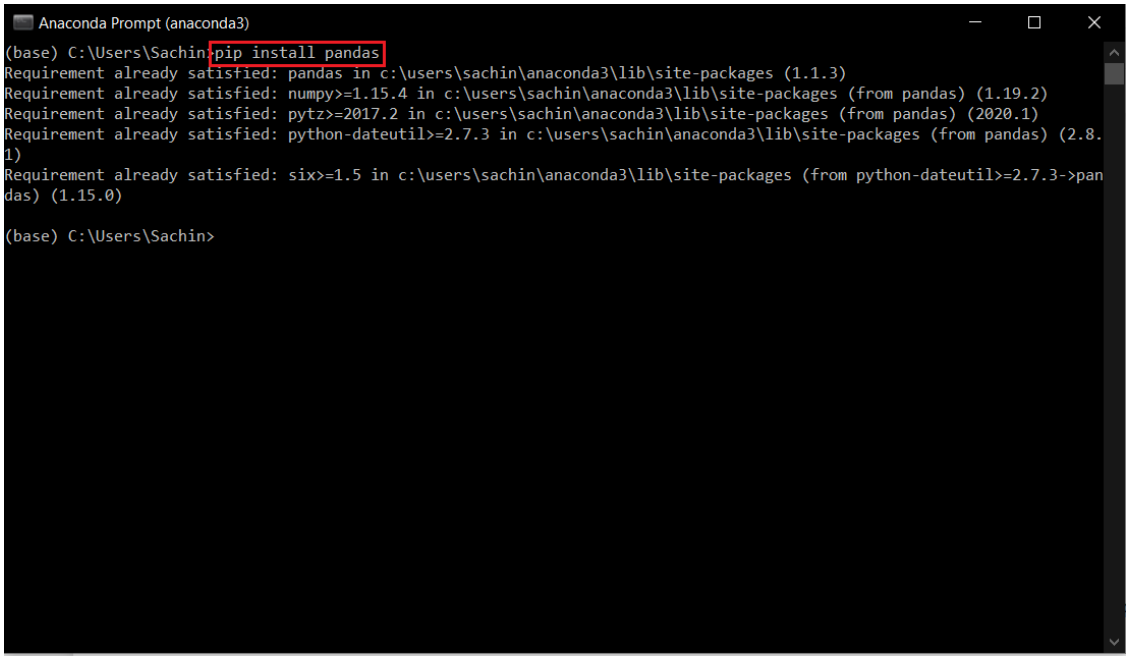
# Pandas

Pandas is a Python package providing fast, flexible, and expressive data structures designed to make working with “relational” or “labeled” data both easy and intuitive. It aims to be the fundamental high-level building block for doing practical, real-world data analysis in Python. Additionally, it has the broader goal of becoming the most powerful and flexible open source data analysis/manipulation tool available in any language.

# Installing Pandas

To install Python Pandas, go to your command prompt and type "pip install pandas". Once the installation is completed, go to your IDE (For example: PyCharm) or Anaconda Jupyter Notebook and simply import it by typing: **import pandas as pd**.




# How to import Pandas

In order to start using Pandas and all of the function available in Pandas, You will need to import it. This can be easily done with this import statement.

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

NOTE: We shorten pandas to pd in order to save time and also to keep code standardized so that anyone working with your code can easily understand and run it.

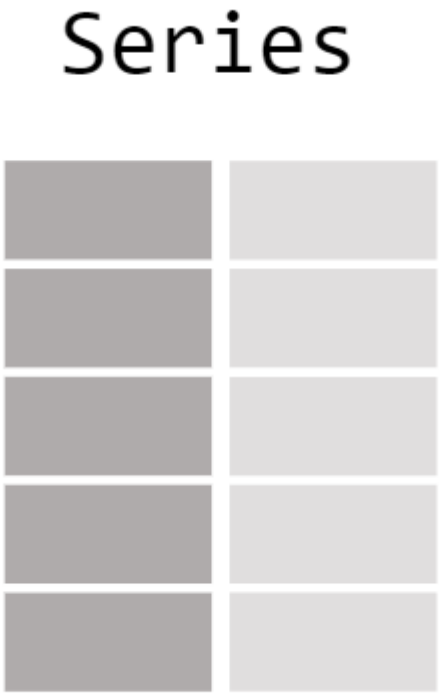
# Data structures:

Pandas deals with the following three data structures −

1. Series
2. DataFrame
3. Panel

# Series:

Series is a one-dimensional labeled array capable of holding any data type (integers, strings, floating point numbers, Python objects, etc.). The axis labels are collectively referred to as the index.




A pandas Series can be created using the following constructor −

Syntax

In [ ]:
```
pandas.Series(data, index, dtype, copy)
```

Here, data can be many different things:

- a Python dict
- an ndarray
- a scalar value (like 5)

Example Create an Empty Series

In [2]:
```
import pandas as pd
s = pd.Series()
print(s)
```

```
Series([], dtype: float64)
<ipython-input-2-7114e1bb196c>:2: DeprecationWarning: The default dtype f
or empty Series will be 'object' instead of 'float64' in a future versio
n. Specify a dtype explicitly to silence this warning.
  s = pd.Series()
```

Example Create a Series from ndarray

In [3]:
```
import pandas as pd
import numpy as np
data = np.array(['a','b','c','d'])
s = pd.Series(data)
print(s)
```

```
0    a
1    b
2    c
3    d
dtype: object
```

Example Create a Series from ndarray with index mentioned

In [4]:
```
import pandas as pd
import numpy as np
data = np.array(['a','b','c','d'])
s = pd.Series(data,index=[100,101,102,103])
print(s)
```

```
100    a
101    b
102    c
103    d
dtype: object
```

Example Create a Series from dict

NOTE: A dict can be passed as input and if no index is specified, then the dictionary keys are taken in a sorted order to construct index. If index is passed, the values in data corresponding to the labels in the index will be pulled out.

In [5]:
```
import pandas as pd
import numpy as np
data = {'a' : 0., 'b' : 1., 'c' : 2.}
s = pd.Series(data)
print(s)
```

```
a    0.0
b    1.0
c    2.0
dtype: float64
```

In [6]:
```
import pandas as pd
import numpy as np
data = {'a' : 0., 'b' : 1., 'c' : 2.}
s = pd.Series(data,index=['b','c','d','a'])
print(s)
```

```
b    1.0
c    2.0
d    NaN
a    0.0
dtype: float64
```

Example Create a Series from Scalar

In [7]:
```
import pandas as pd
```

```
import numpy as np
s = pd.Series(5, index=[0, 1, 2, 3])
print(s)
```

```
0    5
1    5
2    5
3    5
dtype: int64
```

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

**Accessing Data from Series with Position:** To access the data you have to mentioned the position within [] bracket.

In [8]:
```
import pandas as pd
s = pd.Series([1,2,3,4,5],index = ['a','b','c','d','e'])
print("Series are: \n",s)
#retrieve the first element
print(s[0])
print(s[3])
```

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

**Slicing Data from Series with position:** For slicing you can use the index from which index to which index you want.

In [9]:
```
import pandas as pd
s = pd.Series([1,2,3,4,5],index = ['a','b','c','d','e'])
print("Series are: \n",s)
#retrieve the first three element
print(s[:3])
```

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

In [10]:
```
import pandas as pd
s = pd.Series([1,2,3,4,5],index = ['a','b','c','d','e'])
print("Series are: \n",s)
#retrieve the last three element
print(s[-3:])
```

```
Series are:
 a    1
b    2
c    3
d    4
e    5
```

```
dtype: int64
c    3
d    4
e    5
dtype: int64
```

**Retrieve Data Using Label:** To access the data you have to mentioned the label within [] bracket.

In [11]:
```
import pandas as pd
s = pd.Series([1,2,3,4,5],index = ['a','b','c','d','e'])
print("Series are: \n",s)
#retrieve a single element
print(s['a'])
```

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

In [12]:
```
import pandas as pd
s = pd.Series([1,2,3,4,5],index = ['a','b','c','d','e'])
print("Series are: \n",s)
#retrieve multiple elements
print(s[['a','c','d']])
```

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

# Basic functionality of series:

**axes:** Returns the list of the labels of the series.

In [13]:
```
import pandas as pd
import numpy as np
data = np.array(['a','b','c','d'])
s = pd.Series(data,index=[100,101,102,103])
print(s)
print("The axes are: ")
print(s.axes)
```

```
100    a
101    b
102    c
103    d
dtype: object
The axes are:
[Int64Index([100, 101, 102, 103], dtype='int64')]
```

**empty:** Returns the Boolean value saying whether the Object is empty or not. True indicates that the object is empty.

In [14]:
```
import pandas as pd
import numpy as np
data = np.array(['a','b','c','d'])
s = pd.Series(data,index=[100,101,102,103])
print(s)
print("The series is empty or not: ",s.empty)
```

```
100    a
101    b
102    c
103    d
dtype: object
The series is empty or not:  False
```

In [15]:
```
import numpy as np
import pandas as pd
s=pd.Series()
print(s)
print("The series is empty or not: ",s.empty)
```

```
Series([], dtype: float64)
The series is empty or not:  True
<ipython-input-15-500188ae0830>:3: DeprecationWarning: The default dtype
for empty Series will be 'object' instead of 'float64' in a future versio
n. Specify a dtype explicitly to silence this warning.
  s=pd.Series()
```

**ndim:** Returns the number of dimensions of the object. By definition, a Series is a 1D data structure, so it returns 1.

In [16]:
```
import pandas as pd
import numpy as np
data = np.array(['a','b','c','d'])
s = pd.Series(data,index=[100,101,102,103])
print(s)
print("The dimension of s: ",s.ndim)
```

```
100    a
101    b
102    c
103    d
dtype: object
The dimension of s:  1
```

**size:** Returns the size(length) of the series.

In [17]:
```
import pandas as pd
import numpy as np
data = np.array(['a','b','c','d'])
s = pd.Series(data,index=[100,101,102,103])
print(s)
print("The dimension of s: ",s.size)
```

```
100    a
101    b
102    c
103    d
dtype: object
The dimension of s:  4
```

**values:** Returns the actual data in the series as an array.

In [18]:
```
import pandas as pd
import numpy as np
data = np.array(['a','b','c','d'])
s = pd.Series(data,index=[100,101,102,103])
```

```
print(s)
print("The values of s: ",s.values)
```

```
100    a
101    b
102    c
103    d
dtype: object
The values of s:  ['a' 'b' 'c' 'd']
```

**head():** head() returns the first n rows(observe the index values). The default number of elements to display is five, but you may pass a custom number.

**tail():** tail() returns the last n rows(observe the index values). The default number of elements to display is five, but you may pass a custom number.

In [19]:
```
import pandas as pd
import numpy as np
data = np.array(['a','b','c','d','e','f','g','h'])
s = pd.Series(data,index=[100,101,102,103,104,105,106,10])
print(s)
print("**************************")
print("The head of s: \n",s.head())
print("**************************")
print("The tail of s: \n",s.tail())
```

```
100    a
101    b
102    c
103    d
104    e
105    f
106    g
10     h
dtype: object
**************************
The head of s:
 100    a
101    b
102    c
103    d
104    e
dtype: object
**************************
The tail of s:
 103    d
104    e
105    f
106    g
10     h
dtype: object
```

# Explore via coding

**Create a series of age of 15 people acess the fifth element and print the dimension.**

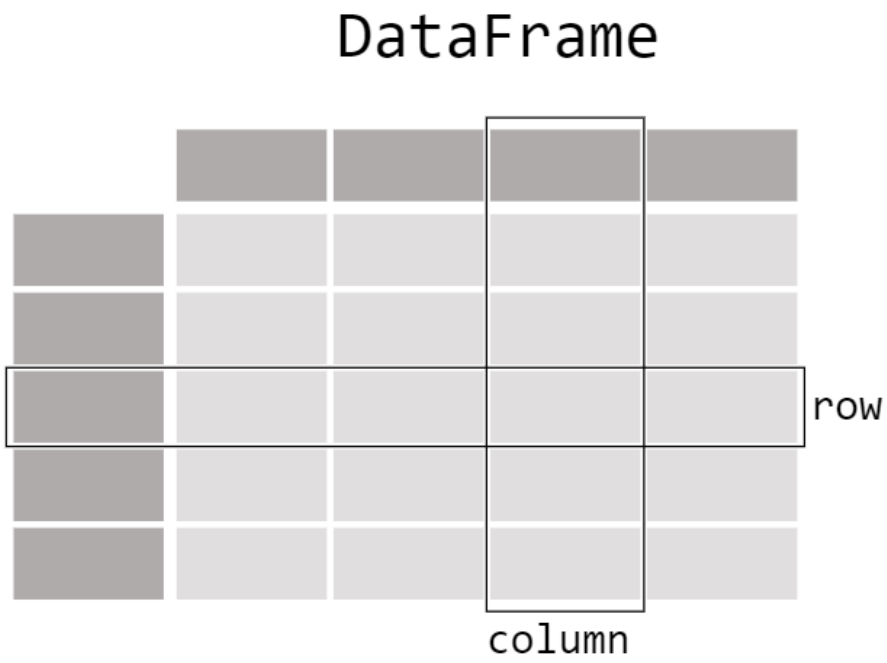
In [20]:
```
import pandas as pd

s=pd.Series([18,19,20,22,24,26,70,69,45,35,76,65,15,35,43],name="age")
print("Series are: \n",s)
print("Fifth element of series are: ",s[4])
print("Dimension is: ",s.ndim)
```

```
Series are:
```

```
 0     18
1     19
2     20
3     22
4     24
5     26
6     70
7     69
8     45
9     35
10    76
11    65
12    15
13    35
14    43
Name: age, dtype: int64
Fifth element of series are:  24
Dimension is:  1
```

# DataFrames:

A DataFrame is a 2-dimensional data structure that can store data of different types (including characters, integers, floating point values, categorical data and more) in columns. It is similar to a spreadsheet, a SQL table.




