Pandas Guide

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Note:

- Created using Python-3.6.4 and Pandas-0.22.0
- CSV files can be downloaded from below link,
  https://bitbucket.org/pythondsp/pandasguide/downloads/

Chapter 1

Pandas Basic

1.1 Introduction

Data processing is important part of analyzing the data, because data is not always available in desired format. Various processing are required before analyzing the data such as cleaning, restructuring or merging etc. Numpy, Scipy, Cython and Panda are the tools available in python which can be used fast processing of the data. Further, Pandas are built on the top of Numpy.

Pandas provides rich set of functions to process various types of data. Further, working with Panda is fast, easy and more expressive than other tools. Pandas provides fast data processing as Numpy along with flexible data manipulation techniques as spreadsheets and relational databases. Lastly, pandas integrates well with matplotlib library, which makes it very handy tool for analyzing the data.

Note:

- In chapter 1, two important data structures i.e. Series and DataFrame are discussed.
- Chapter 2 shows the frequently used features of Pandas with example. And later chapters include various other information about Pandas.

1.2 Data structures

Pandas provides two very useful data structures to process the data i.e. Series and DataFrame, which are discussed in this section.

1.2.1 Series

The Series is a one-dimensional array that can store various data types, including mix data types. The row labels in a Series are called the index. Any list, tuple and dictionary can be converted in to Series using 'series' method as shown below,

```
>>> import pandas as pd

>>> # converting tuple to Series
>>> h = ('AA', '2012-02-01', 100, 10.2)
>>> s = pd.Series(h)

>>> type(s)
<class 'pandas.core.series.Series'>
```

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```
>>> print(s)
0            AA
1    2012-02-01
2           100
3          10.2
dtype: object

>>> # converting dict to Series
>>> d = {'name' : 'IBM', 'date' : '2010-09-08', 'shares' : 100, 'price' : 10.2}
>>> ds = pd.Series(d)

>>> type(ds)
<class 'pandas.core.series.Series'>

>>> print(ds)
date      2010-09-08
name             IBM
price           10.2
shares           100
dtype: object
```

Note that in the tuple-conversion, the index are set to '0, 1, 2 and 3'. We can provide custom index names as follows.

```
>>> f = ['FB', '2001-08-02', 90, 3.2]
>>> f = pd.Series(f, index = ['name', 'date', 'shares', 'price'])

>>> print(f)
name              FB
date      2001-08-02
shares            90
price            3.2
dtype: object

>>> f['shares']
90
>>> f[0]
'FB'
>>>
```

Elements of the Series can be accessed using index name e.g. f['shares'] or f[0] in below code. Further, specific elements can be selected by providing the index in the list,

```
>>> f[['shares', 'price']]
shares     90
price     3.2
dtype: object
```

1.2.2 DataFrame

DataFrame is the widely used data structure of pandas. Note that, Series are used to work with one dimensional array, whereas DataFrame can be used with two dimensional arrays. DataFrame has two different index i.e. column-index and row-index.

The most common way to create a DataFrame is by using the dictionary of equal-length list as shown below. Further, all the spreadsheets and text files are read as DataFrame, therefore it is very important data structure of pandas.

```
>>> data = { 'name' : ['AA', 'IBM', 'GOOG'],
...          'date' : ['2001-12-01', '2012-02-10', '2010-04-09'],
...          'shares' : [100, 30, 90],
...          'price' : [12.3, 10.3, 32.2]
... }

>>> df = pd.DataFrame(data)
>>> type(df)
<class 'pandas.core.frame.DataFrame'>

>>> df
         date  name  price  shares
0  2001-12-01    AA   12.3     100
1  2012-02-10   IBM   10.3      30
2  2010-04-09  GOOG   32.2      90
```

Additional columns can be added after defining a DataFrame as below,

```
>>> df['owner'] = 'Unknown'
>>> df
         date  name  price  shares    owner
0  2001-12-01    AA   12.3     100  Unknown
1  2012-02-10   IBM   10.3      30  Unknown
2  2010-04-09  GOOG   32.2      90  Unknown
```

Currently, the row index are set to 0, 1 and 2. These can be changed using 'index' attribute as below,

```
>>> df.index = ['one', 'two', 'three']
>>> df
             date  name  price  shares    owner
one    2001-12-01    AA   12.3     100  Unknown
two    2012-02-10   IBM   10.3      30  Unknown
three  2010-04-09  GOOG   32.2      90  Unknown
```

Further, any column of the DataFrame can be set as index using 'set_index()' attribute, as shown below,

```
>>> df = df.set_index(['name'])
>>> df
            date  price  shares    owner
name
AA    2001-12-01   12.3     100  Unknown
IBM   2012-02-10   10.3      30  Unknown
GOOG  2010-04-09   32.2      90  Unknown
```

Data can be accessed in two ways i.e. using row and column index,

```
>>> # access data using column-index
>>> df['shares']
name
AA      100
IBM      30
GOOG     90
Name: shares, dtype: int64

>>> # access data by row-index
>>> df.ix['AA']
date      2001-12-01
price           12.3
shares           100
owner        Unknown
Name: AA, dtype: object

```

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```
>>> # access all rows for a column
>>> df.ix[:, 'name']
0      AA
1     IBM
2    GOOG
Name: name, dtype: object

>>> # access specific element from the DataFrame,
>>> df.ix[0, 'shares']
100
```

Any column can be deleted using 'del' or 'drop' commands,

```
>>> del df['owner']
>>> df
            date  price  shares
name
AA    2001-12-01   12.3     100
IBM   2012-02-10   10.3      30
GOOG  2010-04-09   32.2      90

>>> df.drop('shares', axis = 1)
            date  price
name
AA    2001-12-01   12.3
IBM   2012-02-10   10.3
GOOG  2010-04-09   32.2
```

Chapter 2

Overview

In this chapter, various functionalities of pandas are shown with examples, which are explained in later chapters as well.

Note: CSV files can be downloaded from below link,

https://bitbucket.org/pythondsp/pandasguide/downloads/

2.1 Reading files

In this section, two data files are used i.e. 'titles.csv' and 'cast.csv'. The 'titles.csv' file contains the list of movies with the releasing year; whereas 'cast.csv' file has five columns which store the title of movie, releasing year, star-casts, type(actor/actress), characters and ratings for actors, as shown below,

```
>>> import pandas as pd

>>> casts = pd.read_csv('cast.csv', index_col=None)
>>> casts.head()
                 title  year      name   type                character     n
0       Closet Monster  2015  Buffy #1  actor                  Buffy 4  31.0
1      Suuri illusioni  1985    Homo $  actor                   Guests  22.0
2   Battle of the Sexes  2017   $hutter  actor          Bobby Riggs Fan  10.0
3  Secret in Their Eyes  2015   $hutter  actor          2002 Dodger Fan   NaN
4            Steve Jobs  2015   $hutter  actor  1988 Opera House Patron   NaN

>>> titles = pd.read_csv('titles.csv', index_col =None)
>>> titles.tail()
                      title  year
49995                 Rebel  1970
49996               Suzanne  1996
49997                 Bomba  2013
49998  Aao Jao Ghar Tumhara  1984
49999             Mrs. Munck  1995
```

- **read_csv** : read the data from the csv file.
- **index_col = None** : there is no index i.e. first column is data
- **head()** : show only first five elements of the DataFrame
- **tail()** : show only last five elements of the DataFrame

If there is some error while reading the file due to encoding, then try for following option as well,

```
titles = pd.read_csv('titles.csv', index_col=None, encoding='utf-8')
```

If we simply type the name of the DataFrame (i.e. cast in below code), then it will show the first thirty and last twenty rows of the file along with complete list of columns. This can be limited using 'set_options' as below. Further, at the end of the table total number of rows and columns will be displayed.

```
>>> pd.set_option('max_rows', 10, 'max_columns', 10)
>>> titles
                          title  year
0                The Rising Son  1990
1        The Thousand Plane Raid  1969
2              Crucea de piatra  1993
3                       Country  2000
4                    Gaiking II  2011
...                         ...   ...
49995                     Rebel  1970
49996                   Suzanne  1996
49997                     Bomba  2013
49998       Aao Jao Ghar Tumhara  1984
49999                Mrs. Munck  1995

[50000 rows x 2 columns]
```

- **len** : 'len' commmand can be used to see the total number of rows in the file,

```
>>> len(titles)
50000
```

Note: head() and tail() commands can be used for remind ourselves about the header and contents of the file. These two commands will show the first and last 5 lines respectively of the file. Further, we can change the total number of lines to be displayed by these commands,

```
>>> titles.head(3)
                     title  year
0           The Rising Son  1990
1  The Thousand Plane Raid  1969
2         Crucea de piatra  1993
```

2.2 Data operations

In this section, various useful data operations for DataFrame are shown.

2.2.1 Row and column selection

Any row or column of the DataFrame can be selected by passing the name of the column or rows. After selecting one from DataFrame, it becomes one-dimensional therefore it is considered as Series.

- **ix** : use 'ix' command to select a row from the DataFrame.

```
>>> t = titles['title']

>>> type(t)
<class 'pandas.core.series.Series'>

>>> t.head()
0              The Rising Son
1     The Thousand Plane Raid
2           Crucea de piatra
```

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```
3                    Country
4                 Gaiking II
Name: title, dtype: object
>>>

>>> titles.ix[0]
title    The Rising Son
year               1990
Name: 0, dtype: object
>>>
```

2.2.2 Filter Data

Data can be filtered by providing some boolean expression in DataFrame. For example, in below code, movies which released after 1985 are filtered out from the DataFrame 'titles' and stored in a new DataFrame i.e. after85.

```
>>> # movies after 1985
>>> after85 = titles[titles['year'] > 1985]
>>> after85.head()
               title  year
 0    The Rising Son  1990
 2  Crucea de piatra  1993
 3           Country  2000
 4        Gaiking II  2011
 5       Medusa (IV)  2015
>>>
```

Note: When we pass the boolean results to DataFrame, then panda will show all the results which corresponds to True (rather than displaying True and False), as shown in above code. Further, '& (and)' and '| (or)' can be used for joining two conditions as shown below,**

In below code all the movies in decade 1990 (i.e. 1900-1999) are selected. Also 't = titles' is used for simplicity purpose only.

```
>>> # display movie in years 1990 - 1999
>>> t = titles
>>> movies90 = t[ (t['year']>=1990) & (t['year']<2000) ]
>>> movies90.head()
                       title  year
0             The Rising Son  1990
2           Crucea de piatra  1993
12  Poka Makorer Ghar Bosoti  1996
19          Maa Durga Shakti  1999
24      Conflict of Interest  1993
>>>
```

2.2.3 Sorting

Sorting can be performed using 'sort_index' or 'sort_values' keywords,

```
>>> # find all movies named as 'Macbeth'
>>> t = titles
>>> macbeth = t[ t['title'] == 'Macbeth']
>>> macbeth.head()
        title  year
```

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```
4226   Macbeth  1913
9322   Macbeth  2006
11722  Macbeth  2013
17166  Macbeth  1997
25847  Macbeth  1998
```

Note that in above filtering operation, the data is sorted by index i.e. by default 'sort_index' operation is used as shown below,

```
>>> # by default, sort by index i.e. row header
>>> macbeth = t[ t['title'] == 'Macbeth'].sort_index()
>>> macbeth.head()
         title  year
4226   Macbeth  1913
9322   Macbeth  2006
11722  Macbeth  2013
17166  Macbeth  1997
25847  Macbeth  1998
>>>
```

To sort the data by values, the 'sort_value' option can be used. In below code, data is sorted by year now,

```
>>> # sort by year
>>> macbeth = t[ t['title'] == 'Macbeth'].sort_values('year')
>>> macbeth.head()
         title  year
4226   Macbeth  1913
17166  Macbeth  1997
25847  Macbeth  1998
9322   Macbeth  2006
11722  Macbeth  2013
>>>
```

2.2.4 Null values

Note that, various columns may contains no values, which are usually filled as NaN. For example, rows 3-4 of casts are NaN as shown below,

```
>>> casts.ix[3:4]
                  title  year     name   type                character   n
3  Secret in Their Eyes  2015  $hutter  actor          2002 Dodger Fan NaN
4            Steve Jobs  2015  $hutter  actor  1988 Opera House Patron NaN
```

These null values can be easily selected, unselected or contents can be replaced by any other values e.g. empty strings or 0 etc. Various examples of null values are shown in this section.

- **'isnull'** command returns the true value if any row of has null values. Since the rows 3-4 has NaN value, therefore, these are displayed as True.

```
>>> c = casts
>>> c['n'].isnull().head()
0    False
1    False
2    False
3     True
4     True
Name: n, dtype: bool
```

- **'notnull'** is opposite of isnull, it returns true for not null values,

```
>>> c['n'].notnull().head()
0     True
1     True
2     True
3    False
4    False
Name: n, dtype: bool
```

- To display the rows with null values, the condition must be passed in the DataFrame,

```
>>> c[c['n'].isnull()].head(3)
                     title  year     name   type                character   n
3    Secret in Their Eyes  2015  $hutter  actor          2002 Dodger Fan NaN
4              Steve Jobs  2015  $hutter  actor  1988 Opera House Patron NaN
5   Straight Outta Compton 2015  $hutter  actor              Club Patron NaN
>>>
```

- NaN values can be fill by using **fillna**, **ffill(forward fill)**, and **bfill(backward fill)** etc. In below code, 'NaN' values are replace by NA. Further, example of ffill and bfill are shown in later part of the tutorial,

```
>>> c_fill = c[c['n'].isnull()].fillna('NA')
>>> c_fill.head(2)
                   title  year     name   type                character   n
3  Secret in Their Eyes  2015  $hutter  actor          2002 Dodger Fan  NA
4            Steve Jobs  2015  $hutter  actor  1988 Opera House Patron  NA
```

2.2.5 String operations

Various string operations can be performed using **'.str.'** option. Let's search for the movie "Maa" first,

```
>>> t = titles
>>> t[t['title'] == 'Maa']
      title  year
38880   Maa  1968
>>>
```

There is only one movie in the list. Now, we want to search all the movies which starts with 'Maa'. The '.str.' option is required for such queries as shown below,

```
>>> t[t['title'].str.startswith("Maa ")].head(3)
                   title  year
19      Maa Durga Shakti  1999
3046       Maa Aur Mamta  1970
7470  Maa Vaibhav Laxmi  1989
>>>
```

2.2.6 Count Values

Total number of occurrences can be counted using **'value_counts()'** option. In following code, total number of movies are displayed base on years.

