GRIP@The Sparks Foundation ¶

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Task 1: Prediction using Supervised Machine Learning

In this section we will see how the Python Scikit-Learn library for machine learning can be used to implement regression functions. We will start with simple linear regression involving two variables.

- * This is a simple linear regression task as it involves just 2 variables.
- * You can use R, Python, SAS Enterprise Miner or any other tool
- * Data can be found at http://bit.ly/w-data
- * What will be predicted score if a student studies for 9.25 hrs/ day?

Simple Linear Regression

In this regression task we will predict the percentage of marks that a student is expected to score based upon the number of hours they studied. This is a simple linear regression task as it involves just two variables.

Importing Libraries

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

Importing Data

```
In [2]: # Reading data from remote Link
url = "http://bit.ly/w-data"
s_data = pd.read_csv(url)
s_data
```

Out[2]:

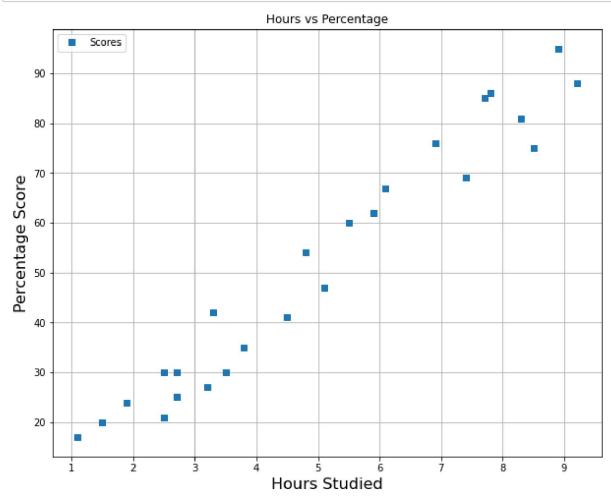
	Hours	Scores
0	2.5	21
1	5.1	47
2	3.2	27
3	8.5	75
4	3.5	30
5	1.5	20
6	9.2	88
7	5.5	60
8	8.3	81
9	2.7	25
10	7.7	85
11	5.9	62
12	4.5	41
13	3.3	42
14	1.1	17
15	8.9	95
16	2.5	30
17	1.9	24
18	6.1	67
19	7.4	69
20	2.7	30
21	4.8	54
22	3.8	35
23	6.9	76
24	7.8	86

Checking missing values

there is no missing value and duplicate values

Ploting the distribution of scores

```
In [14]: s_data.plot(x='Hours', y='Scores', style='s', figsize=(10,8))
    plt.title('Hours vs Percentage')
    plt.xlabel('Hours Studied', fontsize=16 )
    plt.ylabel('Percentage Score', fontsize=16)
    plt.grid(True)
    plt.show()
```



Preparing the data

```
In [15]: X = s_data.iloc[:, :-1].values
y = s_data.iloc[:, 1].values
```

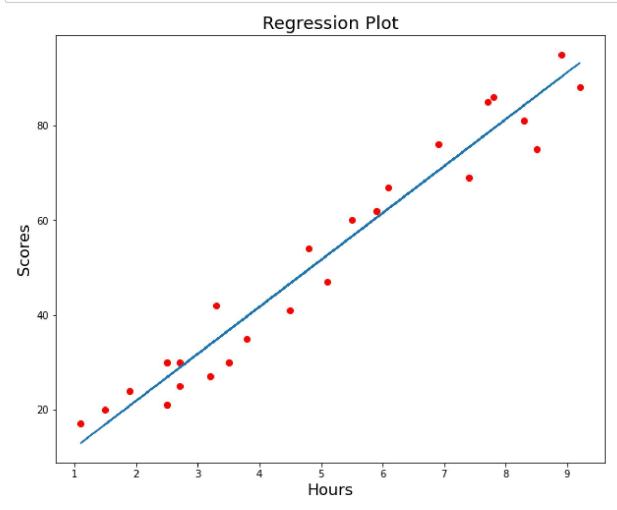
Now that we have our attributes and labels, next step is shuffling and creating train and test dataset using Scikit-Learn.

Training the model

Plotting the Line of Regression

```
In [19]: # Getting the best fitted line
line = regressor.coef_*X+regressor.intercept_

#plotting the best fitted line on the graph
plt.figure(figsize= (10,8))
plt.title('Regression Plot', size = 18)
plt.scatter(X, y,color="red", label="data points")
plt.xlabel(xlabel='Hours',fontsize=16)
plt.ylabel(ylabel='Scores',fontsize=16)
plt.plot(X, line);
plt.show()
```



Making Predictions

Comparing the Predicted with the Actual values

```
In [21]: # Comparing Actual vs Predicted

df = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})

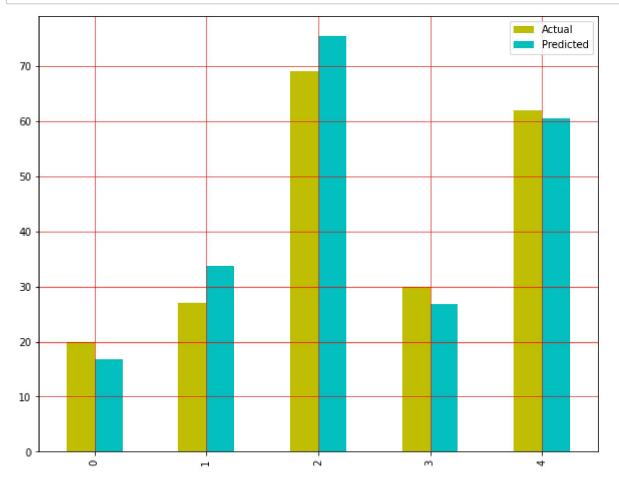
df
```

Out[21]:

	Actual	Predicted
0	20	16.884145
1	27	33.732261
2	69	75.357018
3	30	26.794801
4	62	60.491033

Visually Comparing the Predicted with the Actual values

```
In [38]: df.plot(kind='bar',figsize=(10,8), color='yc')
    plt.grid(which='major', linewidth='0.6', color='red')
    plt.grid(which='minor', linewidth='0.6', color='blue')
    plt.show()
```



Evaluating the model

The final step is to evaluate the performance of algorithm. This step is particularly important to compare how well different algorithms perform on a particular dataset. For simplicity here, we have chosen the mean square error. There are many such metrics.

Small value of Mean absolute error states that the chances of error or wrong forecasting through the model are very less

Result / Conclusion:

Testing the model to predict the percentage of student if he/she studies for 9.25 hrs/day.

```
In [40]: hours = 9.25
pred = regressor.predict(np.array(hours).reshape(-1,1))
print("No of Hours = {}".format(hours))
print("Predicted Score = {}".format(pred[0]))
No of Hours = 9.25
Predicted Score = 93.69173248737538
```

According to the regression model if a student studies for 9.25 hours a day he/she is likely to score 93.89

After evaluating the performance of model it can be concluded that the model did good prediction by predicting the student percentage as 93.69173248737538 % when student studies for 9.25 hours.

Thank you!