DATA COLLECTION

In [1]: # import libraries
 import numpy as np
 import pandas as pd
 import matplotlib.pyplot as plt
 import seaborn as sns

In [2]: # To Import Dataset
sd=pd.read_csv(r"c:\Users\user\Downloads\14_Iris.csv")
sd

Out[2]:

	ld	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

In [3]: # to display top 10 rows
sd.head(10)

Out[3]:		ld	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

DATA CLEANING AND PRE_PROCESSING

```
In [4]: sd.info()
```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 6 columns):

#	Column	Non-Null Count	Dtype
0	Id	150 non-null	int64
1	SepalLengthCm	150 non-null	float64
2	SepalWidthCm	150 non-null	float64
3	PetalLengthCm	150 non-null	float64
4	PetalWidthCm	150 non-null	float64
5	Species	150 non-null	object
dtyp	es: float64(4),	int64(1), object	t(1)

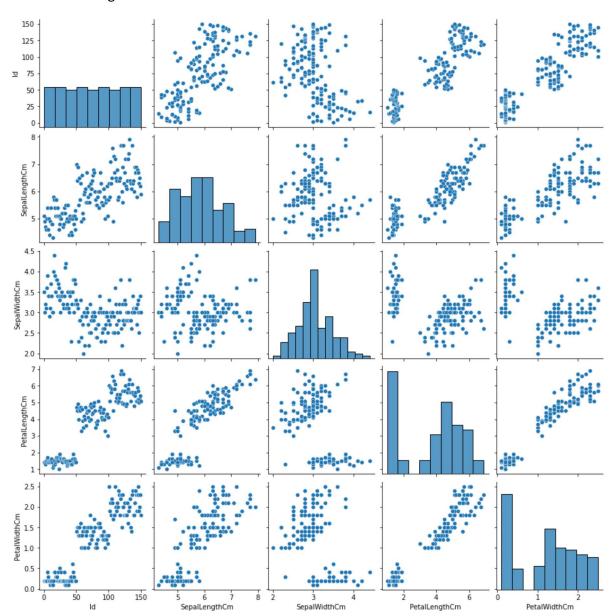
memory usage: 7.2+ KB

```
In [5]: # to display summary of statistics
         sd.describe()
Out[5]:
                         Id SepalLengthCm SepalWidthCm PetalLengthCm PetalWidthCm
                                                150.000000
                                                               150.000000
          count
                 150.000000
                                 150.000000
                                                                             150.000000
                                   5.843333
                                                                 3.758667
           mean
                  75.500000
                                                 3.054000
                                                                               1.198667
             std
                  43.445368
                                   0.828066
                                                 0.433594
                                                                 1.764420
                                                                               0.763161
                   1.000000
                                   4.300000
                                                 2.000000
                                                                 1.000000
                                                                               0.100000
            min
            25%
                  38.250000
                                   5.100000
                                                 2.800000
                                                                 1.600000
                                                                               0.300000
            50%
                  75.500000
                                   5.800000
                                                 3.000000
                                                                 4.350000
                                                                               1.300000
            75%
                 112.750000
                                   6.400000
                                                 3.300000
                                                                 5.100000
                                                                               1.800000
            max
                 150.000000
                                   7.900000
                                                 4.400000
                                                                 6.900000
                                                                               2.500000
In [6]: #to display colums heading
         sd.columns
Out[6]: Index(['Id', 'SepalLengthCm', 'SepalWidthCm', 'PetalLengthCm', 'PetalWidthC
         m',
                  'Species'],
                dtype='object')
```

EDA and visualization

In [7]: sns.pairplot(sd)

Out[7]: <seaborn.axisgrid.PairGrid at 0x1775c7f7220>

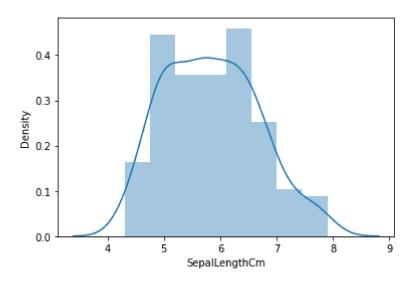


In [8]: sns.distplot(sd['SepalLengthCm'])