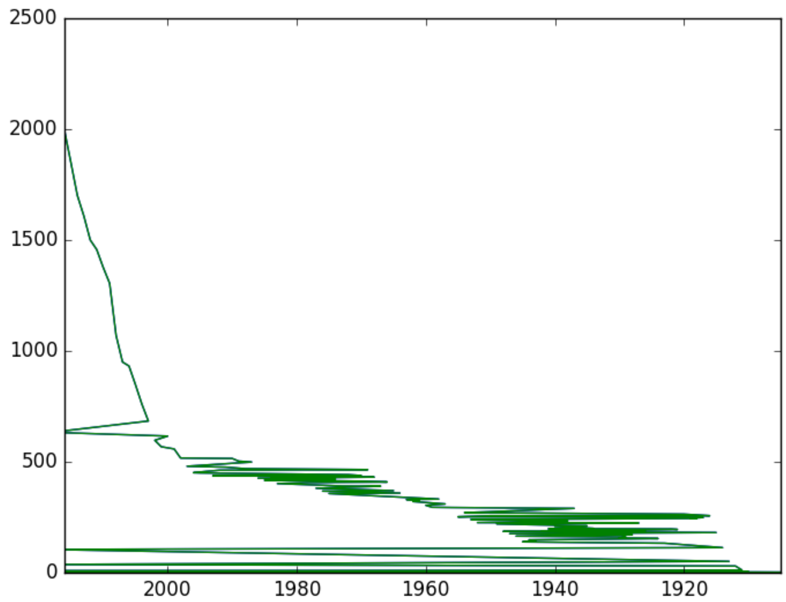
```
>>> t['year'].value_counts().head()
2016    2363
2017    2138
2015    1849
2014    1701
2013    1609
Name: year, dtype: int64
```

2.2.7 Plots

Pandas supports the matplotlib library and can be used to plot the data as well. In previous section, the total numbers of movies/year were filtered out from the DataFrame. In the below code, those values are saved in new DataFrame and then plotted using panda,

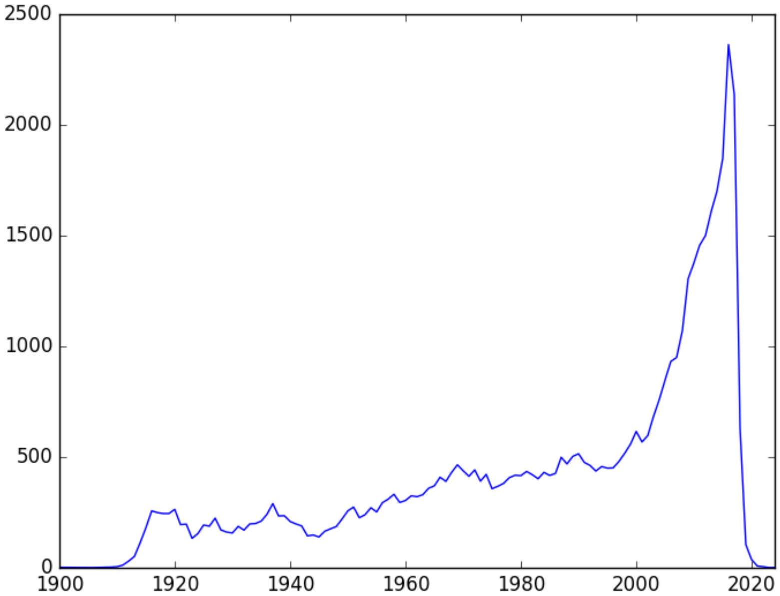
```
>>> import matplotlib.pyplot as plt
>>> t = titles
>>> p = t['year'].value_counts()
>>> p.plot()
<matplotlib.axes._subplots.AxesSubplot object at 0xaf18df6c>
>>> plt.show()
```

Following plot will be generated from above code, which does not provide any useful information.



It's better to sort the years (i.e. index) first and then plot the data as below. Here, the plot shows that number of movies are increasing every year.

```
>>> p.sort_index().plot()
<matplotlib.axes._subplots.AxesSubplot object at 0xa9cd134c>
>>> plt.show()
```



Now, the graph provide some useful information i.e. number of movies are increasing each year.

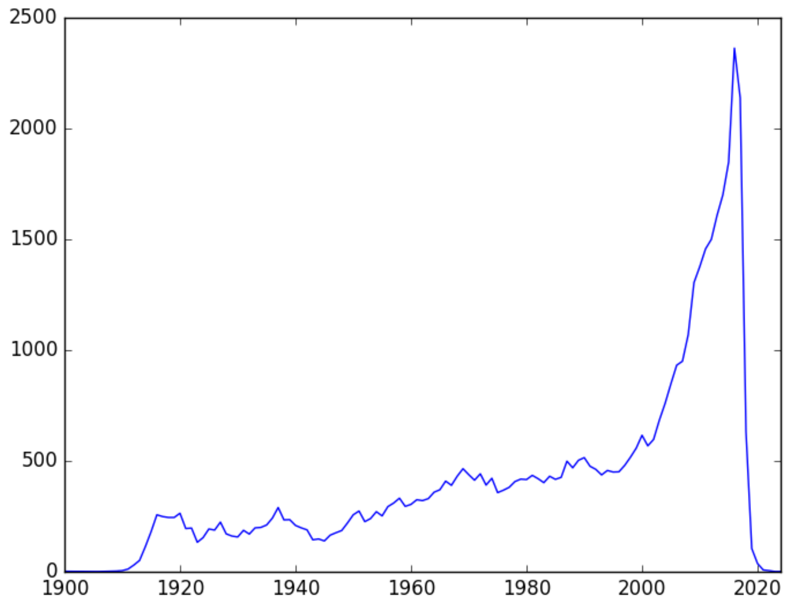
2.3 Groupby

Data can be grouped by columns-headers. Further, custom formats can be defined to group the various elements of the DataFrame.

2.3.1 Groupby with column-names

In Section *Count Values*, the value of movies/year were counted using 'count_values()' method. Same can be achieve by 'groupby' method as well. The 'groupby' command return an object, and we need to an additional functionality to it to get some results. For example, in below code, data is grouped by 'year' and then size() command is used. The **size()** option counts the total number for rows for each year; therefore the result of below code is same as 'count_values()' command.

```
>>> cg = c.groupby(['year']).size()
>>> cg.plot()
<matplotlib.axes._subplots.AxesSubplot object at 0xa9f14b4c>
>>> plt.show()
>>>
```



- Further, groupby option can take multiple parameters for grouping. For example, we want to group the movies of the actor 'Aaron Abrams' based on year,

```
>>> c = casts
>>> cf = c[c['name'] == 'Aaron Abrams']
>>> cf.groupby(['year']).size().head()
year
2003    2
2004    2
2005    2
2006    1
2007    2
dtype: int64
>>>
```

Above list shows that year-2003 is found in two rows with name-entry as 'Aaron Abrams'. In the other word, he did 2 movies in 2003.

- Next, we want to see the list of movies as well, then we can pass two parameters in the list as shown below,

```
>>> cf.groupby(['year', 'title']).size().head()
year  title
2003  The In-Laws                          1
      The Visual Bible: The Gospel of John    1
2004  Resident Evil: Apocalypse            1
      Siblings                             1
2005  Cinderella Man                       1
dtype: int64
>>>
```

In above code, the groupby operation is performed on the 'year' first and then on 'title'. In the other word, first all the movies are grouped by year. After that, the result of this groupby is again grouped based on titles. Note that, first group command arranged the year in order i.e. 2003, 2004 and 2005 etc.; then next group command arranged the title in alphabetical order.

- Next, we want to do grouping based on maximum ratings in a year; i.e. we want to group the items by year and see the maximum rating in those years,

```
>>> c.groupby(['year']).n.max().head()
year
1912     6.0
1913    14.0
1914    39.0
1915    14.0
1916    35.0
Name: n, dtype: float64
```

Above results show that the maximum rating in year 1912 is 6 for Aaron Abrams.

- Similarly, we can check for the minimum rating,

```
>>> c.groupby(['year']).n.min().head()
year
1912    6.0
1913    1.0
1914    1.0
1915    1.0
1916    1.0
Name: n, dtype: float64
```

- Lastly, we want to check the mean rating each year,

```
>>> c.groupby(['year']).n.mean().head()
year
1912    6.000000
1913    4.142857
1914    7.085106
1915    4.236111
1916    5.037736
Name: n, dtype: float64
```

2.3.2 Groupby with custom field

Suppose we want to group the data based on decades, then we need to create a custom groupby field,

```
>>> # decade conversion : 1985//10 = 198, 198*10 = 1980
>>> decade = c['year']//10*10
>>> c_dec = c.groupby(decade).n.size()
>>>
>>> c_dec.head()
year
1910     669
1920    1121
1930    3448
1940    3997
1950    3892
dtype: int64
```

Above results shows the total number of movies in each decade.

2.4 Unstack

Before understanding the unstack, let's consider one case from cast.csv file. In following code, the data is grouped by decade and type i.e. actor and actress.

```
>>> c = casts
>>> c.groupby( [c['year']//10*10, 'type'] ).size().head(8)
year  type
1910  actor       384
      actress     285
1920  actor       710
      actress     411
1930  actor      2628
      actress     820
1940  actor      3014
      actress     983
dtype: int64
>>>
```

Note: Unstack is discussed in Section *Unstack the data* in detail.

Now we want to compare and plot the total number of actors and actresses in each decade. One solution to this problem is to grab even and odd rows separately and plot the data, which is quite complicated operation if types has more varieties e.g. new-actor, new-actress and teen-actors etc. A simple solution to such problem is the **'unstack'**, which allows to create a new DataFrame based on the grouped Dataframe, as shown below.

- Since we want a plot based on actors and actress, therefore first we need to group the data based on 'type' as below,

```
>>> c = casts
>>> c_decade = c.groupby( ['type', c['year']//10*10] ).size()
>>> c_decade
type     year
actor    1910      384
         1920      710
         1930     2628
         [...]
actress  1910      285
         1920      411
         1930      820
         [...]
dtype: int64
>>>
```

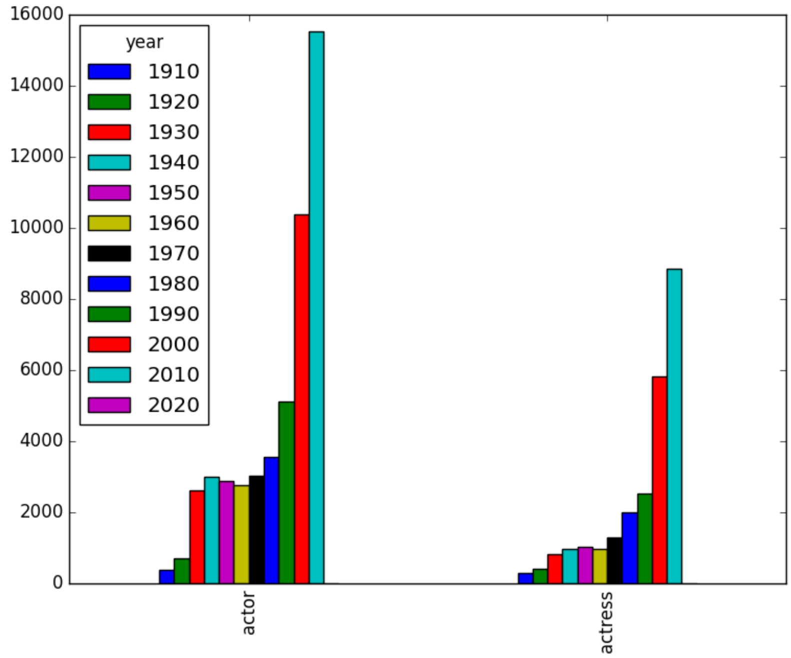
- Now we can create a new DataFrame using 'unstack' command. The 'unstack' command creates a new DataFrame based on index,

```
>>> c_decade.unstack()
year     1910  1920  1930  1940  1950  1960  1970  1980  1990  [...]
type
actor     384   710  2628  3014  2877  2775  3044  3565  5108  [...]
actress   285   411   820   983  1015   968  1299  1989  2544  [...]
```

- Use following commands to plot the above data,

```
>>> c_decade.unstack().plot()
<matplotlib.axes._subplots.AxesSubplot object at 0xb1cec56c>
>>> plt.show()
>>> c_decade.unstack().plot(kind='bar')
<matplotlib.axes._subplots.AxesSubplot object at 0xa8bf778c>
>>> plt.show()
```

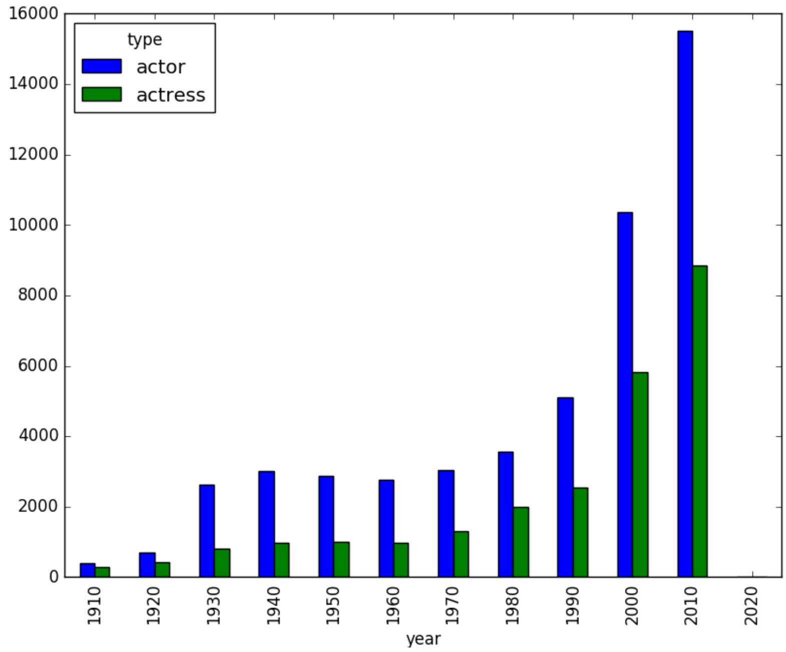
Below figure will be generated from above command. Note that in the plot, actor and actress are plot separately in the groups.