A pandas DataFrame can be created using the following constructor −

Syntax

In [ ]:
```
pandas.DataFrame( data, index, columns, dtype, copy)
```

DataFrame accepts many different kinds of input:

- Dict of 1D ndarrays, lists, dicts, or Series
- 2-D numpy.ndarray
- Structured or record ndarray
- A Series
- Another DataFrame

Example Create an Empty DataFrame

In [21]:
```
import pandas as pd
df = pd.DataFrame()
print(df)
```

```
Empty DataFrame
Columns: []
Index: []
```

Example Create a DataFrame from Lists

In [22]:
```
import pandas as pd
data = [1,2,3,4,5]
df = pd.DataFrame(data)
print(df)
```

```
   0
0  1
1  2
2  3
3  4
4  5
```

In [23]:
```
import pandas as pd
data = [['Alex',10],['Bob',12],['Clarke',13]]
df = pd.DataFrame(data,columns=['Name','Age'])
print(df)
```

```
     Name  Age
0    Alex   10
1     Bob   12
2  Clarke   13
```

In [24]:
```
import pandas as pd
data = [['Alex',10],['Bob',12],['Clarke',13]]
df = pd.DataFrame(data,columns=['Name','Age'],dtype=float)
print(df)
```

```
     Name   Age
0    Alex  10.0
1     Bob  12.0
2  Clarke  13.0
```

Example Create a DataFrame from Dict of ndarrays / Lists

In [25]:
```
import pandas as pd
data = {'Name':['Tom', 'Jack', 'Steve', 'Ricky'],'Age':[28,34,29,42]}
df = pd.DataFrame(data)
print(df)
```

```
    Name  Age
0    Tom   28
1   Jack   34
2  Steve   29
3  Ricky   42
```

In [26]:
```
import pandas as pd
data = {'Name':['Tom', 'Jack', 'Steve', 'Ricky'],'Age':[28,34,29,42]}
df = pd.DataFrame(data, index=['rank1','rank2','rank3','rank4'])
print(df)
```

```
        Name  Age
rank1    Tom   28
rank2   Jack   34
rank3  Steve   29
rank4  Ricky   42
```

Example Create a DataFrame from List of Dicts

In [27]:
```
import pandas as pd
data = [{'a': 1, 'b': 2},{'a': 5, 'b': 10, 'c': 20}]
df = pd.DataFrame(data)
print(df)
```

```
   a   b     c
0  1   2   NaN
1  5  10  20.0
```

In [28]:
```
import pandas as pd
data = [{'a': 1, 'b': 2},{'a': 5, 'b': 10, 'c': 20}]
df = pd.DataFrame(data, index=['first', 'second'])
print(df)
```

```
        a   b     c
first   1   2   NaN
second  5  10  20.0
```

# How do i select specific column from a DataFrame:

**column selection:** We can select the column in data frame by using label. In the data frame you have to pass column name in square bracket.

In [29]:
```
import pandas as pd

d = {'one' : pd.Series([1, 2, 3], index=['a', 'b', 'c']),
   'two' : pd.Series([1, 2, 3, 4], index=['a', 'b', 'c', 'd'])}

df = pd.DataFrame(d)
print("Data frame is: \n",df)
print("***********")
print(df['one'])
```

```
Data frame is:
    one  two
a  1.0    1
b  2.0    2
c  3.0    3
d  NaN    4
***********
a    1.0
b    2.0
c    3.0
d    NaN
Name: one, dtype: float64
```

NOTE: Each column in a DataFrame is a Series. As a single column is selected, the returned object is a pandas Series. We can verify this by checking the type of the output:

In [30]:
```
print(type(df['one']))
```

```
<class 'pandas.core.series.Series'>
```

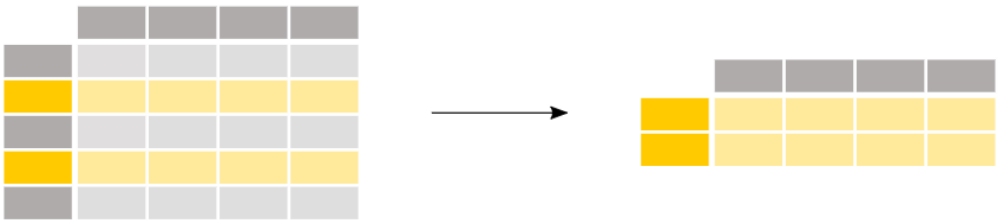
**Multiple column selection:** To select multiple columns, use a list of column names within the selection brackets [].

In [31]:
```
import pandas as pd

d = {'one' : pd.Series([1, 2, 3], index=['a', 'b', 'c']),
   'two' : pd.Series([1, 2, 3, 4], index=['a', 'b', 'c', 'd'])}

df = pd.DataFrame(d)
print("Data frame is: \n",df)
print("***********")
print(df[['one','two']])
```

```
Data frame is:
    one  two
a  1.0    1
b  2.0    2
c  3.0    3
d  NaN    4
***********
   one  two
a  1.0    1
b  2.0    2
c  3.0    3
d  NaN    4
```

# How do I filter specific rows from a DataFrame?

To select rows based on a conditional expression, use a condition inside the selection brackets [].



In [32]:
```
import pandas as pd

d = {'one' : pd.Series([1, 2, 3], index=['a', 'b', 'c']),
   'two' : pd.Series([1, 2, 3, 4], index=['a', 'b', 'c', 'd'])}

df = pd.DataFrame(d)
print("Data frame is: \n",df)
print("***********")
print(df[df['one']>2])
```

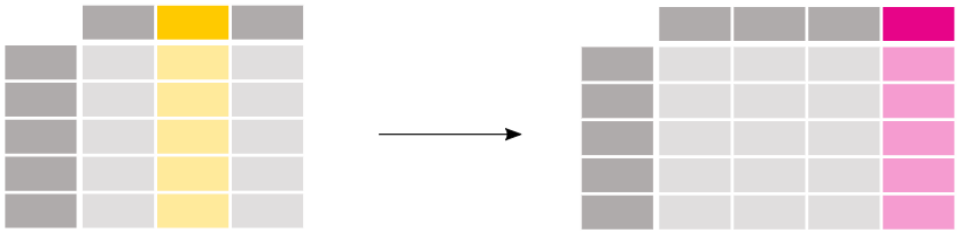
```
Data frame is:
    one  two
a  1.0    1
b  2.0    2
c  3.0    3
d  NaN    4
***********
```

```
   one  two
c  3.0    3
```

The condition inside the selection brackets df[df['one']] > 2 checks for which rows the one column has a value larger than 2

# How to create new columns derived from existing columns?

To create a new column, use the [] brackets with the new column name at the left side of the assignment.



In [33]:
```
import pandas as pd

d = {'one' : pd.Series([1, 2, 3], index=['a', 'b', 'c']),
   'two' : pd.Series([1, 2, 3, 4], index=['a', 'b', 'c', 'd'])}

df = pd.DataFrame(d)

# Adding a new column to an existing DataFrame object with column label

print ("\nAdding a new column by passing as Series:")
df['three']=pd.Series([10,20,30],index=['a','b','c'])
print(df)

print ("\nAdding a new column using the existing columns in DataFrame:")
df['four']=df['one']+df['three']

print(df)
```

```
Adding a new column by passing as Series:
   one  two  three
a  1.0    1   10.0
b  2.0    2   20.0
c  3.0    3   30.0
d  NaN    4    NaN

Adding a new column using the existing columns in DataFrame:
   one  two  three  four
a  1.0    1   10.0  11.0
b  2.0    2   20.0  22.0
c  3.0    3   30.0  33.0
d  NaN    4    NaN   NaN
```

NOTE: The calculation of the values is done element_wise. This means all values in the column['one'] are added with column['two']. You do not need to use a loop to iterate each of the rows!

# How to delete any column from DataFrame

If you want to delete any particular column from Dataframe then you can use del with column name.

In [34]:
```
import pandas as pd

d = {'one' : pd.Series([1, 2, 3], index=['a', 'b', 'c']),
   'two' : pd.Series([1, 2, 3, 4], index=['a', 'b', 'c', 'd']),
   'three' : pd.Series([10,20,30], index=['a','b','c'])}

df = pd.DataFrame(d)
print("Our dataframe is:")
print(df)

# using del function
print ("\nDeleting the first column using DEL function:")
del df['one']
print(df)

# using pop function
print ("\nDeleting another column using POP function:")
df.pop('two')
print(df)
```

```
Our dataframe is:
   one  two  three
a  1.0    1   10.0
b  2.0    2   20.0
c  3.0    3   30.0
d  NaN    4    NaN

Deleting the first column using DEL function:
   two  three
a    1   10.0
b    2   20.0
c    3   30.0
d    4    NaN

Deleting another column using POP function:
   three
a   10.0
b   20.0
c   30.0
d    NaN
```

# Indexing and selecting data

**.loc:** is primarily label based, but may also be used with a boolean array. .loc will raise KeyError when the items are not found. Allowed inputs are:

- A single label, e.g. 5 or 'a' (Note that 5 is interpreted as a label of the index. This use is not an integer position along the index.).
- A list or array of labels ['a', 'b', 'c'].
- A slice object with labels 'a':'f' (Note that contrary to usual Python slices, both the start and the stop are included, when present in the index! See Slicing with labels and Endpoints are inclusive.)
- A boolean array (any NA values will be treated as False).
- A callable function with one argument (the calling Series or DataFrame) and that returns valid output for indexing (one of the above).

In [35]:
```
import pandas as pd

d = {'one' : pd.Series([1, 2, 3], index=['a', 'b', 'c']),
   'two' : pd.Series([1, 2, 3, 4], index=['a', 'b', 'c', 'd'])}

df = pd.DataFrame(d)
print(df)
print("***********")
print(df.loc['b'])
```

```
   one  two
a  1.0    1
b  2.0    2
c  3.0    3
d  NaN    4
***********
one    2.0
two    2.0
Name: b, dtype: float64
```

**.iloc:** is primarily integer position based (from 0 to length-1 of the axis), but may also be used with a boolean array. .iloc will raise IndexError if a requested indexer is out-of-bounds, except slice indexers which allow out-of-bounds indexing. (this conforms with Python/NumPy slice semantics). Allowed inputs are:

- An integer e.g. 5.
- A list or array of integers [4, 3, 0].
- A slice object with ints 1:7.
- A boolean array (any NA values will be treated as False).
- A callable function with one argument (the calling Series or DataFrame) and that returns valid output for indexing (one of the above).

In [36]:
```
import pandas as pd

d = {'one' : pd.Series([1, 2, 3], index=['a', 'b', 'c']),
   'two' : pd.Series([1, 2, 3, 4], index=['a', 'b', 'c', 'd'])}

df = pd.DataFrame(d)
print(df)
print("***********")
print("Zeroth location: \n",df.iloc[0])
print("***********")
print("First location: \n",df.iloc[1])
```

```
   one  two
a  1.0    1
b  2.0    2
c  3.0    3
d  NaN    4
***********
Zeroth location:
 one    1.0
two    1.0
Name: a, dtype: float64
***********
First location:
 one    2.0
two    2.0
Name: b, dtype: float64
```

# Slice Rows

Pandas dataframe slicing refers to accessing portion or a subset of Pandas Dataframe while the original dataframe remain unaffected. You can use indexes of dataframe elements to create dataframe slice as per the following syntax:

slice=[StartIndex : StopIndex : Steps]

- The StartIndex represents the index from where the dataframe slicing is supposed to begin. Its default value is 0, i.r., the dataframe begins from index 0 if no StartIndex is specified.
- The StopIndex represents the last index upto which the dataframe slicing will go on. Its default value is (length(dataframe)-1) or the index of the last element in the dataframe element in the dataframe.
- Steps represent the number of steps. It is an optional parameter. Steps, if defined, specifies the number of elements to jump over while counting from StartIndex to StopIndex. By default it is 1.
- The dataframe slices created, include elements failing between the indexes StartIndex and StopIndex, including StartIndex and not including StopIndex.

In [37]:
```
import pandas as pd

d = {'one' : pd.Series([1, 2, 3], index=['a', 'b', 'c']),
   'two' : pd.Series([1, 2, 3, 4], index=['a', 'b', 'c', 'd'])}

df = pd.DataFrame(d)
print(df[1:])             #by default its stop index is last element in d
```

```
   one  two
b  2.0    2
c  3.0    3
d  NaN    4
```

In [38]:
```
import pandas as pd

d = {'one' : pd.Series([1, 2, 3], index=['a', 'b', 'c']),
   'two' : pd.Series([1, 2, 3, 4], index=['a', 'b', 'c', 'd'])}

df = pd.DataFrame(d)
print(df[:4])          #by default its start index is from first element
```

```
   one  two
a  1.0    1
b  2.0    2
c  3.0    3
d  NaN    4
```

In [39]:
```
import pandas as pd

d = {'one' : pd.Series([1, 2, 3], index=['a', 'b', 'c']),
   'two' : pd.Series([1, 2, 3, 4], index=['a', 'b', 'c', 'd'])}

df = pd.DataFrame(d)
print(df[1:4:2])
```

```
   one  two
b  2.0    2
d  NaN    4
```

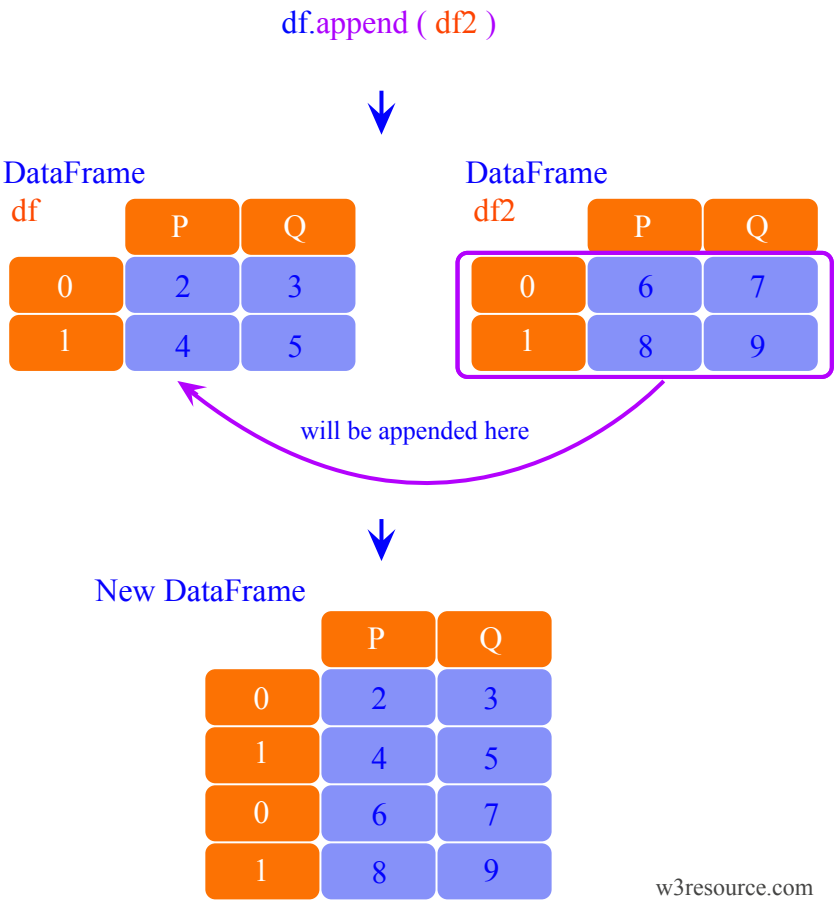
In [40]:
```
import pandas as pd
```

```
d = {'one' : pd.Series([1, 2, 3], index=['a', 'b', 'c']),
   'two' : pd.Series([1, 2, 3, 4], index=['a', 'b', 'c', 'd'])}

df = pd.DataFrame(d)
print(df[::])       #by default its start from first element go till las
```

```
   one  two
a  1.0    1
b  2.0    2
c  3.0    3
d  NaN    4
```

# Appending two DataFrame

append() function is used to append rows of other dataframe to the end of the given dataframe, returning a new dataframe object. Columns not in the original dataframes are added as new columns and the new cells are populated with NaN value.




