Python R training course - Pandas

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1 Introduction

Pandas is an open-source Python Library providing high-performance data manipulation and analysis tool using its powerful data structures. The name Pandas is derived from the word Panel Data – an Econometrics from Multidimensional data.

Python with Pandas is used in a wide range of fields including academic and commercial domains including finance, economics, Statistics, analytics, etc.

Key Features of Pandas

- Fast and efficient DataFrame object with default and customized indexing.
- Tools for loading data into in-memory data objects from different file formats.
- Data alignment and integrated handling of missing data.
- Reshaping and pivoting of date sets.
- Label-based slicing, indexing and subsetting of large data sets.
- Columns from a data structure can be deleted or inserted.
- Group by data for aggregation and transformations.
- High performance merging and joining of data.
- Time Series functionality.

2 Introduction to Data Structures

Pandas deals with the following three data structures:

- DataFrame
- Series
- Panel

These data structures are built on top of Numpy array, which means they are fast.

3 Python Pandas - DataFrame

A Data frame is a two-dimensional data structure, i.e., data is aligned in a tabular fashion in rows and columns.

3.1 Create DataFrame

3.1.1 Create an Empty DataFrame

```
import pandas as pd
df = pd.DataFrame()
print df
```

3.1.2 Create a DataFrame from Lists

```
In [4]: data = [1,2,3,4,5]
        df = pd.DataFrame(data)
        df

Out[4]:    0
        0  1
        1  2
        2  3
        3  4
        4  5

In [9]: data = [['Duyet',10], ['Thinh',12], ['Nam',13]]
        df = pd.DataFrame(data,columns=['Name','Age'])
        df

Out[9]:     Name  Age
        0  Duyet   10
        1  Thinh   12
        2    Nam   13

In [10]: data = [['Duyet',10], ['Thinh',12], ['Nam',13]]
         df = pd.DataFrame(data,columns=['Name','Age'], dtype=float)
         df

Out[10]:     Name   Age
         0  Duyet  10.0
         1  Thinh  12.0
         2    Nam  13.0
```

3.1.3 Create a DataFrame from Dict of ndarrays / Lists

All the ndarrays must be of same length. If index is passed, then the length of the index should equal to the length of the arrays.

If no index is passed, then by default, index will be range(n), where n is the array length.

```
In [11]: data = {'Name':['Tom', 'Jack', 'Steve', 'Ricky'],'Age':[28,34,29,42]}
         df = pd.DataFrame(data)
         df
```

```
Out[11]:    Age   Name
         0   28    Tom
         1   34   Jack
         2   29  Steve
         3   42  Ricky
```

3.1.4 Create a DataFrame from List of Dicts

```
In [14]: data = [{'a': 1, 'b': 2},{'a': 5, 'b': 10, 'c': 20}]
         df = pd.DataFrame(data)
         df

         # PS: NaN (Not a Number) is appended in missing areas.

Out[14]:    a   b     c
         0  1   2   NaN
         1  5  10  20.0
```

3.1.5 Reading from file (CSV, Excel, HDFS, SQL, ...)

Using `pd.read_csv()` function to read dataframe from a CSV file.

```
pandas.read_csv(filepath_or_buffer, sep='\t', delimiter=None, header='infer',
                names=None, index_col=None, usecols=None)
```

Using `pd.read_excel()` to read Excel file.

```
pd.read_excel('foo.xlsx', 'Sheet1', index_col=None, na_values=['NA'])
```

Example: Here is how the csv file data (*data.csv*) looks like:

```
S.No,Name,Age,City,Salary
1,Tom,28,Toronto,20000
2,Lee,32,HongKong,3000
3,Steven,43,Bay Area,8300
4,Ram,38,Hyderabad,3900
```

```
In [6]: df=pd.read_csv("data.csv")
        df

Out[6]:    S.No    Name  Age       City  Salary
        0     1     Tom   28    Toronto   20000
        1     2     Lee   32   HongKong    3000
        2     3  Steven   43   Bay Area    8300
        3     4     Ram   38  Hyderabad    3900
```

Specify the names of the header using the **names** argument.

```
In [17]: df=pd.read_csv("data.csv", names=['a', 'b', 'c','d','e'])
         df
```

```
Out[17]:        a       b    c         d       e
         0  S.No    Name  Age      City  Salary
         1     1     Tom   28   Toronto   20000
         2     2     Lee   32  HongKong    3000
         3     3  Steven   43  Bay Area    8300
         4     4     Ram   38  Hyderabad   3900
```

3.2 Viewing Data

```
In [89]: df.head()
```

```
Out[89]:    S.No    Name  Age       City  Salary     Salary2
         0     1     Tom   28    Toronto   20000  141.421356
         1     2     Lee   32   HongKong    3000   54.772256
         2     3  Steven   43   Bay Area    8300   91.104336
         3     4     Ram   38  Hyderabad    3900   62.449980
```

```
In [91]: df.tail(3)
```

```
Out[91]:    S.No    Name  Age       City  Salary    Salary2
         1     2     Lee   32   HongKong    3000  54.772256
         2     3  Steven   43   Bay Area    8300  91.104336
         3     4     Ram   38  Hyderabad    3900  62.449980
```

```
In [92]: df.T
```

```
Out[92]:                0         1         2          3
         S.No           1         2         3          4
         Name         Tom       Lee    Steven        Ram
         Age           28        32        43         38
         City     Toronto  HongKong  Bay Area  Hyderabad
         Salary     20000      3000      8300       3900
         Salary2  141.421   54.7723   91.1043      62.45
```

3.3 Column Selection

We will understand this by selecting a column from the DataFrame.

```
In [18]: df=pd.read_csv("data.csv")
         df["Name"]
```

```
Out[18]: 0       Tom
         1       Lee
         2    Steven
         3       Ram
         Name: Name, dtype: object
```

```
In [20]: # Or this
         df.Name
```

```
Out[20]: 0       Tom
         1       Lee
         2    Steven
         3       Ram
         Name: Name, dtype: object
```

