows

```
In [8]: pd.concat([rain2013, rain2014], axis=0)
Out[8]:
     Precipitation
Jan       0.096129
Feb       0.067143
Mar       0.061613
Jan       0.050323
Feb       0.082143
Mar       0.070968
```

Using multi-index on rows

```
In [7]: rain1314 = pd.concat([rain2013, rain2014], keys=[2013, 2014], axis=0)

In [8]: print(rain1314)
          Precipitation
2013 Jan       0.096129
     Feb       0.067143
     Mar       0.061613
2014 Jan       0.050323
     Feb       0.082143
     Mar       0.070968
```

Accessing a multi-index

```
In [9]: print(rain1314.loc[2014])
     Precipitation
Jan       0.050323
Feb       0.082143
Mar       0.070968
```

Concatenating columns

```
In [10]: rain1314 = pd.concat([rain2013, rain2014], axis='columns')

In [11]: print(rain1314)
     Precipitation  Precipitation
Jan       0.096129       0.050323
Feb       0.067143       0.082143
Mar       0.061613       0.070968
```

Using a multi-index on columns

```
In [12]: rain1314 = pd.concat([rain2013, rain2014], keys=[2013, 2014], axis='columns')

In [13]: print(rain1314)

          2013          2014
Precipitation Precipitation
Jan      0.096129      0.050323
Feb      0.067143      0.082143
Mar      0.061613      0.070968

In [14]: rain1314[2013]
Out[14]:
     Precipitation
Jan       0.096129
Feb       0.067143
Mar       0.061613
```

pd.concat() with dict

```
In [15]: rain_dict = {2013: rain2013, 2014: rain2014}

In [16]: rain1314 = pd.concat(rain_dict, axis='columns')

In [17]: print(rain1314)
             2013          2014
    Precipitation Precipitation
Jan      0.096129      0.050323
Feb      0.067143      0.082143
Mar      0.061613      0.070968
```

MERGING DATAFRAMES WITH PANDAS

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MERGING DATAFRAMES WITH PANDAS

Outer & inner joins

Using with arrays

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

In [2]: import pandas as pd

In [3]: A = np.arange(8).reshape(2,4) + 0.1

In [4]: print(A)
[[ 0.1  1.1  2.1  3.1]
 [ 4.1  5.1  6.1  7.1]]

In [5]: B = np.arange(6).reshape(2,3) + 0.2

In [6]:print(B)
[[ 0.2  1.2  2.2]
 [ 3.2  4.2  5.2]]

In [7]: C = np.arange(12).reshape(3,4) + 0.3

In [8]: print(C)
[[  0.3   1.3   2.3   3.3]
 [  4.3   5.3   6.3   7.3]
 [  8.3   9.3  10.3  11.3]]
```

Stacking arrays horizontally

```
In [6]: np.hstack([B, A])
Out[6]:
array([[ 0.2,  1.2,  2.2,  0.1,  1.1,  2.1,  3.1],
       [ 3.2,  4.2,  5.2,  4.1,  5.1,  6.1,  7.1]])

In [7]: np.concatenate([B, A], axis=1)
Out[7]:
array([[ 0.2,  1.2,  2.2,  0.1,  1.1,  2.1,  3.1],
       [ 3.2,  4.2,  5.2,  4.1,  5.1,  6.1,  7.1]])
```

Stacking arrays vertically

```
In [8]: np.vstack([A, C])
Out[8]:
array([[  0.1,   1.1,   2.1,   3.1],
       [  4.1,   5.1,   6.1,   7.1],
       [  0.3,   1.3,   2.3,   3.3],
       [  4.3,   5.3,   6.3,   7.3],
       [  8.3,   9.3,  10.3,  11.3]])

In [9]: np.concatenate([A, C], axis=0)
Out[9]:
array([[  0.1,   1.1,   2.1,   3.1],
       [  4.1,   5.1,   6.1,   7.1],
       [  0.3,   1.3,   2.3,   3.3],
       [  4.3,   5.3,   6.3,   7.3],
       [  8.3,   9.3,  10.3,  11.3]])
```

Incompatible array dimensions

```
In [11]: np.concatenate([A, B], axis=0) # incompatible columns
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
----> 1 np.concatenate([A, B], axis=0) # incompatible columns

ValueError: all the input array dimensions except for the concatenation axis must match
exactly

In [12]: np.concatenate([A, C], axis=1) # incompatible rows
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
----> 1 np.concatenate([A, C], axis=1) # incompatible rows

ValueError: all the input array dimensions except for the concatenation axis must match
exactly
```

Population & unemployment data

```
In [13]: population = pd.read_csv('population_00.csv',
    ...:                          index_col=0)

In [14]: unemployment = pd.read_csv('unemployment_00.csv',
                                    ...index_col=0)

In [15]: print(population)
              2010 Census Population
Zip Code ZCTA
57538                            322
59916                            130
37660                          40038
2860                           45199

In [16]: print(unemployment)
       unemployment  participants
Zip
2860           0.11         34447
46167          0.02          4800
1097           0.33            42
80808          0.07          4310
```

Converting to arrays

```
In [17]: population_array = np.array(population)

In [18]: print(population_array) # Index info is lost
[[  322]
 [  130]
 [40038]
 [45199]]

In [19]: unemployment_array = np.array(unemployment)

In [20]: print(population_array)
[[  1.10000000e-01   3.44470000e+04]
 [  2.00000000e-02   4.80000000e+03]
 [  3.30000000e-01   4.20000000e+01]
 [  7.00000000e-02   4.31000000e+03]]
```

Manipulating data as arrays

