Linear Regression Task-2

September 9, 2020

1 TASK-2 Supervised Machine Learning Model

1.1 Problem statement

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.

1.2 Data Preprocessing

1.2.1 1. Importing Libraries

```
In [144]: import pandas as pd
          import numpy as np
          import matplotlib.pyplot as plt
          %matplotlib inline
          import seaborn as sns
```

1.2.2 2. Import Dataset

Data can be found at url http://bit.ly/w-data

```
In [145]: dataset =pd.read_csv("student_scores.csv")
```

```
In [146]: type(dataset)
```

```
Out[146]: pandas.core.frame.DataFrame
```

This will provide us our whole datase.

```
In [147]: dataset
```

Out[147]:

	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
```

Now, Using the Head function gives the First five rows of our dataset

```
In [148]: dataset.head()
```

```
Out[148]:    Hours  Scores
          0    2.5      21
          1    5.1      47
          2    3.2      27
          3    8.5      75
          4    3.5      30
```

To check the Overview of our dataset, We use Info function.

```
In [149]: dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 25 entries, 0 to 24
Data columns (total 2 columns):
Hours     25 non-null float64
Scores    25 non-null int64
dtypes: float64(1), int64(1)
memory usage: 480.0 bytes
```

To check how many rows and columns our dataset have, we will use shape.

```
In [150]: dataset.shape     #It shows that our dataset have 25 rows and 2 column
```

```
Out[150]: (25, 2)
```

Let's Check unique values in Both hours and scores column

```
In [151]: dataset['Hours'].unique()      #Below are the unique values in Hours column
```

```
Out[151]: array([2.5, 5.1, 3.2, 8.5, 3.5, 1.5, 9.2, 5.5, 8.3, 2.7, 7.7, 5.9, 4.5,
                 3.3, 1.1, 8.9, 1.9, 6.1, 7.4, 4.8, 3.8, 6.9, 7.8])
```

```
In [152]: dataset['Scores'].unique()  #Below are the uniique values in Scores column
```

```
Out[152]: array([21, 47, 27, 75, 30, 20, 88, 60, 81, 25, 85, 62, 41, 42, 17, 95, 24,
                 67, 69, 54, 35, 76, 86], dtype=int64)
```

Now, To get the datatype of our particuar column, we will use dtypes as shown

```
In [153]: dataset.dtypes
```

```
Out[153]: Hours      float64
          Scores       int64
          dtype: object
```

Now, We will check if our dataset contains any null values or not in both the column

```
In [154]: dataset['Hours'].isnull().sum()     # No null values is present
```

```
Out[154]: 0
```

```
In [155]: dataset['Scores'].isnull().sum()    #No null value is present
```

```
Out[155]: 0
```

3. Statistical Information related to our data.

```
In [156]: dataset.describe()
```

```
Out[156]:            Hours     Scores
          count  25.000000  25.000000
          mean    5.012000  51.480000
          std     2.525094  25.286887
          min     1.100000  17.000000
          25%     2.700000  30.000000
          50%     4.800000  47.000000
          75%     7.400000  75.000000
          max     9.200000  95.000000
```

```
In [159]: dataset.rename(columns={'Hours':'Study_hours'},inplace=True)
```

```
In [160]: dataset.head()
```

```
Out[160]:    Study_hours  Scores
          0          2.5      21
          1          5.1      47
          2          3.2      27
          3          8.5      75
          4          3.5      30
```

1.2.3 4. Split Dependent and Independent variables and Visualize the data:

```
In [161]: dataset.isnull().sum()
```

```
Out[161]: Study_hours    0
          Scores         0
          dtype: int64
```

```
In [162]: x= dataset.iloc[:,:1]
```

```
In [163]: print(x)
```

```
    Study_hours
0           2.5
1           5.1
2           3.2
3           8.5
4           3.5
5           1.5
6           9.2
7           5.5
8           8.3
9           2.7
10          7.7
11          5.9
12          4.5
13          3.3
14          1.1
15          8.9
16          2.5
17          1.9
18          6.1
19          7.4
20          2.7
21          4.8
22          3.8
23          6.9
24          7.8
```