C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2557: Fut ureWarning: `distplot` is a deprecated function and will be removed in a futu re version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

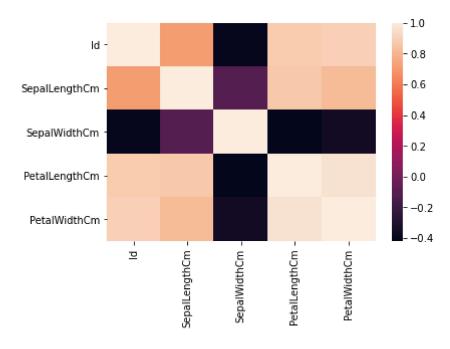
warnings.warn(msg, FutureWarning)

Out[8]: <AxesSubplot:xlabel='SepalLengthCm', ylabel='Density'>



In [9]: sns.heatmap(sd.corr())

Out[9]: <AxesSubplot:>



In [10]: sd1=sd[['Id', 'SepalLengthCm', 'SepalWidthCm', 'PetalLengthCm', 'PetalWidthCm']

TO TRAIN THE MODEL _MODEL BUILDING

we are goint train Liner Regression model; we need to split out the data into two varibles x and y where x is independent on x (output) and y is dependent on x(output) adress coloumn as it is not required our model

```
In [11]: x= sd1[['Id', 'SepalLengthCm', 'SepalWidthCm', 'PetalLengthCm']]
         y=sd1['PetalWidthCm']
In [12]: # To split my dataset into training data and test data
         from sklearn .model_selection import train_test_split
         x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)
In [13]: from sklearn.linear model import LinearRegression
         lr=LinearRegression()
         lr.fit(x_train,y_train)
Out[13]: LinearRegression()
In [14]: | from sklearn.linear_model import LinearRegression
         lr=LinearRegression()
         lr.fit(x_train,y_train)
Out[14]: LinearRegression()
In [15]: |print(lr.intercept_)
         -0.2277368432715572
In [16]:
         coeff= pd.DataFrame(lr.coef_,x.columns,columns=['Co-efficient'])
         coeff
Out[16]:
                        Co-efficient
                     ld
                          0.003760
          SepalLengthCm
                          -0.177068
           SepalWidthCm
                          0.185387
           PetalLengthCm
                          0.432020
```

```
In [17]: | prediction = lr.predict(x_test)
         plt.scatter(y_test,prediction)
Out[17]: <matplotlib.collections.PathCollection at 0x1775f8514f0>
          2.0
          1.5
          1.0
          0.5
                     0.5
                              1.0
                                      1.5
                                               2.0
                                                        2.5
In [18]: |print(lr.score(x_test,y_test))
         0.9269510477479206
In [19]: |lr.score(x_train,y_train)
Out[19]: 0.9510098209828819
In [20]: from sklearn.linear_model import Ridge,Lasso
In [21]: dr=Ridge(alpha=10)
         dr.fit(x_train,y_train)
Out[21]: Ridge(alpha=10)
In [22]: dr.score(x_test,y_test)
Out[22]: 0.9151267065690689
In [23]: |dr.score(x_train,y_train)
Out[23]: 0.9436787566643782
In [24]: la=Lasso(alpha=10)
         la.fit(x_train,y_train)
Out[24]: Lasso(alpha=10)
In [25]: la.score(x_test,y_test)
Out[25]: 0.702177176757073
```

```
In [26]: la.score(x_train,y_train)
Out[26]: 0.7464150340478268
```

ElasticNet

Evaluation metric

```
In [32]: from sklearn import metrics
In [33]: print("mean Absolute Error:",metrics.mean_absolute_error(y_test,prediction))
    mean Absolute Error: 0.27703662364470205
In [34]: print("mean squared Error:",metrics.mean_squared_error(y_test,prediction))
    mean squared Error: 0.1239635747520339
In [35]: print("Root mean Absolytre Error:",np.sqrt(metrics.mean_squared_error(y_test,prediction))
    Root mean Absolytre Error: 0.3520846130577619
In []:
```