In [41]:
```
import pandas as pd

df1 = pd.DataFrame([[2, 3], [4, 5]], columns = ['P','Q'])
df2 = pd.DataFrame([[6, 7], [8, 9]], columns = ['P','Q'])
print("Dataframe1: ")
print(df1)
print("**************")
print("DataFrame2: ")
print(df2)
print("**************")
df = df1.append(df2)
print(df)
```

```
Dataframe1:
   P  Q
0  2  3
1  4  5
**************
DataFrame2:
   P  Q
0  6  7
1  8  9
**************
   P  Q
0  2  3
1  4  5
0  6  7
1  8  9
```

# Deletion of Rows

In [42]:
```
import pandas as pd

df = pd.DataFrame([[1, 2], [3, 4]], columns = ['a','b'])
df2 = pd.DataFrame([[5, 6], [7, 8]], columns = ['a','b'])
print("Dataframe: ")
print(df)
print("**************")
print("DataFrame2: ")
print(df2)
print("**************")
df = df.append(df2)
print("DataFrame is: ")
print(df)
print("**************")
df = df.drop(0)
print(df)
```

```
Dataframe:
   a  b
0  1  2
1  3  4
**************
DataFrame2:
   a  b
0  5  6
1  7  8
**************
DataFrame is:
   a  b
0  1  2
1  3  4
0  5  6
1  7  8
**************
   a  b
1  3  4
1  7  8
```

# Basic functionality of DataFrame:

**T (Transpose):** Returns the transpose of the DataFrame. The rows and columns will interchange.

In [43]:
```
import pandas as pd
import numpy as np
```

```
# Create a Dictionary of series
d = {'Name':pd.Series(['Tom','James','Ricky','Vin','Steve','Smith','Jack
   'Age':pd.Series([25,26,25,23,30,29,23]),
   'Rating':pd.Series([4.23,3.24,3.98,2.56,3.20,4.6,3.8])}

# Create a DataFrame
df = pd.DataFrame(d)
print("The orifinal dataframe is: ")
print(df)
print("************************************")
print("The transpose of the data series is:")
print(df.T)
```

```
The orifinal dataframe is:
    Name  Age  Rating
0    Tom   25    4.23
1  James   26    3.24
2  Ricky   25    3.98
3    Vin   23    2.56
4  Steve   30    3.20
5  Smith   29    4.60
6   Jack   23    3.80
************************************
The transpose of the data series is:
           0      1      2     3      4      5     6
Name     Tom  James  Ricky   Vin  Steve  Smith  Jack
Age       25     26     25    23     30     29    23
Rating  4.23   3.24   3.98  2.56    3.2    4.6   3.8
```

**axes:** Returns the list of row axis labels and column axis labels.

In [44]:
```
import pandas as pd
import numpy as np

#Create a Dictionary of series
d = {'Name':pd.Series(['Tom','James','Ricky','Vin','Steve','Smith','Jack
   'Age':pd.Series([25,26,25,23,30,29,23]),
   'Rating':pd.Series([4.23,3.24,3.98,2.56,3.20,4.6,3.8])}

#Create a DataFrame
df = pd.DataFrame(d)
print("Row axis labels and column axis labels are:")
print(df.axes)
```

```
Row axis labels and column axis labels are:
[RangeIndex(start=0, stop=7, step=1), Index(['Name', 'Age', 'Rating'], dt
ype='object')]
```

**dtypes:** Returns the data type of each column.

In [45]:
```
import pandas as pd
import numpy as np

#Create a Dictionary of series
d = {'Name':pd.Series(['Tom','James','Ricky','Vin','Steve','Smith','Jack
   'Age':pd.Series([25,26,25,23,30,29,23]),
   'Rating':pd.Series([4.23,3.24,3.98,2.56,3.20,4.6,3.8])}

#Create a DataFrame
df = pd.DataFrame(d)
print("The data type of each column are:")
print(df.dtypes)
```

```
The data type of each column are:
Name       object
```

```
Age         int64
Rating    float64
dtype: object
```

**empty:** Returns the Boolean value saying whether the Object is empty or not; True indicates that the object is empty.

In [46]:
```
import pandas as pd
import numpy as np

#Create a Dictionary of series
d = {'Name':pd.Series(['Tom','James','Ricky','Vin','Steve','Smith','Jack
   'Age':pd.Series([25,26,25,23,30,29,23]),
   'Rating':pd.Series([4.23,3.24,3.98,2.56,3.20,4.6,3.8])}

#Create a DataFrame
df = pd.DataFrame(d)
print("Is the object empty?")
print(df.empty)
```

```
Is the object empty?
False
```

**ndim:** Returns the number of dimensions of the object. By definition, DataFrame is a 2D object

In [47]:
```
import pandas as pd
import numpy as np

#Create a Dictionary of series
d = {'Name':pd.Series(['Tom','James','Ricky','Vin','Steve','Smith','Jack
   'Age':pd.Series([25,26,25,23,30,29,23]),
   'Rating':pd.Series([4.23,3.24,3.98,2.56,3.20,4.6,3.8])}

#Create a DataFrame
df = pd.DataFrame(d)
print("Our object is:")
print(df)
print("The dimension of the object is:")
print(df.ndim)
```

```
Our object is:
    Name  Age  Rating
0    Tom   25    4.23
1  James   26    3.24
2  Ricky   25    3.98
3    Vin   23    2.56
4  Steve   30    3.20
5  Smith   29    4.60
6   Jack   23    3.80
The dimension of the object is:
2
```

**shape:** Returns a tuple representing the dimensionality of the DataFrame. Tuple (a,b), where a represents the number of rows and b represents the number of columns.

In [48]:
```
import pandas as pd
import numpy as np

#Create a Dictionary of series
d = {'Name':pd.Series(['Tom','James','Ricky','Vin','Steve','Smith','Jack
   'Age':pd.Series([25,26,25,23,30,29,23]),
   'Rating':pd.Series([4.23,3.24,3.98,2.56,3.20,4.6,3.8])}

#Create a DataFrame
```

```
df = pd.DataFrame(d)
print("Our object is:")
print(df)
print("The shape of the object is:")
print(df.shape)
```

```
Our object is:
    Name  Age  Rating
0    Tom   25    4.23
1  James   26    3.24
2  Ricky   25    3.98
3    Vin   23    2.56
4  Steve   30    3.20
5  Smith   29    4.60
6   Jack   23    3.80
The shape of the object is:
(7, 3)
```

**size:** Returns the number of elements in the DataFrame.

In [49]:
```
import pandas as pd
import numpy as np

#Create a Dictionary of series
d = {'Name':pd.Series(['Tom','James','Ricky','Vin','Steve','Smith','Jack
   'Age':pd.Series([25,26,25,23,30,29,23]),
   'Rating':pd.Series([4.23,3.24,3.98,2.56,3.20,4.6,3.8])}

#Create a DataFrame
df = pd.DataFrame(d)
print("Our object is:")
print(df)
print("The total number of elements in our object is:")
print(df.size)
```

```
Our object is:
    Name  Age  Rating
0    Tom   25    4.23
1  James   26    3.24
2  Ricky   25    3.98
3    Vin   23    2.56
4  Steve   30    3.20
5  Smith   29    4.60
6   Jack   23    3.80
The total number of elements in our object is:
21
```

**values:** Returns the actual data in the DataFrame as an NDarray.

In [50]:
```
import pandas as pd
import numpy as np

#Create a Dictionary of series
d = {'Name':pd.Series(['Tom','James','Ricky','Vin','Steve','Smith','Jack
   'Age':pd.Series([25,26,25,23,30,29,23]),
   'Rating':pd.Series([4.23,3.24,3.98,2.56,3.20,4.6,3.8])}

#Create a DataFrame
df = pd.DataFrame(d)
print("Our object is:")
print(df)
print("The actual data in our data frame is:")
print(df.values)
```

```
Our object is:
    Name  Age  Rating
```

```
0    Tom   25    4.23
1  James   26    3.24
2  Ricky   25    3.98
3    Vin   23    2.56
4  Steve   30    3.20
5  Smith   29    4.60
6   Jack   23    3.80
The actual data in our data frame is:
[['Tom' 25 4.23]
 ['James' 26 3.24]
 ['Ricky' 25 3.98]
 ['Vin' 23 2.56]
 ['Steve' 30 3.2]
 ['Smith' 29 4.6]
 ['Jack' 23 3.8]]
```

**head():** returns the first n rows(observe the index values). The default number of elements to display is five, but you may pass a custom number.

**tail():** returns the last n rows(observe the index values). The default number of elements to display is five, but you may pass a custom number.

In [51]:
```
import pandas as pd
import numpy as np

#Create a Dictionary of series
d = {'Name':pd.Series(['Tom','James','Ricky','Vin','Steve','Smith','Jack
   'Age':pd.Series([25,26,25,23,30,29,23]),
   'Rating':pd.Series([4.23,3.24,3.98,2.56,3.20,4.6,3.8])}

#Create a DataFrame
df = pd.DataFrame(d)
print("Our data frame is:")
print(df)
print("****************************************")
print("The first two rows of the data frame is:")
print(df.head(2))
print("****************************************")
print("The last two rows of the data frame is:")
print(df.tail(2))
```

```
Our data frame is:
    Name  Age  Rating
0    Tom   25    4.23
1  James   26    3.24
2  Ricky   25    3.98
3    Vin   23    2.56
4  Steve   30    3.20
5  Smith   29    4.60
6   Jack   23    3.80
****************************************
The first two rows of the data frame is:
    Name  Age  Rating
0    Tom   25    4.23
1  James   26    3.24
****************************************
The last two rows of the data frame is:
    Name  Age  Rating
5  Smith   29     4.6
6   Jack   23     3.8
```

# Descriptive statistics:

**count():** Count number of non-null observations

**sum():** Sum of values
**mean():** Mean of Values
**median():** Median of Values
**mode():** Mode of values
**std():** Standard Deviation of the Values
**min():** Minimum Value
**max():** Maximum Value
**abs():** Absolute Value
**prod():** Product of Values
**cumsum():** Cumulative Sum
**cumprod():** Cumulative Product **describe()** function computes a summary of statistics pertaining to the DataFrame columns.

In [52]:
```
import pandas as pd
import numpy as np

#Create a Dictionary of series
d = {'Name':pd.Series(['Tom','James','Ricky','Vin','Steve','Smith','Jack
   'Lee','David','Gasper','Betina','Andres']),
   'Age':pd.Series([25,26,25,23,30,29,23,34,40,30,51,46]),
   'Rating':pd.Series([4.23,3.24,3.98,2.56,3.20,4.6,3.8,3.78,2.98,4.80,4
}

#Create a DataFrame
df = pd.DataFrame(d)
print(df)
print("**********************************************************************
print("count is: \n",df.count())
print("**********************************************************************
print("sum is: \n",df.sum())
print("**********************************************************************
print("mean is: \n",df.mean())
print("**********************************************************************
print("mode is: \n",df.mode())
print("**********************************************************************
print("median is: \n",df.median())
print("**********************************************************************
print("Standard deviation is: \n",df.std())
print("**********************************************************************
print("minimum is: \n",df.min())
print("**********************************************************************
print("maximum is: \n",df.max())
print("**********************************************************************
print("Describe is: \n",df.describe())
```

```
      Name  Age  Rating
0      Tom   25    4.23
1    James   26    3.24
2    Ricky   25    3.98
3      Vin   23    2.56
4    Steve   30    3.20
5    Smith   29    4.60
6     Jack   23    3.80
7      Lee   34    3.78
8    David   40    2.98
9   Gasper   30    4.80
10  Betina   51    4.10
11  Andres   46    3.65
**********************************************************************
**********************************************************************
```

```
count is:
 Name      12
Age       12
Rating    12
dtype: int64
**************************************************************************
**************************************
sum is:
 Name      TomJamesRickyVinSteveSmithJackLeeDavidGasperBe...
Age                                                     382
Rating                                                44.92
dtype: object
**************************************************************************
**************************************
mean is:
 Age       31.833333
Rating     3.743333
dtype: float64
**************************************************************************
**************************************
mode is:
       Name   Age  Rating
0   Andres  23.0    2.56
1   Betina  25.0    2.98
2    David  30.0    3.20
3   Gasper   NaN    3.24
4     Jack   NaN    3.65
5    James   NaN    3.78
6      Lee   NaN    3.80
7    Ricky   NaN    3.98
8    Smith   NaN    4.10
9    Steve   NaN    4.23
10     Tom   NaN    4.60
11     Vin   NaN    4.80
**************************************************************************
**************************************
median is:
 Age       29.50
Rating     3.79
dtype: float64
**************************************************************************
**************************************
Standard deviation is:
 Age       9.232682
Rating    0.661628
dtype: float64
**************************************************************************
**************************************
minimum is:
 Name      Andres
Age           23
Rating      2.56
dtype: object
**************************************************************************
**************************************
maximum is:
 Name      Vin
Age        51
Rating    4.8
dtype: object
**************************************************************************
**************************************
Describe is:
              Age     Rating
count  12.000000  12.000000
mean   31.833333   3.743333
std     9.232682   0.661628
min    23.000000   2.560000
```

```
25%    25.000000   3.230000
50%    29.500000   3.790000
75%    35.500000   4.132500
max    51.000000   4.800000
```

NOTE: describe() function 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 [53]:
```
import pandas as pd
import numpy as np

#Create a Dictionary of series
d = {'Name':pd.Series(['Tom','James','Ricky','Vin','Steve','Smith','Jack
     'Age':pd.Series([25,26,25,23,30,29,23,34,40,30,51,46]),
     'Rating':pd.Series([4.23,3.24,3.98,2.56,3.20,4.6,3.8,3.78,2.98,4.80
}

#Create a DataFrame
df = pd.DataFrame(d)
print(df.describe())
print("*******************************************************************
print(df.describe(include=['object']))
print("*******************************************************************
print(df.describe(include='all'))
```

```
             Age     Rating
count  12.000000  12.000000
mean   31.833333   3.743333
std     9.232682   0.661628
min    23.000000   2.560000
25%    25.000000   3.230000
50%    29.500000   3.790000
75%    35.500000   4.132500
max    51.000000   4.800000
*******************************************************************************
****************************************
         Name
count      12
unique     12
top     Ricky
freq        1
*******************************************************************************
****************************************
         Name        Age     Rating
count      12  12.000000  12.000000
unique     12        NaN        NaN
top     Ricky        NaN        NaN
freq        1        NaN        NaN
mean      NaN  31.833333   3.743333
std       NaN   9.232682   0.661628
min       NaN  23.000000   2.560000
25%       NaN  25.000000   3.230000
50%       NaN  29.500000   3.790000
75%       NaN  35.500000   4.132500
max       NaN  51.000000   4.800000
```

# Function application:

**Table wise function application/pipe():** Dataframe.pipe() method with appropriate number of argument operation is performed on the whole dataframe.