3.4 Sort

```
In [94]: df.sort_values(by='Age')
```

```
Out[94]:    S.No    Name  Age       City  Salary     Salary2
         0     1     Tom   28    Toronto   20000  141.421356
         1     2     Lee   32   HongKong    3000   54.772256
         3     4     Ram   38  Hyderabad    3900   62.449980
         2     3  Steven   43   Bay Area    8300   91.104336
```

```
In [96]: df.sort_values(by='Salary', ascending=False)
```

```
Out[96]:    S.No    Name  Age       City  Salary     Salary2
         0     1     Tom   28    Toronto   20000  141.421356
         2     3  Steven   43   Bay Area    8300   91.104336
         3     4     Ram   38  Hyderabad    3900   62.449980
         1     2     Lee   32   HongKong    3000   54.772256
```

3.5 Column Addition

```
In [21]: df=pd.read_csv("data.csv")
         df
```

```
Out[21]:    S.No    Name  Age       City  Salary
         0     1     Tom   28    Toronto   20000
         1     2     Lee   32   HongKong    3000
         2     3  Steven   43   Bay Area    8300
         3     4     Ram   38  Hyderabad    3900
```

```
In [22]: # Add new column "Address"
         df["Address"] = ["HCM", "HN", "DN", "HCM"]
         df
```

```
Out[22]:    S.No    Name  Age       City  Salary Address
         0     1     Tom   28    Toronto   20000     HCM
         1     2     Lee   32   HongKong    3000      HN
         2     3  Steven   43   Bay Area    8300      DN
         3     4     Ram   38  Hyderabad    3900     HCM
```

```
In [23]: # Or new column with default value
         df["LastSalary"] = 1000
         df
```

```
Out[23]:    S.No    Name  Age       City  Salary Address  LastSalary
         0     1     Tom   28    Toronto   20000     HCM        1000
         1     2     Lee   32   HongKong    3000      HN        1000
         2     3  Steven   43   Bay Area    8300      DN        1000
         3     4     Ram   38  Hyderabad    3900     HCM        1000
```

```
In [24]: # New column base on old columns
         df["NewSalary"] = df.Salary + df.LastSalary
         df
```

```
Out[24]:    S.No    Name  Age       City  Salary Address  LastSalary  NewSalary
         0     1     Tom   28    Toronto   20000     HCM        1000      21000
         1     2     Lee   32   HongKong    3000      HN        1000       4000
         2     3  Steven   43   Bay Area    8300      DN        1000       9300
         3     4     Ram   38  Hyderabad    3900     HCM        1000       4900
```

3.6 Column Deletion

Columns can be deleted or popped; let us take an example to understand how.

```
In [25]: del df["NewSalary"]
         df
```

```
Out[25]:    S.No    Name  Age       City  Salary Address  LastSalary
         0     1     Tom   28    Toronto   20000     HCM        1000
         1     2     Lee   32   HongKong    3000      HN        1000
         2     3  Steven   43   Bay Area    8300      DN        1000
         3     4     Ram   38  Hyderabad    3900     HCM        1000
```

```
In [26]: LastSalary = df.pop('LastSalary')
         df
```

```
Out[26]:    S.No    Name  Age       City  Salary Address
         0     1     Tom   28    Toronto   20000     HCM
         1     2     Lee   32   HongKong    3000      HN
         2     3  Steven   43   Bay Area    8300      DN
         3     4     Ram   38  Hyderabad    3900     HCM
```

```
In [27]: LastSalary
```

```
Out[27]: 0    1000
         1    1000
         2    1000
         3    1000
         Name: LastSalary, dtype: int64
```

3.7 Row Selection, Addition, and Deletion

We will now understand row selection, addition and deletion through examples

3.7.1 Selection by Label

```
In [28]: df["City"]
```

```
Out[28]: 0      Toronto
         1     HongKong
         2     Bay Area
         3    Hyderabad
         Name: City, dtype: object
```

3.7.2 Selection by integer location

```
In [29]: df.iloc[2]
```

```
Out[29]: S.No              3
         Name         Steven
         Age              43
         City       Bay Area
         Salary         8300
         Address          DN
         Name: 2, dtype: object
```

3.7.3 Slice Rows

Multiple rows can be selected using ':' operator.

```
In [31]: df[2:4]
```

```
Out[31]:    S.No    Name  Age       City  Salary Address
         2     3  Steven   43   Bay Area    8300      DN
         3     4     Ram   38  Hyderabad    3900     HCM
```

3.7.4 Addition of Rows

Add new rows to a DataFrame using the **append** function. This function will append the rows at the end.

```
In [32]: df1 = pd.DataFrame([[1, 2], [3, 4]], columns = ['a','b'])
         df2 = pd.DataFrame([[5, 6], [7, 8]], columns = ['a','b'])

         df1.append(df2)
```

```
Out[32]:    a  b
         0  1  2
         1  3  4
         0  5  6
         1  7  8
```

3.7.5 Boolean Indexing

Using a single column's values to select data.

```
In [98]: df[df.Salary > 4000]
```

```
Out[98]:    S.No    Name  Age      City  Salary     Salary2
         0     1     Tom   28   Toronto   20000  141.421356
         2     3  Steven   43  Bay Area    8300   91.104336
```

Using the **isin()** method for filtering:

```
In [100]: df[df.Name.isin(['Tom', 'Ram'])]
```

```
Out[100]:    S.No Name  Age       City  Salary     Salary2
          0     1  Tom   28    Toronto   20000  141.421356
          3     4  Ram   38  Hyderabad    3900   62.449980
```

3.7.6 Drop duplicates

```
In [101]: df.drop_duplicates()
```

```
Out[101]:    S.No    Name  Age       City  Salary     Salary2
          0     1     Tom   28    Toronto   20000  141.421356
          1     2     Lee   32   HongKong    3000   54.772256
          2     3  Steven   43   Bay Area    8300   91.104336
          3     4     Ram   38  Hyderabad    3900   62.449980
```

```
In [102]: df2 = df.copy()
          df2["Company"] = [ "JVN", "JVN", "UIT", "UIT" ]
          df2
```

```
Out[102]:    S.No    Name  Age       City  Salary     Salary2 Company
          0     1     Tom   28    Toronto   20000  141.421356     JVN
          1     2     Lee   32   HongKong    3000   54.772256     JVN
          2     3  Steven   43   Bay Area    8300   91.104336     UIT
          3     4     Ram   38  Hyderabad    3900   62.449980     UIT
```

```
In [103]: df2.drop_duplicates("Company")
```

```
Out[103]:    S.No    Name  Age      City  Salary     Salary2 Company
          0     1     Tom   28   Toronto   20000  141.421356     JVN
          2     3  Steven   43  Bay Area    8300   91.104336     UIT
```

4 Python Pandas - Series

Series is a one-dimensional labeled array capable of holding data of any type (integer, string, float, python objects, etc.). The axis labels are collectively called index.