- To plot the data side by side, use unstack(0) option as shown below (by default unstack(-1) is used),

```
>>> c_decade.unstack(0)
type  actor  actress
year
1910    384      285
1920    710      411
1930   2628      820
1940   3014      983
1950   2877     1015
1960   2775      968
1970   3044     1299
1980   3565     1989
1990   5108     2544
2000  10368     5831
2010  15523     8853
2020      4        3

>>> c_decade.unstack(0).plot(kind='bar')
<matplotlib.axes._subplots.AxesSubplot object at 0xb1d218cc>
>>> plt.show()
```



2.5 Merge

Usually, different data of same project are available in various files. To get the useful information from these files, we need to combine these files. Also, we need to merge to different data in the same file to get some specific information. In this section, we will understand these two merges i.e. merge with different file and merge with same file.

2.5.1 Merge with different files

In this section, we will merge the data of two table i.e. 'release_dates.csv' and 'cast.csv'. The 'release_dates.csv' file contains the release date of movies in different countries.

- First, load the 'release_dates.csv' file, which contains the release dates of some of the movies, listed in 'cast.csv'. Following are the content of 'release_dates.csv' file,

```
>>> release = pd.read_csv('release_dates.csv', index_col=None)
>>> release.head()
                     title  year      country        date
0    #73, Shaanthi Nivaasa  2007        India  2007-06-15
1                  #Beings  2015      Romania  2015-01-29
2                #Declimax  2018  Netherlands  2018-01-21
3   #Ewankosau saranghaeyo  2015  Philippines  2015-01-21
4                  #Horror  2015          USA  2015-11-20


>>> casts.head()
                   title  year      name   type                character     n
0         Closet Monster  2015  Buffy #1  actor                  Buffy 4  31.0
1        Suuri illusioni  1985    Homo $  actor                   Guests  22.0
2    Battle of the Sexes  2017   $hutter  actor          Bobby Riggs Fan  10.0
3   Secret in Their Eyes  2015   $hutter  actor          2002 Dodger Fan   NaN
4             Steve Jobs  2015   $hutter  actor  1988 Opera House Patron   NaN
```

- Let's we want to see the release date of the movie 'Amelia'. For this first, filter out the Amelia from the DataFrame 'cast' as below. There are only two entries for the movie Amelia.

```
>>> c_amelia = casts[ casts['title'] == 'Amelia']
>>> c_amelia.head()
        title  year             name   type    character     n
5767   Amelia  2009     Aaron Abrams  actor  Slim Gordon   8.0
23319  Amelia  2009  Jeremy Akerman  actor      Sheriff  19.0
>>>
```

- Next, we will see the entries of movie 'Amelia' in release dates as below. In the below result, we can see that there are two different release years for the movie i.e. 1966 and 2009.

```
>>> release [ release['title'] == 'Amelia' ].head()
        title  year    country        date
20543  Amelia  1966     Mexico  1966-03-10
20544  Amelia  2009     Canada  2009-10-23
20545  Amelia  2009        USA  2009-10-23
20546  Amelia  2009  Australia  2009-11-12
20547  Amelia  2009  Singapore  2009-11-12
>>>
```

- Since there is not entry for Amelia-1966 in casts DataFrame, therefore merge command will not merge the Amelia-1966 release dates. In following results, we can see that only Amelia 2009 release dates are merges with casts DataFrame.

```
>>> c_amelia.merge(release).head()
    title  year          name   type    character    n    country        date
0  Amelia  2009  Aaron Abrams  actor  Slim Gordon  8.0     Canada  2009-10-23
1  Amelia  2009  Aaron Abrams  actor  Slim Gordon  8.0        USA  2009-10-23
2  Amelia  2009  Aaron Abrams  actor  Slim Gordon  8.0  Australia  2009-11-12
3  Amelia  2009  Aaron Abrams  actor  Slim Gordon  8.0  Singapore  2009-11-12
4  Amelia  2009  Aaron Abrams  actor  Slim Gordon  8.0    Ireland  2009-11-13
```

2.5.2 Merge table with itself

Suppose, we want see the list of co-actors in the movies. For this, we need to merge the table with itself based on the title and year, as shown below. In the below code, co-star for actor 'Aaron Abrams' are displayed,

- First, filter out the results for 'Aaron Abrams',

```
>>> c = casts[ casts['name']=='Aaron Abrams' ]
>>> c.head(2)
                    title  year          name   type       character    n
5765        #FromJennifer  2017  Aaron Abrams  actor  Ralph Sinclair  NaN
5766  388 Arletta Avenue  2011  Aaron Abrams  actor            Alex  4.0
>>>
```

- Next, to find the co-stars, merge the DataFrame with itself based on 'title' and 'year' i.e. for being a co-star, the name of the movie and the year must be same,
- Note that 'casts' is used inside the bracket instead of c.

```
c.merge(casts, on=['title', 'year']).head()
```

The problem with above joining is that it displays the 'Aaron Abrams' as his co-actor as well (see first row). This problem can be avoided as below,

```
c_costar = c.merge (casts, on=['title', 'year'])
c_costar = c_costar[c_costar['name_y'] != 'Aaron Abrams']
c_costar.head()
```

2.6 Index

In the previous section, we saw some uses of index for sorting and plotting the data. In this section, index are discussed in detail.

Index is very important tool in pandas. It is used to organize the data and to provide us fast access to data. In this section, time for data-access are compared for the data with and without indexing. For this section, Jupyter notebook is used as '%%timeit' is very easy to use in it to compare the time required for various access-operations.

2.6.1 Creating index

```
import pandas as pd
cast = pd.read_csv('cast.csv', index_col=None)
cast.head()
```

```
%%time

# data access without indexing
cast[cast['title']=='Macbeth']
```

```
CPU times: user 8 ms, sys: 4 ms, total: 12 ms
Wall time: 13.8 ms
```

'%%timeit' can be used for more precise results as it run the shell various times and display the average time; but it will not show the output of the shell,

```
%%timeit

# data access without indexing
cast[cast['title']=='Macbeth']
```

```
100 loops, best of 3: 9.85 ms per loop
```

'set_index' can be used to create an index for the data. Note that, in below code, 'title' is set at index, therefore index-numbers are replaced by 'title' (see the first column).

```
# below line will not work for multiple index
# c = cast.set_index('title')

c = cast.set_index(['title'])
c.head(4)
```

To use the above indexing, **'.loc'** should be used for fast operations,

```
%%time

# data access with indexing
# note that there is minor performance improvement
c.loc['Macbeth']
```

```
CPU times: user 36 ms, sys: 0 ns, total: 36 ms
Wall time: 36.2 ms
```

```
%%timeit

# data access with indexing
# note that there is minor performance improvement
c.loc['Macbeth']
```

```
100 loops, best of 3: 5.64 ms per loop
```

** We can see that, there is performance improvement (i.e. 11ms to 6ms) using indexing, because speed will increase further if the index are in sorted order. **

Next, we will sort the index and perform the filter operation,

```
cs = cast.set_index(['title']).sort_index()
cs.tail(4)
```

```
%%time

# data access with indexing
# note that there is huge performance improvement
cs.loc['Macbeth']
```

```
CPU times: user 36 ms, sys: 0 ns, total: 36 ms
Wall time: 38.8 ms
```

Now, filtering is completing in around '0.5 ms' (rather than 4 ms), as shown by below results,

```
%%timeit

# data access with indexing
# note that there huge performance improvement
cs.loc['Macbeth']
```

```
1000 loops, best of 3: 480 µs per loop
```

2.6.2 Multiple index

Further, we can have multiple indexes in the data,

```
# data with two index i.e. title and n
cm = cast.set_index(['title', 'n']).sort_index()
cm.tail(30)
```

```
>>> cm.loc['Macbeth']
       year                 name     type        character
n
 4.0   1916  Spottiswoode Aitken    actor           Duncan
 6.0   1916          Mary Alden  actress     Lady Macduff
 18.0  1948       William Alland    actor  Second Murderer
 21.0  1997         Stevie Allen    actor         Murderer
NaN    2015       Darren Adamson    actor          Soldier
NaN    1948          Robert Alan    actor   Third Murderer
NaN    2016        John Albasiny    actor           Doctor
NaN    2014          Moyo Akand?  actress            Witch
```

In above result, 'title' is removed from the index list, which represents that there is one more level of index, which can be used for filtering. Lets filter the data again with second index as well,

```
# show Macbeth with ranking 4-18
cm.loc['Macbeth'].loc[4:18]
```

If there is only one match data, then Series will return (instead of DataFrame),

```
# show Macbeth with ranking 4
cm.loc['Macbeth'].loc[4]
```

```
year                        1916
name         Spottiswoode Aitken
type                       actor
character                 Duncan
Name: 4.0, dtype: object
```

2.6.3 Reset index

Index can be reset using **'reset_index'** command. Let's look at the 'cm' DataFrame again.

```
cm.head(2)
```

In 'cm' DataFrame, there are two index; and one of these i.e. n is removed using 'reset_index' command.

```
# remove 'n' from index
cm = cm.reset_index('n')
cm.head(2)
```

2.7 Implement using Python-CSV library

Note that, all the above logic can be implemented using python-csv library as well. In this section, some of the logics of above sections are re-implemented using python-csv library. By looking at following examples, we can see that how easy is it to work with pandas as compare to python-csv library. However, we have more fun with python built-in libraries,

2.7.1 Read the file

```
import csv
titles = list(csv.DictReader(open('titles.csv')))
titles[0:5]  # display first 5 rows
```

```
[OrderedDict([('title', 'The Rising Son'), ('year', '1990')]),
OrderedDict([('title', 'The Thousand Plane Raid'), ('year', '1969')]),
OrderedDict([('title', 'Crucea de piatra'), ('year', '1993')]),
OrderedDict([('title', 'Country'), ('year', '2000')]),
OrderedDict([('title', 'Gaiking II'), ('year', '2011')])]
```

```
# display last 5 rows
titles[-5:]
```

```
[OrderedDict([('title', 'Rebel'), ('year', '1970')]),
OrderedDict([('title', 'Suzanne'), ('year', '1996')]),
OrderedDict([('title', 'Bomba'), ('year', '2013')]),
OrderedDict([('title', 'Aao Jao Ghar Tumhara'), ('year', '1984')]),
OrderedDict([('title', 'Mrs. Munck'), ('year', '1995')])]
```

- Display title and year in separate row,

```
for k, v in titles[0].items():
    print(k, ':',  v)
```

```
title : The Rising Son
year : 1990
```

2.7.2 Display movies according to year

- Display all movies in year 1985

```
year85 = [a for a in titles if a['year'] == '1985']
year85[:5]
```

```
[OrderedDict([('title', 'Insaaf Main Karoonga'), ('year', '1985')]),
OrderedDict([('title', 'Vivre pour survivre'), ('year', '1985')]),
OrderedDict([('title', 'Water'), ('year', '1985')]),
OrderedDict([('title', 'Doea tanda mata'), ('year', '1985')]),
OrderedDict([('title', 'Koritsia gia tsibima'), ('year', '1985')])]
```

- Movies in years 1990 - 1999,

```
# movies from 1990 to 1999
movies90 = [m for m in titles if (int(m['year']) < int('2000')) and (int(m['year']) > int('1989'))]
movies90[:5]
```

```
[OrderedDict([('title', 'The Rising Son'), ('year', '1990')]),
OrderedDict([('title', 'Crucea de piatra'), ('year', '1993')]),
OrderedDict([('title', 'Poka Makorer Ghar Bosoti'), ('year', '1996')]),
OrderedDict([('title', 'Maa Durga Shakti'), ('year', '1999')]),
OrderedDict([('title', 'Conflict of Interest'), ('year', '1993')])]
```

- Find all movies 'Macbeth',

```
# find Macbeth movies
macbeth = [m for m in titles if m['title']=='Macbeth']
macbeth[:3]
```

```
[OrderedDict([('title', 'Macbeth'), ('year', '1913')]),
OrderedDict([('title', 'Macbeth'), ('year', '2006')]),
OrderedDict([('title', 'Macbeth'), ('year', '2013')])]
```

2.7.3 operator.iemgetter

- Sort movies by year,

```
# sort based on year and display 3
from operator import itemgetter
sorted(macbeth, key=itemgetter('year'))[:3]
```

```
[OrderedDict([('title', 'Macbeth'), ('year', '1913')]),
OrderedDict([('title', 'Macbeth'), ('year', '1997')]),
OrderedDict([('title', 'Macbeth'), ('year', '1998')])]
```

2.7.4 Replace empty string with 0

```
casts = list(csv.DictReader(open('cast.csv')))
```

```
casts[3:5]
```

```
[OrderedDict([('title', 'Secret in Their Eyes'),
    ('year', '2015'),
    ('name', '$hutter'),
```

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```
    ('type', 'actor'),
    ('character', '2002 Dodger Fan'),
    ('n', '')]),
OrderedDict([('title', 'Steve Jobs'),
    ('year', '2015'),
    ('name', '$hutter'),
    ('type', 'actor'),
    ('character', '1988 Opera House Patron'),
    ('n', '')])]
```

```
# replace '' with 0
cast0 = [{**c, 'n':c['n'].replace('', '0')} for c in casts]
cast0[3:5]
```

```
[{'title': 'Secret in Their Eyes',
    'year': '2015', 'name': '$hutter',
    'type': 'actor', 'character': '2002 Dodger Fan',
    'n': '0'},
{'title': 'Steve Jobs',
'year': '2015', 'name': '$hutter',
'type': 'actor', 'character': '1988 Opera House Patron',
'n': '0'}]
```

- Movies starts with ‘Maa’

```
# Movies starts with Maa
maa = [m for m in titles if m['title'].startswith('Maa')]
maa[:3]
```