In [54]:
```
import numpy as np
import pandas as pd

def adder(ele1,num):
   return ele1+num

data=[[1,2],[3,4],[5,6],[7,8],[9,10]]
df=pd.DataFrame(data,columns=['col1','col2'])
print("Original dataframe is : \n",df)
print("\nAfter apply pipe method: \n",df.pipe(adder,2))
```

```
Original dataframe is :
    col1  col2
0     1     2
1     3     4
2     5     6
3     7     8
4     9    10

After apply pipe method:
    col1  col2
0     3     4
1     5     6
2     7     8
3     9    10
4    11    12
```

**Row or column wise function application/apply() :** Dataframe.apply() allow the users to pass a function and apply it on every single value of the Pandas series.

In [55]:
```
import numpy as np
import pandas as pd

data=[[1,2],[3,4],[5,6],[7,8],[9,10]]
df=pd.DataFrame(data,columns=['col1','col2'])
print("Original dataframe is : \n",df)
print("\nAfter apply  method: \n",df.apply(np.mean))
print("\nAfter apply  method: \n",df.apply(np.mean,axis=1))
```

```
Original dataframe is :
    col1  col2
0     1     2
1     3     4
2     5     6
3     7     8
4     9    10

After apply  method:
 col1    5.0
col2    6.0
dtype: float64

After apply  method:
 0    1.5
1    3.5
2    5.5
3    7.5
4    9.5
dtype: float64
```

**Element wise function application:** Dataframe.applymap() method applies a function that accepts and returns a scalar to every element of a DataFrame.

In [56]:
```
import numpy as np
import pandas as pd

data=[[1,2],[3,4],[5,6],[7,8],[9,10]]
df=pd.DataFrame(data,columns=['col1','col2'])
print("Original dataframe is : \n",df)
print("************************")
print("After applymap: \n",df.applymap(lambda x:x*100))
print("************************")
print(df.apply(np.mean))
```

```
Original dataframe is :
    col1  col2
0     1     2
1     3     4
2     5     6
3     7     8
4     9    10
************************
After applymap:
    col1  col2
0   100   200
1   300   400
2   500   600
3   700   800
4   900  1000
************************
col1    5.0
col2    6.0
dtype: float64
```

# Sorting:

There are two kinds of sorting available in Pandas. They are −

By label

By Actual Value

In [57]:
```
import pandas as pd
import numpy as np

unsorted_df=pd.DataFrame(np.random.randn(10,2),index=[1,4,6,2,3,5,9,8,0,
print(unsorted_df)
```

```
       col1      col2
1 -0.660139  1.441730
4 -0.071603  0.269932
6 -0.336583  0.661928
2 -0.599720 -0.988778
3 -0.642074  1.693148
5  0.745967  0.146820
9  0.567836 -0.175232
8  2.101790 -1.293133
0  0.379764 -1.057593
7  0.009930  1.400048
```

**By label:**

In [58]:
```
import pandas as pd
```

```
import numpy as np

unsorted_df = pd.DataFrame(np.random.randn(10,2),index=[1,4,6,2,3,5,9,8,

sorted_df=unsorted_df.sort_index()
print("Sorted index wise")
print(sorted_df)
print("**********************************************************************
sorted_df = unsorted_df.sort_index(ascending=False)
print("Sorted ascending wise")
print(sorted_df)
```

```
Sorted index wise
       col1      col2
0 -0.048471 -0.698869
1  0.625944  0.237917
2 -0.790532  0.529453
3  0.024598  0.263129
4  0.417039  2.403819
5 -2.513857 -1.429845
6  0.569424 -1.110645
7  0.475258 -0.431311
8 -0.644009  0.827621
9  1.565836  0.983716
**********************************************************************
*****
Sorted ascending wise
       col1      col2
9  1.565836  0.983716
8 -0.644009  0.827621
7  0.475258 -0.431311
6  0.569424 -1.110645
5 -2.513857 -1.429845
4  0.417039  2.403819
3  0.024598  0.263129
2 -0.790532  0.529453
1  0.625944  0.237917
0 -0.048471 -0.698869
```

**Sort the columns:**

In [59]:

```
import pandas as pd
import numpy as np

unsorted_df = pd.DataFrame(np.random.randn(10,2),index=[1,4,6,2,3,5,9,8,

sorted_df=unsorted_df.sort_values(by=['col1'])
print("Sorted by column1")
print(sorted_df)
print("***************************")
sorted_df=unsorted_df.sort_values(by=['col1'], ascending=False)
print("Sorted ascending wise")
print(sorted_df)
```

```
Sorted by column1
       col2      col1
3 -0.097653 -1.920968
1 -0.759541 -1.707629
7 -1.469773 -1.487811
0  0.879300 -0.587653
9 -0.730604 -0.349882
8  1.683559  0.068307
2  0.088240  0.474390
6  0.321830  0.559457
5  1.209454  1.314141
4  1.011382  2.085866
***************************
```

```
Sorted ascending wise
       col2      col1
4  1.011382  2.085866
5  1.209454  1.314141
6  0.321830  0.559457
2  0.088240  0.474390
8  1.683559  0.068307
9 -0.730604 -0.349882
0  0.879300 -0.587653
7 -1.469773 -1.487811
1 -0.759541 -1.707629
3 -0.097653 -1.920968
```

In [60]:

```
import pandas as pd
import numpy as np

unsorted_df = pd.DataFrame(np.random.randn(10,2),index=[1,4,6,2,3,5,9,8,

sorted_df=unsorted_df.sort_values(by=['col2'])
print("Sorted by column2")
print(sorted_df)
print("****************************")
sorted_df=unsorted_df.sort_values(by=['col2'], ascending=False)
print("Sorted ascending wise")
print(sorted_df)
```

```
Sorted by column2
       col2      col1
0 -0.425260 -3.586128
6 -0.042807  0.638521
9  0.035894 -0.236678
4  0.159201  0.591428
8  0.251322 -0.403187
3  0.300296 -0.230369
2  0.537355  1.990105
7  0.587931  0.276665
5  1.096417 -0.990225
1  1.297242 -0.630314
****************************
Sorted ascending wise
       col2      col1
1  1.297242 -0.630314
5  1.096417 -0.990225
7  0.587931  0.276665
2  0.537355  1.990105
3  0.300296 -0.230369
8  0.251322 -0.403187
4  0.159201  0.591428
9  0.035894 -0.236678
6 -0.042807  0.638521
0 -0.425260 -3.586128
```

In [61]:

```
import pandas as pd
import numpy as np

unsorted_df = pd.DataFrame(np.random.randn(10,2),index=[1,4,6,2,3,5,9,8,

sorted_df=unsorted_df.sort_values(by=['col1','col2'])
print("Sorted by column2")
print(sorted_df)
```

```
Sorted by column2
       col2      col1
5 -0.315270 -0.895541
6  0.171963 -0.782162
1 -1.041005 -0.385329
4  1.139732 -0.247565
```

```
8  0.375400 -0.184219
9  0.180701 -0.161054
7  1.647876 -0.133221
2  1.144221  0.332937
0 -1.437100  0.359159
3  0.973520  0.953666
```

**sorting algorithm**

sort_values() provides a provision to choose the algorithm from mergesort, heapsort and quicksort. Mergesort is the only stable algorithm

In [62]:
```
import pandas as pd
import numpy as np

unsorted_df = pd.DataFrame(np.random.randn(10,2),index=[1,4,6,2,3,5,9,8,

sorted_df=unsorted_df.sort_values(by='col1',kind='mergesort')

print(sorted_df)
```

```
       col1      col2
9 -1.060151 -0.442039
7 -0.296782  1.002019
5 -0.192444 -0.952711
8 -0.181269 -0.397951
1  0.013056 -1.617972
3  0.206970  1.799657
2  0.700612  0.923792
6  1.125891  0.352842
4  2.050384  1.861975
0  2.301670 -0.121701
```

In [63]:
```
import pandas as pd
import numpy as np

unsorted_df = pd.DataFrame(np.random.randn(10,2),index=[1,4,6,2,3,5,9,8,

sorted_df=unsorted_df.sort_values(by='col1',kind='heapsort')

print(sorted_df)
```

```
       col1      col2
4 -1.335856 -0.788297
1 -1.261907  1.613686
8 -1.135699 -0.346609
6 -0.942440  0.117917
5 -0.850910 -0.937891
2 -0.783147  0.706686
9 -0.750098  1.560976
3 -0.222333 -0.871196
0 -0.182771  2.533929
7  0.499805 -0.290617
```

In [64]:
```
import pandas as pd
import numpy as np

unsorted_df = pd.DataFrame(np.random.randn(10,2),index=[1,4,6,2,3,5,9,8,

sorted_df=unsorted_df.sort_values(by='col1',kind='quicksort')

print(sorted_df)
```

```
       col1      col2
4 -2.044142 -1.594567
3 -1.753194 -0.596760
```

```
0 -1.105143  1.601309
6 -0.525228  2.713795
2 -0.502357 -0.234311
7 -0.399640  1.158663
9  0.576452  0.337318
1  0.593772  0.258689
8  1.159961  0.705333
5  1.579399 -0.090990
```

NOTE: all string operation u can perform on string column

# Find missing values:

**Check for missing value:** For checking missing values we have two function in Pandas. Let's have a look.

**isnull():** isnull() method stores True for ever NaN value and False for a Not null value and returned it.
**notnull():** notnull() method stores True for ever NON-NULL value and False for a null value and returned it.

In [65]:
```
import pandas as pd
import numpy as np

df = pd.DataFrame(np.random.randn(5, 3), index=['a', 'c', 'e', 'f','h'],

df = df.reindex(['a', 'b', 'c', 'd', 'e', 'f', 'g', 'h'])
print(df)
print("**********************")
print(df['one'].isnull())
print("**********************")
print(df['one'].notnull())
```

```
        one       two     three
a -1.023612  0.522151 -1.969415
b       NaN       NaN       NaN
c -1.863194 -1.077297 -0.747627
d       NaN       NaN       NaN
e  0.572640  1.153686 -0.419022
f -1.648816  1.961191  0.952571
g       NaN       NaN       NaN
h  1.287714 -1.507602  0.289768
**********************
a    False
b     True
c    False
d     True
e    False
f    False
g     True
h    False
Name: one, dtype: bool
**********************
a     True
b    False
c     True
d    False
e     True
f     True
g    False
h     True
Name: one, dtype: bool
```

# Filling missing data

**fillna():** DataFrame.fillna() method fills(replaces) NA or NaN values in the DataFrame with the specified values.

In [66]:
```
import pandas as pd
import numpy as np

df = pd.DataFrame(np.random.randn(5, 3), index=['a', 'c', 'e', 'f','h'],

df = df.reindex(['a', 'b', 'c', 'd', 'e', 'f', 'g', 'h'])
print("Original dataframe is: \n",df)
print("************************************************")
print("After filling missing data with 0: \n",df.fillna(0))
```

```
Original dataframe is:
          one       two     three
a  0.332844  0.162040 -1.015734
b       NaN       NaN       NaN
c  1.328551 -0.061478  1.807803
d       NaN       NaN       NaN
e  0.330107 -1.252296  0.053072
f  0.348133  0.630093 -3.212920
g       NaN       NaN       NaN
h -0.667607  1.193277 -0.621246
************************************************
After filling missing data with 0:
          one       two     three
a  0.332844  0.162040 -1.015734
b  0.000000  0.000000  0.000000
c  1.328551 -0.061478  1.807803
d  0.000000  0.000000  0.000000
e  0.330107 -1.252296  0.053072
f  0.348133  0.630093 -3.212920
g  0.000000  0.000000  0.000000
h -0.667607  1.193277 -0.621246
```

**Fill NA forward and backward:**

In [67]:
```
import pandas as pd
import numpy as np

df = pd.DataFrame(np.random.randn(5, 3), index=['a', 'c', 'e', 'f','h'],

df = df.reindex(['a', 'b', 'c', 'd', 'e', 'f', 'g', 'h'])
print("Original dataframe is: \n",df)
print("************************************************")
print(df.fillna(method='pad'))
print("************************************************")
print(df.fillna(method='bfill'))
```

```
Original dataframe is:
          one       two     three
a -2.290439 -0.227909  0.945807
b       NaN       NaN       NaN
c -0.103820 -0.478348 -0.000502
d       NaN       NaN       NaN
e  0.238314  0.352345  0.072301
f  0.100810 -1.036068 -0.000516
g       NaN       NaN       NaN
h -0.852017 -0.824285  0.346426
************************************************
          one       two     three
a -2.290439 -0.227909  0.945807
b -2.290439 -0.227909  0.945807
```

```
c -0.103820 -0.478348 -0.000502
d -0.103820 -0.478348 -0.000502
e  0.238314  0.352345  0.072301
f  0.100810 -1.036068 -0.000516
g  0.100810 -1.036068 -0.000516
h -0.852017 -0.824285  0.346426
**********************************************
        one       two     three
a -2.290439 -0.227909  0.945807
b -0.103820 -0.478348 -0.000502
c -0.103820 -0.478348 -0.000502
d  0.238314  0.352345  0.072301
e  0.238314  0.352345  0.072301
f  0.100810 -1.036068 -0.000516
g -0.852017 -0.824285  0.346426
h -0.852017 -0.824285  0.346426
```