4.1 Create a Series

4.1.1 Create an Empty Series

```
In [34]: s = pd.Series()
         s

Out[34]: Series([], dtype: float64)
```

4.1.2 Create a Series from ndarray

```
In [39]: # Ex1
         s = pd.Series([1,2,3,4])
         s

Out[39]: 0    1
         1    2
         2    3
         3    4
         dtype: int64

In [40]: # Ex2
         import numpy as np
         data = np.array([1,2,3,4])
         s = pd.Series(data)
         s

Out[40]: 0    1
         1    2
         2    3
         3    4
         dtype: int64

In [42]: # Ex3
         data = np.array(['a','b','c','d'])
         s = pd.Series(data,index=[100,101,102,103])
         s

Out[42]: 100    a
         101    b
         102    c
         103    d
         dtype: object
```

4.1.3 Create a Series from Scalar

If data is a scalar value, an index must be provided. The value will be repeated to match the length of index

```
In [43]: s = pd.Series(5, index=[0, 1, 2, 3])
         s
```

```
Out[43]: 0    5
         1    5
         2    5
         3    5
         dtype: int64
```

4.2 Accessing Data from Series with Position

Data in the series can be accessed similar to that in an ndarray.

Ex1: Retrieve the first element. As we already know, the counting starts from zero for the array, which means the first element is stored at zeroth position and so on.

```
In [47]: s = pd.Series([1,2,3,4,5],index = ['a','b','c','d','e'])

         print s

         print "\nretrieve the first element:"
         print s[0]
```

```
a    1
b    2
c    3
d    4
e    5
dtype: int64

retrieve the first element:
1
```

```
In [48]: # Retrieve the first three elements in the Series
         print s[:3]
```

```
a    1
b    2
c    3
dtype: int64
```

4.3 Retrieve Data Using Label (Index)

A Series is like a fixed-size dict in that you can get and set values by index label.

```
In [51]: s = pd.Series([1,2,3,4,5],index = ['a','b','c','d','e'])

         print s

         print
         #retrieve a single element
         print s['a']
```

```
a    1
b    2
c    3
d    4
e    5
dtype: int64

1
```

```
In [52]: #retrieve multiple elements
         print s[['a','c','d']]
```

```
a    1
c    3
d    4
dtype: int64
```

```
In [53]: # If a label is not contained, an exception is raised.
         print s['f']
```

```
        ---------------------------------------------------------------------------

        KeyError                                  Traceback (most recent call last)

        <ipython-input-53-fec766af88eb> in <module>()
          1 # If a label is not contained, an exception is raised.
    ----> 2 print s['f']


        /home/duyetdev/.local/lib/python2.7/site-packages/pandas/core/series.pyc in __getitem__(
        599         key = com._apply_if_callable(key, self)
        600         try:
    --> 601             result = self.index.get_value(self, key)
        602 
        603             if not is_scalar(result):


        /home/duyetdev/.local/lib/python2.7/site-packages/pandas/core/indexes/base.pyc in get_va
       2489                     raise InvalidIndexError(key)
       2490                 else:
    -> 2491                     raise e1
       2492             except Exception:  # pragma: no cover
       2493                 raise e1
```

```
KeyError: 'f'
```

5 Python Pandas - Descriptive Statistics

A large number of methods collectively compute descriptive statistics and other related operations on DataFrame. Most of these are aggregations like sum(), mean(), but some of them, like sumsum(), produce an object of the same size. Generally speaking, these methods take an axis argument, just like ndarray.{sum, std, ...}, but the axis can be specified by name or integer.

Let's create a DataFrame and use this object throughout this chapter for all the operations.

```
In [54]: df = pd.read_csv("data.csv")
         df

Out[54]:    S.No    Name  Age       City  Salary
         0     1     Tom   28    Toronto   20000
         1     2     Lee   32   HongKong    3000
         2     3  Steven   43   Bay Area    8300
         3     4     Ram   38  Hyderabad    3900
```

5.1 sum()

Returns the sum of the values for the requested axis. By default, axis is index (axis=0).

```
In [55]: df.sum()

Out[55]: S.No                                 10
         Name                     TomLeeStevenRam
         Age                                 141
         City      TorontoHongKongBay AreaHyderabad
         Salary                            35200
         dtype: object

In [56]: df.sum(axis=1)

Out[56]: 0    20029
         1     3034
         2     8346
         3     3942
         dtype: int64
```

5.2 mean()

```
In [57]: df.mean()
```

```
Out[57]: S.No         2.50
         Age         35.25
         Salary    8800.00
         dtype: float64
```

```
In [58]: df.mean(1)
```

```
Out[58]: 0    6676.333333
         1    1011.333333
         2    2782.000000
         3    1314.000000
         dtype: float64
```

5.3 std()

Returns the Bressel standard deviation of the numerical columns.

```
In [59]: df.std()
```

```
Out[59]: S.No         1.290994
         Age          6.601767
         Salary    7817.501732
         dtype: float64
```

5.4 Functions & Description

The following table list down the important functions

S.No.	Function	Description
1	count()	Number of non-null observations
2	sum()	Sum of values
3	mean()	Mean of Values
4	median()	Median of Values
5	mode()	Mode of values
6	std()	Standard Deviation of the Values
7	min()	Minimum Value
8	max()	Maximum Value
9	abs()	Absolute Value
10	prod()	Product of Values
11	cumsum()	Cumulative Sum
12	cumprod()	Cumulative Product

5.5 Summarizing Data

The **describe()** function computes a summary of statistics pertaining to the DataFrame columns.

```
In [60]: df.describe()
```

```
Out[60]:            S.No        Age        Salary
         count  4.000000   4.000000      4.000000
         mean   2.500000  35.250000   8800.000000
         std    1.290994   6.601767   7817.501732
         min    1.000000  28.000000   3000.000000
         25%    1.750000  31.000000   3675.000000
         50%    2.500000  35.000000   6100.000000
         75%    3.250000  39.250000  11225.000000
         max    4.000000  43.000000  20000.000000
```

And, function excludes the character columns and given summary about numeric columns. **'include'** is the argument which is used to pass necessary information regarding what columns need to be considered for summarizing. Takes the list of values; by default, 'number'.