```
[OrderedDict([('title', 'Maa Durga Shakti'), ('year', '1999')]),
OrderedDict([('title', 'Maarek hob'), ('year', '2004')]),
OrderedDict([('title', 'Maa Aur Mamta'), ('year', '1970')])]
```

2.7.5 collections.Counter

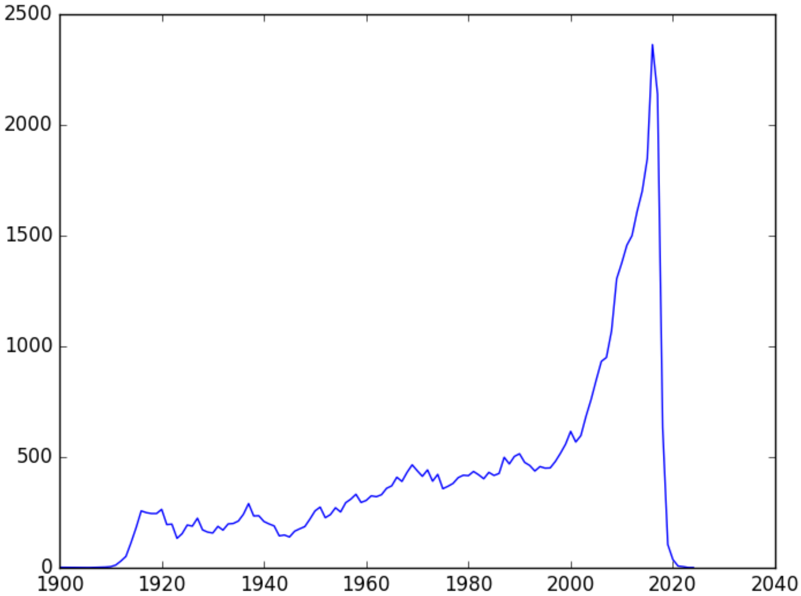
- Count movies by year,

```
# Most release movies
from collections import Counter
by_year = Counter(t['year'] for t in titles)
by_year.most_common(3)
# by_year.elements # to see the complete dictionary
```

```
['1990', '1969', '1993', '2000', '2011']
```

- plot the data

```
import matplotlib.pyplot as plt
data = by_year.most_common(len(titles))
data = sorted(data)  # sort the data for proper axis
x = [c[0] for c in data]   # extract year
y = [c[1] for c in data]   # extract total number of movies
plt.plot(x, y)
plt.show()
```



2.7.6 collections.defaultdict

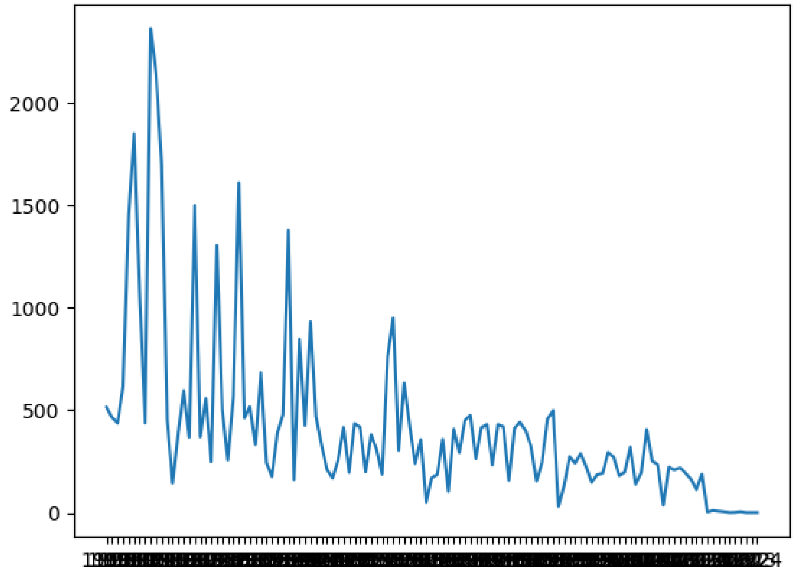
- append movies in dictionary by year,

```
from collections import defaultdict
```

```
d = defaultdict(list)
for row in titles:
    d[row['year']].append(row['title'])

xx=[]
yy=[]
for k, v in d.items():
    xx.append(k)# = k
    yy.append(len(v))# = len(v)

plt.plot(sorted(xx), yy)
plt.show()
```




```
xx[:5]  # display content of xx
```

```
['1976', '1964', '1914', '1934', '1952']
```

```
yy[:5] # display content of yy
```

```
[515, 465, 437, 616, 1457]
```

- show all movies of Aaron Abrams

```
# show all movies of Aaron Abrams
cf = [c for c in casts if c['name']=='Aaron Abrams']
cf[:3]
```

```
[OrderedDict([('title', '#FromJennifer'), ('year', '2017'),
    ('name', 'Aaron Abrams'), ('type', 'actor'),
    ('character', 'Ralph Sinclair'), ('n', '')]),
OrderedDict([('title', '388 Arletta Avenue'), ('year', '2011'),
    ('name', 'Aaron Abrams'), ('type', 'actor'),
    ('character', 'Alex'), ('n', '4')]),
OrderedDict([('title', 'Amelia'), ('year', '2009'),
    ('name', 'Aaron Abrams'), ('type', 'actor'),
    ('character', 'Slim Gordon'), ('n', '8')])]
```

- Collect all movies of Aaron Abrams by year,

```
# Display movies of Aaron Abrams by year
dcf = defaultdict(list)
for row in cf:
    dcf[row['year']].append(row['title'])

dcf
```

```
defaultdict(<class 'list'>, {
    '2017': ['#FromJennifer', 'The Go-Getters'],
    '2011': ['388 Arletta Avenue', 'Jesus Henry Christ', 'Jesus Henry Christ', 'Take This Waltz', 'The
↪Chicago 8'], '2009': ['Amelia', 'At Home by Myself... with You'],
```

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```
    '2005': ['Cinderella Man', 'Sabah'],
    '2015': ['Closet Monster', 'Regression'],
    '2018': ['Code 8'], '2007': ['Firehouse Dog', 'Young People Fucking'],
    '2008': ['Flash of Genius'], '2013': ['It Was You Charlie'],
    '2004': ['Resident Evil: Apocalypse', 'Siblings'],
    '2003': ['The In-Laws', 'The Visual Bible: The Gospel of John'],
    '2006': ['Zoom']})
```

Chapter 3

Numpy

Numerical Python (Numpy) is used for performing various numerical computation in python. Calculations using Numpy arrays are faster than the normal python array. Further, pandas are build over numpy array, therefore better understanding of python can help us to use pandas more effectively.

3.1 Creating Arrays

Defining multidimensional arrays are very easy in numpy as shown in below examples,

```
>>> import numpy as np

>>> # 1-D array
>>> d = np.array([1, 2, 3])
>>> type(d)
<class 'numpy.ndarray'>
>>> d
array([1, 2, 3])
>>>

>>> # multi dimensional array
>>> nd = np.array([[1, 2, 3], [3, 4, 5], [10, 11, 12]])
>>> type(nd)
<class 'numpy.ndarray'>
>>> nd
array([[ 1,  2,  3],
       [ 3,  4,  5],
       [10, 11, 12]])
>>> nd.shape  #  shape of array
(3, 3)
>>> nd.dtype  #  data type
dtype('int32')
>>>

>>> #  define zero matrix
>>> np.zeros(3)
array([ 0.,  0.,  0.])
>>> np.zeros([3, 2])
array([[ 0.,  0.],
       [ 0.,  0.],
       [ 0.,  0.]])

>>> # diagonal matrix
>>> e = np.eye(3)
```

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```
array([[ 1.,  0.,  0.],
       [ 0.,  1.,  0.],
       [ 0.,  0.,  1.]])

>>> # add 2 to e
>>> e2 = e + 2
>>> e2
array([[ 3.,  2.,  2.],
       [ 2.,  3.,  2.],
       [ 2.,  2.,  3.]])


>>> # create matrix with all entries as 1 and size as 'e2'
>>> o = np.ones_like(e2)
>>> o
array([[ 1.,  1.,  1.],
       [ 1.,  1.,  1.],
       [ 1.,  1.,  1.]])

>>> # changing data type
>>> o = np.ones_like(e2)
>>> o.dtype
dtype('float64')
>>> oi = o.astype(np.int32)
>>> oi
array([[1, 1, 1],
       [1, 1, 1],
       [1, 1, 1]])
>>> oi.dtype
dtype('int32')
>>>

>>> # convert string-list to float
>>> a = ['1', '2', '3']
>>> a_arr = np.array(a, dtype=np.string_)  # convert list to ndarray
>>> af = a_arr.astype(float)  # change ndarray type
>>> af
array([ 1.,  2.,  3.])
>>> af.dtype
dtype('float64')
```

3.2 Boolean indexing

Boolean indexing is very important feature of numpy, which is frequently used in pandas,

```
>>> # accessing data with boolean indexing
>>> data = np.random.randn(5, 3)
>>> data
array([[ 0.96174001,  1.49352768, -0.31277422],
       [ 0.25044202,  2.35367396,  0.5697222 ],
       [-1.21536074,  0.82088599, -1.85503026],
       [-1.31492648,  1.24546252,  0.27972961],
       [ 0.23487862, -0.20627825,  0.41470205]])
>>> name = np.array(['a', 'b', 'c', 'a', 'b'])
>>> name=='a'
array([ True, False, False,  True, False], dtype=bool)
>>> data[name=='a']
array([[ 0.96174001,  1.49352768, -0.31277422],
```

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```
       [-1.31492648,  1.24546252,  0.27972961]])

>>> data[name != 'a']
array([[ 0.25044202,  2.35367396,  0.5697222 ],
       [-1.21536074,  0.82088599, -1.85503026],
       [ 0.23487862, -0.20627825,  0.41470205]])
>>> data[(name == 'b')  |  (name=='c')]
array([[ 0.25044202,  2.35367396,  0.5697222 ],
       [-1.21536074,  0.82088599, -1.85503026],
       [ 0.23487862, -0.20627825,  0.41470205]])

>>> data[ (data > 1) & (data < 2) ]
array([ 1.49352768,  1.24546252])
```

3.3 Reshaping arrays

```
>>> a = np.arange(0, 20)
>>> a
array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
       17, 18, 19])

>>> # reshape array a
>>> a45 = a.reshape(4, 5)
>>> a45
array([[ 0,  1,  2,  3,  4],
       [ 5,  6,  7,  8,  9],
       [10, 11, 12, 13, 14],
       [15, 16, 17, 18, 19]])

>>> # select row 2, 0 and 1 from a45 and store in b
>>> b = a45[ [2, 0, 1] ]
>>> b
array([[10, 11, 12, 13, 14],
       [ 0,  1,  2,  3,  4],
       [ 5,  6,  7,  8,  9]])

>>> # transpose array b
>>> b.T
array([[10,  0,  5],
       [11,  1,  6],
       [12,  2,  7],
       [13,  3,  8],
       [14,  4,  9]])
```

3.4 Concatenating the data

We can combine the data to two arrays using 'concatenate' command,

```
>>> arr = np.arange(12).reshape(3,4)
>>> rn = np.random.randn(3, 4)
>>> arr
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])
>>> rn
array([[-0.25178434,  0.98443663, -0.99723191, -0.64737102],
```

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```
       [ 1.29179768, -0.88437251, -1.25608884, -1.60265896],
       [-0.60085171,  0.8569506 ,  0.62657649,  1.43647342]])

>>> # merge data of rn below the arr
>>> np.concatenate([arr, rn])
array([[  0.        ,   1.        ,   2.        ,   3.        ],
       [  4.        ,   5.        ,   6.        ,   7.        ],
       [  8.        ,   9.        ,  10.        ,  11.        ],
       [ -0.25178434,   0.98443663,  -0.99723191,  -0.64737102],
       [  1.29179768,  -0.88437251,  -1.25608884,  -1.60265896],
       [ -0.60085171,   0.8569506 ,   0.62657649,   1.43647342]])

>>> # merge dataof rn on the right side of the arr
>>> np.concatenate([arr, rn], axis=1)
array([[  0.        ,   1.        ,   2.        ,   3.        ,
         -0.25178434,   0.98443663,  -0.99723191,  -0.64737102],
       [  4.        ,   5.        ,   6.        ,   7.        ,
          1.29179768,  -0.88437251,  -1.25608884,  -1.60265896],
       [  8.        ,   9.        ,  10.        ,  11.        ,
         -0.60085171,   0.8569506 ,   0.62657649,   1.43647342]])
>>>
```

Chapter 4

Data processing

Most of programming work in data analysis and modeling is spent on data preparation e.g. loading, cleaning and rearranging the data etc. Pandas along with python libraries gives us provide us a high performance, flexible and high level environment for processing the data.

In chapter 1, we saw basics of pandas; then various examples are shown in chapter 2 for better understanding of pandas; whereas chapter 3 presented some basics of numpy. In this chapter, we will see some more functionality of pandas to process the data effectively.

4.1 Hierarchical indexing

Hierarchical indexing is an important feature of pandas that enable us to have multiple index levels. We already see an example of it in Section *Multiple index*. In this section, we will learn more about indexing and access to data with these indexing.

4.1.1 Creating multiple index

- Following is an example of series with multiple index,

```
>>> import pandas as pd
>>> data = pd.Series([10, 20, 30, 40, 15, 25, 35, 25], index = [['a', 'a',
... 'a', 'a', 'b', 'b', 'b', 'b'], ['obj1', 'obj2', 'obj3', 'obj4', 'obj1',
... 'obj2', 'obj3', 'obj4']])
>>> data
a  obj1    10
   obj2    20
   obj3    30
   obj4    40
b  obj1    15
   obj2    25
   obj3    35
   obj4    25
dtype: int64
```

- There are two level of index here i.e. (a, b) and (obj1, ..., obj4). The index can be seen using 'index' command as shown below,

```
>>> data.index
MultiIndex(levels=[['a', 'b'], ['obj1', 'obj2', 'obj3', 'obj4']],
           labels=[[0, 0, 0, 0, 1, 1, 1, 1], [0, 1, 2, 3, 0, 1, 2, 3]])
```

4.1.2 Partial indexing

Choosing a particular index from a hierarchical indexing is known as partial indexing.

- In the below code, index 'b' is extracted from the data,

```
>>> data['b']
obj1    15
obj2    25
obj3    35
obj4    25
dtype: int64
```

- Further, the data can be extracted based on inner level i.e. 'obj'. Below result shows the two available values for 'obj2' in the Series.

