Machine Learning Fundamentals Lab-2

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Aim:

- a) To show Logistic Regression without using sci-kit learn and using the inbuilt formula and using matplotlib to visualize the regression lines.
- b) Using sci-kit learn library of logistic Regression for array data using numpy.
- c) Using sci-kit learn to use the Logistic Regression library and the using the metrics from scikit learn to evaluate and then plotting to visualize. (Using 50-startups dataset)

Software Required:

- 1) Ananconda Navigator
- 2) Jupyter Notebook

Libraries Required: Numpy, Matplotlib, Scik-kit learn, Pandas

Code and Outputs:

a) Logistic Regression Mathematically:

```
In [2]: import numpy as np
    import matplotlib.pyplot as plt
    from sklearn.linear_model import LinearRegression
    from sklearn.metrics import mean_squared_error, r2_score

In [4]: x = np.array([1,2,3,4,5])
    y = np.array([7,14,15,18,19])
    n = np.size(x)
    print(n)

5

In [5]: x_mean = np.mean(x)
    y_mean = np.mean(y)
    print(x_mean, y_mean)
    3.0 14.6

In [6]: Sxy = np.sum(x*y) - n*x_mean*y_mean
    Sxx = np.sum(x*x) - n*x_mean*x_mean
    print(Sxy, Sxx)
    28.0 10.0

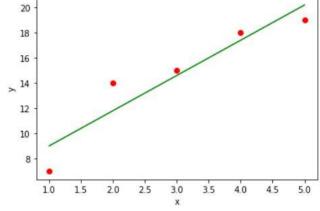
In [10]: b1 = Sxy/Sxx
    b0 = y_mean-b1*x_mean
    print('Slope is:', b1)
    print('Intercept is:', b0)
    Slope is: 2.8
    Intercept is: 6.2000000000000001
```

```
In [8]: %matplotlib inline
In [9]: plt.scatter(x,y)
           plt.xlabel('Independent variable x')
plt.ylabel('Dependent variable y')
Out[9]: Text(0, 0.5, 'Dependent variable y')
               18
            Dependent variable y 12 10
                 8
                     1.0
                           1.5
                                   2.0
                                          2.5
                                                 3.0
                                                        3.5
                                                               4.0
                                                                      4.5
                                                                             5.0
                                       Independent variable x
```

```
In [11]: y_pred = b1 * x + b0

plt.scatter(x, y, color = 'red')
plt.plot(x, y_pred, color = 'green')
plt.xlabel('x')
plt.ylabel('y')

Out[11]: Text(0, 0.5, 'y')
```



```
In [12]: error = y - y_pred
    se = np.sum(error**2)
    print('squared error is:', se)
```

squared error is: 10.8000000000000004

```
In [13]: mse = se/n
           print('mean squared error is:', mse)
           mean squared error is: 2.1600000000000001
  In [14]: rmse = np.sqrt(mse)
           print('root mean squared error is:', rmse)
           root mean squared error is: 1.4696938456699071
 In [15]: sst = np.sum((y - y_mean)** 2)
           r2 = 1 - (se/sst)
           print('R square is:', r2)
           R square is: 0.8789237668161435
 In [16]: x = x.reshape(-1, 1)
           regression_model = LinearRegression()
 In [18]: regression_model.fit(x, y)
 Out[18]: LinearRegression()
In [19]: y_predict = regression_model.predict(x)
In [20]: mse_fun = mean_squared_error(y, y_predict)
         print('MSE using sci-kit learn is:', mse_fun)
         MSE using sci-kit learn is: 2.1600000000000001
In [21]: rmse_fun = np.sqrt(mean_squared_error(y, y_predict))
         print('RMSE using sci-kit learn is:', rmse_fun)
         RMSE using sci-kit learn is: 1.4696938456699071
In [22]: r2_fun = r2_score(y, y_predict)
         print('R2 score using sci-kit learn is:', r2_fun)
         R2 score using sci-kit learn is: 0.8789237668161435
In [23]: print('Slope is:', regression_model.coef_)
         print('Intercept is:', regression_model.intercept_)
         Slope is: [2.8]
         Intercept is: 6.199999999999975
```