# Drop missing values:

**dropna():** dropna() method removes the missing values and returns the DataFrame with NA entries dropped from it.

In [68]:
```
import pandas as pd
import numpy as np

df = pd.DataFrame(np.random.randn(5, 3), index=['a', 'c', 'e', 'f','h'],

df = df.reindex(['a', 'b', 'c', 'd', 'e', 'f', 'g', 'h'])
print(df.dropna())
```

```
        one       two     three
a -0.707849 -0.410537 -1.222403
c  2.110150 -0.226322 -0.104206
e  0.121394 -0.509421  0.985301
f  0.534284  0.943747 -0.917127
h  0.808615  0.617646  0.724728
```

# Replace missing values:

**replace():** The replace() function is used to replace values given in to_replace with value.

In [69]:
```
import pandas as pd
import numpy as np

df = pd.DataFrame({'one':[10,20,30,40,50,2000], 'two':[1000,0,30,40,50,6
print(df)
print("*************")
print(df.replace({1000:10,2000:60}))
```

```
    one   two
0    10  1000
1    20     0
2    30    30
3    40    40
4    50    50
5  2000    60
*************
   one  two
0   10   10
1   20    0
2   30   30
3   40   40
```

```
4   50   50
5   60   60
```

# Group by:

In [70]:
```
import pandas as pd

ipl_data = {'Team': ['Riders', 'Riders', 'Devils', 'Devils', 'Kings',
   'kings', 'Kings', 'Kings', 'Riders', 'Royals', 'Royals', 'Riders'],
   'Rank': [1, 2, 2, 3, 3,4 ,1 ,1,2 , 4,1,2],
   'Year': [2014,2015,2014,2015,2014,2015,2016,2017,2016,2014,2015,2017]
   'Points':[876,789,863,673,741,812,756,788,694,701,804,690]}
df = pd.DataFrame(ipl_data)
print(df)
print("**********************")
df.groupby('Team')
```

```
      Team  Rank  Year  Points
0   Riders     1  2014     876
1   Riders     2  2015     789
2   Devils     2  2014     863
3   Devils     3  2015     673
4    Kings     3  2014     741
5    kings     4  2015     812
6    Kings     1  2016     756
7    Kings     1  2017     788
8   Riders     2  2016     694
9   Royals     4  2014     701
10  Royals     1  2015     804
11  Riders     2  2017     690
**********************
```

Out[70]:
```
<pandas.core.groupby.generic.DataFrameGroupBy object at 0x0000022ACAF0ABE
0>
```

**Iterating through Groups:** With the groupby object in hand, we can iterate through the object similar to itertools.obj.

In [71]:
```
import pandas as pd

ipl_data = {'Team': ['Riders', 'Riders', 'Devils', 'Devils', 'Kings',
   'Kings', 'Kings', 'Kings', 'Riders', 'Royals', 'Royals', 'Riders'],
   'Rank': [1, 2, 2, 3, 3,4 ,1 ,1,2 , 4,1,2],
   'Year': [2014,2015,2014,2015,2014,2015,2016,2017,2016,2014,2015,2017]
   'Points':[876,789,863,673,741,812,756,788,694,701,804,690]}
df = pd.DataFrame(ipl_data)
print(df)
print("**********************")
grouped=df.groupby('Team')

for name,group in grouped:
    print("Name: ",name)
    print("Group: \n")
    print(group)
```

```
      Team  Rank  Year  Points
0   Riders     1  2014     876
1   Riders     2  2015     789
2   Devils     2  2014     863
3   Devils     3  2015     673
4    Kings     3  2014     741
5    Kings     4  2015     812
6    Kings     1  2016     756
7    Kings     1  2017     788
8   Riders     2  2016     694
```

```
9   Royals     4  2014     701
10  Royals     1  2015     804
11  Riders     2  2017     690
**********************
Name:  Devils
Group:

     Team  Rank  Year  Points
2  Devils     2  2014     863
3  Devils     3  2015     673
Name:  Kings
Group:

    Team  Rank  Year  Points
4  Kings     3  2014     741
5  Kings     4  2015     812
6  Kings     1  2016     756
7  Kings     1  2017     788
Name:  Riders
Group:

      Team  Rank  Year  Points
0   Riders     1  2014     876
1   Riders     2  2015     789
8   Riders     2  2016     694
11  Riders     2  2017     690
Name:  Royals
Group:

      Team  Rank  Year  Points
9   Royals     4  2014     701
10  Royals     1  2015     804
```

**Select a Group:** Using the get_group() method, we can select a single group.

In [72]:
```
import pandas as pd

ipl_data = {'Team': ['Riders', 'Riders', 'Devils', 'Devils', 'Kings',
   'kings', 'Kings', 'Kings', 'Riders', 'Royals', 'Royals', 'Riders'],
   'Rank': [1, 2, 2, 3, 3,4 ,1 ,1,2 , 4,1,2],
   'Year': [2014,2015,2014,2015,2014,2015,2016,2017,2016,2014,2015,2017]
   'Points':[876,789,863,673,741,812,756,788,694,701,804,690]}
df = pd.DataFrame(ipl_data)

grouped = df.groupby('Year')
print(grouped.get_group(2014))
```

```
     Team  Rank  Year  Points
0  Riders     1  2014     876
2  Devils     2  2014     863
4   Kings     3  2014     741
9  Royals     4  2014     701
```

# Merging/Joining:

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

In [73]:
```
import pandas as pd
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']})
print(pd.merge(left,right,on='id'))
```

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

In [74]:
```
import pandas as pd
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']})
print(pd.merge(right,left,on='id'))
```

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

In [75]:
```
import pandas as pd
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']})
print(pd.merge(left,right,on=['id','subject_id']))
```

```
   id  Name_x subject_id Name_y
0   4   Alice       sub6  Bryce
1   5  Ayoung       sub5  Betty
```

**Merge using how arguments:**

Merge Method SQL Equivalent Description left LEFT OUTER JOIN Use keys from left object right RIGHT OUTER JOIN Use keys from right object outer FULL OUTER JOIN Use union of keys inner INNER JOIN Use intersection of keys

In [76]:
```
import pandas as pd
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']})
print(pd.merge(left, right, on='subject_id', how='left'))
print("************************************************************")
print(pd.merge(left, right, on='subject_id', how='right'))
print("************************************************************")
print(pd.merge(left, right, on='subject_id', how='inner'))
print("************************************************************")
```

```
print(pd.merge(left, right, on='subject_id', how='outer'))
print("************************************************************")
```

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

# Concatenation:

In [77]:

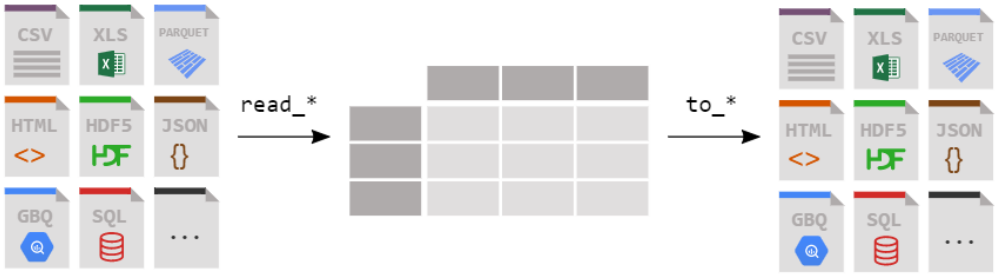
```
import pandas as pd

one = pd.DataFrame({
   'Name': ['Alex', 'Amy', 'Allen', 'Alice', 'Ayoung'],
   'subject_id':['sub1','sub2','sub4','sub6','sub5'],
   'Marks_scored':[98,90,87,69,78]},
   index=[1,2,3,4,5])

two = pd.DataFrame({
   'Name': ['Billy', 'Brian', 'Bran', 'Bryce', 'Betty'],
   'subject_id':['sub2','sub4','sub3','sub6','sub5'],
   'Marks_scored':[89,80,79,97,88]},
   index=[1,2,3,4,5])
print(pd.concat([one,two],keys=['x','y'],ignore_index=True))
```

```
     Name subject_id  Marks_scored
0    Alex       sub1            98
1     Amy       sub2            90
2   Allen       sub4            87
3   Alice       sub6            69
4  Ayoung       sub5            78
5   Billy       sub2            89
6   Brian       sub4            80
7    Bran       sub3            79
8   Bryce       sub6            97
9   Betty       sub5            88
```

# How do I read and write tabular data?

**read_csv():** read*csv() function to read data stored as a csv file into a pandas DataFrame.*

*pandas supports many different file formats or data sources out of the box (csv, excel, sql, json, parquet, …), each of them with the prefix read**




In [78]:
```
#https://www.kaggle.com/uciml/iris        (You can download the iris dat
```

In [79]:
```
import pandas as pd
iris=pd.read_csv("D:\Python learning track and notes\Dataset\Iris.csv")
```

# Explore via coding

### Load the iris dataset

In [80]:
```
import pandas as pd
iris=pd.read_csv("D:\Python learning track and notes\Dataset\Iris.csv")
iris
```

Out[80]:

| | Id | SepalLengthCm | SepalWidthCm | PetalLengthCm | PetalWidthCm | Species |
|---|---|---|---|---|---|---|
| **0** | 1 | 5.1 | 3.5 | 1.4 | 0.2 | Iris-setosa |
| **1** | 2 | 4.9 | 3.0 | 1.4 | 0.2 | Iris-setosa |
| **2** | 3 | 4.7 | 3.2 | 1.3 | 0.2 | Iris-setosa |
| **3** | 4 | 4.6 | 3.1 | 1.5 | 0.2 | Iris-setosa |
| **4** | 5 | 5.0 | 3.6 | 1.4 | 0.2 | Iris-setosa |
| **...** | ... | ... | ... | ... | ... | ... |
| **145** | 146 | 6.7 | 3.0 | 5.2 | 2.3 | Iris-virginica |
| **146** | 147 | 6.3 | 2.5 | 5.0 | 1.9 | Iris-virginica |
| **147** | 148 | 6.5 | 3.0 | 5.2 | 2.0 | Iris-virginica |
| **148** | 149 | 6.2 | 3.4 | 5.4 | 2.3 | Iris-virginica |
| **149** | 150 | 5.9 | 3.0 | 5.1 | 1.8 | Iris-virginica |

150 rows × 6 columns

### Create a copy of the data set.

In [81]:
```
ds=iris.copy()  #if any changes make to ds it will not affect the iris d
ds
```

Out[81]:

| | Id | SepalLengthCm | SepalWidthCm | PetalLengthCm | PetalWidthCm | Species |
|---|---|---|---|---|---|---|
| **0** | 1 | 5.1 | 3.5 | 1.4 | 0.2 | Iris-setosa |
| **1** | 2 | 4.9 | 3.0 | 1.4 | 0.2 | Iris-setosa |

| | | | | | | |
|---|---|---|---|---|---|---|
| **2** | 3 | 4.7 | 3.2 | 1.3 | 0.2 | Iris-setosa |
| **3** | 4 | 4.6 | 3.1 | 1.5 | 0.2 | Iris-setosa |
| **4** | 5 | 5.0 | 3.6 | 1.4 | 0.2 | Iris-setosa |
| **...** | ... | ... | ... | ... | ... | ... |
| **145** | 146 | 6.7 | 3.0 | 5.2 | 2.3 | Iris-virginica |
| **146** | 147 | 6.3 | 2.5 | 5.0 | 1.9 | Iris-virginica |
| **147** | 148 | 6.5 | 3.0 | 5.2 | 2.0 | Iris-virginica |
| **148** | 149 | 6.2 | 3.4 | 5.4 | 2.3 | Iris-virginica |
| **149** | 150 | 5.9 | 3.0 | 5.1 | 1.8 | Iris-virginica |

150 rows × 6 columns

**Select SepalLengthCm column from dataset.**

In [82]:
```
ds['SepalLengthCm']
```

Out[82]:
```
0      5.1
1      4.9
2      4.7
3      4.6
4      5.0
      ...
145    6.7
146    6.3
147    6.5
148    6.2
149    5.9
Name: SepalLengthCm, Length: 150, dtype: float64
```

In [83]:
```
print(type(ds['SepalLengthCm']))
```

```
<class 'pandas.core.series.Series'>
```

**Select SepalLengthCm and PetalLengthCm.**

In [84]:
```
ds[['SepalLengthCm','PetalLengthCm']]
```

Out[84]:

| | SepalLengthCm | PetalLengthCm |
|---|---|---|
| **0** | 5.1 | 1.4 |
| **1** | 4.9 | 1.4 |
| **2** | 4.7 | 1.3 |
| **3** | 4.6 | 1.5 |
| **4** | 5.0 | 1.4 |
| **...** | ... | ... |
| **145** | 6.7 | 5.2 |
| **146** | 6.3 | 5.0 |
| **147** | 6.5 | 5.2 |
| **148** | 6.2 | 5.4 |
| **149** | 5.9 | 5.1 |

150 rows × 2 columns

**filter out the column which have SepalLength >5**

In [85]:
```
ds['SepalLengthCm']>5
```

Out[85]:
```
0       True
1      False
2      False
3      False
4      False
       ...
145     True
146     True
147     True
148     True
149     True
Name: SepalLengthCm, Length: 150, dtype: bool
```

**Create new column which is TotalPetalCm=PetalLengthCm+PetalWidthCm.**

In [86]:
```
ds['TotalPetalCm']=ds['PetalLengthCm']+ds['PetalWidthCm']
ds
```

Out[86]:

| | Id | SepalLengthCm | SepalWidthCm | PetalLengthCm | PetalWidthCm | Species | TotalPeta |
|---|---|---|---|---|---|---|---|
| **0** | 1 | 5.1 | 3.5 | 1.4 | 0.2 | Iris-setosa | |
| **1** | 2 | 4.9 | 3.0 | 1.4 | 0.2 | Iris-setosa | |
| **2** | 3 | 4.7 | 3.2 | 1.3 | 0.2 | Iris-setosa | |
| **3** | 4 | 4.6 | 3.1 | 1.5 | 0.2 | Iris-setosa | |
| **4** | 5 | 5.0 | 3.6 | 1.4 | 0.2 | Iris-setosa | |
| **...** | ... | ... | ... | ... | ... | ... | |
| **145** | 146 | 6.7 | 3.0 | 5.2 | 2.3 | Iris-virginica | |
| **146** | 147 | 6.3 | 2.5 | 5.0 | 1.9 | Iris-virginica | |
| **147** | 148 | 6.5 | 3.0 | 5.2 | 2.0 | Iris-virginica | |
| **148** | 149 | 6.2 | 3.4 | 5.4 | 2.3 | Iris-virginica | |
| **149** | 150 | 5.9 | 3.0 | 5.1 | 1.8 | Iris-virginica | |

