

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

```
In [2]: df=pd.read_csv("14_Iris.csv")
df
```

```
Out[2]:
```

| | 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

```
In [3]: df.head()
```

```
Out[3]:
```

| | 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 |

DATA CLEANING AND DATA PREPROCESSING

```
In [4]: df.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 |

dtypes: float64(4), int64(1), object(1)
memory usage: 7.2+ KB

In [5]:

```
df.describe()
```

Out[5]:

| | Id | SepalLengthCm | SepalWidthCm | PetalLengthCm | PetalWidthCm |
|-------|------------|---------------|--------------|---------------|--------------|
| count | 150.000000 | 150.000000 | 150.000000 | 150.000000 | 150.000000 |
| mean | 75.500000 | 5.843333 | 3.054000 | 3.758667 | 1.198667 |
| std | 43.445368 | 0.828066 | 0.433594 | 1.764420 | 0.763161 |
| min | 1.000000 | 4.300000 | 2.000000 | 1.000000 | 0.100000 |
| 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]:

```
df.columns
```

Out[6]:

Index(['Id', 'SepalLengthCm', 'SepalWidthCm', 'PetalLengthCm', 'PetalWidthCm', 'Species'], dtype='object')

In [7]:

```
df1=df.dropna(axis=1)  
df1
```

Out[7]:

| | 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 |

| | Id | SepalLengthCm | SepalWidthCm | PetalLengthCm | PetalWidthCm | Species |
|------------|-----------|----------------------|---------------------|----------------------|---------------------|----------------|
| 149 | 150 | 5.9 | 3.0 | 5.1 | 1.8 | Iris-virginica |

150 rows × 6 columns

```
In [8]: df1.columns
```

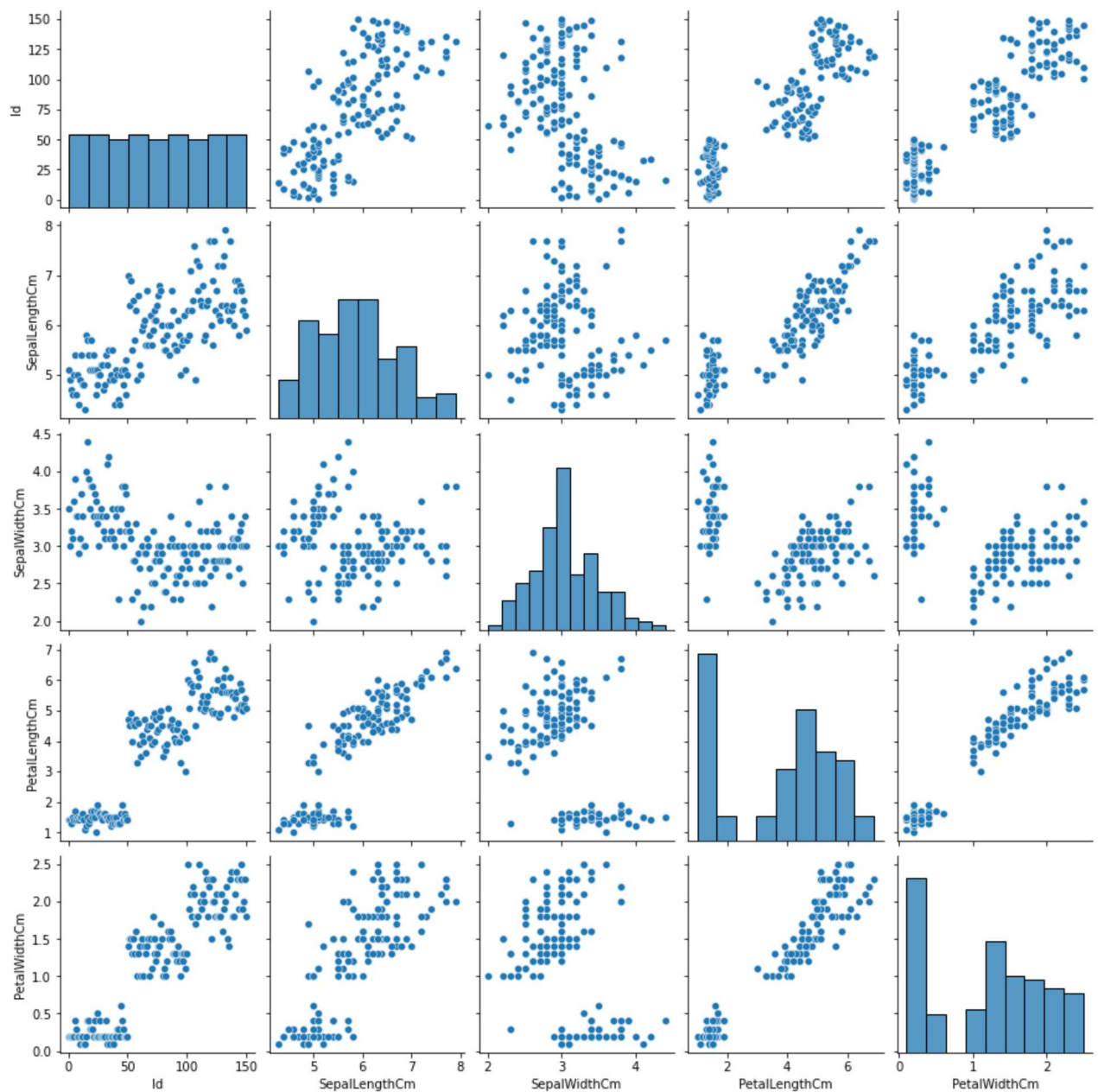
```
Out[8]: Index(['Id', 'SepalLengthCm', 'SepalWidthCm', 'PetalLengthCm', 'PetalWidthCm',  
              'Species'],  
             dtype='object')
```