```
>>> data[:, 'obj2']
a    20
b    25
dtype: int64
>>>
```

4.1.3 Unstack the data

We saw the use of unstack operation in the Section *Unstack*. Unstack changes the row header to column header. Since the row index is changed to column index, therefore the Series will become the DataFrame in this case. Following are the some more example of unstacking the data,

```
>>> # unstack based on first level i.e. a, b
>>> # note that data row-labels are a and b
>>> data.unstack(0)
       a   b
obj1  10  15
obj2  20  25
obj3  30  35
obj4  40  25

>>> # unstack based on second level i.e. 'obj'
>>> data.unstack(1)
   obj1  obj2  obj3  obj4
a    10    20    30    40
b    15    25    35    25
>>>

>>> # by default innermost level is used for unstacking
>>> d = data.unstack()
>>> d
   obj1  obj2  obj3  obj4
a    10    20    30    40
b    15    25    35    25
```

- 'stack()' operation converts the column index to row index again. In above code, DataFrame 'd' has 'obj' as column index, this can be converted into row index using 'stack' operation,

```
>>> d.stack()
a  obj1    10
   obj2    20
   obj3    30
   obj4    40
b  obj1    15
```

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```
   obj2    25
   obj3    35
   obj4    25
dtype: int64
```

4.1.4 Column indexing

Remember that, the column indexing is possible for DataFrame only (not for Series), because column-indexing require two dimensional data. Let's create a new DataFrame as below for understanding the columns with multiple index,

```
>>> import numpy as np
>>> df = pd.DataFrame(np.arange(12).reshape(4, 3),
...     index = [['a', 'a', 'b', 'b'], ['one', 'two', 'three', 'four']],
...     columns = [['num1', 'num2', 'num3'], ['red', 'green', 'red']]
... )
>>>
>>> df
        num1  num2 num3
         red green  red
a one      0     1    2
  two      3     4    5
b three    6     7    8
  four     9    10   11
>>>

>>> # display row index
>>> df.index
MultiIndex(levels=[['a', 'b'], ['four', 'one', 'three', 'two']],
           labels=[[0, 0, 1, 1], [1, 3, 2, 0]])

>>> # display column index
>>> df.columns
MultiIndex(levels=[['num1', 'num2', 'num3'], ['green', 'red']],
           labels=[[0, 1, 2], [1, 0, 1]])
```

- Note that, in previous section, we used the numbers for stack and unstack operation e.g. unstack(0) etc. We can give name to index as well as below,

```
>>> df.index.names=['key1', 'key2']
>>> df.columns.names=['n', 'color']
>>> df
n           num1  num2 num3
color        red green  red
key1 key2
a    one       0     1    2
     two       3     4    5
b    three     6     7    8
     four      9    10   11
```

- Now, we can perform the partial indexing operations. In following code, various ways to access the data in a DataFrame are shown,

```
>>> # accessing the column for num1
>>> df['num1']  #  df.ix[:, 'num1']
color        red
key1 key2
a    one       0
     two       3
```

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```
b    three    6
     four     9

>>> # accessing the column for a
>>> df.ix['a']
n      num1  num2 num3
color  red green  red
key2
one       0     1    2
two       3     4    5

>>> # access row 0 only
>>> df.ix[0]
n      color
num1   red      0
num2   green    1
num3   red      2
Name: (a, one), dtype: int32
```

4.1.5 Swap and sort level

We can swap the index level using 'swaplevel' command, which takes two level-numbers as input,

```
>>> df.swaplevel('key1', 'key2')
n           num1  num2 num3
color        red green  red
key2  key1
one   a        0     1    2
two   a        3     4    5
three b        6     7    8
four  b        9    10   11
>>>
```

Levels can be sorted using 'sort_index' command. In below code, data is sorted by 'key2' names i.e. key2 is arranged alphabatically,

```
>>> df.sort_index(level='key2')
n           num1  num2 num3
color        red green  red
key1 key2
b    four      9    10   11
a    one       0     1    2
b    three     6     7    8
a    two       3     4    5
>>>
```

4.1.6 Summary statistics by level

We saw the example of groupby command in Section *Groupby*. Pandas provides some easier ways to perform those operations using 'level' shown below,

```
>>> # add all rows with similar key1 name
>>> df.sum(level = 'key1')
n      num1  num2 num3
color  red green  red
key1
a         3     5    7
```

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```
b        15    17    19
>>>

>>> # add all the columns based on similar color
>>> df.sum(level= 'color', axis=1)
color       green  red
key1 key2
a    one        1    2
     two        4    8
b    three      7   14
     four      10   20
```

4.2 File operations

In this section, various methods for reading and writing the files are discussed.

4.2.1 Reading files

Pandas supports various types of file format e.g. csv, text, excel and different database etc. Files are often stored in different formats as well e.g. files may or may not contain header, footer and comments etc.; therefore we need to process the content of file. Pandas provides various features which can process some of the common processing while reading the file. Some of these processing are shown in this section.

- Files can be read using 'read_csv', 'read_table' or 'DataFrame.from_csv' options, as shown below. Note that, the output of all these methods are same, but we need to provide different parameters to read the file correctly.

Following are the contents of 'ex1.csv' file,

```
$ cat ex1.csv
a,b,c,d,message
1,2,3,4,hello
5,6,7,8,world
9,10,11,12,foo
```

Below are the outputs of different file reading methods. 'read_csv' is general purpose method for reading the files, hence this method is used for rest of the tutorial,

```
>>> import pandas as pd

>>> # DataFrame.from_csv
>>> df = pd.DataFrame.from_csv('ex1.csv', index_col=None)
>>> df
   a   b   c   d message
0  1   2   3   4   hello
1  5   6   7   8   world
2  9  10  11  12     foo

>>> # read_csv
>>> df = pd.read_csv('ex1.csv')
>>> df
   a   b   c   d message
0  1   2   3   4   hello
1  5   6   7   8   world
2  9  10  11  12     foo

>>> # read_table
```

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```
>>> df = pd.read_table('ex1.csv', sep=',')
>>> df
   a   b   c   d message
0  1   2   3   4   hello
1  5   6   7   8   world
2  9  10  11  12     foo
>>>
```

- Note that, in above outputs, the headers are added from the file; but not all the files contain header. In this case, we need to explicitly define the header as below,

Following are the contents of 'ex2.csv' file,

```
$ cat ex2.csv
1,2,3,4,hello
5,6,7,8,world
9,10,11,12,food
```

Since header is not present in above file, therefore we need to provide the "header" argument explicitly.

```
>>> import pandas as pd

>>> # set header as none, default values will be used as header
>>> pd.read_csv('ex2.csv', header=None)
   0   1   2   3      4
0  1   2   3   4  hello
1  5   6   7   8  world
2  9  10  11  12    foo

>>> # specify the header using 'names'
>>> pd.read_csv('ex2.csv', names=['a', 'b', 'c', 'd', 'message'])
   a   b   c   d message
0  1   2   3   4   hello
1  5   6   7   8   world
2  9  10  11  12     foo

>>> # specify the row and column header both
>>> pd.read_csv('ex2.csv', names=['a', 'b', 'c', 'd', 'message'], index_col='message')
         a   b   c   d
message
hello    1   2   3   4
world    5   6   7   8
foo      9  10  11  12
>>>
```

- Hierarchical index can be created by providing a list to 'index_col' argument,

Following are the contents of 'csv_mindex.csv' file,

```
$ cat csv_mindex.csv
key1,key2,value1,value2
one,a,1,2
one,b,3,4
one,c,5,6
one,d,7,8
two,a,9,10
two,b,11,12
two,c,13,14
two,d,15,16
```

The hierarchical index can be created with 'key' values as below,

```
>>> pd.read_csv('csv_mindex.csv', index_col=['key1', 'key2'])
             value1  value2
key1 key2
one     a         1       2
        b         3       4
        c         5       6
        d         7       8
two     a         9      10
        b        11      12
        c        13      14
        d        15      16
>>>
```

- Some files may contain additional information or comments, therefore we need to remove these information for processing the data. This can be done by using 'skiprows' command,

Following are the content of 'ex4.csv' file,

```
$ cat ex4.csv
# hey!
a,b,c,d,message
# just wanted to make things more difficult for you
# who reads CSV files with computers, anyway?
1,2,3,4,hello
5,6,7,8,world
9,10,11,12,foodh
```

In above results, lines 0, 2 and 3 contains some comments. These can be removed as follows,

```
>>> d = pd.read_csv('ex4.csv', skiprows=[0,2,3])
>>> d
   a   b   c   d message
0  1   2   3   4   hello
1  5   6   7   8   world
2  9  10  11  12     foo
```

4.2.2 Writing data to a file

The 'to_csv' command is used to save the file. In following code, previous data 'd' is saved in two files i.e. d_out.csv and d_out2.csv with and without index respectively,

```
>>> d.to_csv('d_out.csv')

>>> # save without headers
>>> d.to_csv('d_out2.csv', header=False, index=False)
```

Contents of above two files are shown below,

```
$ cat d_out.csv
,a,b,c,d,message
0,1,2,3,4,hello
1,5,6,7,8,world
2,9,10,11,12,foo

$ cat d_out2.csv
0,1,2,3,4,hello
1,5,6,7,8,world
2,9,10,11,12,foo
```

4.3 Merge

Merge or joins operations combine the data sets by liking rows using one or more keys. The 'merge' function is the main entry point for using these algorithms on the data. Let's understand this by following examples,

```
>>> df1 = pd.DataFrame({ 'key' : ['b', 'b', 'a', 'c', 'a', 'a', 'b'],
...                     'data1' : range(7)})

>>> df2 = pd.DataFrame({ 'key' : ['a', 'b', 'd'],
...                      'data2' : range(3)})

>>> df1
   data1 key
0      0   b
1      1   b
2      2   a
3      3   c
4      4   a
5      5   a
6      6   b

>>> df2 = pd.DataFrame({ 'key' : ['a', 'b', 'd', 'b'],
...                      'data2' : range(4)})
>>> df2
   data2 key
0      0   a
1      1   b
2      2   d
3      3   b
>>>
```

4.3.1 Many to one

- 'Many to one' merge joins the Cartesian product of the rows, e.g. df1 and df2 has total 3 and 2 rows of 'b' respectively, therefore join will result in total 6 rows. Further, it is better to define 'on' keyword while using the joins, as it makes code more readable,

```
>>> pd.merge(df1, df2)  # or pd.merge(df1, df2, on='key')
    data1 key  data2
 0      0   b      1
 1      0   b      3
 2      1   b      1
 3      1   b      3
 4      6   b      1
 5      6   b      3
 6      2   a      0
 7      4   a      0
 8      5   a      0
 >>>
```

- In previous case, both the DataFrame have the same header 'key'. In the following example data are joined based on different keys using 'left_on' and 'right_on' keywords,

```
>>> # data is same as previous, only 'key' is replaces with 'key1' and 'key2'
>>> df1 = pd.DataFrame({ 'key1' : ['b', 'b', 'a', 'c', 'a', 'a', 'b'],
...                     'data1' : range(7)})
>>> df2 = pd.DataFrame({ 'key2' : ['a', 'b', 'd', 'b'],
...                     'data1' : range(4)})
```

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```
>>> pd.merge(df1, df2, left_on='key1', right_on='key2')
   data1_x key1  data1_y key2
0        0    b        1    b
1        0    b        3    b
2        1    b        1    b
3        1    b        3    b
4        6    b        1    b
5        6    b        3    b
6        2    a        0    a
7        4    a        0    a
8        5    a        0    a
>>>
```

4.3.2 Inner and outer join

In previous example, we can see that uncommon entries in DataFrame 'df1' and 'df2' are missing from the merge e.g. 'd' is not in the merged data. This is an example of 'inner join' where only common keys are merged together. By default, pandas perform the inner join. To perform outer join, we need to use 'how' keyword which can have 3 different values i.e. 'left', 'right' and 'outer'. 'left' option takes the left DataFrame and merge all it's entries with other DataFrame. Similarly, 'right' option merge the entries of the right DataFrame with left DataFrame. Lastly, the 'outer' option merge all the entries from both the DataFrame, as shown below. Note that, the missing entries after joining the table are represented as 'NaN'.

```
>>> # left join
>>> pd.merge(df1, df2, left_on='key1', right_on='key2', how="left")
   data1_x key1  data1_y key2
0        0    b      1.0    b
1        0    b      3.0    b
2        1    b      1.0    b
3        1    b      3.0    b
4        2    a      0.0    a
5        3    c      NaN  NaN
6        4    a      0.0    a
7        5    a      0.0    a
8        6    b      1.0    b
9        6    b      3.0    b

>>> # right join
>>> pd.merge(df1, df2, left_on='key1', right_on='key2', how="right")
    data1_x key1  data1_y key2
0      0.0    b        1    b
1      1.0    b        1    b
2      6.0    b        1    b
3      0.0    b        3    b
4      1.0    b        3    b
5      6.0    b        3    b
6      2.0    a        0    a
7      4.0    a        0    a
8      5.0    a        0    a
9      NaN  NaN        2    d

>>> # outer join
>>> pd.merge(df1, df2, left_on='key1', right_on='key2', how="outer")
    data1_x key1  data1_y key2
0       0.0    b      1.0    b
1       0.0    b      3.0    b
2       1.0    b      1.0    b
3       1.0    b      3.0    b
4       6.0    b      1.0    b
```

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```
5       6.0    b      3.0    b
6       2.0    a      0.0    a
7       4.0    a      0.0    a
8       5.0    a      0.0    a
9       3.0    c      NaN  NaN
10      NaN  NaN      2.0    d
```

4.3.3 Concatenating the data

We saw concatenation of data in Numpy. Pandas concatenation is more generalized than Numpy. It allows concatenation based on union or intersection of data along with labeling to visualize the grouping as shown in this section,

```
>>> s1 = pd.Series([0, 1], index=['a', 'b'])
>>> s2 = pd.Series([2, 1, 3], index=['c', 'd', 'e'])
>>> s3 = pd.Series([4, 7], index=['a', 'e'])

>>> s1
a    0
b    1
dtype: int64

>>> s2
c    2
d    1
e    3
dtype: int64

>>> s3
a    4
e    7
dtype: int64

>>> # concatenate s1 and s2
>>> pd.concat([s1, s2])
a    0
b    1
c    2
d    1
e    3
dtype: int64

>>> # join on axis 1
>>> pd.concat([s1, s2], axis=1)
     0    1
a  0.0  NaN
b  1.0  NaN
c  NaN  2.0
d  NaN  1.0
e  NaN  3.0
```

- In above results , it is difficult to identify the different pieces of concatenate operation. We can provide 'keys' to make the operation identifiable,

```
>>> pd.concat([s1, s2, s3], keys=['one', 'two', 'three'])
one    a    0
       b    1
two    c    2
       d    1
```

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```
       e    3
three  a    4
       e    7
dtype: int64
```

Note: Above concatenate operation are the union of two data set i.e. it is outer join. We can use "join='inner'" for intersection of data.

```
>>> pd.concat([s1, s3], join='inner', axis=1)
    0  1
 a  0  4
```

- Concatenating the DataFrame is same as above. Following is the example of the concatenation of DataFrame. Note that 'df1' and 'df2' are defined at the beginning of this section.

```
>>> pd.concat([df1, df2], join='inner', axis=1, keys=['one', 'two'])
    one        two
  data1 key1 data1 key2
0     0    b     0    a
1     1    b     1    b
2     2    a     2    d
3     3    c     3    b
```

- We can pass the DataFrame as dictionary as well for the concatenation operation. In this case, the keys of the dictionary will be used as 'keys' for the operation,

```
>>> pd.concat({ 'level1':df1, 'level2':df2}, axis=1, join='inner')
    level1      level2
     data1 key1  data1 key2
  0      0    b      0    a
  1      1    b      1    b
  2      2    a      2    d
  3      3    c      3    b
  >>>
```

4.4 Data transformation

In previous section, we saw various operations to join the various data. Next, important step is the data transformation i.e. cleaning and filtering the data e.g. removing the duplicate entries and replacing the NaN values etc.