150 rows × 7 columns

**Delete column TotalPetalCm from dataset**

In [87]:
```
del ds['TotalPetalCm']
ds
```

Out[87]:

| | Id | SepalLengthCm | SepalWidthCm | PetalLengthCm | PetalWidthCm | Species |
|---|---|---|---|---|---|---|
| **0** | 1 | 5.1 | 3.5 | 1.4 | 0.2 | Iris-setosa |
| **1** | 2 | 4.9 | 3.0 | 1.4 | 0.2 | Iris-setosa |

| | | | | | | |
|---|---|---|---|---|---|---|
| **2** | 3 | 4.7 | 3.2 | 1.3 | 0.2 | Iris-setosa |
| **3** | 4 | 4.6 | 3.1 | 1.5 | 0.2 | Iris-setosa |
| **4** | 5 | 5.0 | 3.6 | 1.4 | 0.2 | Iris-setosa |
| **...** | ... | ... | ... | ... | ... | ... |
| **145** | 146 | 6.7 | 3.0 | 5.2 | 2.3 | Iris-virginica |
| **146** | 147 | 6.3 | 2.5 | 5.0 | 1.9 | Iris-virginica |
| **147** | 148 | 6.5 | 3.0 | 5.2 | 2.0 | Iris-virginica |
| **148** | 149 | 6.2 | 3.4 | 5.4 | 2.3 | Iris-virginica |
| **149** | 150 | 5.9 | 3.0 | 5.1 | 1.8 | Iris-virginica |

150 rows × 6 columns

### Acess the dataframe

In [88]:
```
ds.iloc[0:10]
```

Out[88]:

| | Id | SepalLengthCm | SepalWidthCm | PetalLengthCm | PetalWidthCm | Species |
|---|---|---|---|---|---|---|
| **0** | 1 | 5.1 | 3.5 | 1.4 | 0.2 | Iris-setosa |
| **1** | 2 | 4.9 | 3.0 | 1.4 | 0.2 | Iris-setosa |
| **2** | 3 | 4.7 | 3.2 | 1.3 | 0.2 | Iris-setosa |
| **3** | 4 | 4.6 | 3.1 | 1.5 | 0.2 | Iris-setosa |
| **4** | 5 | 5.0 | 3.6 | 1.4 | 0.2 | Iris-setosa |
| **5** | 6 | 5.4 | 3.9 | 1.7 | 0.4 | Iris-setosa |
| **6** | 7 | 4.6 | 3.4 | 1.4 | 0.3 | Iris-setosa |
| **7** | 8 | 5.0 | 3.4 | 1.5 | 0.2 | Iris-setosa |
| **8** | 9 | 4.4 | 2.9 | 1.4 | 0.2 | Iris-setosa |
| **9** | 10 | 4.9 | 3.1 | 1.5 | 0.1 | Iris-setosa |

### Delete the first row from the dataframe

In [89]:
```
ds.drop(0, inplace=True)
ds
```

Out[89]:

| | Id | SepalLengthCm | SepalWidthCm | PetalLengthCm | PetalWidthCm | Species |
|---|---|---|---|---|---|---|
| **1** | 2 | 4.9 | 3.0 | 1.4 | 0.2 | Iris-setosa |
| **2** | 3 | 4.7 | 3.2 | 1.3 | 0.2 | Iris-setosa |
| **3** | 4 | 4.6 | 3.1 | 1.5 | 0.2 | Iris-setosa |
| **4** | 5 | 5.0 | 3.6 | 1.4 | 0.2 | Iris-setosa |
| **5** | 6 | 5.4 | 3.9 | 1.7 | 0.4 | Iris-setosa |
| **...** | ... | ... | ... | ... | ... | ... |
| **145** | 146 | 6.7 | 3.0 | 5.2 | 2.3 | Iris-virginica |
| **146** | 147 | 6.3 | 2.5 | 5.0 | 1.9 | Iris-virginica |
| **147** | 148 | 6.5 | 3.0 | 5.2 | 2.0 | Iris-virginica |
| **148** | 149 | 6.2 | 3.4 | 5.4 | 2.3 | Iris-virginica |

| | | | | | | |
|---|---|---|---|---|---|---|
| **149** | 150 | 5.9 | 3.0 | 5.1 | 1.8 | Iris-virginica |

149 rows × 6 columns

### Delete the first 10 rows from dataframe

In [90]:
```
ds.drop(ds.index[1:10],inplace=True)
ds
```

Out[90]:

| | Id | SepalLengthCm | SepalWidthCm | PetalLengthCm | PetalWidthCm | Species |
|---|---|---|---|---|---|---|
| **1** | 2 | 4.9 | 3.0 | 1.4 | 0.2 | Iris-setosa |
| **11** | 12 | 4.8 | 3.4 | 1.6 | 0.2 | Iris-setosa |
| **12** | 13 | 4.8 | 3.0 | 1.4 | 0.1 | Iris-setosa |
| **13** | 14 | 4.3 | 3.0 | 1.1 | 0.1 | Iris-setosa |
| **14** | 15 | 5.8 | 4.0 | 1.2 | 0.2 | Iris-setosa |
| **...** | ... | ... | ... | ... | ... | ... |
| **145** | 146 | 6.7 | 3.0 | 5.2 | 2.3 | Iris-virginica |
| **146** | 147 | 6.3 | 2.5 | 5.0 | 1.9 | Iris-virginica |
| **147** | 148 | 6.5 | 3.0 | 5.2 | 2.0 | Iris-virginica |
| **148** | 149 | 6.2 | 3.4 | 5.4 | 2.3 | Iris-virginica |
| **149** | 150 | 5.9 | 3.0 | 5.1 | 1.8 | Iris-virginica |

140 rows × 6 columns

### Reindex the dataframe

In [91]:
```
ds.reset_index(inplace=True, drop=True)
ds
```

Out[91]:

| | Id | SepalLengthCm | SepalWidthCm | PetalLengthCm | PetalWidthCm | Species |
|---|---|---|---|---|---|---|
| **0** | 2 | 4.9 | 3.0 | 1.4 | 0.2 | Iris-setosa |
| **1** | 12 | 4.8 | 3.4 | 1.6 | 0.2 | Iris-setosa |
| **2** | 13 | 4.8 | 3.0 | 1.4 | 0.1 | Iris-setosa |
| **3** | 14 | 4.3 | 3.0 | 1.1 | 0.1 | Iris-setosa |
| **4** | 15 | 5.8 | 4.0 | 1.2 | 0.2 | Iris-setosa |
| **...** | ... | ... | ... | ... | ... | ... |
| **135** | 146 | 6.7 | 3.0 | 5.2 | 2.3 | Iris-virginica |
| **136** | 147 | 6.3 | 2.5 | 5.0 | 1.9 | Iris-virginica |
| **137** | 148 | 6.5 | 3.0 | 5.2 | 2.0 | Iris-virginica |
| **138** | 149 | 6.2 | 3.4 | 5.4 | 2.3 | Iris-virginica |
| **139** | 150 | 5.9 | 3.0 | 5.1 | 1.8 | Iris-virginica |

140 rows × 6 columns

### Use describe function.

In [92]:
```
ds.describe()
```

Out[92]:

| | Id | SepalLengthCm | SepalWidthCm | PetalLengthCm | PetalWidthCm |
|---|---|---|---|---|---|
| **count** | 140.000000 | 140.000000 | 140.000000 | 140.000000 | 140.000000 |
| **mean** | 80.435714 | 5.910000 | 3.030714 | 3.922857 | 1.268571 |
| **std** | 40.676511 | 0.812696 | 0.432642 | 1.711465 | 0.741677 |
| **min** | 2.000000 | 4.300000 | 2.000000 | 1.000000 | 0.100000 |
| **25%** | 45.750000 | 5.200000 | 2.800000 | 1.675000 | 0.400000 |
| **50%** | 80.500000 | 5.850000 | 3.000000 | 4.500000 | 1.400000 |
| **75%** | 115.250000 | 6.425000 | 3.300000 | 5.100000 | 1.800000 |
| **max** | 150.000000 | 7.900000 | 4.400000 | 6.900000 | 2.500000 |

**find the setosa flower describe**

In [93]:
```
ds[ds['Species']=="Iris-virginica"].describe()
```

Out[93]:

| | Id | SepalLengthCm | SepalWidthCm | PetalLengthCm | PetalWidthCm |
|---|---|---|---|---|---|
| **count** | 50.00000 | 50.00000 | 50.000000 | 50.000000 | 50.00000 |
| **mean** | 125.50000 | 6.58800 | 2.974000 | 5.552000 | 2.02600 |
| **std** | 14.57738 | 0.63588 | 0.322497 | 0.551895 | 0.27465 |
| **min** | 101.00000 | 4.90000 | 2.200000 | 4.500000 | 1.40000 |
| **25%** | 113.25000 | 6.22500 | 2.800000 | 5.100000 | 1.80000 |
| **50%** | 125.50000 | 6.50000 | 3.000000 | 5.550000 | 2.00000 |
| **75%** | 137.75000 | 6.90000 | 3.175000 | 5.875000 | 2.30000 |
| **max** | 150.00000 | 7.90000 | 3.800000 | 6.900000 | 2.50000 |

**find the virginica flower describe**

In [94]:
```
ds[ds['Species']=="Iris-virginica"].describe()
```

Out[94]:

| | Id | SepalLengthCm | SepalWidthCm | PetalLengthCm | PetalWidthCm |
|---|---|---|---|---|---|
| **count** | 50.00000 | 50.00000 | 50.000000 | 50.000000 | 50.00000 |
| **mean** | 125.50000 | 6.58800 | 2.974000 | 5.552000 | 2.02600 |
| **std** | 14.57738 | 0.63588 | 0.322497 | 0.551895 | 0.27465 |
| **min** | 101.00000 | 4.90000 | 2.200000 | 4.500000 | 1.40000 |
| **25%** | 113.25000 | 6.22500 | 2.800000 | 5.100000 | 1.80000 |
| **50%** | 125.50000 | 6.50000 | 3.000000 | 5.550000 | 2.00000 |
| **75%** | 137.75000 | 6.90000 | 3.175000 | 5.875000 | 2.30000 |
| **max** | 150.00000 | 7.90000 | 3.800000 | 6.900000 | 2.50000 |

**find the virginica flower describe**

In [95]:
```
ds[ds['Species']=="Iris-versicolor"].describe()
```

Out[95]:

| | Id | SepalLengthCm | SepalWidthCm | PetalLengthCm | PetalWidthCm |
|---|---|---|---|---|---|

| | | | | | |
|---|---|---|---|---|---|
| **count** | 50.00000 | 50.000000 | 50.000000 | 50.000000 | 50.000000 |
| **mean** | 75.50000 | 5.936000 | 2.770000 | 4.260000 | 1.326000 |
| **std** | 14.57738 | 0.516171 | 0.313798 | 0.469911 | 0.197753 |
| **min** | 51.00000 | 4.900000 | 2.000000 | 3.000000 | 1.000000 |
| **25%** | 63.25000 | 5.600000 | 2.525000 | 4.000000 | 1.200000 |
| **50%** | 75.50000 | 5.900000 | 2.800000 | 4.350000 | 1.300000 |
| **75%** | 87.75000 | 6.300000 | 3.000000 | 4.600000 | 1.500000 |
| **max** | 100.00000 | 7.000000 | 3.400000 | 5.100000 | 1.800000 |

**Sort the dataframe according to SepalLengthCm.**

In [96]:
```
ds.sort_values(by='SepalLengthCm')
```

Out[96]:

| | Id | SepalLengthCm | SepalWidthCm | PetalLengthCm | PetalWidthCm | Species |
|---|---|---|---|---|---|---|
| **3** | 14 | 4.3 | 3.0 | 1.1 | 0.1 | Iris-setosa |
| **32** | 43 | 4.4 | 3.2 | 1.3 | 0.2 | Iris-setosa |
| **28** | 39 | 4.4 | 3.0 | 1.3 | 0.2 | Iris-setosa |
| **31** | 42 | 4.5 | 2.3 | 1.3 | 0.3 | Iris-setosa |
| **37** | 48 | 4.6 | 3.2 | 1.4 | 0.2 | Iris-setosa |
| **...** | ... | ... | ... | ... | ... | ... |
| **112** | 123 | 7.7 | 2.8 | 6.7 | 2.0 | Iris-virginica |
| **108** | 119 | 7.7 | 2.6 | 6.9 | 2.3 | Iris-virginica |
| **125** | 136 | 7.7 | 3.0 | 6.1 | 2.3 | Iris-virginica |
| **107** | 118 | 7.7 | 3.8 | 6.7 | 2.2 | Iris-virginica |
| **121** | 132 | 7.9 | 3.8 | 6.4 | 2.0 | Iris-virginica |

140 rows × 6 columns

**Check for the null values in PetalLengthCm.**

In [97]:
```
ds['PetalLengthCm'].isnull().sum()
```

Out[97]: 0

**Rename the SepalLengthCm column as SP(Cm)**

In [98]:
```
ds.rename(columns={'SepalLengthCm':'SP(Cm)'},inplace=True)
ds
```

Out[98]:

| | Id | SP(Cm) | SepalWidthCm | PetalLengthCm | PetalWidthCm | Species |
|---|---|---|---|---|---|---|
| **0** | 2 | 4.9 | 3.0 | 1.4 | 0.2 | Iris-setosa |
| **1** | 12 | 4.8 | 3.4 | 1.6 | 0.2 | Iris-setosa |
| **2** | 13 | 4.8 | 3.0 | 1.4 | 0.1 | Iris-setosa |
| **3** | 14 | 4.3 | 3.0 | 1.1 | 0.1 | Iris-setosa |
| **4** | 15 | 5.8 | 4.0 | 1.2 | 0.2 | Iris-setosa |
| **...** | ... | ... | ... | ... | ... | ... |

| | | | | | | |
|---|---|---|---|---|---|---|
| **135** | 146 | 6.7 | 3.0 | 5.2 | 2.3 | Iris-virginica |
| **136** | 147 | 6.3 | 2.5 | 5.0 | 1.9 | Iris-virginica |
| **137** | 148 | 6.5 | 3.0 | 5.2 | 2.0 | Iris-virginica |
| **138** | 149 | 6.2 | 3.4 | 5.4 | 2.3 | Iris-virginica |
| **139** | 150 | 5.9 | 3.0 | 5.1 | 1.8 | Iris-virginica |