```
In [9]: df1=df1[[ 'Id', 'SepalLengthCm', 'SepalWidthCm', 'PetalLengthCm', 'PetalWidthCm']]
```

EDA AND VISUALIZATION

```
In [10]: sns.pairplot(df1)
```

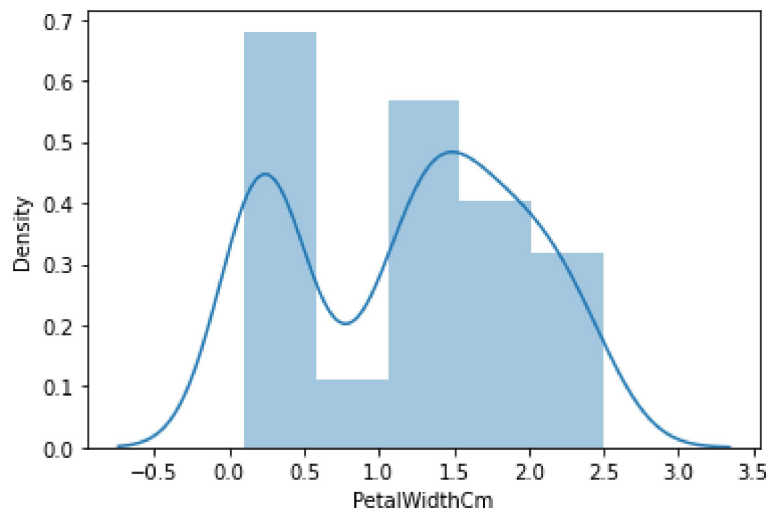
```
Out[10]: <seaborn.axisgrid.PairGrid at 0x27fdc40a3d0>
```



```
In [11]: sns.distplot(df1['PetalWidthCm'])
```

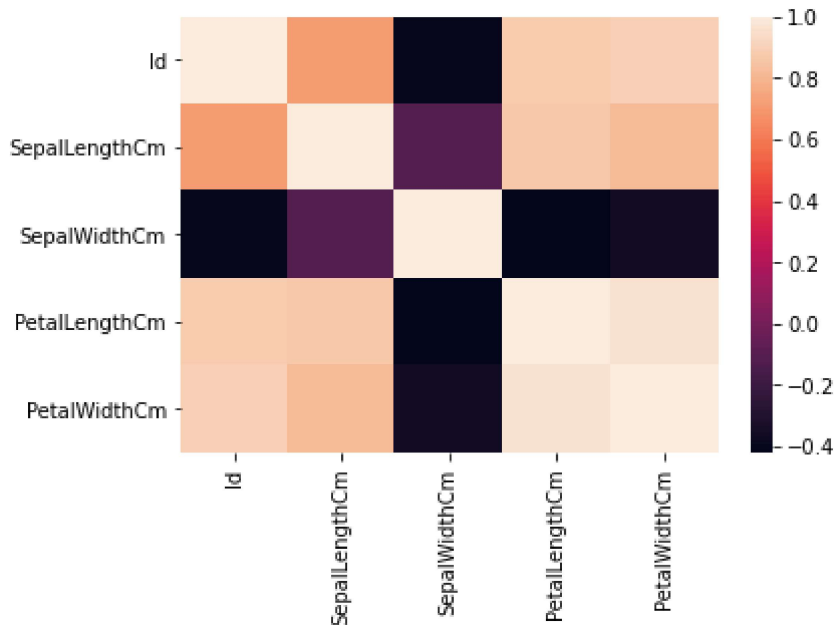
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2557: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function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