- **object** – Summarizes String columns
- **number** – Summarizes Numeric columns
- **all** – Summarizes all columns together (Should not pass it as a list value)

```
In [62]: df.describe(include=['object'])
```

```
Out[62]:          Name      City
         count       4         4
         unique      4         4
         top    Steven  Bay Area
         freq        1         1
```

6 Python Pandas - Function Application

To apply your own or another library's functions to Pandas objects, you should be aware of the three important methods. The methods have been discussed below. The appropriate method to use depends on whether your function expects to operate on an entire DataFrame, row- or column-wise, or element wise.

- Table wise Function Application: pipe()
- Row or Column Wise Function Application: apply()
- Element wise Function Application: applymap()

```
In [63]: df
```

```
Out[63]:    S.No    Name  Age       City  Salary
         0     1     Tom   28    Toronto   20000
         1     2     Lee   32   HongKong    3000
         2     3  Steven   43   Bay Area    8300
         3     4     Ram   38  Hyderabad    3900
```

```
In [67]: df['Salary2'] = df.Salary.apply(np.sqrt)
         df
```

```
Out[67]:    S.No    Name  Age       City  Salary     Salary2
         0     1     Tom   28    Toronto   20000  141.421356
         1     2     Lee   32   HongKong    3000   54.772256
         2     3  Steven   43   Bay Area    8300   91.104336
         3     4     Ram   38  Hyderabad    3900   62.449980
```

7 GroupBy

Reference: https://www.tutorialspoint.com/python_pandas/python_pandas_groupby.htm

```
In [74]: df.groupby("Name").count()
```

```
Out[74]:         S.No  Age  City  Salary  Salary2
         Name
         Lee        1    1     1       1        1
         Ram        1    1     1       1        1
         Steven     1    1     1       1        1
         Tom        1    1     1       1        1
```

```
In [75]: df.groupby("Name")['Salary'].count()
```

```
Out[75]: Name
         Lee       1
         Ram       1
         Steven    1
         Tom       1
         Name: Salary, dtype: int64
```

```
In [76]: df.groupby("Name")['Salary'].mean()
```

```
Out[76]: Name
         Lee        3000
         Ram        3900
         Steven     8300
         Tom       20000
         Name: Salary, dtype: int64
```

8 Merging/Joining

Pandas has full-featured, high performance in-memory join operations idiomatically very similar to relational databases like SQL.

```
pd.merge(left, right, how='inner', on=None, left_on=None, right_on=None,
    left_index=False, right_index=False, sort=True)
```

- **left** – A DataFrame object.
- **right** – Another DataFrame object.
- **on** – Columns (names) to join on. Must be found in both the left and right DataFrame objects.

- **left_on** – Columns from the left DataFrame to use as keys. Can either be column names or arrays with length equal to the length of the DataFrame.
- **right_on** – Columns from the right DataFrame to use as keys. Can either be column names or arrays with length equal to the length of the DataFrame.
- **left_index** – If True, use the index (row labels) from the left DataFrame as its join key(s). In case of a DataFrame with a MultiIndex (hierarchical), the number of levels must match the number of join keys from the right DataFrame.
- **right_index** – Same usage as left_index for the right DataFrame.
- **how** – One of ’left’, ’right’, ’outer’, ’inner’. Defaults to inner. Each method has been described below.
- **sort** – Sort the result DataFrame by the join keys in lexicographical order. Defaults to True, setting to False will improve the performance substantially in many cases.* **left** – A DataFrame object.
- **right** – Another DataFrame object.
- **on** – Columns (names) to join on. Must be found in both the left and right DataFrame objects.
- **left_on** – Columns from the left DataFrame to use as keys. Can either be column names or arrays with length equal to the length of the DataFrame.
- **right_on** – Columns from the right DataFrame to use as keys. Can either be column names or arrays with length equal to the length of the DataFrame.
- **left_index** – If True, use the index (row labels) from the left DataFrame as its join key(s). In case of a DataFrame with a MultiIndex (hierarchical), the number of levels must match the number of join keys from the right DataFrame.
- **right_index** – Same usage as left_index for the right DataFrame.
- **how** – One of ’left’, ’right’, ’outer’, ’inner’. Defaults to inner. Each method has been described below.
- **sort** – Sort the result DataFrame by the join keys in lexicographical order. Defaults to True, setting to False will improve the performance substantially in many cases.

```
In [78]: left = pd.DataFrame({
                  'id':[1,2,3,4,5],
                  'Name': ['Alex', 'Amy', 'Allen', 'Alice', 'Ayoung'],
                  'subject_id':['sub1','sub2','sub4','sub6','sub5']})
         right = pd.DataFrame(
                  {'id':[1,2,3,4,5],
                  'Name': ['Billy', 'Brian', 'Bran', 'Bryce', 'Betty'],
                  'subject_id':['sub2','sub4','sub3','sub6','sub5']})
         left
```

```
Out[78]:       Name  id subject_id
         0     Alex   1       sub1
         1      Amy   2       sub2
         2    Allen   3       sub4
         3    Alice   4       sub6
         4   Ayoung   5       sub5
```

```
In [79]: right
```

```
Out[79]:      Name  id subject_id
         0   Billy   1       sub2
         1  Brian   2       sub4
         2   Bran   3       sub3
         3  Bryce   4       sub6
         4  Betty   5       sub5
```

8.1 Merge Two DataFrames on a Key

```
In [80]: pd.merge(left,right,on='id')
```

```
Out[80]:    Name_x  id subject_id_x Name_y subject_id_y
         0    Alex   1         sub1  Billy         sub2
         1     Amy   2         sub2  Brian         sub4
         2   Allen   3         sub4   Bran         sub3
         3   Alice   4         sub6  Bryce         sub6
         4  Ayoung   5         sub5  Betty         sub5
```

8.2 Merge Two DataFrames on Multiple Keys

```
In [81]: pd.merge(left,right,on=['id','subject_id'])
```

```
Out[81]:    Name_x  id subject_id Name_y
         0   Alice   4       sub6  Bryce
         1  Ayoung   5       sub5  Betty
```