```
In [21]: print(np.concatenate([population_array, unemployment_array],
    ...:                      axis=1))
[[  3.22000000e+02   1.10000000e-01   3.44470000e+04]
 [  1.30000000e+02   2.00000000e-02   4.80000000e+03]
 [  4.00380000e+04   3.30000000e-01   4.20000000e+01]
 [  4.51990000e+04   7.00000000e-02   4.31000000e+03]]
```

Joins

- Joining tables: Combining rows of multiple tables
- Outer join
  - Union of index sets (all labels, no repetition)
  - Missing fields filled with NaN
- Inner join
  - Intersection of index sets (only common labels)

Concatenation & inner join

```
In [22]: pd.concat([population, unemployment], axis=1, join='inner')
Out[22]:
      2010 Census Population  unemployment  participants
2860                   45199          0.11         34447
```

Concatenation & outer join

```
In [23]: pd.concat([population, unemployment], axis=1, join='outer')
Out[23]:
       2010 Census Population  unemployment  participants
1097                      NaN          0.33          42.0
2860                  45199.0          0.11       34447.0
37660                 40038.0           NaN           NaN
46167                     NaN          0.02        4800.0
57538                   322.0           NaN           NaN
59916                   130.0           NaN           NaN
80808                     NaN          0.07        4310.0
```

Inner join on other axis

```
In [24]: pd.concat([population, unemployment], join='inner', axis=0)
Out[24]:
Empty DataFrame
Columns: []
Index: [2860, 46167, 1097, 80808, 57538, 59916, 37660, 2860]
```

MERGING DATAFRAMES WITH PANDAS

Let's practice!

MERGING DATAFRAMES WITH PANDAS

Merging DataFrames

Population DataFrame

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

In [2]: population = pd.read_csv('pa_zipcode_population.csv')

In [3]: print(population)
   Zipcode  2010 Census Population
0    16855                     282
1    15681                    5241
2    18657                   11985
3    17307                    5899
4    15635                     220
```

Cities DataFrame

```
In [4]: cities = pd.read_csv('pa_zipcode_city.csv')

In [5]: print(cities)
    Zipcode              City State
0     17545           MANHEIM    PA
1     18455     PRESTON PARK     PA
2     17307      BIGLERVILLE     PA
3     15705           INDIANA    PA
4     16833     CURWENSVILLE     PA
5     16220            CROWN     PA
6     18618     HARVEYS LAKE     PA
7     16855  MINERAL SPRINGS     PA
8     16623         CASSVILLE    PA
9     15635       HANNASTOWN     PA
10    15681        SALTSBURG     PA
11    18657      TUNKHANNOCK     PA
12    15279       PITTSBURGH     PA
13    17231        LEMASTERS     PA
14    18821       GREAT BEND     PA
```

Merging

```
In [6]: pd.merge(population, cities)
Out[6]:
   Zipcode  2010 Census Population             City State
0    16855                     282  MINERAL SPRINGS    PA
1    15681                    5241       SALTSBURG    PA
2    18657                   11985     TUNKHANNOCK    PA
3    17307                    5899     BIGLERVILLE    PA
4    15635                     220      HANNASTOWN    PA
```

Medal DataFrames

```
In [7]: bronze = pd.read_csv('bronze_sorted.csv')

In [8]: gold = pd.read_csv('gold_sorted.csv')

In [9]: print(bronze)
   NOC          Country   Total
0  USA    United States  1052.0
1  URS     Soviet Union   584.0
2  GBR  United Kingdom   505.0
3  FRA           France   475.0
4  GER          Germany   454.0

In [10]: print(gold)
   NOC          Country   Total
0  USA    United States  2088.0
1  URS     Soviet Union   838.0
2  GBR  United Kingdom   498.0
3  ITA           Italy   460.0
4  GER          Germany   407.0
```

Merging all columns

```
In [11]: pd.merge(bronze, gold)
Out[11]:
Empty DataFrame
Columns: [NOC, Country, Total]
Index: []
```

Merging on

```
In [12]: pd.merge(bronze, gold, on='NOC')
Out[12]:
   NOC       Country_x  Total_x       Country_y  Total_y
0  USA   United States   1052.0   United States   2088.0
1  URS    Soviet Union    584.0    Soviet Union    838.0
2  GBR  United Kingdom    505.0  United Kingdom    498.0
3  GER         Germany    454.0         Germany    407.0
```

Merging on multiple columns

```
In [13]: pd.merge(bronze, gold, on=['NOC', 'Country'])
Out[13]:
   NOC         Country  Total_x  Total_y
0  USA   United States   1052.0   2088.0
1  URS    Soviet Union    584.0    838.0
2  GBR  United Kingdom    505.0    498.0
3  GER         Germany    454.0    407.0
```

Using suffixes

```
In [14]: pd.merge(bronze, gold, on=['NOC', 'Country'], suffixes=['_bronze', '_gold'])
Out[14]:
   NOC         Country  Total_bronze  Total_gold
0  USA   United States        1052.0      2088.0
1  URS    Soviet Union         584.0       838.0
2  GBR  United Kingdom         505.0       498.0
3  GER         Germany         454.0       407.0
```

Counties DataFrame

```
In [15]: counties = pd.read_csv('pa_counties.csv')

In [16]: print(counties)
          CITY NAME    COUNTY NAME
0         SALTSBURG        INDIANA
1  MINERAL SPRINGS     CLEARFIELD
2       BIGLERVILLE          ADAMS
3        HANNASTOWN   WESTMORELAND
4       TUNKHANNOCK        WYOMING

In [17]: print(cities.tail())
    Zipcode          City State
10    15681     SALTSBURG    PA
11    18657  TUNKHANNOCK     PA
12    15279   PITTSBURGH     PA
13    17231    LEMASTERS     PA
14    18821   GREAT BEND     PA
```

Specifying columns to merge

```
In [18]: pd.merge(counties, cities, left_on='CITY NAME', right_on='City')
Out[18]:
          CITY NAME    COUNTY NAME  Zipcode              City State
0         SALTSBURG        INDIANA    15681         SALTSBURG    PA
1  MINERAL SPRINGS     CLEARFIELD    16855  MINERAL SPRINGS     PA
2      BIGLERVILLE          ADAMS    17307      BIGLERVILLE     PA
3       HANNASTOWN  WESTMORELAND    15635       HANNASTOWN     PA
4      TUNKHANNOCK        WYOMING    18657      TUNKHANNOCK     PA
```