```
In [164]: type(x)
```

```
Out[164]: pandas.core.frame.DataFrame
```

```
In [165]: x= dataset.iloc[:,:-1].values
```

```
In [166]: print(x)
```

```
[[2.5]
 [5.1]
```

 ```
 [3.2]
 [8.5]
 [3.5]
 [1.5]
 [9.2]
 [5.5]
 [8.3]
 [2.7]
 [7.7]
 [5.9]
 [4.5]
 [3.3]
 [1.1]
 [8.9]
 [2.5]
 [1.9]
 [6.1]
 [7.4]
 [2.7]
 [4.8]
 [3.8]
 [6.9]
 [7.8]]
```

```
In [167]: x.ndim
```

```
Out[167]: 2
```

```
In [168]: type(x)
```

```
Out[168]: numpy.ndarray
```

```
In [169]: y= dataset.iloc[:,1:]
```

```
In [170]: print(y)
```

```
    Scores
0       21
1       47
2       27
3       75
4       30
5       20
6       88
7       60
8       81
9       25
10      85
```

```
11      62
12      41
13      42
14      17
15      95
16      30
17      24
18      67
19      69
20      30
21      54
22      35
23      76
24      86
```

```
In [171]: type(y)
```

```
Out[171]: pandas.core.frame.DataFrame
```

```
In [172]: y= dataset.iloc[:,1:].values   #convert from dataframe to numpy array
```

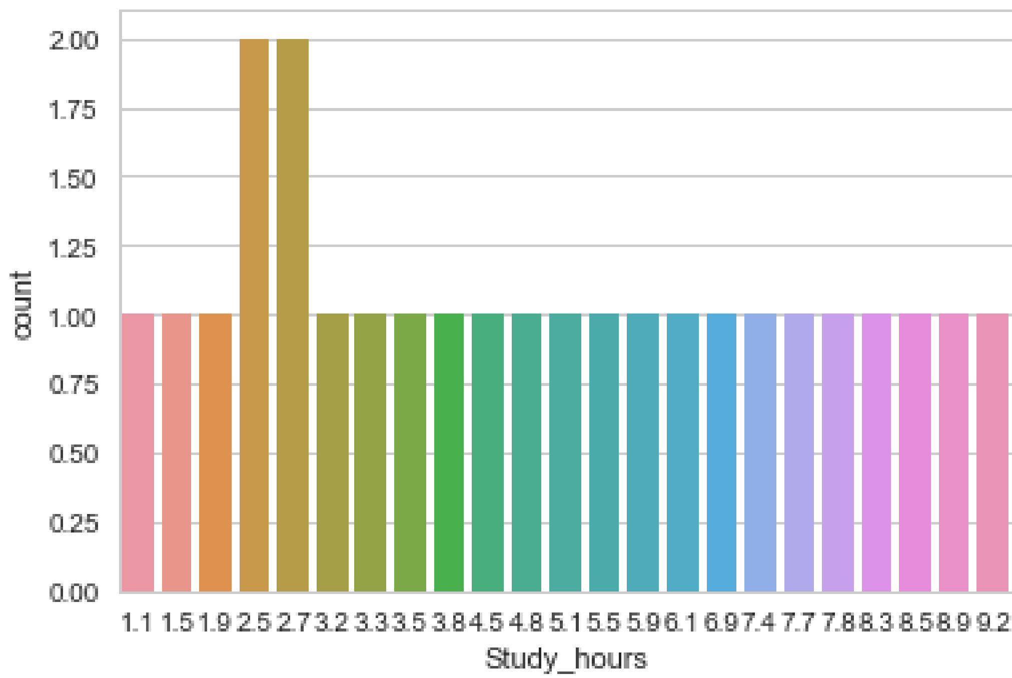
```
In [173]: print(y)
```