4.4.1 Removing duplicates

- Removing duplicate entries are quite easy with 'drop_duplicates' command. Also, 'duplicate()' command can be used to check the duplicate entries as shown below,

```
>>> # create DataFrame with duplicate entries
>>> df = pd.DataFrame({'k1':['one']*3 + ['two']*4,
...                    'k2':[1,1,2,3,3,4,4]})
>>> df
    k1  k2
0  one   1
1  one   1
2  one   2
```

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```
3  two   3
4  two   3
5  two   4
6  two   4

>>> # see the duplicate entries
>>> df.duplicated()
0    false
1     true
2    false
3    false
4     true
5    false
6     true
dtype: bool

>>> # drop the duplicate entries
>>> df.drop_duplicates()
    k1  k2
0  one   1
2  one   2
3  two   3
5  two   4
```

- Currently, last entry is removed by drop_duplicates commnad. If we want to keep the last entry, then 'keep' keyword can be used,

```
>>> df.drop_duplicates(keep="last")
    k1  k2
1  one   1
2  one   2
4  two   3
6  two   4
>>>
```

- We can drop all the duplicate values from based on the specific columns as well,

```
>>> # drop duplicate entries based on k1 only
>>> df.drop_duplicates(['k1'])
    k1  k2
0  one   1
3  two   3

>>> # drop if k1 and k2 column matched
>>> df.drop_duplicates(['k1', 'k2'])
    k1  k2
0  one   1
2  one   2
3  two   3
5  two   4
>>>
```

4.4.2 Replacing values

Replacing value is very easy using pandas as below,

```
>>> # replace 'one' with 'One'
>>> df.replace('one', 'One')
    k1  k2
```

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```
0  One   1
1  One   1
2  One   2
3  two   3
4  two   3
5  two   4
6  two   4

>>> # replace 'one'->'One'  and 3->30
>>> df.replace(['one', 3], ['One', '30'])
    k1  k2
0  One   1
1  One   1
2  One   2
3  two  30
4  two  30
5  two   4
6  two   4
>>>
```

- Arguments can be passed as dictionary as well,

```
>>> df.replace({'one':'One', 3:30})
    k1  k2
0  One   1
1  One   1
2  One   2
3  two  30
4  two  30
5  two   4
6  two   4
```

4.5 Groupby and data aggregation

4.5.1 Basics

We saw various groupby operation in Section *Groupby*. Here, some more features of gropby operations are discussed.

Let's create a DataFrame first,

```
>>> df = pd.DataFrame({'k1':['a', 'a', 'b', 'b', 'a'],
...                     'k2':['one', 'two', 'one', 'two', 'one'],
...                     'data1': [2, 3, 3, 2, 4],
...                     'data2': [5, 5, 5, 5, 10]})
>>> df
   data1  data2 k1   k2
0      2      5  a  one
1      3      5  a  two
2      3      5  b  one
3      2      5  b  two
4      4     10  a  one
```

- Now, create a group based on 'k1' and find the mean value as below. In the following code, rows (0, 1, 4) and (2, 3) are grouped together. Therefore mean values are 3 and 2.5.

```
>>> gp1 = df['data1'].groupby(df['k1'])
>>> gp1
<pandas.core.groupby.SeriesGroupBy object at 0xb21f6bcc>
```

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```
>>> gp1.mean()
k1
a    3.0
b    2.5
Name: data1, dtype: float64
```

- We can pass multiple parameters for grouping as well,

```
>>> gp2 = df['data1'].groupby([df['k1'], df['k2']])
>>> mean = gp2.mean()
>>> mean
k1  k2
a   one    3
    two    3
b   one    3
    two    2
Name: data1, dtype: int64
>>>
```

4.5.2 Iterating over group

- The groupby operation supports iteration which generates the tuple with two values i.e. group-name and data.

```
>>> for name, group in gp1:
...     print(name)
...     print(group)
...
a
0    2
1    3
4    4
Name: data1, dtype: int64
b
2    3
3    2
Name: data1, dtype: int64
```

- If groupby operation is performed based on multiple keys, then it will generate a tuple for keys as well,

```
>>> for name, group in gp2:
...     print(name)
...     print(group)
...
('a', 'one')
0    2
4    4
Name: data1, dtype: int64
('a', 'two')
1    3
Name: data1, dtype: int64
('b', 'one')
2    3
Name: data1, dtype: int64
('b', 'two')
3    2
Name: data1, dtype: int64
```

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```
>>> # seperate key values as well
>>> for (k1, k2), group in gp2:
...     print(k1, k2)
...     print(group)
...
a one
0    2
4    4
Name: data1, dtype: int64
a two
1    3
Name: data1, dtype: int64
b one
2    3
Name: data1, dtype: int64
b two
3    2
Name: data1, dtype: int64
>>>
```

4.5.3 Data aggregation

We can perform various aggregation operation on the grouped data as well,

```
>>> gp1.max()
k1
a    4
b    3
Name: data1, dtype: int64
>>> gp2.min()
k1  k2
a   one    2
    two    3
b   one    3
    two    2
Name: data1, dtype: int64
```

Chapter 5

Time series

5.1 Dates and times

5.1.1 Generate series of time

A series of time can be generated using 'date_range' command. In below code, 'periods' is the total number of samples; whereas freq = 'M' represents that series must be generated based on 'Month'.

- By default, pandas consider 'M' as end of the month. Use 'MS' for start of the month. Similarly, other options are also available for day ('D'), business days ('B') and hours ('H') etc.

```
>>> import pandas as pd
>>> import numpy as np
>>> rng = pd.date_range('2011-03-01 10:15', periods = 10, freq = 'M')
>>> rng
DatetimeIndex(['2011-03-31 10:15:00', '2011-04-30 10:15:00',
               '2011-05-31 10:15:00', '2011-06-30 10:15:00',
               '2011-07-31 10:15:00', '2011-08-31 10:15:00',
               '2011-09-30 10:15:00', '2011-10-31 10:15:00',
               '2011-11-30 10:15:00', '2011-12-31 10:15:00'],
              dtype='datetime64[ns]', freq='M')

>>> rng = pd.date_range('2015 Jul 2 10:15', periods = 10, freq = 'M')
>>> rng
DatetimeIndex(['2015-07-31 10:15:00', '2015-08-31 10:15:00',
               '2015-09-30 10:15:00', '2015-10-31 10:15:00',
               '2015-11-30 10:15:00', '2015-12-31 10:15:00',
               '2016-01-31 10:15:00', '2016-02-29 10:15:00',
               '2016-03-31 10:15:00', '2016-04-30 10:15:00'],
              dtype='datetime64[ns]', freq='M')
```

- Similarly, we can generate the time series using 'start' and 'end' parameters as below,

```
>>> rng = pd.date_range(start = '2015 Jul 2 10:15', end = '2015 July 12', freq = '12H')
>>> rng
DatetimeIndex(['2015-07-02 10:15:00', '2015-07-02 22:15:00',
               '2015-07-03 10:15:00', '2015-07-03 22:15:00',
               '2015-07-04 10:15:00', '2015-07-04 22:15:00',
               '2015-07-05 10:15:00', '2015-07-05 22:15:00',
               '2015-07-06 10:15:00', '2015-07-06 22:15:00',
               '2015-07-07 10:15:00', '2015-07-07 22:15:00',
               '2015-07-08 10:15:00', '2015-07-08 22:15:00',
               '2015-07-09 10:15:00', '2015-07-09 22:15:00',
               '2015-07-10 10:15:00', '2015-07-10 22:15:00',
```

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```
               '2015-07-11 10:15:00', '2015-07-11 22:15:00'],
              dtype='datetime64[ns]', freq='12H')
>>> len(rng)
20
```

- Time zone can be specified for generating the series,

```
>>> rng = pd.date_range(start = '2015 Jul 2 10:15', end = '2015 July 12', freq = '12H', tz=
↪'Asia/Kolkata')
>>> rng
DatetimeIndex(['2015-07-02 10:15:00+05:30', '2015-07-02 22:15:00+05:30',
               '2015-07-03 10:15:00+05:30', '2015-07-03 22:15:00+05:30',
               '2015-07-04 10:15:00+05:30', '2015-07-04 22:15:00+05:30',
               '2015-07-05 10:15:00+05:30', '2015-07-05 22:15:00+05:30',
               '2015-07-06 10:15:00+05:30', '2015-07-06 22:15:00+05:30',
               '2015-07-07 10:15:00+05:30', '2015-07-07 22:15:00+05:30',
               '2015-07-08 10:15:00+05:30', '2015-07-08 22:15:00+05:30',
               '2015-07-09 10:15:00+05:30', '2015-07-09 22:15:00+05:30',
               '2015-07-10 10:15:00+05:30', '2015-07-10 22:15:00+05:30',
               '2015-07-11 10:15:00+05:30', '2015-07-11 22:15:00+05:30'],
              dtype='datetime64[ns, Asia/Kolkata]', freq='12H')
 >>>
```

- Further, we can change the time zone of the data for various comparison,

```
>>> rng.tz_convert('Australia/Sydney')DatetimeIndex(['2015-07-02 14:45:00+10:00', '2015-07-03␣
↪02:45:00+10:00',
               '2015-07-03 14:45:00+10:00', '2015-07-04 02:45:00+10:00',
               '2015-07-04 14:45:00+10:00', '2015-07-05 02:45:00+10:00',
               '2015-07-05 14:45:00+10:00', '2015-07-06 02:45:00+10:00',
               '2015-07-06 14:45:00+10:00', '2015-07-07 02:45:00+10:00',
               '2015-07-07 14:45:00+10:00', '2015-07-08 02:45:00+10:00',
               '2015-07-08 14:45:00+10:00', '2015-07-09 02:45:00+10:00',
               '2015-07-09 14:45:00+10:00', '2015-07-10 02:45:00+10:00',
               '2015-07-10 14:45:00+10:00', '2015-07-11 02:45:00+10:00',
               '2015-07-11 14:45:00+10:00', '2015-07-12 02:45:00+10:00'],
              dtype='datetime64[ns, Australia/Sydney]', freq='12H')
```

- Note that types of these dates are Timestamp,

```
>>> type(rng[0])
<class 'pandas.tslib.Timestamp'>
>>>
```

5.1.2 Convert string to dates

Dates in string formats can be converted into time stamp using 'to_datetime' option as below,

```
>>> dd = ['07/07/2015', '08/12/2015', '12/04/2015']
>>> dd
['07/07/2015', '08/12/2015', '12/04/2015']
>>> type(dd[0])
<class 'str'>

>>> # American style
>>> list(pd.to_datetime(dd))
[Timestamp('2015-07-07 00:00:00'), Timestamp('2015-08-12 00:00:00'), Timestamp('2015-12-04 00:00:00')]

>>> # European format
```

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```
>>> d = list(pd.to_datetime(dd, dayfirst=True))
>>> d
[Timestamp('2015-07-07 00:00:00'), Timestamp('2015-12-08 00:00:00'), Timestamp('2015-04-12 00:00:00')]
>>> type(d[0])
<class 'pandas.tslib.Timestamp'>
>>>
```

5.1.3 Periods

Periods represents the time span e.g. days, years, quarter or month etc. Period class in pandas allows us to convert the frequency easily.

5.1.3.1 Generating periods and frequency conversion

In following code, period is generated using 'Period' command with frequency 'M'. Note that, when we use 'asfreq' operation with 'start' operation the date is '01' where as it is '31' with 'end' option.

```
>>> pr = pd.Period('2012', freq='M')
>>> pr.asfreq('D', 'start')
Period('2012-01-01', 'D')
>>> pr.asfreq('D', 'end')
Period('2012-01-31', 'D')
>>>
```

5.1.3.2 Period arithmetic

We can perform various arithmetic operation on periods. All the operations will be performed based on 'freq',

```
>>> pr = pd.Period('2012', freq='A')  # Annual
>>> pr
Period('2012', 'A-DEC')
>>> pr + 1
Period('2013', 'A-DEC')

>>> # Year to month conversion
>>> prMonth = pr.asfreq('M')
>>> prMonth
Period('2012-12', 'M')
>>> prMonth - 1
Period('2012-11', 'M')
>>>
```

5.1.3.3 Creating period range

A range of periods can be created using 'period_range' command,

```
>>> prg = pd.period_range('2010', '2015', freq='A')
>>> prg
PeriodIndex(['2010', '2011', '2012', '2013', '2014', '2015'], dtype='int64', freq='A-DEC')

>>> # create a series with index as 'prg'
>>> data = pd.Series(np.random.rand(len(prg)), index=prg)
>>> data
2010    0.785453
2011    0.606939
```

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```
2012    0.558619
2013    0.321185
2014    0.224793
2015    0.561374
Freq: A-DEC, dtype: float64
>>>
```

5.1.3.4 Converting string-dates to period

Conversion of string-dates to period is the two step process, i.e. first we need to convert the string to date format and then convert the dates in periods as shown below,

```
>>> # dates as string
>>> dates = ['2013-02-02', '2012-02-02', '2013-02-02']

>>> # convert string to date format
>>> d = pd.to_datetime(dates)
>>> d
DatetimeIndex(['2013-02-02', '2012-02-02', '2013-02-02'], dtype='datetime64[ns]', freq=None)

>>> # create PeriodIndex from DatetimeIndex
>>> prd = d.to_period(freq='M')
>>> prd
PeriodIndex(['2013-02', '2012-02', '2013-02'], dtype='int64', freq='M')

>>> # change frequency type
>>> prd.asfreq('D')
PeriodIndex(['2013-02-28', '2012-02-29', '2013-02-28'], dtype='int64', freq='D')
>>> prd.asfreq('Y')
PeriodIndex(['2013', '2012', '2013'], dtype='int64', freq='A-DEC')
```

5.1.3.5 Convert periods to timestamps

Periods can be converted back to timestamps using 'to_timestamp' command,

```
>>> prd
PeriodIndex(['2013-02', '2012-02', '2013-02'], dtype='int64', freq='M')
>>> prd.to_timestamp()
DatetimeIndex(['2013-02-01', '2012-02-01', '2013-02-01'], dtype='datetime64[ns]', freq=None)
>>> prd.to_timestamp(how='end')
DatetimeIndex(['2013-02-28', '2012-02-29', '2013-02-28'], dtype='datetime64[ns]', freq=None)
>>>
```

5.1.4 Time offsets

Time offset can be defined as follows. Further we can perform various operations on time as as well e.g. adding and subtracting etc.