Switching left/right DataFrames

```
In [19]: pd.merge(cities, counties, left_on='City', right_on='CITY NAME')
Out[19]:
   Zipcode              City State         CITY NAME     COUNTY NAME
0    17307         BIGLERVILLE    PA       BIGLERVILLE           ADAMS
1    16855  MINERAL SPRINGS    PA  MINERAL SPRINGS      CLEARFIELD
2    15635         HANNASTOWN    PA       HANNASTOWN    WESTMORELAND
3    15681          SALTSBURG    PA        SALTSBURG         INDIANA
4    18657       TUNKHANNOCK    PA       TUNKHANNOCK         WYOMING
```

MERGING DATAFRAMES WITH PANDAS

Let's practice!

MERGING DATAFRAMES WITH PANDAS

Joining DataFrames

Medal DataFrames

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

In [2]: bronze = pd.read_csv('bronze_sorted.csv')

In [3]: gold = pd.read_csv('gold_sorted.csv')

In [4]: print(bronze)
   NOC         Country   Total
0  USA   United States  1052.0
1  URS    Soviet Union   584.0
2  GBR  United Kingdom   505.0
3  FRA          France   475.0
4  GER         Germany   454.0

In [5]: print(gold)
   NOC         Country   Total
0  USA   United States  2088.0
1  URS    Soviet Union   838.0
2  GBR  United Kingdom   498.0
3  ITA           Italy   460.0
4  GER         Germany   407.0
```

Merging with inner join

```
In [6]: pd.merge(bronze, gold, on=['NOC', 'Country'],
   ...:          suffixes=['_bronze', '_gold'], how='inner')
Out[6]:
   NOC         Country  Total_bronze  Total_gold
0  USA   United States        1052.0      2088.0
1  URS    Soviet Union         584.0       838.0
2  GBR  United Kingdom         505.0       498.0
3  GER         Germany         454.0       407.0
```

Merging with left join

- Keeps all rows of the left DF in the merged DF
- For rows in the left DF with matches in the right DF:
  - Non-joining columns of right DF are appended to left DF
- For rows in the left DF with no matches in the right DF:
  - Non-joining columns are filled with nulls

Merging with left join

```
In [7]: pd.merge(bronze, gold, on=['NOC', 'Country'],
   ...:          suffixes=['_bronze', '_gold'], how='left')
Out[7]:
   NOC         Country  Total_bronze  Total_gold
0  USA   United States        1052.0      2088.0
1  URS    Soviet Union         584.0       838.0
2  GBR  United Kingdom         505.0       498.0
3  FRA          France         475.0         NaN
4  GER         Germany         454.0       407.0
```

Merging with right join

```
In [8]: pd.merge(bronze, gold, on=['NOC', 'Country'],
   ...:          suffixes=['_bronze', '_gold'], how='right')
Out[8]:
   NOC         Country  Total_bronze  Total_gold
0  USA   United States        1052.0      2088.0
1  URS    Soviet Union         584.0       838.0
2  GBR  United Kingdom         505.0       498.0
3  GER         Germany         454.0       407.0
4  ITA           Italy           NaN       460.0
```

Merging with outer join

```
In [9]: pd.merge(bronze, gold, on=['NOC', 'Country'],
   ...:          suffixes=['_bronze', '_gold'], how='outer')
Out[9]:
   NOC         Country  Total_bronze  Total_gold
0  USA   United States        1052.0      2088.0
1  URS    Soviet Union         584.0       838.0
2  GBR  United Kingdom         505.0       498.0
3  FRA          France         475.0         NaN
4  GER         Germany         454.0       407.0
5  ITA           Italy           NaN       460.0
```

Population & unemployment data

```
In [10]: population = pd.read_csv('population_00.csv', index_col=0)

In [11]: unemployment = pd.read_csv('unemployment_00.csv', index_col=0)

In [12]: print(population)
               2010 Census Population
Zip Code ZCTA
57538                             322
59916                             130
37660                           40038
2860                            45199

In [13]: print(unemployment)
       unemployment  participants
Zip
2860           0.11         34447
46167          0.02          4800
1097           0.33            42
80808          0.07          4310
```

Using .join(how='left')

```
In [16]: population.join(unemployment)
Out[16]:
                2010 Census Population  unemployment  participants
Zip Code ZCTA
57538                              322           NaN           NaN
59916                              130           NaN           NaN
37660                            40038           NaN           NaN
2860                             45199          0.11       34447.0
```

Using .join(how='right')

```
In [17]: population.join(unemployment, how= 'right')
Out[17]:
       2010 Census Population  unemployment  participants
Zip
2860                  45199.0          0.11         34447
46167                     NaN          0.02          4800
1097                      NaN          0.33            42
80808                     NaN          0.07          4310
```

Using .join(how='inner')

```
In [18]: population.join(unemployment, how='inner')
Out[18]:
      2010 Census Population  unemployment  participants
2860                   45199          0.11         34447
```

Using .join(how='outer')

```
In [19]: population.join(unemployment, how= 'outer')
Out[19]:
       2010 Census Population  unemployment  participants
1097                      NaN          0.33          42.0
2860                  45199.0          0.11       34447.0
37660                 40038.0           NaN           NaN
46167                     NaN          0.02        4800.0
57538                   322.0           NaN           NaN
59916                   130.0           NaN           NaN
80808                     NaN          0.07        4310.0
```

Which should you use?

- df1.append(df2): stacking vertically
- pd.concat([df1, df2]):
  - stacking many horizontally or vertically
  - simple inner/outer joins on Indexes
- df1.join(df2): inner/outer/left/right joins on Indexes
- pd.merge([df1, df2]): many joins on multiple columns

MERGING DATAFRAMES WITH PANDAS

Let's practice!

MERGING DATAFRAMES WITH PANDAS

Ordered merges

Software & hardware sales

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

In [2]: software = pd.read_csv('feb-sales-Software.csv', parse_dates=['Date'])
   ...:                .sort_values('Date')

In [3]: hardware = pd.read_csv('feb-sales-Hardware.csv', parse_dates=['Date'])
   ...:                .sort_values('Date')
```