140 rows × 6 columns

**Rename the PetalLengthCm column as PL(Cm), SepalWidthCm as SW(Cm) and PetalWidthCm as PW(Cm).**

In [99]:
```
ds.rename(columns={'PetalLengthCm':'PL(Cm)','SepalWidthCm':'SW(Cm)','Pet
ds
```

Out[99]:

| | Id | SP(Cm) | SW(Cm) | PL(Cm) | PW(Cm) | Species |
|---|---|---|---|---|---|---|
| **0** | 2 | 4.9 | 3.0 | 1.4 | 0.2 | Iris-setosa |
| **1** | 12 | 4.8 | 3.4 | 1.6 | 0.2 | Iris-setosa |
| **2** | 13 | 4.8 | 3.0 | 1.4 | 0.1 | Iris-setosa |
| **3** | 14 | 4.3 | 3.0 | 1.1 | 0.1 | Iris-setosa |
| **4** | 15 | 5.8 | 4.0 | 1.2 | 0.2 | Iris-setosa |
| **...** | ... | ... | ... | ... | ... | ... |
| **135** | 146 | 6.7 | 3.0 | 5.2 | 2.3 | Iris-virginica |
| **136** | 147 | 6.3 | 2.5 | 5.0 | 1.9 | Iris-virginica |
| **137** | 148 | 6.5 | 3.0 | 5.2 | 2.0 | Iris-virginica |
| **138** | 149 | 6.2 | 3.4 | 5.4 | 2.3 | Iris-virginica |
| **139** | 150 | 5.9 | 3.0 | 5.1 | 1.8 | Iris-virginica |

140 rows × 6 columns

**Find and print count of each kind of flower. Print the count as integer value.**

In [100…
```
ds['Species'].value_counts()
```

Out[100…
```
Iris-virginica     50
Iris-versicolor    50
Iris-setosa        40
Name: Species, dtype: int64
```

In [101…
```
df=ds[ds['Species']=="Iris-setosa"]
print("Count of setosa flower: ",df['Id'].count())

df=ds[ds['Species']=="Iris-virginica"]
print("Count of virginica flower: ",df['Id'].count())

df=ds[ds['Species']=="Iris-versicolor"]
print("Count of versicolor flower: ",df['Id'].count())
```

```
Count of setosa flower:  40
Count of virginica flower:  50
Count of versicolor flower:  50
```

**Find the data of flower "iris-virginiva" type where petal-length>1.5**

In [102…

```
df=ds[ds['Species']=="Iris-virginica"]
df[df['PL(Cm)']>1.5]
```

Out[102…

| | Id | SP(Cm) | SW(Cm) | PL(Cm) | PW(Cm) | Species |
|---|---|---|---|---|---|---|
| **90** | 101 | 6.3 | 3.3 | 6.0 | 2.5 | Iris-virginica |
| **91** | 102 | 5.8 | 2.7 | 5.1 | 1.9 | Iris-virginica |
| **92** | 103 | 7.1 | 3.0 | 5.9 | 2.1 | Iris-virginica |
| **93** | 104 | 6.3 | 2.9 | 5.6 | 1.8 | Iris-virginica |
| **94** | 105 | 6.5 | 3.0 | 5.8 | 2.2 | Iris-virginica |
| **95** | 106 | 7.6 | 3.0 | 6.6 | 2.1 | Iris-virginica |
| **96** | 107 | 4.9 | 2.5 | 4.5 | 1.7 | Iris-virginica |
| **97** | 108 | 7.3 | 2.9 | 6.3 | 1.8 | Iris-virginica |
| **98** | 109 | 6.7 | 2.5 | 5.8 | 1.8 | Iris-virginica |
| **99** | 110 | 7.2 | 3.6 | 6.1 | 2.5 | Iris-virginica |
| **100** | 111 | 6.5 | 3.2 | 5.1 | 2.0 | Iris-virginica |
| **101** | 112 | 6.4 | 2.7 | 5.3 | 1.9 | Iris-virginica |
| **102** | 113 | 6.8 | 3.0 | 5.5 | 2.1 | Iris-virginica |
| **103** | 114 | 5.7 | 2.5 | 5.0 | 2.0 | Iris-virginica |
| **104** | 115 | 5.8 | 2.8 | 5.1 | 2.4 | Iris-virginica |
| **105** | 116 | 6.4 | 3.2 | 5.3 | 2.3 | Iris-virginica |
| **106** | 117 | 6.5 | 3.0 | 5.5 | 1.8 | Iris-virginica |
| **107** | 118 | 7.7 | 3.8 | 6.7 | 2.2 | Iris-virginica |
| **108** | 119 | 7.7 | 2.6 | 6.9 | 2.3 | Iris-virginica |
| **109** | 120 | 6.0 | 2.2 | 5.0 | 1.5 | Iris-virginica |
| **110** | 121 | 6.9 | 3.2 | 5.7 | 2.3 | Iris-virginica |
| **111** | 122 | 5.6 | 2.8 | 4.9 | 2.0 | Iris-virginica |
| **112** | 123 | 7.7 | 2.8 | 6.7 | 2.0 | Iris-virginica |
| **113** | 124 | 6.3 | 2.7 | 4.9 | 1.8 | Iris-virginica |
| **114** | 125 | 6.7 | 3.3 | 5.7 | 2.1 | Iris-virginica |
| **115** | 126 | 7.2 | 3.2 | 6.0 | 1.8 | Iris-virginica |
| **116** | 127 | 6.2 | 2.8 | 4.8 | 1.8 | Iris-virginica |
| **117** | 128 | 6.1 | 3.0 | 4.9 | 1.8 | Iris-virginica |
| **118** | 129 | 6.4 | 2.8 | 5.6 | 2.1 | Iris-virginica |
| **119** | 130 | 7.2 | 3.0 | 5.8 | 1.6 | Iris-virginica |
| **120** | 131 | 7.4 | 2.8 | 6.1 | 1.9 | Iris-virginica |
| **121** | 132 | 7.9 | 3.8 | 6.4 | 2.0 | Iris-virginica |
| **122** | 133 | 6.4 | 2.8 | 5.6 | 2.2 | Iris-virginica |
| **123** | 134 | 6.3 | 2.8 | 5.1 | 1.5 | Iris-virginica |
| **124** | 135 | 6.1 | 2.6 | 5.6 | 1.4 | Iris-virginica |
| **125** | 136 | 7.7 | 3.0 | 6.1 | 2.3 | Iris-virginica |

| | | | | | | |
|---|---|---|---|---|---|---|
| **126** | 137 | 6.3 | 3.4 | 5.6 | 2.4 | Iris-virginica |
| **127** | 138 | 6.4 | 3.1 | 5.5 | 1.8 | Iris-virginica |
| **128** | 139 | 6.0 | 3.0 | 4.8 | 1.8 | Iris-virginica |
| **129** | 140 | 6.9 | 3.1 | 5.4 | 2.1 | Iris-virginica |
| **130** | 141 | 6.7 | 3.1 | 5.6 | 2.4 | Iris-virginica |
| **131** | 142 | 6.9 | 3.1 | 5.1 | 2.3 | Iris-virginica |
| **132** | 143 | 5.8 | 2.7 | 5.1 | 1.9 | Iris-virginica |
| **133** | 144 | 6.8 | 3.2 | 5.9 | 2.3 | Iris-virginica |
| **134** | 145 | 6.7 | 3.3 | 5.7 | 2.5 | Iris-virginica |
| **135** | 146 | 6.7 | 3.0 | 5.2 | 2.3 | Iris-virginica |
| **136** | 147 | 6.3 | 2.5 | 5.0 | 1.9 | Iris-virginica |
| **137** | 148 | 6.5 | 3.0 | 5.2 | 2.0 | Iris-virginica |
| **138** | 149 | 6.2 | 3.4 | 5.4 | 2.3 | Iris-virginica |
| **139** | 150 | 5.9 | 3.0 | 5.1 | 1.8 | Iris-virginica |

**Find and print the minimum and maximum of the feature for each kind of flower.**

In [103…

```
df=ds[ds['Species']=="Iris-setosa"]
print("Setosa")
print("The minimum value of: \n",df.min())
print("The maximum value of: \n",df.max())
print("**********************************")
df=ds[ds['Species']=="Iris-virginica"]
df=ds[ds['Species']==""]
print("Verginica")
print("The minimum value of: \n",df.min())
print("The maximum value of: \n",df.max())
print("**********************************")
df=ds[ds['Species']=="Iris-versicolor"]
print("Versicolor")
print("The minimum value of: \n",df.min())
print("The maximum value of: \n",df.max())
```

```
Setosa
The minimum value of:
 Id                   2
SP(Cm)             4.3
SW(Cm)             2.3
PL(Cm)               1
PW(Cm)             0.1
Species    Iris-setosa
dtype: object
The maximum value of:
 Id                  50
SP(Cm)             5.8
SW(Cm)             4.4
PL(Cm)             1.9
PW(Cm)             0.6
Species    Iris-setosa
dtype: object
**********************************
Verginica
The minimum value of:
 Id        NaN
SP(Cm)    NaN
SW(Cm)    NaN
```

```
PL(Cm)     NaN
PW(Cm)     NaN
Species    NaN
dtype: float64
The maximum value of:
 Id         NaN
SP(Cm)     NaN
SW(Cm)     NaN
PL(Cm)     NaN
PW(Cm)     NaN
Species    NaN
dtype: float64
************************************
Versicolor
The minimum value of:
 Id                      51
SP(Cm)                  4.9
SW(Cm)                    2
PL(Cm)                    3
PW(Cm)                    1
Species    Iris-versicolor
dtype: object
The maximum value of:
 Id                     100
SP(Cm)                   7
SW(Cm)                 3.4
PL(Cm)                 5.1
PW(Cm)                 1.8
Species    Iris-versicolor
dtype: object
```

**Use group by on species.**

In [104…

```
import pandas as pd
iris=pd.read_csv("D:\Python learning track and notes\Dataset\Iris.csv")
grouped_df=iris.groupby('Species')
for name,group in grouped_df:
    print("Name is: ",name)
    print("Group is:")
    print(group)
```

```
Name is:  Iris-setosa
Group is:
    Id  SepalLengthCm  SepalWidthCm  PetalLengthCm  PetalWidthCm      Spe
cies
0    1            5.1           3.5            1.4           0.2  Iris-se
tosa
1    2            4.9           3.0            1.4           0.2  Iris-se
tosa
2    3            4.7           3.2            1.3           0.2  Iris-se
tosa
3    4            4.6           3.1            1.5           0.2  Iris-se
tosa
4    5            5.0           3.6            1.4           0.2  Iris-se
tosa
5    6            5.4           3.9            1.7           0.4  Iris-se
tosa
6    7            4.6           3.4            1.4           0.3  Iris-se
tosa
7    8            5.0           3.4            1.5           0.2  Iris-se
tosa
8    9            4.4           2.9            1.4           0.2  Iris-se
tosa
9   10            4.9           3.1            1.5           0.1  Iris-se
tosa
10  11            5.4           3.7            1.5           0.2  Iris-se
tosa
11  12            4.8           3.4            1.6           0.2  Iris-se
```