```
[[21]
 [47]
 [27]
 [75]
 [30]
 [20]
 [88]
 [60]
 [81]
 [25]
 [85]
 [62]
 [41]
 [42]
 [17]
 [95]
 [30]
 [24]
 [67]
 [69]
 [30]
 [54]
 [35]
 [76]
 [86]]
```

1.2.4 5. Countplot:

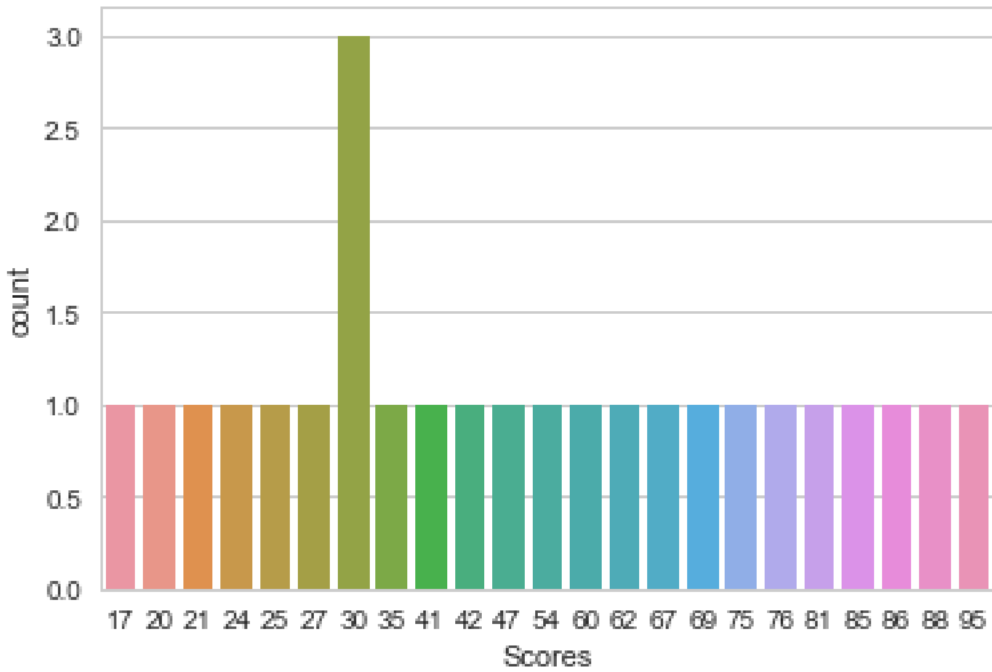
```
In [174]: sns.countplot(x='Study_hours',data=dataset)
```