Software & hardware sales

```
In [4]: print(software)
                  Date           Company   Product  Units
2 2015-02-02 08:33:01             Hooli  Software      3
1 2015-02-03 14:14:18           Initech  Software     13
7 2015-02-04 15:36:29         Streeplex  Software     13
3 2015-02-05 01:53:06  Acme Coporation   Software     19
5 2015-02-09 13:09:55         Mediacore  Software      7
4 2015-02-11 20:03:08           Initech  Software      7
6 2015-02-11 22:50:44             Hooli  Software      4
0 2015-02-16 12:09:19             Hooli  Software     10
8 2015-02-21 05:01:26         Mediacore  Software      3

In [5]: print(hardware)
                  Date           Company   Product  Units
3 2015-02-02 20:54:49         Mediacore  Hardware      9
0 2015-02-04 21:52:45  Acme Coporation   Hardware     14
1 2015-02-07 22:58:10  Acme Coporation   Hardware      1
2 2015-02-19 10:59:33         Mediacore  Hardware     16
4 2015-02-21 20:41:47             Hooli  Hardware      3
```

Using merge()

```
In [6]: pd.merge(hardware, software)
Out[6]:
Empty DataFrame
Columns: [Date, Company, Product, Units]
Index: []
```

Using merge(how='outer')

```
In [7]: pd.merge(hardware, software, how='outer')
Out[7]:
                  Date          Company   Product  Units
0  2015-02-02 20:54:49        Mediacore  Hardware      9
1  2015-02-04 21:52:45  Acme Coporation  Hardware     14
2  2015-02-07 22:58:10  Acme Coporation  Hardware      1
3  2015-02-19 10:59:33        Mediacore  Hardware     16
4  2015-02-21 20:41:47            Hooli  Hardware      3
5  2015-02-02 08:33:01            Hooli  Software      3
6  2015-02-03 14:14:18          Initech  Software     13
7  2015-02-04 15:36:29        Streeplex  Software     13
8  2015-02-05 01:53:06  Acme Coporation  Software     19
9  2015-02-09 13:09:55        Mediacore  Software      7
10 2015-02-11 20:03:08          Initech  Software      7
11 2015-02-11 22:50:44            Hooli  Software      4
12 2015-02-16 12:09:19            Hooli  Software     10
13 2015-02-21 05:01:26        Mediacore  Software      3
```

Sorting merge(how='outer')

```
In [8]: pd.merge(hardware, software, how='outer').sorted_values('Date')
Out[8]:
                  Date          Company   Product  Units
0  2015-02-02 20:54:49        Mediacore  Hardware      9
1  2015-02-04 21:52:45  Acme Coporation  Hardware     14
2  2015-02-07 22:58:10  Acme Coporation  Hardware      1
3  2015-02-19 10:59:33        Mediacore  Hardware     16
4  2015-02-21 20:41:47            Hooli  Hardware      3
5  2015-02-02 08:33:01            Hooli  Software      3
6  2015-02-03 14:14:18          Initech  Software     13
7  2015-02-04 15:36:29        Streeplex  Software     13
8  2015-02-05 01:53:06  Acme Coporation  Software     19
9  2015-02-09 13:09:55        Mediacore  Software      7
10 2015-02-11 20:03:08          Initech  Software      7
11 2015-02-11 22:50:44            Hooli  Software      4
12 2015-02-16 12:09:19            Hooli  Software     10
13 2015-02-21 05:01:26        Mediacore  Software      3
```

Using merge_ordered()

```
In [9]: pd.merge_ordered(hardware, software)
Out[9]:
                  Date          Company   Product  Units
0  2015-02-02 08:33:01            Hooli  Software    3.0
1  2015-02-02 20:54:49        Mediacore  Hardware    9.0
2  2015-02-03 14:14:18          Initech  Software   13.0
3  2015-02-04 15:36:29        Streeplex  Software   13.0
4  2015-02-04 21:52:45  Acme Coporation  Hardware   14.0
5  2015-02-05 01:53:06  Acme Coporation  Software   19.0
6  2015-02-07 22:58:10  Acme Coporation  Hardware    1.0
7  2015-02-09 13:09:55        Mediacore  Software    7.0
8  2015-02-11 20:03:08          Initech  Software    7.0
9  2015-02-11 22:50:44            Hooli  Software    4.0
10 2015-02-16 12:09:19            Hooli  Software   10.0
11 2015-02-19 10:59:33        Mediacore  Hardware   16.0
12 2015-02-21 05:01:26        Mediacore  Software    3.0
13 2015-02-21 20:41:47            Hooli  Hardware    3.0
```

Using on & suffixes

```
In [10]: pd.merge_ordered(hardware, software, on=['Date', 'Company'],
    ...:                  suffixes=['_hardware', '_software']).head()
Out[10]:
                  Date          Company Product_hardware  \
0 2015-02-02 08:33:01            Hooli              NaN
1 2015-02-02 20:54:49        Mediacore         Hardware
2 2015-02-03 14:14:18          Initech              NaN
3 2015-02-04 15:36:29        Streeplex              NaN
4 2015-02-04 21:52:45  Acme Coporation         Hardware

   Units_hardware Product_software  Units_software
0             NaN         Software             3.0
1             9.0              NaN             NaN
2             NaN         Software            13.0
3             NaN         Software            13.0
4            14.0              NaN             NaN
```