8.3 Left/Right Join

```
In [82]: pd.merge(left, right, on='subject_id', how='left')
```

```
Out[82]:    Name_x  id_x subject_id Name_y  id_y
         0    Alex     1       sub1    NaN   NaN
         1     Amy     2       sub2  Billy   1.0
         2   Allen     3       sub4  Brian   2.0
         3   Alice     4       sub6  Bryce   4.0
         4  Ayoung     5       sub5  Betty   5.0
```

```
In [83]: pd.merge(left, right, on='subject_id', how='right')
```

```
Out[83]:    Name_x  id_x subject_id Name_y  id_y
         0     Amy   2.0       sub2  Billy     1
         1   Allen   3.0       sub4  Brian     2
         2   Alice   4.0       sub6  Bryce     4
         3  Ayoung   5.0       sub5  Betty     5
         4     NaN   NaN       sub3   Bran     3
```

8.4 Inner/Outer Join

```
In [84]: pd.merge(left, right, on='subject_id', how='inner')
```

```
Out[84]:    Name_x  id_x subject_id Name_y  id_y
         0     Amy     2       sub2  Billy     1
         1   Allen     3       sub4  Brian     2
         2   Alice     4       sub6  Bryce     4
         3  Ayoung     5       sub5  Betty     5
```

```
In [85]: pd.merge(left, right, on='subject_id', how='outer')
```

```
Out[85]:    Name_x  id_x subject_id Name_y  id_y
         0    Alex   1.0       sub1    NaN   NaN
         1     Amy   2.0       sub2  Billy   1.0
         2   Allen   3.0       sub4  Brian   2.0
         3   Alice   4.0       sub6  Bryce   4.0
         4  Ayoung   5.0       sub5  Betty   5.0
         5     NaN   NaN       sub3   Bran   3.0
```

9 Concatenation

Pandas provides various facilities for easily combining together Series, DataFrame, and Panel objects.

```
pd.concat(objs,axis=0,join='outer',join_axes=None, ignore_index=False)
```

```
In [86]: pd.concat([left, right])
```

```
Out[86]:      Name  id subject_id
         0    Alex   1       sub1
         1     Amy   2       sub2
         2   Allen   3       sub4
         3   Alice   4       sub6
         4  Ayoung   5       sub5
         0   Billy   1       sub2
         1   Brian   2       sub4
         2    Bran   3       sub3
         3   Bryce   4       sub6
         4   Betty   5       sub5
```

```
In [87]: pd.concat([left, right], keys=['x', 'y'])
```

```
Out[87]:        Name  id subject_id
         x 0    Alex   1       sub1
           1     Amy   2       sub2
           2   Allen   3       sub4
           3   Alice   4       sub6
           4  Ayoung   5       sub5
         y 0   Billy   1       sub2
           1   Brian   2       sub4
           2    Bran   3       sub3
           3   Bryce   4       sub6
           4   Betty   5       sub5
```

Concatenating Using append

```
In [88]: left.append(right)
```

```
Out[88]:      Name  id subject_id
         0    Alex   1       sub1
         1     Amy   2       sub2
         2   Allen   3       sub4
         3   Alice   4       sub6
         4  Ayoung   5       sub5
         0   Billy   1       sub2
         1   Brian   2       sub4
         2    Bran   3       sub3
         3   Bryce   4       sub6
         4   Betty   5       sub5
```

10 Histogramming

See more at Histogramming and Discretization

```
In [108]: s = pd.Series(np.random.randint(0, 7, size=10))
```

```
In [109]: s.value_counts()
```

```
Out[109]: 6    3
          5    2
          4    1
          3    1
          2    1
          1    1
          0    1
          dtype: int64
```

11 Time Series

pandas has simple, powerful, and efficient functionality for performing resampling operations during frequency conversion (e.g., converting secondly data into 5-minutely data). This is extremely common in, but not limited to, financial applications. See the Time Series section

```
In [112]: rng = pd.date_range('1/1/2012', periods=100, freq='S')
          rng[:5]
```

```
Out[112]: DatetimeIndex(['2012-01-01 00:00:00', '2012-01-01 00:00:01',
                         '2012-01-01 00:00:02', '2012-01-01 00:00:03',
                         '2012-01-01 00:00:04'],
                        dtype='datetime64[ns]', freq='S')
```

```
In [113]: ts = pd.Series(np.random.randint(0, 500, len(rng)), index=rng)
          ts
```

```
Out[113]: 2012-01-01 00:00:00    187
          2012-01-01 00:00:01    314
          2012-01-01 00:00:02    211
          2012-01-01 00:00:03    141
          2012-01-01 00:00:04     90
          2012-01-01 00:00:05      0
          2012-01-01 00:00:06    255
          2012-01-01 00:00:07    393
          2012-01-01 00:00:08    237
          2012-01-01 00:00:09    109
          2012-01-01 00:00:10     90
          2012-01-01 00:00:11    115
          2012-01-01 00:00:12     91
          2012-01-01 00:00:13      7
          2012-01-01 00:00:14    472
          2012-01-01 00:00:15    125
          2012-01-01 00:00:16    468
          2012-01-01 00:00:17    243
          2012-01-01 00:00:18    495
          2012-01-01 00:00:19    221
          2012-01-01 00:00:20    428
          2012-01-01 00:00:21     35
          2012-01-01 00:00:22    451
          2012-01-01 00:00:23    440
          2012-01-01 00:00:24    213
          2012-01-01 00:00:25    171
          2012-01-01 00:00:26    267
          2012-01-01 00:00:27    167
          2012-01-01 00:00:28    484
          2012-01-01 00:00:29    454
                                ...
          2012-01-01 00:01:10     33
          2012-01-01 00:01:11    209
          2012-01-01 00:01:12     37
          2012-01-01 00:01:13    495
          2012-01-01 00:01:14     46
          2012-01-01 00:01:15    440
          2012-01-01 00:01:16    349
          2012-01-01 00:01:17    170
          2012-01-01 00:01:18    353
          2012-01-01 00:01:19    172
          2012-01-01 00:01:20     76
          2012-01-01 00:01:21    475
          2012-01-01 00:01:22    360
          2012-01-01 00:01:23    185
          2012-01-01 00:01:24    305
          2012-01-01 00:01:25    458
          2012-01-01 00:01:26    222
          2012-01-01 00:01:27    264
          2012-01-01 00:01:28    480
          2012-01-01 00:01:29    418
          2012-01-01 00:01:30    255
          2012-01-01 00:01:31    293
          2012-01-01 00:01:32    146
          2012-01-01 00:01:33    199
          2012-01-01 00:01:34     92
          2012-01-01 00:01:35    305
          2012-01-01 00:01:36    454
          2012-01-01 00:01:37     45
          2012-01-01 00:01:38     71
          2012-01-01 00:01:39    436
          Freq: S, Length: 100, dtype: int64
```

```
In [114]: ts.resample('5Min').sum()
```

