```
In [1]: import numpy as np
   import pandas as pd
   import matplotlib.pyplot as plt
   import seaborn as sns
   from sklearn.model_selection import train_test_split
   from sklearn.linear_model import LinearRegression
```

In [2]: df = pd.read_csv("Iris.csv")
.dropna(axis="columns")
df

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]: df.head()

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 |

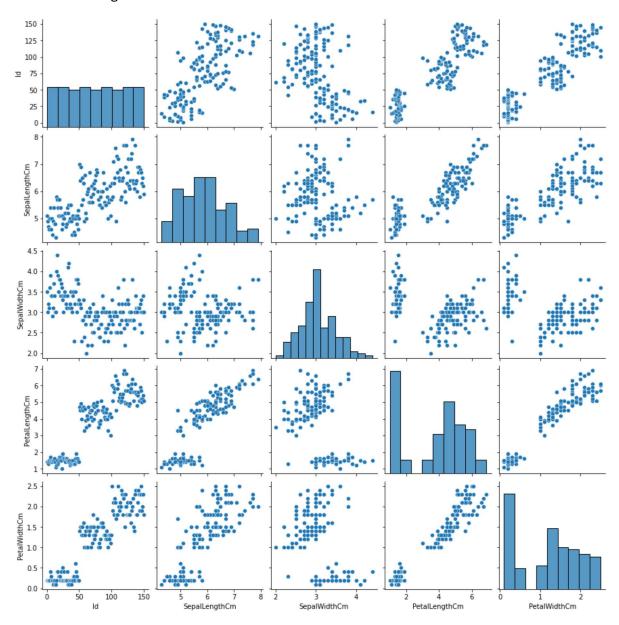
Data cleaning and pre processing

```
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
              Ιd
                               150 non-null
                                                 int64
              SepalLengthCm 150 non-null
                                                 float64
          1
          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
         df.describe()
In [5]:
Out[5]:
                           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
                 43.445368
                                 0.828066
                                               0.433594
                                                             1.764420
                                                                           0.763161
            std
                  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]: df.columns
Out[6]: Index(['Id', 'SepalLengthCm', 'SepalWidthCm', 'PetalLengthCm', 'PetalWidthC
         m',
                 'Species'],
                dtype='object')
```

EDA and VISUALIZATION

In [7]: sns.pairplot(df)

Out[7]: <seaborn.axisgrid.PairGrid at 0x1fc6d446280>

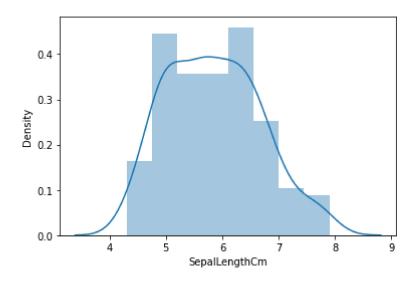


In [8]: sns.distplot(df['SepalLengthCm'])

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 hi stograms).

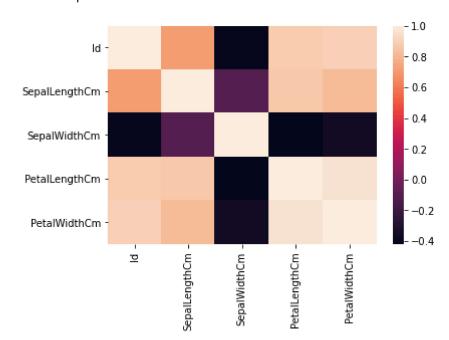
warnings.warn(msg, FutureWarning)

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



In [10]: sns.heatmap(df1.corr())

Out[10]: <AxesSubplot:>



```
In [11]: x = df1[['Id', 'SepalLengthCm', 'SepalWidthCm', 'PetalWidthCm']]
y = df1[ 'PetalLengthCm']
```

split the data into training and test data

```
In [12]: |x_train, x_test, y_train, y_test = train_test_split(x,y,test_size=0.3)
In [13]: | lr = LinearRegression()
         lr.fit(x_train, y_train)
Out[13]: LinearRegression()
In [14]: | lr.intercept
Out[14]: -0.2752468379329023
         coeff = pd.DataFrame(lr.coef_, x.columns, columns =['Co-efficient'])
In [15]:
         coeff
Out[15]:
                         Co-efficient
                     ld
                           0.001377
          SepalLengthCm
                           0.733720
           SepalWidthCm
                          -0.645673
            PetalWidthCm
                           1.344928
In [16]:
         prediction = lr.predict(x_test)
         plt.scatter(y_test, prediction)
Out[16]: <matplotlib.collections.PathCollection at 0x1fc6ec6a9d0>
           7
           6
           5
           4
           3
           2
In [17]: |lr.score(x_test,y_test)
```

Out[17]: 0.9702082337641564

ACURACY

```
In [18]: from sklearn.linear model import Ridge, Lasso
In [19]: rr=Ridge(alpha=10)
         rr.fit(x_train,y_train)
         rr.score(x_test,y_test)
         rr.score(x_train,y_train)
Out[19]: 0.9469166829095399
In [20]: |rr.score(x_test,y_test)
Out[20]: 0.9526805633458773
In [21]: la = Lasso(alpha=10)
         la.fit(x_train,y_train)
Out[21]: Lasso(alpha=10)
In [22]: la.score(x_test,y_test)
Out[22]: 0.7692575517416311
In [23]: from sklearn.linear model import ElasticNet
         en = ElasticNet()
         en.fit(x train,y train)
Out[23]: ElasticNet()
In [24]: print(en.coef_)
         [ 0.03639067 0.
                                                0.
                                                          1
                                   -0.
In [25]:
         print(en.intercept_)
         1.0031375554410276
In [26]: print(en.predict(x_test))
         [6.02504962 3.11379625 5.73392428 6.09783095 6.42534695 2.20402957
          4.05995359 2.53154557 2.85906158 6.20700295 5.22445494 2.93184291
          3.00462425 3.33214025 4.89693894 5.29723627 1.54899756 1.9492949
          1.8401229 1.6217789 4.96972027 1.33065356 1.58538823 1.87651357
          2.0584669 5.33362694 5.40640827 5.87948695 5.80670561 6.06144028
          6.27978429 5.15167361 6.24339362 1.07591889 6.46173762 3.04101491
          3.44131225 1.47621623 1.29426289 5.26084561 2.82267091 5.07889227
          5.95226828 2.78628024 5.11528294]
```

```
In [27]: print(en.score(x_test,y_test))
      0.7784645511260997

In [28]: # Evaluation Metrics
      from sklearn import metrics

In [29]: print("Mean Absolute Error:",metrics.mean_absolute_error(y_test,prediction))
      Mean Absolute Error: 0.2719506202609821

In [30]: print("Mean Squared Error:",metrics.mean_squared_error(y_test,prediction))
      Mean Squared Error: 0.11051406483015257

In [31]: print("Root Mean Squared Error:",np.sqrt(metrics.mean_squared_error(y_test,prediction))
      Root Mean Squared Error: 0.3324365576018266
```