```
Out[174]: <matplotlib.axes._subplots.AxesSubplot at 0x1f58dad5978>
```




```
In [175]: sns.countplot('Scores',data=dataset)
```

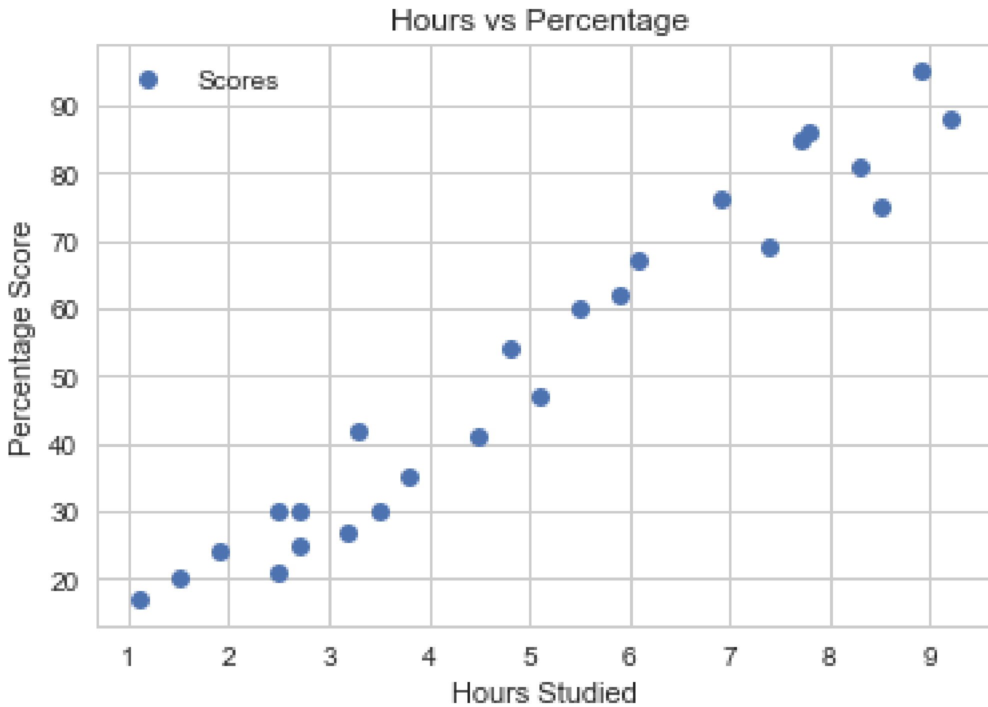
```
Out[175]: <matplotlib.axes._subplots.AxesSubplot at 0x1f58dad5748>
```



1.2.5 6. Plotting the distribution of scores

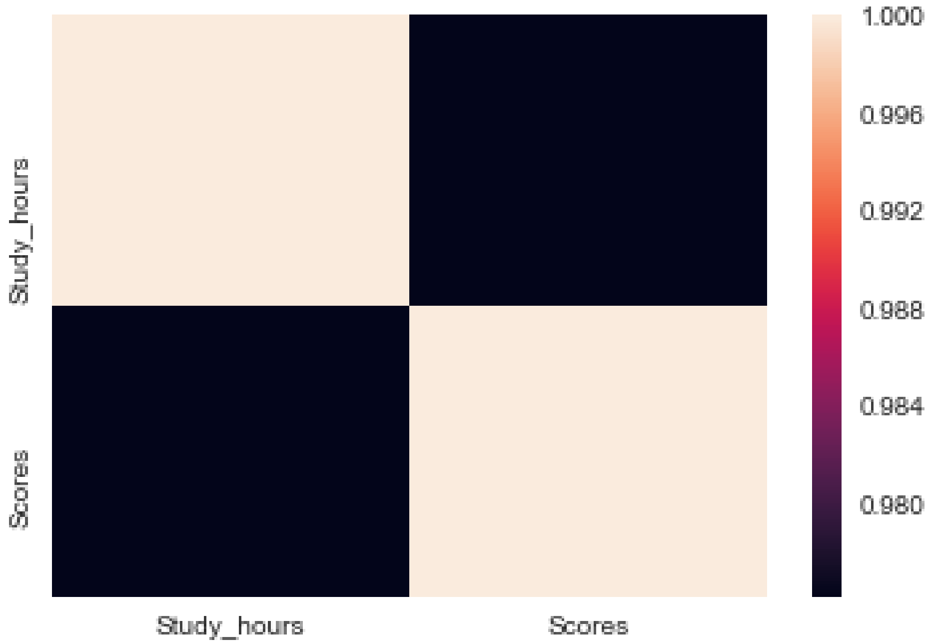
Let's plot our data points on 2-D graph to eyeball our dataset and see if we can manually find any relationship between the data. We can create the plot with the following script:

```
In [177]: dataset.plot(x='Study_hours', y='Scores', style='o')
          plt.title('Hours vs Percentage ')
          plt.xlabel('Hours Studied')
          plt.ylabel('Percentage Score')
          plt.show()
```



In [178]: `sns.heatmap(dataset.corr())`

Out[178]: <matplotlib.axes._subplots.AxesSubplot at 0x1f58dd3fd68>



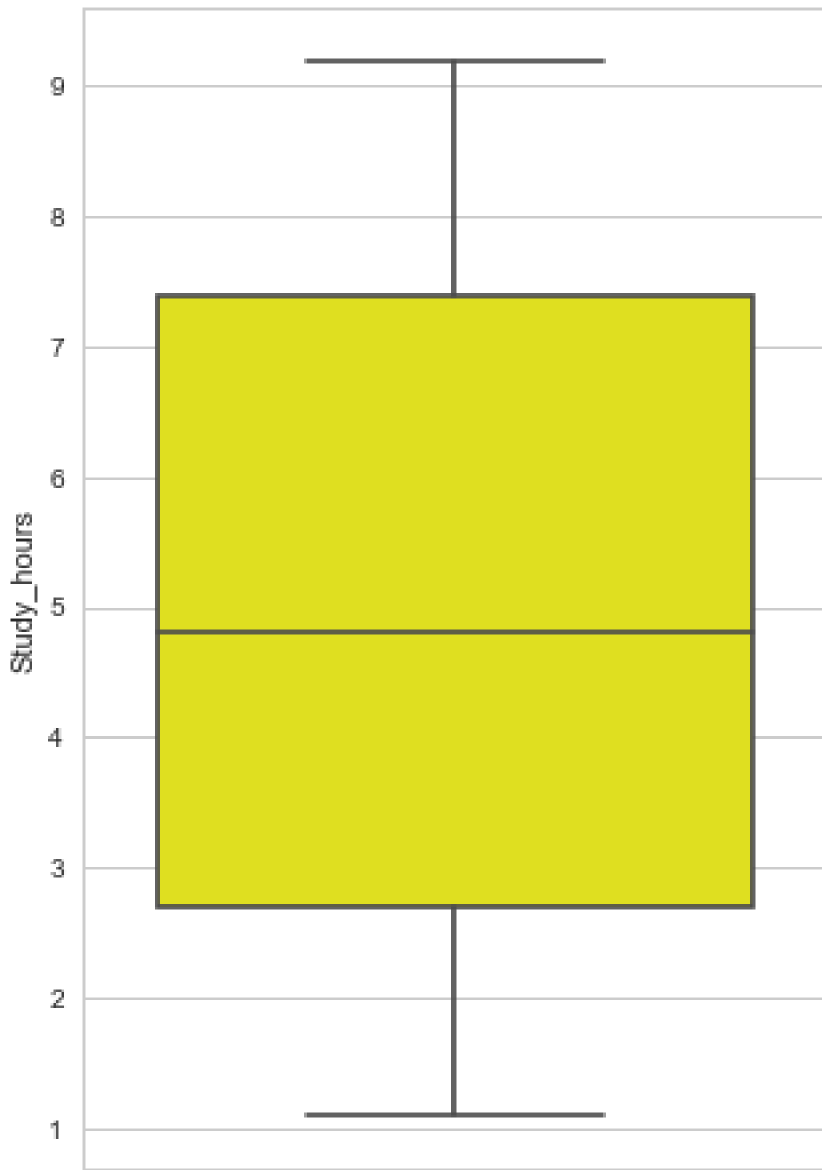
From the graph above, we can clearly see that there is a positive linear relation between the number of hours studied and percentage of score.

1.2.6 7. BOX PLOT

Box plots plays an important role as it provide us a visual summary of data all the statistical values in terms of graph.