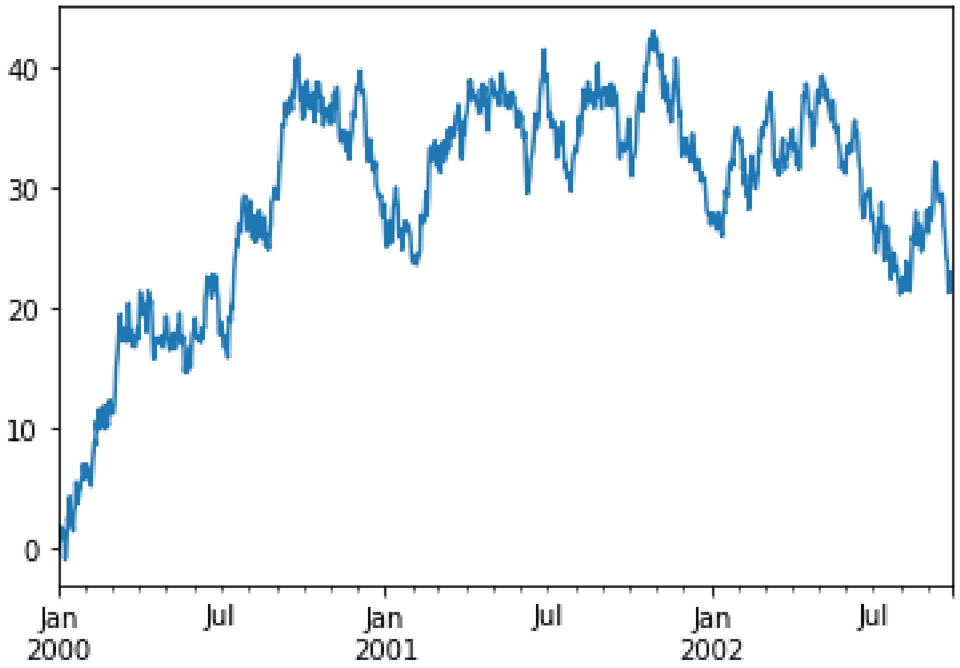
```
Out[114]: 2012-01-01    26667
          Freq: 5T, dtype: int64
```

12 Plotting

See more: https://pandas.pydata.org/pandas-docs/stable/visualization.html#visualization

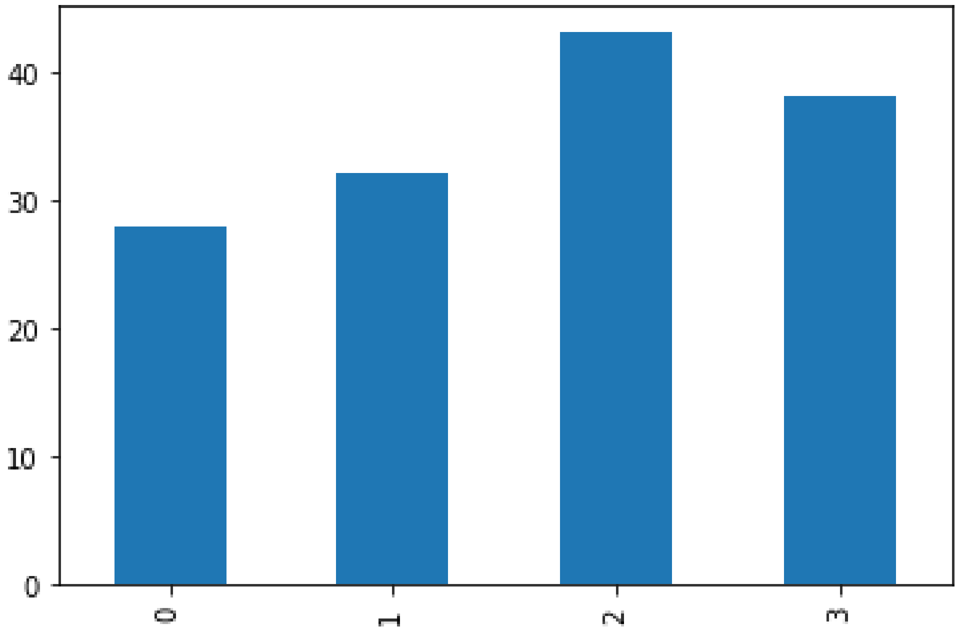
```
In [5]: ts = pd.Series(np.random.randn(1000), index=pd.date_range('1/1/2000', periods=1000))
        ts = ts.cumsum()
        ts.plot()
```

```
Out[5]: <matplotlib.axes._subplots.AxesSubplot at 0x7f73e36a7710>
```



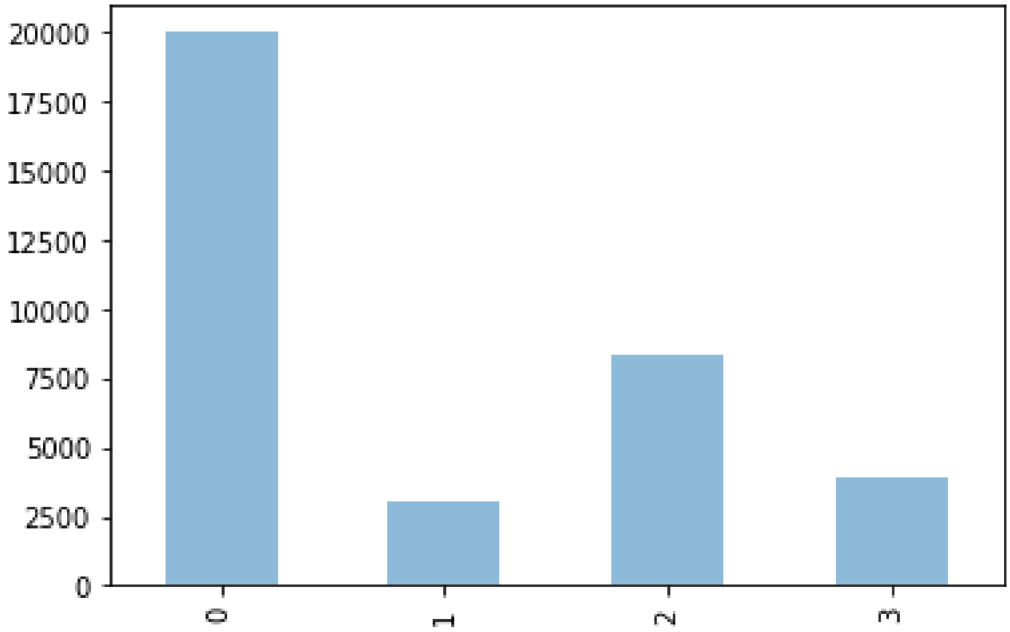
```
In [8]: df.Age.plot(kind='bar')

Out[8]: <matplotlib.axes._subplots.AxesSubplot at 0x7f73e12e6390>
```