```
>>> # generate time offset
>>> pd.Timedelta('3 days')
Timedelta('3 days 00:00:00')
>>> pd.Timedelta('3M')
Timedelta('0 days 00:03:00')
>>> pd.Timedelta('4 days 3M')
Timedelta('4 days 00:03:00')
>>>
```

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```
>>> # adding Timedelta to time
>>> pd.Timestamp('9 July 2016 12:00') + pd.Timedelta('1 day 3 min')
Timestamp('2016-07-10 12:03:00')
>>>

>>> # add Timedelta to complete rng
>>> rng + pd.Timedelta('1 day')
DatetimeIndex(['2015-07-03 10:15:00+05:30', '2015-07-03 22:15:00+05:30',
               '2015-07-04 10:15:00+05:30', '2015-07-04 22:15:00+05:30',
               '2015-07-05 10:15:00+05:30', '2015-07-05 22:15:00+05:30',
               '2015-07-06 10:15:00+05:30', '2015-07-06 22:15:00+05:30',
               '2015-07-07 10:15:00+05:30', '2015-07-07 22:15:00+05:30',
               '2015-07-08 10:15:00+05:30', '2015-07-08 22:15:00+05:30',
               '2015-07-09 10:15:00+05:30', '2015-07-09 22:15:00+05:30',
               '2015-07-10 10:15:00+05:30', '2015-07-10 22:15:00+05:30',
               '2015-07-11 10:15:00+05:30', '2015-07-11 22:15:00+05:30',
               '2015-07-12 10:15:00+05:30', '2015-07-12 22:15:00+05:30'],
              dtype='datetime64[ns, Asia/Kolkata]', freq='12H')
>>>
```

5.1.5 Index data with time

In this section, time is used as index for Series and DataFrame; and then various operations are performed on these data structures.

- First, create a time series using 'date_range' option as below.

```
>>> dates = pd.date_range('2015-01-12', '2015-06-14', freq = 'M')
>>> dates
DatetimeIndex(['2015-01-31', '2015-02-28', '2015-03-31', '2015-04-30',
               '2015-05-31'],
              dtype='datetime64[ns]', freq='M')
>>> len(dates)
5
```

- Next, create a Series of temperature of length same as dates,

```
>>> atemp = pd.Series([100.2, 98, 93, 98, 100], index=dates)
>>> atemp
2015-01-31    100.2
2015-02-28     98.0
2015-03-31     93.0
2015-04-30     98.0
2015-05-31    100.0
Freq: M, dtype: float64
>>>
```

- Now, time index can be used to access the temperatures as below,

```
>>> idx = atemp.index[3]
>>> idx
Timestamp('2015-04-30 00:00:00', offset='M')
>>> atemp[idx]
98.0
>>>
```

- Next, make another temperature series 'stemp' and create a DataFrame using 'stemp' and 'atemp' as below,

```
>>> stemp = pd.Series([89, 98, 100, 88, 89], index=dates)
>>> stemp
2015-01-31     89
2015-02-28     98
2015-03-31    100
2015-04-30     88
2015-05-31     89
Freq: M, dtype: int64
>>>

>>> # create DataFrame
>>> temps = pd.DataFrame({'Auckland':atemp, 'Delhi':stemp})
>>> temps
            Auckland  Delhi
2015-01-31     100.2     89
2015-02-28      98.0     98
2015-03-31      93.0    100
2015-04-30      98.0     88
2015-05-31     100.0     89
>>>

>>> # check the temperature of Auckland
>>> temps['Auckland']  # or temps.Auckland
2015-01-31    100.2
2015-02-28     98.0
2015-03-31     93.0
2015-04-30     98.0
2015-05-31    100.0
Freq: M, Name: Auckland, dtype: float64
>>>
```

- We can add one more column to DataFrame 'temp' which shows the temperature differences between these two cities,

```
>>> temps['Diff'] = temps['Auckland'] - temps['Delhi']
>>> temps
            Auckland  Delhi  Diff
2015-01-31     100.2     89  11.2
2015-02-28      98.0     98   0.0
2015-03-31      93.0    100  -7.0
2015-04-30      98.0     88  10.0
2015-05-31     100.0     89  11.0
>>>

>>> # delete the temp['Diff']
>>> del temps['Diff']
>>> temps
            Auckland  Delhi
2015-01-31     100.2     89
2015-02-28      98.0     98
2015-03-31      93.0    100
2015-04-30      98.0     88
2015-05-31     100.0     89
>>>
```

5.2 Application

In previous section, we saw some basics of time series. In this section, we will learn some usage of time series with an example,

5.2.1 Basics

- First, load the stocks.csv file as below,

```
>>> import pandas as pd
>>> df = pd.read_csv('stocks.csv')
>>> df.head()
                  date    AA    GE    IBM  MSFT
0  1990-02-01 00:00:00  4.98  2.87  16.79  0.51
1  1990-02-02 00:00:00  5.04  2.87  16.89  0.51
2  1990-02-05 00:00:00  5.07  2.87  17.32  0.51
3  1990-02-06 00:00:00  5.01  2.88  17.56  0.51
4  1990-02-07 00:00:00  5.04  2.91  17.93  0.51
>>>
```

- If we check the format of 'date' column, we will find that it is string (not the date),

```
>>> d = df.date[0]
>>> d
'1990-02-01 00:00:00'
>>> type(d)
<class 'str'>
>>>
```

- To import 'date' as time stamp, 'parse_dates' option can be used as below,

```
>>> df = pd.DataFrame.from_csv('stocks.csv', parse_dates=['date'])
>>> d = df.date[0]
>>> d
Timestamp('1990-02-01 00:00:00')
>>> type(d)
<class 'pandas.tslib.Timestamp'>
>>>

>>> df.head()
        date    AA    GE    IBM  MSFT
0 1990-02-01  4.98  2.87  16.79  0.51
1 1990-02-02  5.04  2.87  16.89  0.51
2 1990-02-05  5.07  2.87  17.32  0.51
3 1990-02-06  5.01  2.88  17.56  0.51
4 1990-02-07  5.04  2.91  17.93  0.51
```

- Since, we want to used the date as index, therefore load it as index,

```
>>> df = pd.DataFrame.from_csv('stocks.csv', parse_dates=['date'], index_col='date')
>>> df.head()
            Unnamed: 0    AA    GE    IBM  MSFT
date
1990-02-01           0  4.98  2.87  16.79  0.51
1990-02-02           1  5.04  2.87  16.89  0.51
1990-02-05           2  5.07  2.87  17.32  0.51
1990-02-06           3  5.01  2.88  17.56  0.51
1990-02-07           4  5.04  2.91  17.93  0.51
```

- Since, 'Unnamed: 0' is not a useful column, therefore we can remove it as below,

```
>>> del df['Unnamed: 0']
>>> df.head()
              AA    GE    IBM  MSFT
date
1990-02-01  4.98  2.87  16.79  0.51
1990-02-02  5.04  2.87  16.89  0.51
```

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```
1990-02-05  5.07  2.87  17.32  0.51
1990-02-06  5.01  2.88  17.56  0.51
1990-02-07  5.04  2.91  17.93  0.51
>>>
```

- Before going further, let's check the name of the index as it will be used at various places along with plotting the data, where index will be used automatically for plots. **Note that, data is used as columns as well as index by using 'drop' keyword.**

```
>>> # check the name of the index
>>> df.index.name
'date'
>>>
```

- Let's redo all the above steps in different ways,

```
>>> # load and display first file line of the file
>>> stocks = pd.DataFrame.from_csv('stocks.csv', parse_dates=['date'])
>>> stocks.head()
        date    AA    GE    IBM  MSFT
0 1990-02-01  4.98  2.87  16.79  0.51
1 1990-02-02  5.04  2.87  16.89  0.51
2 1990-02-05  5.07  2.87  17.32  0.51
3 1990-02-06  5.01  2.88  17.56  0.51
4 1990-02-07  5.04  2.91  17.93  0.51

>>> stocks.index.name  # nothing is set as index
>>> # set date as index but do not remove it from column
>>> stocks = stocks.set_index('date', drop=False)
>>> stocks.index.name
'date'
>>> stocks.head()
                 date    AA    GE    IBM  MSFT
date
1990-02-01 1990-02-01  4.98  2.87  16.79  0.51
1990-02-02 1990-02-02  5.04  2.87  16.89  0.51
1990-02-05 1990-02-05  5.07  2.87  17.32  0.51
1990-02-06 1990-02-06  5.01  2.88  17.56  0.51
1990-02-07 1990-02-07  5.04  2.91  17.93  0.51
>>>

>>> # check the type of date
>>> type(stocks.date[0])
<class 'pandas.tslib.Timestamp'>
>>>
```

- Data can be accessed by providing the date in any valid format, as shown below,

```
>>> # all four commands have same results
>>> # stocks.ix['1990, 02, 01']
>>> # stocks.ix['1990-02-01']
>>> # stocks.ix['1990/02/01']
>>> stocks.ix['1990-Feb-01']
date    1990-02-01 00:00:00
AA                     4.98
GE                     2.87
IBM                   16.79
MSFT                   0.51
Name: 1990-02-01 00:00:00, dtype: object
>>>
```

- We can display the results in between some range with slice operation e.g. from 01/Feb/90 to 06/Feb/90.

Note that, last date of the slice is included in the results,

```
>>> stocks.ix['1990-Feb-01':'1990-Feb-06']
                 date    AA    GE    IBM  MSFT
date
1990-02-01 1990-02-01  4.98  2.87  16.79  0.51
1990-02-02 1990-02-02  5.04  2.87  16.89  0.51
1990-02-05 1990-02-05  5.07  2.87  17.32  0.51
1990-02-06 1990-02-06  5.01  2.88  17.56  0.51
>>>

>>> # select all from Feb-1990 and display first 5
>>> stocks.ix['1990-Feb'].head()
                date    AA    GE    IBM  MSFT
date
1990-02-01 1990-02-01  4.98  2.87  16.79  0.51
1990-02-02 1990-02-02  5.04  2.87  16.89  0.51
1990-02-05 1990-02-05  5.07  2.87  17.32  0.51
1990-02-06 1990-02-06  5.01  2.88  17.56  0.51
1990-02-07 1990-02-07  5.04  2.91  17.93  0.51
>>>

>>> # use python-timedelta or pandas-offset for defining range
>>> from datetime import datetime, timedelta
>>> start = datetime(1990, 2, 1)
>>> # stocks.ix[start:start+timedelta(days=5)]  # python-timedelta
>>> stocks.ix[start:start+pd.offsets.Day(5)]  # pandas-offset
                 date    AA    GE    IBM  MSFT
date
1990-02-01 1990-02-01  4.98  2.87  16.79  0.51
1990-02-02 1990-02-02  5.04  2.87  16.89  0.51
1990-02-05 1990-02-05  5.07  2.87  17.32  0.51
1990-02-06 1990-02-06  5.01  2.88  17.56  0.51
>>>
```

Note: Above slice operation works only if the dates are in sorted order. If dates are not sorted then we need to sort them first by using sort_index() command i.e. stocks.sort_index()

5.2.2 Resampling

Resampling is the conversion of time series from one frequency to another. If we convert higher frequency data to lower frequency, then it is known as down-sampling; whereas if data is converted to low frequency to higher frequency, then it is called up-sampling.

- Suppose, we want to see the data at the end of each month only (not on daily basis), then we can use following resampling code,

```
>>> stocks.ix[pd.date_range(stocks.index[0], stocks.index[-1], freq='M')].head()
                 date    AA    GE    IBM  MSFT
1990-02-28 1990-02-28  5.22  2.89  18.06  0.54
1990-03-31        NaT   NaN   NaN    NaN   NaN   # it is not business day i.e. sat/sun
1990-04-30 1990-04-30  5.07  2.99  18.95  0.63
1990-05-31 1990-05-31  5.39  3.24  21.10  0.80
1990-06-30        NaT   NaN   NaN    NaN   NaN

>>> # 'BM' can be used for 'business month'
>>> stocks.ix[pd.date_range(stocks.index[0], stocks.index[-1], freq='BM')].head()
                 date    AA    GE    IBM  MSFT
1990-02-28 1990-02-28  5.22  2.89  18.06  0.54
```

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```
1990-03-30 1990-03-30  5.26  3.01  18.45  0.60
1990-04-30 1990-04-30  5.07  2.99  18.95  0.63
1990-05-31 1990-05-31  5.39  3.24  21.10  0.80
1990-06-29 1990-06-29  5.21  3.26  20.66  0.83
>>>

>>> # confirm the entry on 1990-03-30
>>> stocks.ix['1990-Mar-30']
date    1990-03-30 00:00:00
AA                     5.26
GE                     3.01
IBM                   18.45
MSFT                    0.6
Name: 1990-03-30 00:00:00, dtype: object
```

- Pandas provides easier way to write the above code i.e. using 'resampling'. Further, resampling provides various features e.g. resample the data and show the mean value of the resampled data or maximum value of the data etc., as shown below,