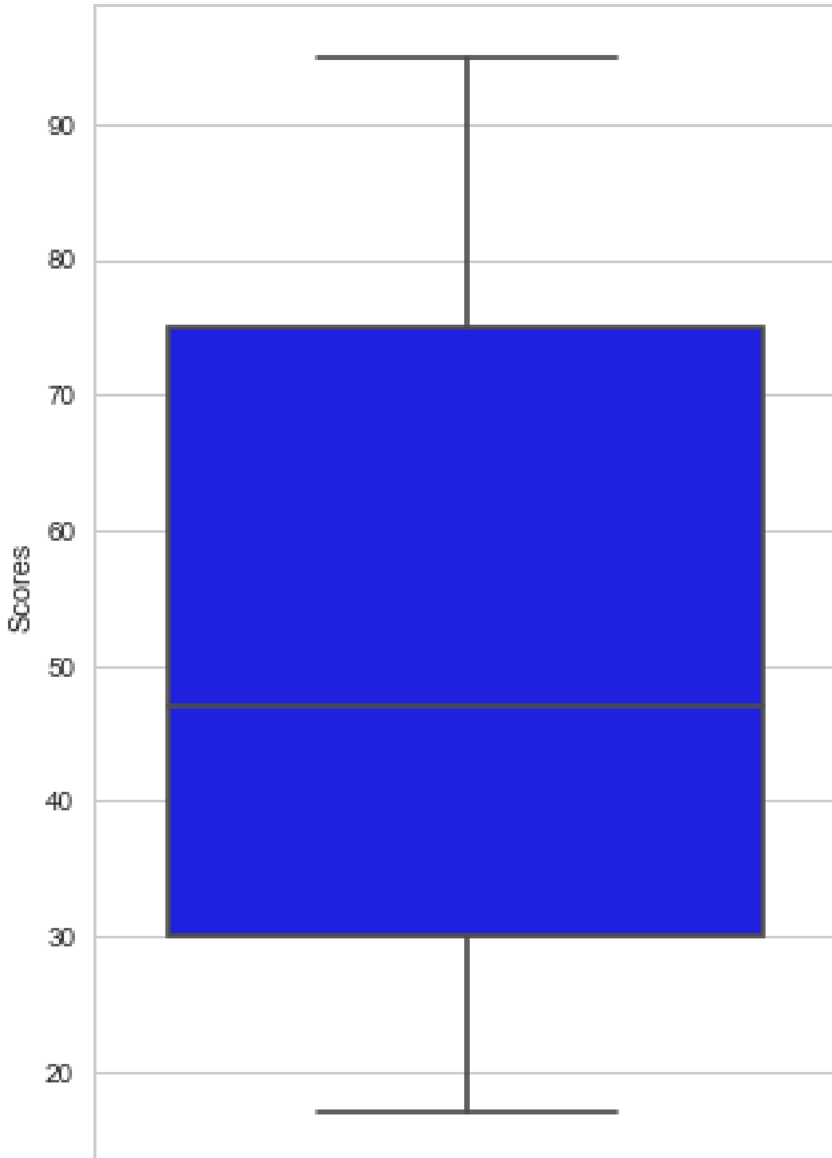
In [98]:
```
plt.figure(figsize=(5,8))
sns.boxplot(y='Study_hours',data=dataset,color='yellow')
```

Out[98]: <matplotlib.axes._subplots.AxesSubplot at 0x1f58d0ef080>



In [96]:
```
plt.figure(figsize=(5,8))
sns.boxplot(y='Scores',data=dataset,color='blue')
```

Out[96]: <matplotlib.axes._subplots.AxesSubplot at 0x1f58d0efba8>



1.2.7 8. Prepare the data

The next step is to divide the data into "attributes" (inputs) and "labels" (outputs).

In [99]:
```
x=dataset.iloc[:,:-1].values
y=dataset.iloc[:,1].values
```

Split Test and train data