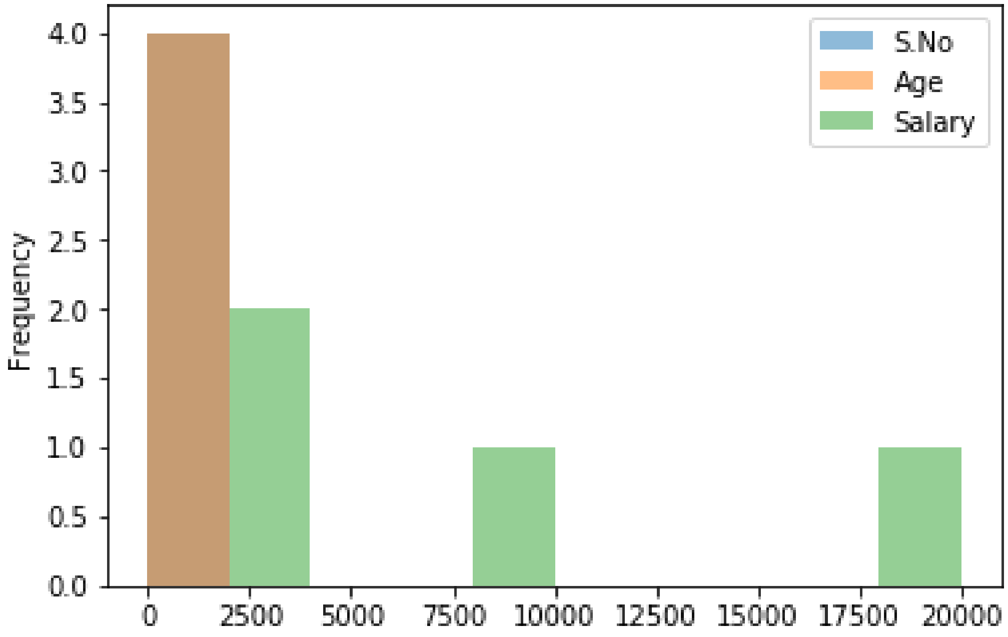
```
In [29]: df.Salary.plot.bar(alpha=0.5)
```

```
Out[29]: <matplotlib.axes._subplots.AxesSubplot at 0x7f73dfb29450>
```



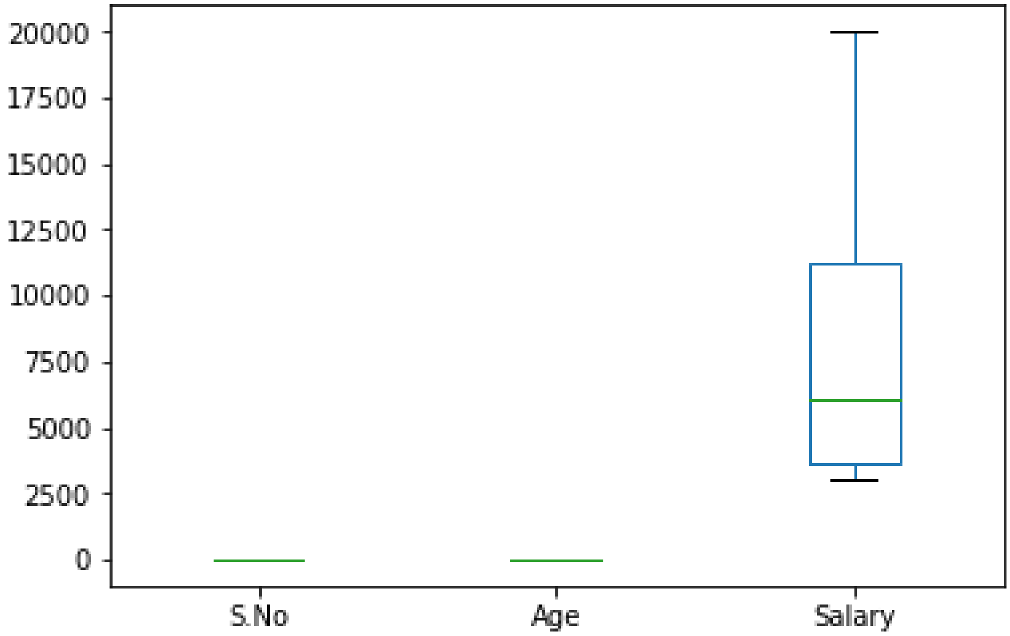
```
In [13]: df.plot.hist(alpha=0.5)
```

```
Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x7f73e0f27cd0>
```