Downsampling

Following is the example of downsampling.

```
>>> # resample and find mean of each bin
>>> stocks.resample('BM').mean().head()
                  AA        GE        IBM      MSFT
date
1990-02-28  5.043684  2.873158  17.781579  0.523158
1990-03-30  5.362273  2.963636  18.466818  0.595000
1990-04-30  5.141000  3.037500  18.767500  0.638500
1990-05-31  5.278182  3.160000  20.121818  0.731364
1990-06-29  5.399048  3.275714  20.933810  0.821429

>>> # size() : total number of rows in each bin
>>> stocks.resample('BM').size().head(3)
date
1990-02-28    19  # total 19 business days in Feb-90
1990-03-30    22
1990-04-30    20
Freq: BM, dtype: int64

>>> # count total number of rows in each bin for each column
>>> stocks.resample('BM').count().head(3)
            date  AA  GE  IBM  MSFT
date
1990-02-28    19  19  19   19    19
1990-03-30    22  22  22   22    22
1990-04-30    20  20  20   20    20
>>>

>>> # display last resample value from each bin
>>> ds = stocks.resample('BM').asfreq().head()
>>> ds
                 date    AA    GE    IBM  MSFT
date
1990-02-28 1990-02-28  5.22  2.89  18.06  0.54
1990-03-30 1990-03-30  5.26  3.01  18.45  0.60
1990-04-30 1990-04-30  5.07  2.99  18.95  0.63
1990-05-31 1990-05-31  5.39  3.24  21.10  0.80
```

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```
1990-06-29 1990-06-29  5.21  3.26  20.66  0.83
>>>
```

Upsampling

- When we upsample the data, the values are filled by NaN; therefore we need to use 'fillna' method to replace the NaN value with some other values,as shown below,

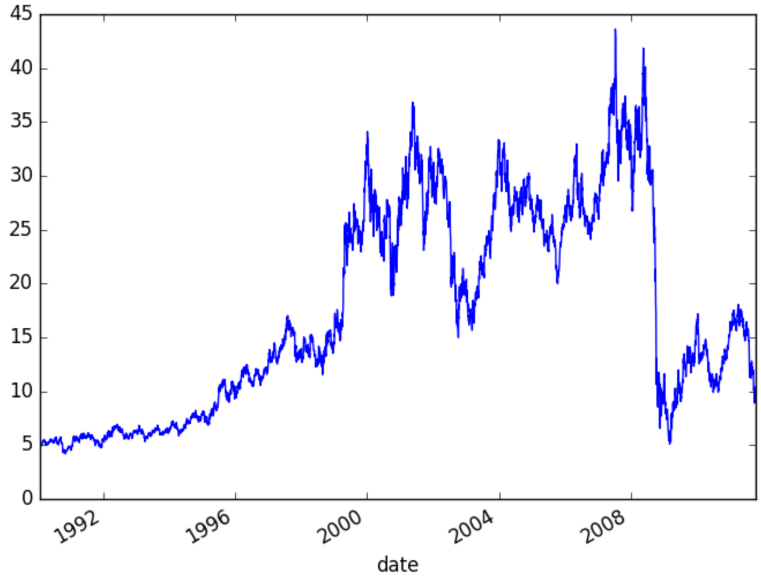
```
>>> # blank places are filled by NaN
>>> rs = ds.resample('B').asfreq()
>>> rs.head()
                 date    AA    GE    IBM  MSFT
date
1990-02-28 1990-02-28  5.22  2.89  18.06  0.54
1990-03-01        NaT   NaN   NaN    NaN   NaN
1990-03-02        NaT   NaN   NaN    NaN   NaN
1990-03-05        NaT   NaN   NaN    NaN   NaN
1990-03-06        NaT   NaN   NaN    NaN   NaN


>>> # forward fill the NaN
>>> rs = ds.resample('B').asfreq().fillna(method='ffill')
>>> rs.head()
                 date    AA    GE    IBM  MSFT
date
1990-02-28 1990-02-28  5.22  2.89  18.06  0.54
1990-03-01 1990-02-28  5.22  2.89  18.06  0.54
1990-03-02 1990-02-28  5.22  2.89  18.06  0.54
1990-03-05 1990-02-28  5.22  2.89  18.06  0.54
1990-03-06 1990-02-28  5.22  2.89  18.06  0.54
>>>
```

5.2.3 Plotting the data

In this section, we will plot various data from the DataFrame 'stocks' for various time ranges,

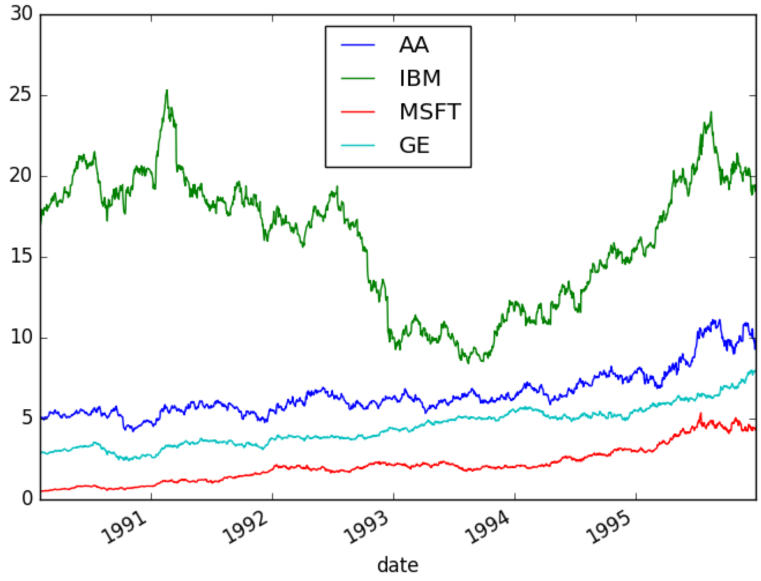
- First, plot the data of 'AA' for complete range,

```
>>> import matplotlib.pyplot as plt
>>> stocks.AA.plot()
<matplotlib.axes._subplots.AxesSubplot object at 0xa9c3060c>
>>> plt.show()
```



- We can plot various data in the same window, by selecting the column using 'ix',

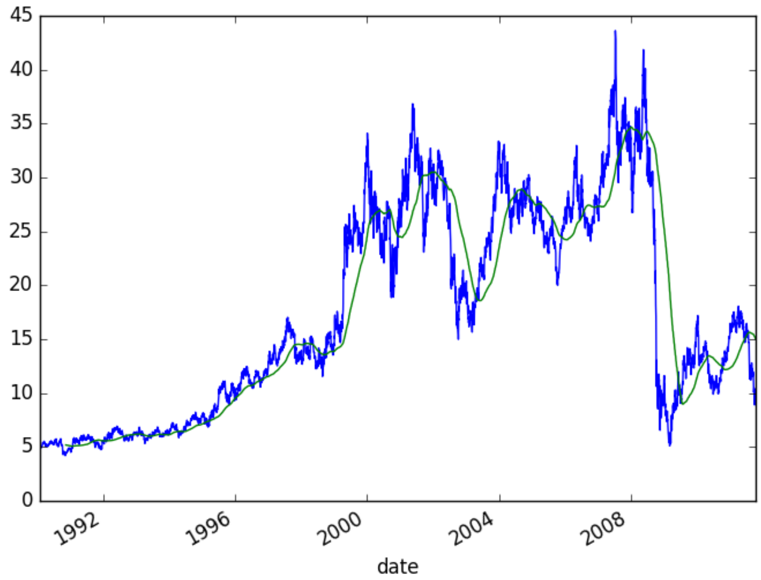
```
>>> stocks.ix['1990':'1995', ['AA', 'IBM', 'MSFT', 'GE']].plot()
<matplotlib.axes._subplots.AxesSubplot object at 0xa9c2d2ac>
>>> plt.show()
>>>
```



5.2.4 Moving windows functions

Pandas provide the ways to analyze the data over a sliding window e.g. in below code the data of 'AA' is plotted aalong with the mean value over a window of length 250,

```
>>> stocks.AA.plot()
<matplotlib.axes._subplots.AxesSubplot object at 0xa9c5f4ec>
>>> stocks.AA.rolling(window=200,center=False).mean().plot()
<matplotlib.axes._subplots.AxesSubplot object at 0xa9c5f4ec>
>>> plt.show()
>>>
```



Chapter 6

Reading multiple files

In previous chapters, we used only one or two files to read the data. In this chapter, multiple files are concatenated to analyze the data.

6.1 Example: Baby names trend

In this section, various operations are performed on the various text-files to gather the useful information from it. These text file contains the list to names of babies since 1880. Each record in the individual annual files has the format "name,sex,number," where name is 2 to 15 characters, sex is M (male) or F (female) and "number" is the number of occurrences of the name. Each file is sorted first on sex and then on number of occurrences in descending order. When there is a tie on the number of occurrences, names are listed in alphabetical order. Following is the list of files on which various operations will be performed.

```
$ ls
yob1880.txt  yob1882.txt  yob1884.txt  yob1886.txt
yob1881.txt  yob1883.txt  yob1885.txt  yob1887.txt
```

Following are the first ten lines in the yob1880.txt file,

```
$ head -n 10 yob1980.txt
Jennifer,F,58375
Amanda,F,35817
Jessica,F,33914
Melissa,F,31625
Sarah,F,25737
Heather,F,19965
Nicole,F,19910
Amy,F,19832
Elizabeth,F,19523
Michelle,F,19113
```

6.2 Total boys and girls in year 1880

- First, we will read one file and then check to total number of rows in that file,

```
>>> import pandas as pd
>>> names1880 = pd.read_csv('yob1880.txt', names=['name', 'gender', 'birthcount'])
>>> # total number of rows in yob1880.txt
>>> len(names1880)
2000
```

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```
>>>
>>> names1880.head()
        name gender  birthcount
0       Mary      F        7065
1       Anna      F        2604
2       Emma      F        2003
3  Elizabeth      F        1939
4     Minnie      F        1746
>>>
```

- Note that, the file contains 2000 rows; and each row contains a name and total number of babies with that particular name along with the gender information. We can calculate the total number of boys and girls by adding the 'birthcount' based on gender; i.e. we need to group the data based on gender and then add the individual group's birthcount,

```
>>> # total number of boys and girls in year 1880
>>> names1880.groupby('gender').birthcount.sum()
gender
F     90993
M    110493
Name: birthcount, dtype: int64
>>>
```

6.3 pivot_table

In previous chapters, we saw various examples of groupby and unstack operations. These two operations can be performed by a single operation as well i.e. pivot_table. In this section, we will calculate the total number of births in years 1880 to 1887 using pivot_table. For this first we need to merge the data from the files for these year.

```
>>> years = range(1880, 1887)
>>> pieces = []
>>> columns = ['name', 'gender', 'birthcount']
>>> for year in years:
...     path = 'yob{}.txt'.format(year)
...     columns = ['name', 'gender', 'birthcount']
...     for year in years:
...             path =  'yob{}.txt'.format(year)
...             df = pd.read_csv(path, names=columns)
...             df['year']=year
...             pieces.append(df)
...             allData = pd.concat(pieces, ignore_index=True)
...
>>>
>>> len(allData)
105903
>>>
>>> allData.head(2)
   name gender  birthcount  year
0  Mary      F        7065  1880
1  Anna      F        2604  1880
```

- Total number of birth can be calculated using pivot_table, as shown below,

```
>>> import matplotlib.pyplot as plt
>>> total_births = allData.pivot_table('birthcount', index=['year'], columns=['gender'], aggfunc=sum)
>>> total_births.head(3)
gender       F       M
```

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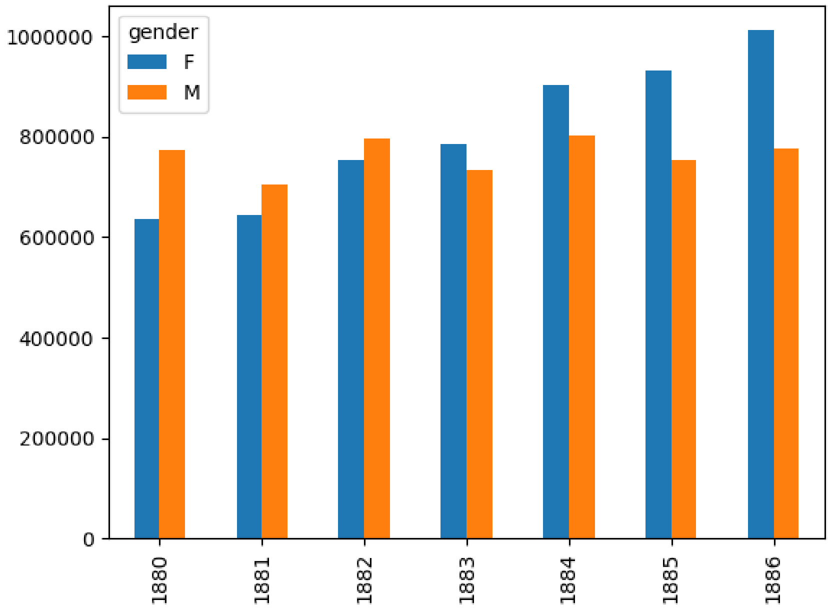
```
year
1880     636951  773451
1881     643685  705236
1882     754957  795809


>>> total_births.plot(kind='bar')
<matplotlib.axes._subplots.AxesSubplot object at 0xa580b44c>
>>> plt.show()
>>>
```



- Same can be achieved by using 'groupby' option as below,

```
>>> allData.groupby(['year', 'gender']).sum().unstack('gender').head(3)
      birthcount
gender          F       M
year
1880       636951  773451
1881       643685  705236
1882       754957  795809
```

- Next, we want to check the ratio of the names with total number of names. For this, we can write a function, which calculates the ration and apply it to groupby option,

```
>>> # calculate ratio
... def add_prop(group):
...     births = group.birthcount.astype(float)
...     group['prop'] = births/births.sum()  # add column prop
...     return group
...
>>>
>>> names = allData.groupby(['year', 'gender']).apply(add_prop)

>>> names.head()
        name gender  birthcount  year      prop
0       Mary      F        7065  1880  0.011092
1       Anna      F        2604  1880  0.004088
```

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```
2       Emma      F        2003  1880  0.003145
3  Elizabeth      F        1939  1880  0.003044
4     Minnie      F        1746  1880  0.00274
```