Stocks data

```
In [11]: stocks = pd.read_csv('stocks-2013.csv')

In [12]: print(stocks)
          Date        AAPL         IBM       CSCO       MSFT
0   2013-01-31  497.822381  197.271905  20.699524  27.236667
1   2013-02-28  456.808953  200.735788  20.988947  27.704211
2   2013-03-31  441.840998  210.978001  21.335000  28.141000
3   2013-04-30  419.764998  204.733636  20.914545  29.870909
4   2013-05-31  446.452730  205.263639  22.386364  33.950909
5   2013-06-30  425.537999  200.850000  24.375500  34.632500
6   2013-07-31  429.157272  194.354546  25.378636  33.650454
7   2013-08-31  484.843635  187.125000  24.948636  32.485000
8   2013-09-30  480.184499  188.767000  24.080000  32.523500
9   2013-10-31  504.744783  180.710002  22.847391  34.382174
10  2013-11-30  524.616499  181.333502  22.204000  37.362500
11  2013-12-31  559.657613  179.114763  21.257619  37.455715
```

GDP data

```
In [13]: gdp = pd.read_csv('gdp-2013.csv')

In [14]: print(gdp)
         Date      GDP
0  2012-03-31  15973.9
1  2012-06-30  16121.9
2  2012-09-30  16227.9
3  2012-12-31  16297.3
4  2013-03-31  16475.4
5  2013-06-30  16541.4
6  2013-09-30  16749.3
7  2013-12-31  16999.9
```

Ordered merge

```
In [15]: pd.merge_ordered(stocks, gdp, on='Date')
Out[15]:
          Date        AAPL         IBM       CSCO       MSFT      GDP
0   2012-03-31         NaN         NaN        NaN        NaN  15973.9
1   2012-06-30         NaN         NaN        NaN        NaN  16121.9
2   2012-09-30         NaN         NaN        NaN        NaN  16227.9
3   2012-12-31         NaN         NaN        NaN        NaN  16297.3
4   2013-01-31  497.822381  197.271905  20.699524  27.236667      NaN
5   2013-02-28  456.808953  200.735788  20.988947  27.704211      NaN
6   2013-03-31  441.840998  210.978001  21.335000  28.141000  16475.4
7   2013-04-30  419.764998  204.733636  20.914545  29.870909      NaN
8   2013-05-31  446.452730  205.263639  22.386364  33.950909      NaN
9   2013-06-30  425.537999  200.850000  24.375500  34.632500  16541.4
10  2013-07-31  429.157272  194.354546  25.378636  33.650454      NaN
11  2013-08-31  484.843635  187.125000  24.948636  32.485000      NaN
12  2013-09-30  480.184499  188.767000  24.080000  32.523500  16749.3
13  2013-10-31  504.744783  180.710002  22.847391  34.382174      NaN
14  2013-11-30  524.616499  181.333502  22.204000  37.362500      NaN
15  2013-12-31  559.657613  179.114763  21.257619  37.455715  16999.9
```

Ordered merge with ffill

```
In [16]: pd.merge_ordered(stocks, gdp, on='Date', fill_method='ffill')
Out[16]:
          Date        AAPL         IBM       CSCO       MSFT      GDP
0   2012-03-31         NaN         NaN        NaN        NaN  15973.9
1   2012-06-30         NaN         NaN        NaN        NaN  16121.9
2   2012-09-30         NaN         NaN        NaN        NaN  16227.9
3   2012-12-31         NaN         NaN        NaN        NaN  16297.3
4   2013-01-31  497.822381  197.271905  20.699524  27.236667  16297.3
5   2013-02-28  456.808953  200.735788  20.988947  27.704211  16297.3
6   2013-03-31  441.840998  210.978001  21.335000  28.141000  16475.4
7   2013-04-30  419.764998  204.733636  20.914545  29.870909  16475.4
8   2013-05-31  446.452730  205.263639  22.386364  33.950909  16475.4
9   2013-06-30  425.537999  200.850000  24.375500  34.632500  16541.4
10  2013-07-31  429.157272  194.354546  25.378636  33.650454  16541.4
11  2013-08-31  484.843635  187.125000  24.948636  32.485000  16541.4
12  2013-09-30  480.184499  188.767000  24.080000  32.523500  16749.3
13  2013-10-31  504.744783  180.710002  22.847391  34.382174  16749.3
14  2013-11-30  524.616499  181.333502  22.204000  37.362500  16749.3
15  2013-12-31  559.657613  179.114763  21.257619  37.455715  16999.9
```