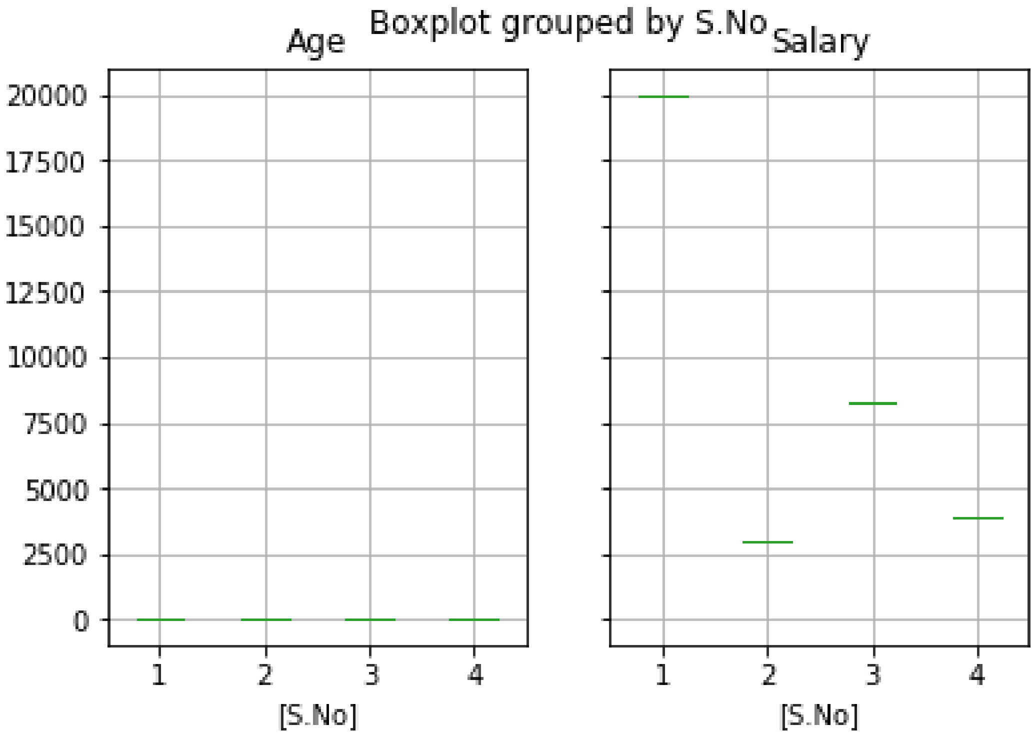
```
In [14]: df.plot.box()

Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x7f73e0c74190>
```



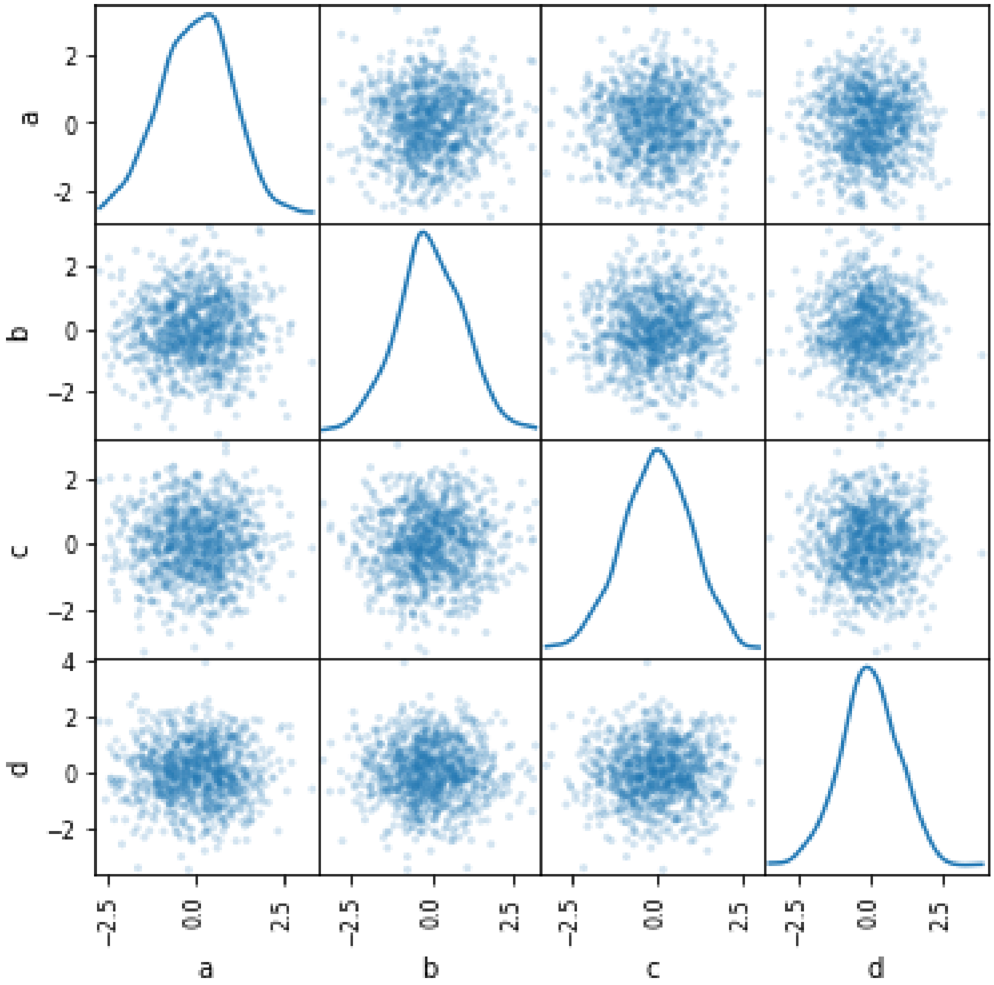
```
In [17]: df.boxplot(by='S.No')

Out[17]: array([<matplotlib.axes._subplots.AxesSubplot object at 0x7f73e066d3d0>,
                <matplotlib.axes._subplots.AxesSubplot object at 0x7f73e05e4c50>], dtype=object)
```



```
In [30]: from pandas.plotting import scatter_matrix
         df_plot = pd.DataFrame(np.random.randn(1000, 4), columns=['a', 'b', 'c', 'd'])
         scatter_matrix(df_plot, alpha=0.2, figsize=(6, 6), diagonal='kde')
```

```
Out[30]: array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7f73d70c9f10>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x7f73d605e810>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x7f73d5f65890>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x7f73d5f57310>],
                [<matplotlib.axes._subplots.AxesSubplot object at 0x7f73d5ede350>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x7f73d5e43c90>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x7f73d5dcae90>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x7f73d5d40750>],
                [<matplotlib.axes._subplots.AxesSubplot object at 0x7f73d5cc6850>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x7f73d5c392d0>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x7f73d5bbe750>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x7f73d5bf3f90>],
                [<matplotlib.axes._subplots.AxesSubplot object at 0x7f73d5b5aa10>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x7f73d5ae0890>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x7f73d5a46f50>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x7f73d59cdf90>]], dtype=objec
```



13 References

- Python Pandas Tutorial (tutorialspoint)
- Lessons for New pandas Users (pandas.pydata.org)
- Exercises for New Users (pandas.pydata.org)