tosa
12 13 4.8 3.0 1.4 0.1 Iris-se
tosa
13 14 4.3 3.0 1.1 0.1 Iris-se
tosa
14 15 5.8 4.0 1.2 0.2 Iris-se
tosa
15 16 5.7 4.4 1.5 0.4 Iris-se
tosa
16 17 5.4 3.9 1.3 0.4 Iris-se
tosa
17 18 5.1 3.5 1.4 0.3 Iris-se
tosa
18 19 5.7 3.8 1.7 0.3 Iris-se
tosa
19 20 5.1 3.8 1.5 0.3 Iris-se
tosa
20 21 5.4 3.4 1.7 0.2 Iris-se
tosa
21 22 5.1 3.7 1.5 0.4 Iris-se
tosa
22 23 4.6 3.6 1.0 0.2 Iris-se
tosa
23 24 5.1 3.3 1.7 0.5 Iris-se
tosa
24 25 4.8 3.4 1.9 0.2 Iris-se
tosa
25 26 5.0 3.0 1.6 0.2 Iris-se
tosa
26 27 5.0 3.4 1.6 0.4 Iris-se
tosa
27 28 5.2 3.5 1.5 0.2 Iris-se
tosa
28 29 5.2 3.4 1.4 0.2 Iris-se
tosa
29 30 4.7 3.2 1.6 0.2 Iris-se
tosa
30 31 4.8 3.1 1.6 0.2 Iris-se
tosa
31 32 5.4 3.4 1.5 0.4 Iris-se
tosa
32 33 5.2 4.1 1.5 0.1 Iris-se
tosa
33 34 5.5 4.2 1.4 0.2 Iris-se
tosa
34 35 4.9 3.1 1.5 0.1 Iris-se
tosa
35 36 5.0 3.2 1.2 0.2 Iris-se
tosa
36 37 5.5 3.5 1.3 0.2 Iris-se
tosa
37 38 4.9 3.1 1.5 0.1 Iris-se
tosa
38 39 4.4 3.0 1.3 0.2 Iris-se
tosa
39 40 5.1 3.4 1.5 0.2 Iris-se
tosa
40 41 5.0 3.5 1.3 0.3 Iris-se
tosa
41 42 4.5 2.3 1.3 0.3 Iris-se
tosa
42 43 4.4 3.2 1.3 0.2 Iris-se
tosa
43 44 5.0 3.5 1.6 0.6 Iris-se
tosa
44 45 5.1 3.8 1.9 0.4 Iris-se
tosa
45 46 4.8 3.0 1.4 0.3 Iris-se

```
tosa
46  47            5.1           3.8            1.6           0.2  Iris-se
tosa
47  48            4.6           3.2            1.4           0.2  Iris-se
tosa
48  49            5.3           3.7            1.5           0.2  Iris-se
tosa
49  50            5.0           3.3            1.4           0.2  Iris-se
tosa
Name is:  Iris-versicolor
Group is:
     Id  SepalLengthCm  SepalWidthCm  PetalLengthCm  PetalWidthCm  \
50   51            7.0           3.2            4.7           1.4
51   52            6.4           3.2            4.5           1.5
52   53            6.9           3.1            4.9           1.5
53   54            5.5           2.3            4.0           1.3
54   55            6.5           2.8            4.6           1.5
55   56            5.7           2.8            4.5           1.3
56   57            6.3           3.3            4.7           1.6
57   58            4.9           2.4            3.3           1.0
58   59            6.6           2.9            4.6           1.3
59   60            5.2           2.7            3.9           1.4
60   61            5.0           2.0            3.5           1.0
61   62            5.9           3.0            4.2           1.5
62   63            6.0           2.2            4.0           1.0
63   64            6.1           2.9            4.7           1.4
64   65            5.6           2.9            3.6           1.3
65   66            6.7           3.1            4.4           1.4
66   67            5.6           3.0            4.5           1.5
67   68            5.8           2.7            4.1           1.0
68   69            6.2           2.2            4.5           1.5
69   70            5.6           2.5            3.9           1.1
70   71            5.9           3.2            4.8           1.8
71   72            6.1           2.8            4.0           1.3
72   73            6.3           2.5            4.9           1.5
73   74            6.1           2.8            4.7           1.2
74   75            6.4           2.9            4.3           1.3
75   76            6.6           3.0            4.4           1.4
76   77            6.8           2.8            4.8           1.4
77   78            6.7           3.0            5.0           1.7
78   79            6.0           2.9            4.5           1.5
79   80            5.7           2.6            3.5           1.0
80   81            5.5           2.4            3.8           1.1
81   82            5.5           2.4            3.7           1.0
82   83            5.8           2.7            3.9           1.2
83   84            6.0           2.7            5.1           1.6
84   85            5.4           3.0            4.5           1.5
85   86            6.0           3.4            4.5           1.6
86   87            6.7           3.1            4.7           1.5
87   88            6.3           2.3            4.4           1.3
88   89            5.6           3.0            4.1           1.3
89   90            5.5           2.5            4.0           1.3
90   91            5.5           2.6            4.4           1.2
91   92            6.1           3.0            4.6           1.4
92   93            5.8           2.6            4.0           1.2
93   94            5.0           2.3            3.3           1.0
94   95            5.6           2.7            4.2           1.3
95   96            5.7           3.0            4.2           1.2
96   97            5.7           2.9            4.2           1.3
97   98            6.2           2.9            4.3           1.3
98   99            5.1           2.5            3.0           1.1
99  100            5.7           2.8            4.1           1.3

           Species
50  Iris-versicolor
51  Iris-versicolor
52  Iris-versicolor
53  Iris-versicolor
```

```
54  Iris-versicolor
55  Iris-versicolor
56  Iris-versicolor
57  Iris-versicolor
58  Iris-versicolor
59  Iris-versicolor
60  Iris-versicolor
61  Iris-versicolor
62  Iris-versicolor
63  Iris-versicolor
64  Iris-versicolor
65  Iris-versicolor
66  Iris-versicolor
67  Iris-versicolor
68  Iris-versicolor
69  Iris-versicolor
70  Iris-versicolor
71  Iris-versicolor
72  Iris-versicolor
73  Iris-versicolor
74  Iris-versicolor
75  Iris-versicolor
76  Iris-versicolor
77  Iris-versicolor
78  Iris-versicolor
79  Iris-versicolor
80  Iris-versicolor
81  Iris-versicolor
82  Iris-versicolor
83  Iris-versicolor
84  Iris-versicolor
85  Iris-versicolor
86  Iris-versicolor
87  Iris-versicolor
88  Iris-versicolor
89  Iris-versicolor
90  Iris-versicolor
91  Iris-versicolor
92  Iris-versicolor
93  Iris-versicolor
94  Iris-versicolor
95  Iris-versicolor
96  Iris-versicolor
97  Iris-versicolor
98  Iris-versicolor
99  Iris-versicolor
Name is:  Iris-virginica
Group is:
      Id  SepalLengthCm  SepalWidthCm  PetalLengthCm  PetalWidthCm  \
100  101            6.3           3.3            6.0           2.5
101  102            5.8           2.7            5.1           1.9
102  103            7.1           3.0            5.9           2.1
103  104            6.3           2.9            5.6           1.8
104  105            6.5           3.0            5.8           2.2
105  106            7.6           3.0            6.6           2.1
106  107            4.9           2.5            4.5           1.7
107  108            7.3           2.9            6.3           1.8
108  109            6.7           2.5            5.8           1.8
109  110            7.2           3.6            6.1           2.5
110  111            6.5           3.2            5.1           2.0
111  112            6.4           2.7            5.3           1.9
112  113            6.8           3.0            5.5           2.1
113  114            5.7           2.5            5.0           2.0
114  115            5.8           2.8            5.1           2.4
115  116            6.4           3.2            5.3           2.3
116  117            6.5           3.0            5.5           1.8
117  118            7.7           3.8            6.7           2.2
118  119            7.7           2.6            6.9           2.3
```

| | | | | | |
|---|---|---|---|---|---|
| 119 | 120 | 6.0 | 2.2 | 5.0 | 1.5 |
| 120 | 121 | 6.9 | 3.2 | 5.7 | 2.3 |
| 121 | 122 | 5.6 | 2.8 | 4.9 | 2.0 |
| 122 | 123 | 7.7 | 2.8 | 6.7 | 2.0 |
| 123 | 124 | 6.3 | 2.7 | 4.9 | 1.8 |
| 124 | 125 | 6.7 | 3.3 | 5.7 | 2.1 |
| 125 | 126 | 7.2 | 3.2 | 6.0 | 1.8 |
| 126 | 127 | 6.2 | 2.8 | 4.8 | 1.8 |
| 127 | 128 | 6.1 | 3.0 | 4.9 | 1.8 |
| 128 | 129 | 6.4 | 2.8 | 5.6 | 2.1 |
| 129 | 130 | 7.2 | 3.0 | 5.8 | 1.6 |
| 130 | 131 | 7.4 | 2.8 | 6.1 | 1.9 |
| 131 | 132 | 7.9 | 3.8 | 6.4 | 2.0 |
| 132 | 133 | 6.4 | 2.8 | 5.6 | 2.2 |
| 133 | 134 | 6.3 | 2.8 | 5.1 | 1.5 |
| 134 | 135 | 6.1 | 2.6 | 5.6 | 1.4 |
| 135 | 136 | 7.7 | 3.0 | 6.1 | 2.3 |
| 136 | 137 | 6.3 | 3.4 | 5.6 | 2.4 |
| 137 | 138 | 6.4 | 3.1 | 5.5 | 1.8 |
| 138 | 139 | 6.0 | 3.0 | 4.8 | 1.8 |
| 139 | 140 | 6.9 | 3.1 | 5.4 | 2.1 |
| 140 | 141 | 6.7 | 3.1 | 5.6 | 2.4 |
| 141 | 142 | 6.9 | 3.1 | 5.1 | 2.3 |
| 142 | 143 | 5.8 | 2.7 | 5.1 | 1.9 |
| 143 | 144 | 6.8 | 3.2 | 5.9 | 2.3 |
| 144 | 145 | 6.7 | 3.3 | 5.7 | 2.5 |
| 145 | 146 | 6.7 | 3.0 | 5.2 | 2.3 |
| 146 | 147 | 6.3 | 2.5 | 5.0 | 1.9 |
| 147 | 148 | 6.5 | 3.0 | 5.2 | 2.0 |
| 148 | 149 | 6.2 | 3.4 | 5.4 | 2.3 |
| 149 | 150 | 5.9 | 3.0 | 5.1 | 1.8 |

| | Species |
|---|---|
| 100 | Iris-virginica |
| 101 | Iris-virginica |
| 102 | Iris-virginica |
| 103 | Iris-virginica |
| 104 | Iris-virginica |
| 105 | Iris-virginica |
| 106 | Iris-virginica |
| 107 | Iris-virginica |
| 108 | Iris-virginica |
| 109 | Iris-virginica |
| 110 | Iris-virginica |
| 111 | Iris-virginica |
| 112 | Iris-virginica |
| 113 | Iris-virginica |
| 114 | Iris-virginica |
| 115 | Iris-virginica |
| 116 | Iris-virginica |
| 117 | Iris-virginica |
| 118 | Iris-virginica |
| 119 | Iris-virginica |
| 120 | Iris-virginica |
| 121 | Iris-virginica |
| 122 | Iris-virginica |
| 123 | Iris-virginica |
| 124 | Iris-virginica |
| 125 | Iris-virginica |
| 126 | Iris-virginica |
| 127 | Iris-virginica |
| 128 | Iris-virginica |
| 129 | Iris-virginica |
| 130 | Iris-virginica |
| 131 | Iris-virginica |
| 132 | Iris-virginica |
| 133 | Iris-virginica |
| 134 | Iris-virginica |

```
135  Iris-virginica
136  Iris-virginica
137  Iris-virginica
138  Iris-virginica
139  Iris-virginica
140  Iris-virginica
141  Iris-virginica
142  Iris-virginica
143  Iris-virginica
144  Iris-virginica
145  Iris-virginica
146  Iris-virginica
147  Iris-virginica
148  Iris-virginica
149  Iris-virginica
```

In [105…

```
grouped_df.get_group('Iris-versicolor')
```

Out[105…

| | Id | SepalLengthCm | SepalWidthCm | PetalLengthCm | PetalWidthCm | Species |
|---|---|---|---|---|---|---|
| **50** | 51 | 7.0 | 3.2 | 4.7 | 1.4 | Iris-versicolor |
| **51** | 52 | 6.4 | 3.2 | 4.5 | 1.5 | Iris-versicolor |
| **52** | 53 | 6.9 | 3.1 | 4.9 | 1.5 | Iris-versicolor |
| **53** | 54 | 5.5 | 2.3 | 4.0 | 1.3 | Iris-versicolor |
| **54** | 55 | 6.5 | 2.8 | 4.6 | 1.5 | Iris-versicolor |
| **55** | 56 | 5.7 | 2.8 | 4.5 | 1.3 | Iris-versicolor |
| **56** | 57 | 6.3 | 3.3 | 4.7 | 1.6 | Iris-versicolor |
| **57** | 58 | 4.9 | 2.4 | 3.3 | 1.0 | Iris-versicolor |
| **58** | 59 | 6.6 | 2.9 | 4.6 | 1.3 | Iris-versicolor |
| **59** | 60 | 5.2 | 2.7 | 3.9 | 1.4 | Iris-versicolor |
| **60** | 61 | 5.0 | 2.0 | 3.5 | 1.0 | Iris-versicolor |
| **61** | 62 | 5.9 | 3.0 | 4.2 | 1.5 | Iris-versicolor |
| **62** | 63 | 6.0 | 2.2 | 4.0 | 1.0 | Iris-versicolor |
| **63** | 64 | 6.1 | 2.9 | 4.7 | 1.4 | Iris-versicolor |
| **64** | 65 | 5.6 | 2.9 | 3.6 | 1.3 | Iris-versicolor |
| **65** | 66 | 6.7 | 3.1 | 4.4 | 1.4 | Iris-versicolor |
| **66** | 67 | 5.6 | 3.0 | 4.5 | 1.5 | Iris-versicolor |
| **67** | 68 | 5.8 | 2.7 | 4.1 | 1.0 | Iris-versicolor |
| **68** | 69 | 6.2 | 2.2 | 4.5 | 1.5 | Iris-versicolor |
| **69** | 70 | 5.6 | 2.5 | 3.9 | 1.1 | Iris-versicolor |
| **70** | 71 | 5.9 | 3.2 | 4.8 | 1.8 | Iris-versicolor |
| **71** | 72 | 6.1 | 2.8 | 4.0 | 1.3 | Iris-versicolor |
| **72** | 73 | 6.3 | 2.5 | 4.9 | 1.5 | Iris-versicolor |
| **73** | 74 | 6.1 | 2.8 | 4.7 | 1.2 | Iris-versicolor |
| **74** | 75 | 6.4 | 2.9 | 4.3 | 1.3 | Iris-versicolor |
| **75** | 76 | 6.6 | 3.0 | 4.4 | 1.4 | Iris-versicolor |
| **76** | 77 | 6.8 | 2.8 | 4.8 | 1.4 | Iris-versicolor |
| **77** | 78 | 6.7 | 3.0 | 5.0 | 1.7 | Iris-versicolor |

| | | | | | | |
|---|---|---|---|---|---|---|
| **78** | 79 | 6.0 | 2.9 | 4.5 | 1.5 | Iris-versicolor |
| **79** | 80 | 5.7 | 2.6 | 3.5 | 1.0 | Iris-versicolor |
| **80** | 81 | 5.5 | 2.4 | 3.8 | 1.1 | Iris-versicolor |
| **81** | 82 | 5.5 | 2.4 | 3.7 | 1.0 | Iris-versicolor |
| **82** | 83 | 5.8 | 2.7 | 3.9 | 1.2 | Iris-versicolor |
| **83** | 84 | 6.0 | 2.7 | 5.1 | 1.6 | Iris-versicolor |
| **84** | 85 | 5.4 | 3.0 | 4.5 | 1.5 | Iris-versicolor |
| **85** | 86 | 6.0 | 3.4 | 4.5 | 1.6 | Iris-versicolor |
| **86** | 87 | 6.7 | 3.1 | 4.7 | 1.5 | Iris-versicolor |
| **87** | 88 | 6.3 | 2.3 | 4.4 | 1.3 | Iris-versicolor |
| **88** | 89 | 5.6 | 3.0 | 4.1 | 1.3 | Iris-versicolor |
| **89** | 90 | 5.5 | 2.5 | 4.0 | 1.3 | Iris-versicolor |
| **90** | 91 | 5.5 | 2.6 | 4.4 | 1.2 | Iris-versicolor |
| **91** | 92 | 6.1 | 3.0 | 4.6 | 1.4 | Iris-versicolor |
| **92** | 93 | 5.8 | 2.6 | 4.0 | 1.2 | Iris-versicolor |
| **93** | 94 | 5.0 | 2.3 | 3.3 | 1.0 | Iris-versicolor |
| **94** | 95 | 5.6 | 2.7 | 4.2 | 1.3 | Iris-versicolor |
| **95** | 96 | 5.7 | 3.0 | 4.2 | 1.2 | Iris-versicolor |
| **96** | 97 | 5.7 | 2.9 | 4.2 | 1.3 | Iris-versicolor |
| **97** | 98 | 6.2 | 2.9 | 4.3 | 1.3 | Iris-versicolor |
| **98** | 99 | 5.1 | 2.5 | 3.0 | 1.1 | Iris-versicolor |
| **99** | 100 | 5.7 | 2.8 | 4.1 | 1.3 | Iris-versicolor |