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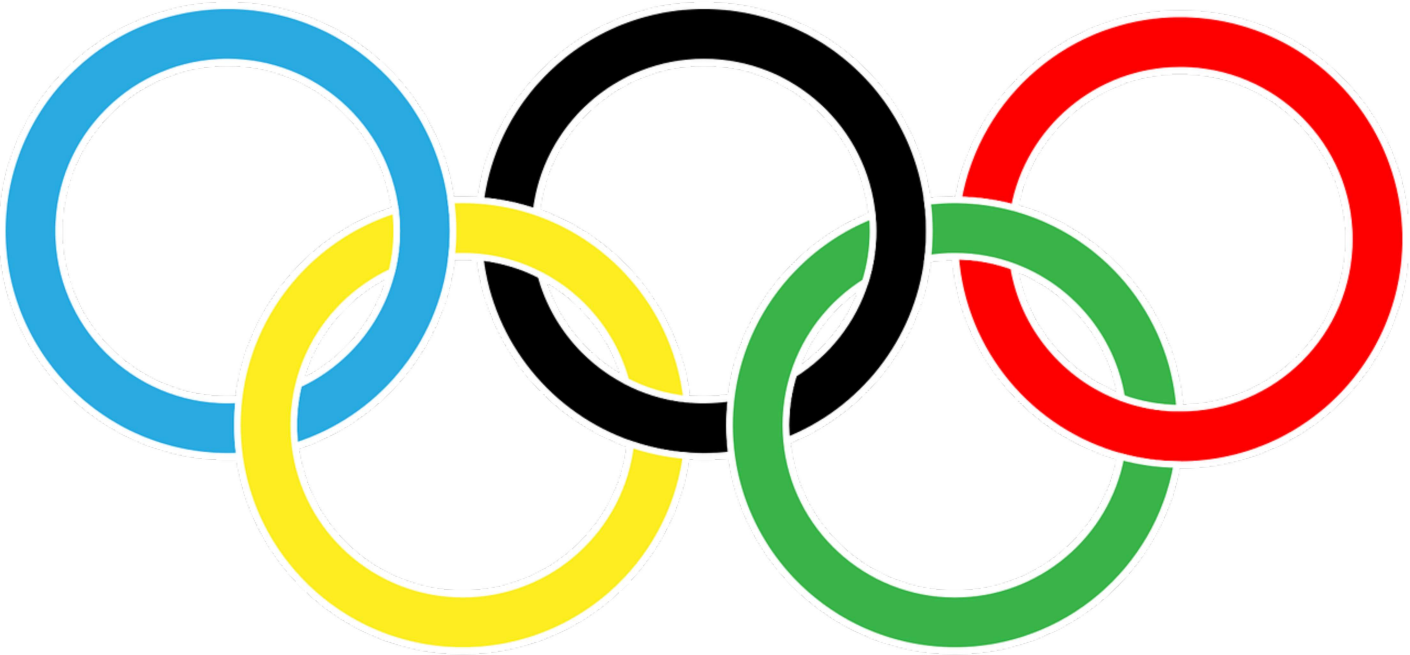
Medals in the Summer Olympics

Does a host country win more medals?



Summer Olympic medalists 1896 to 2008 - IOC COUNTRY CODES.csv

Country	NOC	ISO code
Afghanistan	AFG	AF
Albania	ALB	AL
Algeria	ALG	DZ
American Samoa*	ASA	AS
Andorra	AND	AD
Angola	ANG	AO
Antigua and Barbuda	ANT	AG
Argentina	ARG	AR
Armenia	ARM	AM
Aruba*	ARU	AW
Australia	AUS	AU
Austria	AUT	AT

Summer Olympic medalists 1896 to 2008 - EDITIONS.tsv

Edition	Bronze	Gold	Silver	Grand Total	City	Country
1896	40	64	47	151	Athens	Greece
1900	142	178	192	512	Paris	France
1904	123	188	159	470	St. Louis	United States
1908	211	311	282	804	London	United Kingdom
1912	284	301	300	885	Stockholm	Sweden
1920	355	497	446	1298	Antwerp	Belgium
1924	285	301	298	884	Paris	France
1928	242	229	239	710	Amsterdam	Netherlands
1932	196	213	206	615	Los Angeles	United States
1936	282	299	294	875	Berlin	Germany
1948	268	276	270	814	London	United Kingdom
1952	299	300	290	889	Helsinki	Finland

summer_1896.csv, summer_1900.csv, ..., summer_2008.csv

Sport	Discipline	Athlete	NOC	Gender	Event	Event_gender	Medal
Aquatics	Diving	XIAO, Hailiang	CHN	Men	10m platform	M	Bronze
Aquatics	Diving	SAUTIN, Dmitry	RUS	Men	10m platform	M	Gold
Aquatics	Diving	HEMPEL, Jan	GER	Men	10m platform	M	Silver
Aquatics	Diving	CLARK, Mary Ellen	USA	Women	10m platform	W	Bronze
Aquatics	Diving	FU, Mingxia	CHN	Women	10m platform	W	Gold
Aquatics	Diving	WALTER, Annika	GER	Women	10m platform	W	Silver
Aquatics	Diving	LENZI, Mark Edward	USA	Men	3m springboard	M	Bronze
Aquatics	Diving	XIONG, Ni	CHN	Men	3m springboard	M	Gold
Aquatics	Diving	YU, Zhuocheng	CHN	Men	3m springboard	M	Silver
Aquatics	Diving	PELLETIER, Annie	CAN	Women	3m springboard	W	Bronze
Aquatics	Diving	FU, Mingxia	CHN	Women	3m springboard	W	Gold
Aquatics	Diving	LASHKO, Irina	RUS	Women	3m springboard	W	Silver

Reminder: loading & merging files

- pd.read_csv() (& its many options)
- Looping over files, e.g.,
  - [pd.read_csv(f) for f in glob('*.csv')]
- Concatenating & appending, e.g.,
  - pd.concat([df1, df2], axis=0)
  - df1.append(df2)

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Quantifying performance

Medals DataFrame

	Sport	Discipline	Athlete	NOC	Gender	Event	Event_gender	Medal	Edition
0	Aquatics	Swimming	HAJOS, Alfred	HUN	Men	100m freestyle	M	Gold	1896
1	Aquatics	Swimming	HERSCHMANN, Otto	AUT	Men	100m freestyle	M	Silver	1896
2	Aquatics	Swimming	DRIVAS, Dimitrios	GRE	Men	100m freestyle for sailors	M	Bronze	1896
3	Aquatics	Swimming	MALOKINIS, Ioannis	GRE	Men	100m freestyle for sailors	M	Gold	1896
4	Aquatics	Swimming	CHASAPIS, Spiridon	GRE	Men	100m freestyle for sailors	M	Silver	1896
5	Aquatics	Swimming	CHOROPHAS, Efstathios	GRE	Men	1200m freestyle	M	Bronze	1896
6	Aquatics	Swimming	HAJOS, Alfred	HUN	Men	1200m freestyle	M	Gold	1896
7	Aquatics	Swimming	ANDREOU, Joannis	GRE	Men	1200m freestyle	M	Silver	1896
8	Aquatics	Swimming	CHOROPHAS, Efstathios	GRE	Men	400m freestyle	M	Bronze	1896
9	Aquatics	Swimming	NEUMANN, Paul	AUT	Men	400m freestyle	M	Gold	1896
10	Aquatics	Swimming	PEPANOS, Antonios	GRE	Men	400m freestyle	M	Silver	1896
11	Athletics	Athletics	LANE, Francis	USA	Men	100m	M	Bronze	1896