```
In [101]: from sklearn.model_selection import train_test_split
          x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state
```

It splits 80% of the data to training set while 20% of the data to test set. The test_size variable is where we actually specify the proportion of test set.

1.2.8 9. Training the Algorithm

```
In [104]: from sklearn.linear_model import LinearRegression
          regressor = LinearRegression()
          regressor.fit(x_train, y_train)
          print("End of Training")

End of Training
```

To retrieve the intercept:

```
In [105]: print(regressor.intercept_)

2.018160041434683
```

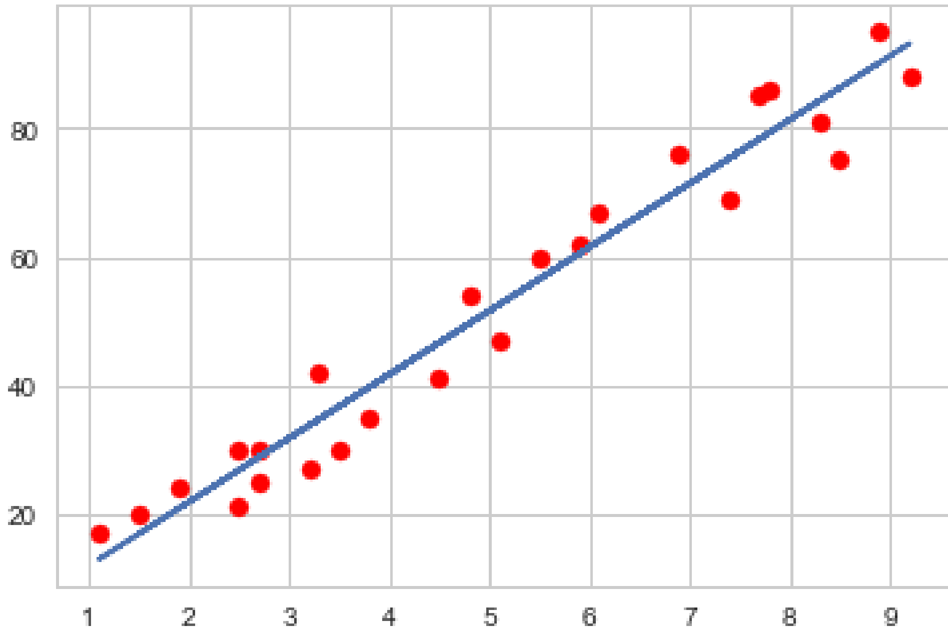
For retrieving the slope (coefficient of x):

```
In [106]: print(regressor.coef_)

[9.91065648]
```

```
In [107]: line = regressor.coef_*x+regressor.intercept_
          line

Out[107]: array([[26.79480124],
                 [52.56250809],
                 [33.73226078],
                 [86.25874013],
                 [36.70545772],
                 [16.88414476],
                 [93.19619966],
                 [56.52677068],
                 [84.27660883],
                 [28.77693254],
                 [78.33021494],
                 [60.49103328],
                 [46.6161142 ],
                 [34.72332643],
                 [12.91988217],
```

```
                [90.22300272],
                [26.79480124],
                [20.84840735],
                [62.47316457],
                [75.357018  ],
                [28.77693254],
                [49.58931115],
                [39.67865467],
                [70.40168976],
                [79.32128059]])
```

In [108]:
```
plt.scatter(x, y,color='r')
plt.plot(x, line);
plt.show()
```



1.2.9 10. Predicting the Values:

As our model is already trained now it's time to make some prediction.

In [109]:
```
print(x_test) # Testing data - In Hours
y_pred = regressor.predict(x_test) # Predicting the scores
```

```
[[1.5]
 [3.2]
 [7.4]
 [2.5]
 [5.9]]
```

In [110]:
```
data = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})
data
```

Out[110]:

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

In [121]:
```
from sklearn.linear_model import LinearRegression
lr=LinearRegression()
```

In [122]:
```
lr.fit(x_train,y_train)
```

Out[122]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=False)
```

In [123]:
```
y_predict=lr.predict(x_test)
```

In [124]:
```
y_predict
```

Out[124]:
```
array([16.88414476, 33.73226078, 75.357018  , 26.79480124, 60.49103328])
```