b) Logistic Regression for Numpy array fitting and Predicting:

```
In [1]: import numpy as np
         import matplotlib.pyplot as plt
         from sklearn.linear_model import LinearRegression
         from sklearn.metrics import mean_squared_error, r2_score
In [2]: x = np.array([1,2,3,4,5])
        y = np.array([7,14,15,18,19])
        n = np.size(x)
In [3]: x
Out[3]: array([1, 2, 3, 4, 5])
In [4]: x = x. reshape(-1,1)
         regression_model = LinearRegression ()
In [5]: # Fit the data (train the model)
         regression_model.fit(x, y)
Out[5]: LinearRegression()
In [6]: x
Out[6]: array([[1],
                [2],
                [3],
                [4],
                [5]])
In [7]: # Predict
        y_predicted = regression_model.predict(x)
In [6]: x
Out[6]: array([[1],
                [2],
                [3],
                [4],
                [5]])
In [7]: # Predict
         y_predicted = regression_model.predict(x)
In [8]: # model evaluation
         mse=mean_squared_error(y,y_predicted)
         rmse = np.sqrt(mean_squared_error(y, y_predicted))
         r2 = r2_score(y, y_predicted)
         #printing values
         print('Slope:', regression_model.coef_)
         print('Intercept:', regression_model.intercept_)
         print('MSE:', mse)
         print('Root mean squared error: ', rmse)
         print('R2 score: ', r2)
         Slope: [2.8]
         Intercept: 6.199999999999975
         MSE: 2.1600000000000001
         Root mean squared error: 1.4696938456699071
         R2 score: 0.8789237668161435
```

c) <u>Logistic Regression using Sci-kit learn and 50 startups dataset:</u>

```
In [16]: import numpy as np
            import matplotlib.pyplot as plt
            import pandas as pd
            from sklearn.linear model import LinearRegression
            from sklearn.model_selection import train_test_split
            from sklearn.metrics import mean_squared_error, r2_score
 In [10]: dataset = pd.read csv('50 Startups.csv')
            X = dataset.iloc[:,: -1]
            y = dataset.iloc[:, 4]
 In [11]: print(dataset.head(10))
                R&D Spend Administration Marketing Spend State Profit 165349.20 136897.80 471784.10 New York 192261.83
                              136897.80
            0 165349.20
            1 162597.70
                                                       443898.53 California 191792.06
            1 162597.70 151377.59 443898.53 California 191/92.00 2 153441.51 101145.55 407934.54 Florida 191050.39 3 144372.41 118671.85 383199.62 New York 182901.99 4 142107.34 91391.77 366168.42 Florida 166187.94 5 131876.90 99814.71 362861.36 New York 156991.12 6 134615.46 147198.87 127716.82 California 156122.51 7 130298.13 145530.06 323876.68 Florida 155752.60 8 120542.52 148718.95 311613.29 New York 152211.77 1203234.20 1406770.47 204091.63 California 140759.96
                                   151377.59
            8 120542.52 148718.95
9 123334.88 108679.17
                                                     304981.62 California 149759.96
 In [13]: states = pd.get_dummies(X['State'], drop_first = True)
 In [14]: X = X.drop('State', axis=1)
            X = pd.concat([X, states], axis=1)
In [18]: regressor = LinearRegression()
               regressor.fit(X train, y train)
Out[18]: LinearRegression()
In [22]: y_pred = regressor.predict(X_test)
               score = r2_score(y_test, y_pred)
               print('R2 is:',score)
               R2 is: 0.9603594733442932
In [21]: mse = mean squared error(y test, y pred)
               rmse = np.sqrt(mean squared error(y test, y pred))
               print('MSE is:', mse)
               print('RMSE is:', rmse)
               MSE is: 43035873.733029984
               RMSE is: 6560.173300533301
```

Inference:

So from the above two parts, we understand logistic regression mathematically by implementing the mathematical logic in the code and in the second part we have used in the inbuilt libraries using scikit learn and various metrics and the graphs are visualized using matplotlib.

Results:

Logistic Regression is proved and the metrics scored are verified both theortically and the graphs are visualized and plotted using matplotlib.