Constructing a pivot table

- Apply DataFrame pivot_table() method
  - index: column to use as index of pivot table
  - values: column(s) to aggregate
  - aggfunc: function to apply for aggregation
  - columns: categories as columns of pivot table

Constructing a pivot table

NOC	AFG	AHO	ALG	ANZ	ARG	ARM	AUS	AUT	AZE	BAH	...	URS	URU	USA	UZB	VEN	VIE	YUG	ZAM	ZIM	ZZX
Edition																					
1896	NaN	NaN	NaN	NaN	NaN	NaN	2.0	5.0	NaN	NaN	...	NaN	NaN	20.0	NaN	NaN	NaN	NaN	NaN	NaN	6.0
1900	NaN	NaN	NaN	NaN	NaN	NaN	5.0	6.0	NaN	NaN	...	NaN	NaN	55.0	NaN	NaN	NaN	NaN	NaN	NaN	34.0
1904	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1.0	NaN	NaN	...	NaN	NaN	394.0	NaN	NaN	NaN	NaN	NaN	NaN	8.0
1908	NaN	NaN	NaN	19.0	NaN	NaN	NaN	1.0	NaN	NaN	...	NaN	NaN	63.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1912	NaN	NaN	NaN	10.0	NaN	NaN	NaN	14.0	NaN	NaN	...	NaN	NaN	101.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1920	NaN	NaN	NaN	NaN	NaN	NaN	6.0	NaN	NaN	NaN	...	NaN	NaN	193.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1924	NaN	NaN	NaN	NaN	11.0	NaN	10.0	4.0	NaN	NaN	...	NaN	22.0	198.0	NaN	NaN	NaN	2.0	NaN	NaN	NaN
1928	NaN	NaN	NaN	NaN	32.0	NaN	4.0	4.0	NaN	NaN	...	NaN	22.0	84.0	NaN	NaN	NaN	12.0	NaN	NaN	NaN
1932	NaN	NaN	NaN	NaN	4.0	NaN	5.0	5.0	NaN	NaN	...	NaN	1.0	181.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1936	NaN	NaN	NaN	NaN	11.0	NaN	1.0	50.0	NaN	NaN	...	NaN	NaN	92.0	NaN	NaN	NaN	1.0	NaN	NaN	NaN
1948	NaN	NaN	NaN	NaN	12.0	NaN	16.0	4.0	NaN	NaN	...	NaN	3.0	148.0	NaN	NaN	NaN	16.0	NaN	NaN	NaN
1952	NaN	NaN	NaN	NaN	6.0	NaN	20.0	3.0	NaN	NaN	...	117.0	14.0	130.0	NaN	1.0	NaN	24.0	NaN	NaN	NaN

Computing fractions

NOC	AFG	AHO	ALG	ANZ	ARG	ARM	AUS	AUT	AZE	BAH	...	URS	URU	USA	UZB
Edition															
1896	NaN	NaN	NaN	NaN	NaN	NaN	0.013245	0.033113	NaN	NaN	...	NaN	NaN	0.132450	NaN
1900	NaN	NaN	NaN	NaN	NaN	NaN	0.009766	0.011719	NaN	NaN	...	NaN	NaN	0.107422	NaN
1904	NaN	NaN	NaN	NaN	NaN	NaN	NaN	0.002128	NaN	NaN	...	NaN	NaN	0.838298	NaN
1908	NaN	NaN	NaN	0.023632	NaN	NaN	NaN	0.001244	NaN	NaN	...	NaN	NaN	0.078358	NaN
1912	NaN	NaN	NaN	0.011299	NaN	NaN	NaN	0.015819	NaN	NaN	...	NaN	NaN	0.114124	NaN
1920	NaN	NaN	NaN	NaN	NaN	NaN	0.004622	NaN	NaN	NaN	...	NaN	NaN	0.148690	NaN
1924	NaN	NaN	NaN	NaN	0.012443	NaN	0.011312	0.004525	NaN	NaN	...	NaN	0.024887	0.223982	NaN
1928	NaN	NaN	NaN	NaN	0.045070	NaN	0.005634	0.005634	NaN	NaN	...	NaN	0.030986	0.118310	NaN
1932	NaN	NaN	NaN	NaN	0.006504	NaN	0.008130	0.008130	NaN	NaN	...	NaN	0.001626	0.294309	NaN
1936	NaN	NaN	NaN	NaN	0.012571	NaN	0.001143	0.057143	NaN	NaN	...	NaN	NaN	0.105143	NaN

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Reshaping and plotting

Reshaping the data

NOC	AFG	AHO	ALG	ANZ	ARG	ARM	...	VEN	VIE	YUG	ZAM	ZIM	ZZX
Edition													
1896	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	NaN
1900	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	33.561198
1904	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	-22.642384
1908	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	0.000000
1912	NaN	NaN	NaN	-26.092774	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	0.000000
1920	NaN	NaN	NaN	0.000000	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	0.000000
1924	NaN	NaN	NaN	0.000000	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	0.000000
1928	NaN	NaN	NaN	0.000000	131.101152	NaN	...	NaN	NaN	323.521127	NaN	NaN	0.000000
1932	NaN	NaN	NaN	0.000000	-25.794206	NaN	...	NaN	NaN	0.000000	NaN	NaN	0.000000
1936	NaN	NaN	NaN	0.000000	-10.271982	NaN	...	NaN	NaN	-29.357594	NaN	NaN	0.000000
1948	NaN	NaN	NaN	0.000000	-4.601500	NaN	...	NaN	NaN	47.596769	NaN	NaN	0.000000
1952	NaN	NaN	NaN	0.000000	-10.508545	NaN	...	NaN	NaN	34.043608	NaN	NaN	0.000000