```
Out[11]: <AxesSubplot:xlabel='PetalWidthCm', ylabel='Density'>
```



```
In [12]: sns.heatmap(df1.corr())
```

```
Out[12]: <AxesSubplot:>
```



TO TRAIN THE MODEL AND MODEL BULDING

```
In [13]: x=df[['Id', 'SepalLengthCm', 'SepalWidthCm', 'PetalLengthCm']]
          y=df['PetalWidthCm']
```

```
In [14]: 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 [15]: from sklearn.linear_model import LinearRegression
          lr=LinearRegression()
          lr.fit(x_train,y_train)
```

Out[15]: LinearRegression()

In [16]: `lr.intercept_`

Out[16]: -0.47736225693244916

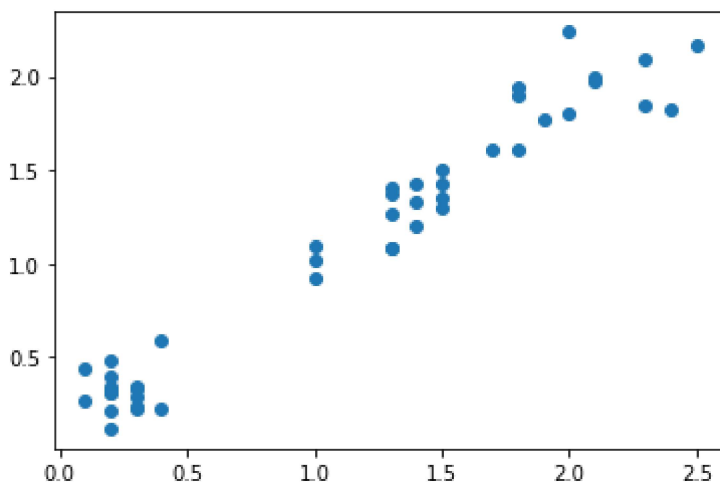
In [17]: `coeff=pd.DataFrame(lr.coef_,x.columns,columns=['Co-efficient'])`
`coeff`

Out[17]:

| | Co-efficient |
|----------------------|--------------|
| Id | 0.003733 |
| SepalLengthCm | -0.135218 |
| SepalWidthCm | 0.218362 |
| PetalLengthCm | 0.401056 |

In [18]: `prediction =lr.predict(x_test)`
`plt.scatter(y_test,prediction)`

Out[18]: <matplotlib.collections.PathCollection at 0x27fdf3f6bb0>



ACCURACY

In [19]: `lr.score(x_test,y_test)`

Out[19]: 0.9409273295201579

In [20]: `lr.score(x_train,y_train)`

Out[20]: 0.9465258791952714

In [21]: `from sklearn.linear_model import Ridge,Lasso`

```
In [22]: rr=Ridge(alpha=10)
         rr.fit(x_train,y_train)
```

```
Out[22]: Ridge(alpha=10)
```

```
In [23]: rr.score(x_test,y_test)
```

```
Out[23]: 0.9264835466268884
```

```
In [24]: rr.score(x_train,y_train)
```

```
Out[24]: 0.9395633706029578
```

```
In [25]: la=Lasso(alpha=10)
         la.fit(x_train,y_train)
```

```
Out[25]: Lasso(alpha=10)
```

```
In [26]: la.score(x_test,y_test)
```

```
Out[26]: 0.6599439158258447
```

```
In [27]: la.score(x_train,y_train)
```

```
Out[27]: 0.7366835261199427
```

```
In [28]: from sklearn.linear_model import ElasticNet
         en=ElasticNet()
         en.fit(x_train,y_train)
```

```
Out[28]: ElasticNet()
```

```
In [29]: en.coef_
```

```
Out[29]: array([0.01519841, 0.          , 0.          , 0.          ])
```

```
In [30]: en.intercept_
```

```
Out[30]: 0.046241798566508674
```

```
In [31]: prediction=en.predict(x_test)
```

```
In [32]: en.score(x_test,y_test)
```

Out[32]: 0.7675363452723879

```
In [33]: from sklearn import metrics  
print(metrics.mean_absolute_error(y_test,prediction))  
print(metrics.mean_squared_error(y_test,prediction))  
print(np.sqrt(metrics.mean_squared_error(y_test,prediction)))
```

0.3060629031091528
0.13636719775354592
0.36927929505124696