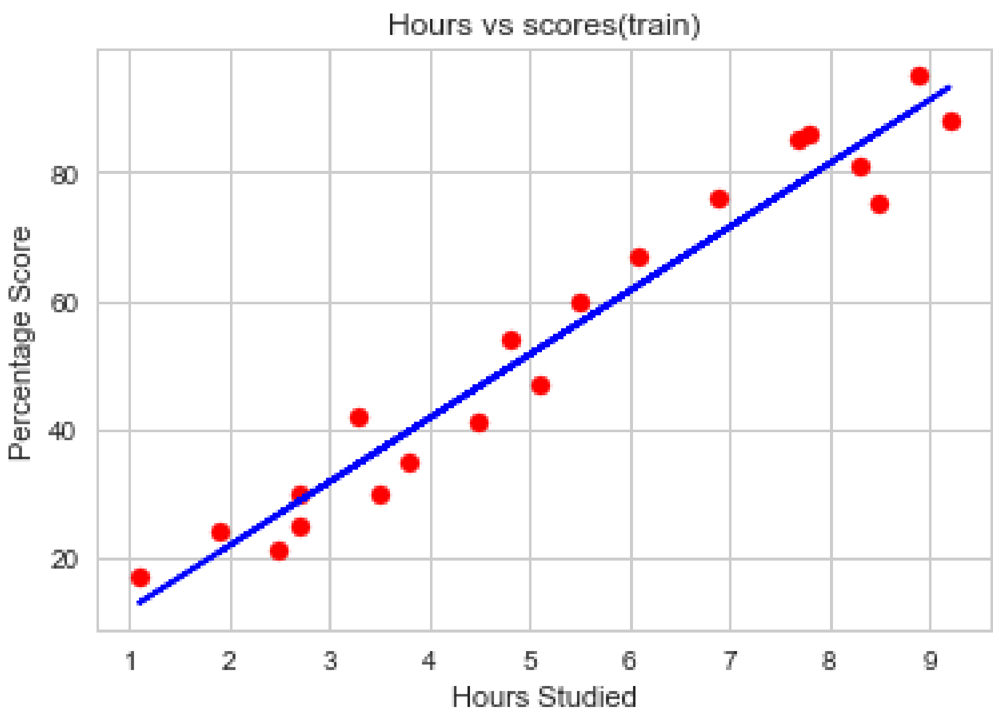
In [125]:
```
y_test
```

Out[125]:
```
array([20, 27, 69, 30, 62], dtype=int64)
```

In [126]:
```
lr.predict(np.array([[5]]))
```

Out[126]:
```
array([51.57144244])
```

In [127]:
```
#visualization of trained data
plt.scatter(x_train,y_train,color = 'Red')
plt.plot(x_train,lr.predict(x_train),color = 'blue')
plt.xlabel("Hours Studied")
plt.ylabel("Percentage Score")
plt.title("Hours vs scores(train)")
plt.show()
```




```
In [129]: #visualization of Predicted data
          plt.scatter(x_test,y_test,color = 'Red')
          plt.plot(x_test,lr.predict(x_test),color = 'blue')
          plt.xlabel("Hours Studied")
          plt.ylabel("Percentage Score")
          plt.title("Hours vs scores(train)")
          plt.show()
```

You can also test your own data as given below.

```
In [130]: Study_hours=9.25
          own_prediction=regressor.predict([[Study_hours]]).round(2)
          print("No of Hours = {}".format(Study_hours))
          print("Predicted Score = {}".format(own_prediction[0]))
```

```
No of Hours = 9.25
Predicted Score = 93.69
```

1.2.10 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.

```
In [136]: from sklearn import metrics
          print('Mean Absolute Error:',
                metrics.mean_absolute_error(y_test, y_pred))
          print('Root Of Mean Squared Error:',np.sqrt(metrics.mean_squared_error(y_test, y_prec
```

```
Mean Absolute Error: 4.183859899002975
Root Of Mean Squared Error: 4.6474476121003665
```

```
In [134]: print('Mean Squared Error:',metrics.mean_squared_error(y_test,y_pred))
```

```
Mean Squared Error: 21.5987693072174
```

Here the difference between MAE and RMSE are very less ,means that error size are less,our data and model are more representative with respect to mean. Hence, our linear regression model works successfully.