	Edition	NOC	Change
0	1896	AFG	NaN
1	1900	AFG	NaN
2	1904	AFG	NaN
3	1908	AFG	NaN
4	1912	AFG	NaN
5	1920	AFG	NaN
6	1924	AFG	NaN
7	1928	AFG	NaN
8	1932	AFG	NaN
9	1936	AFG	NaN
10	1948	AFG	NaN
11	1952	AFG	NaN

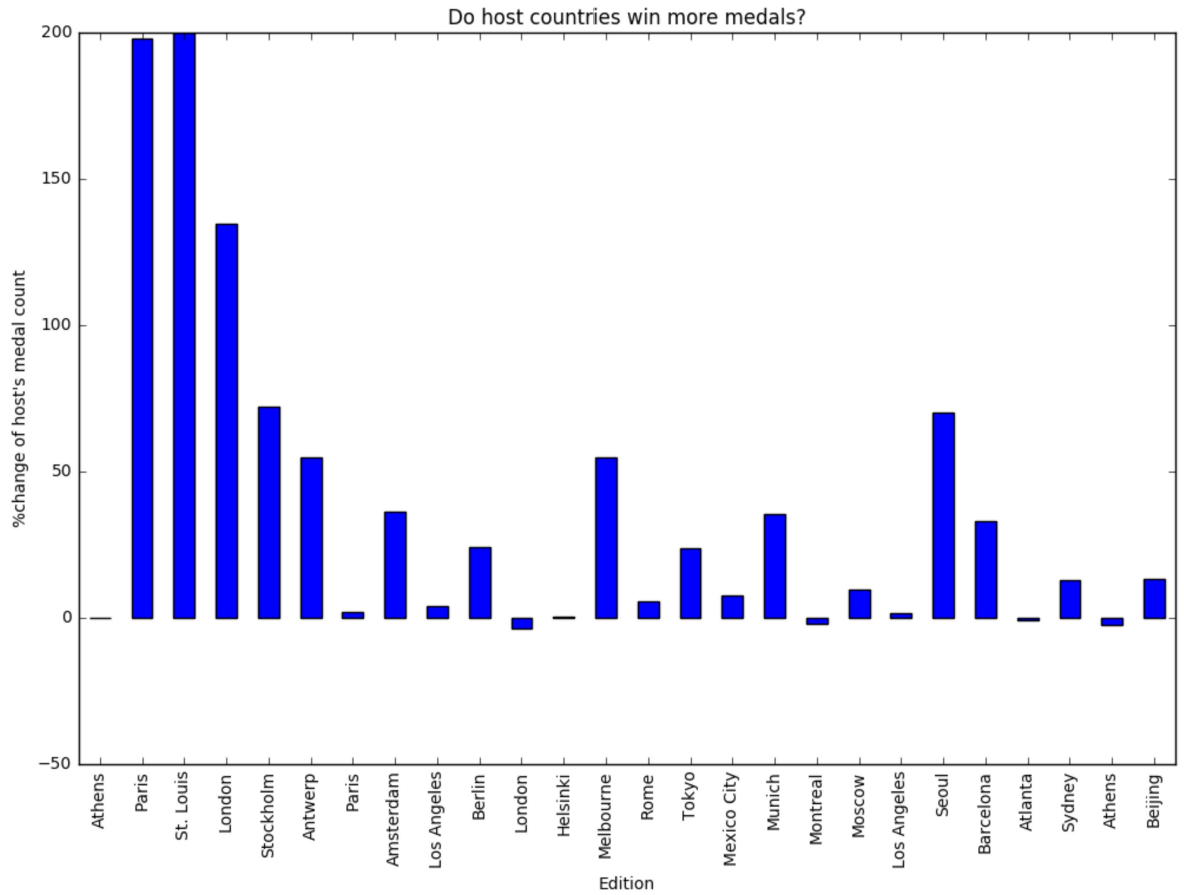
Host country data

	Edition	Bronze	Gold	Silver	Grand Total	City	Country	Host_NOC
0	1896	40	64	47	151	Athens	Greece	GRE
1	1900	142	178	192	512	Paris	France	FRA
2	1904	123	188	159	470	St. Louis	United States	USA
3	1908	211	311	282	804	London	United Kingdom	GBR
4	1912	284	301	300	885	Stockholm	Sweden	SWE
5	1920	355	497	446	1298	Antwerp	Belgium	BEL
6	1924	285	301	298	884	Paris	France	FRA
7	1928	242	229	239	710	Amsterdam	Netherlands	NED
8	1932	196	213	206	615	Los Angeles	United States	USA
9	1936	282	299	294	875	Berlin	Germany	GER
10	1948	268	276	270	814	London	United Kingdom	GBR
11	1952	299	300	290	889	Helsinki	Finland	FIN

Quantifying influence

	NOC	count	Host_NOC	Grand Total	fraction	change
Edition						
1896	GRE	52	GRE	151	0.344371	NaN
1900	FRA	185	FRA	512	0.361328	198.002486
1904	USA	394	USA	470	0.838298	199.651245
1908	GBR	347	GBR	804	0.431592	134.489218
1912	SWE	173	SWE	885	0.195480	71.896226
1920	BEL	188	BEL	1298	0.144838	54.757887
1924	FRA	122	FRA	884	0.138009	2.046362
1928	NED	65	NED	710	0.091549	36.315243
1932	USA	181	USA	615	0.294309	3.739184
1936	GER	210	GER	875	0.240000	24.108011
1948	GBR	56	GBR	814	0.068796	-3.635059
1952	FIN	40	FIN	889	0.044994	0.121662

Graphical summary



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Final thoughts