Student Score - Supervised ML - The Spark Foundation

July 15, 2022

1 Student Score Prediction Using Supervised ML

[29]:
```
# Importing all libraries required in this notebook
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

[30]:
```
import warnings
warnings.filterwarnings('ignore')
```

[31]:
```
#Uploading dataset

data = "https://raw.githubusercontent.com/AdiPersonalWorks/Random/master/
↪student_scores%20-%20student_scores.csv"
student_data = pd.read_csv(data)
student_data.head(10)
```

[31]:

	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

[32]:
```
student_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 25 entries, 0 to 24
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
```

```
 0   Hours   25 non-null     float64
 1   Scores  25 non-null     int64
dtypes: float64(1), int64(1)
memory usage: 528.0 bytes
```

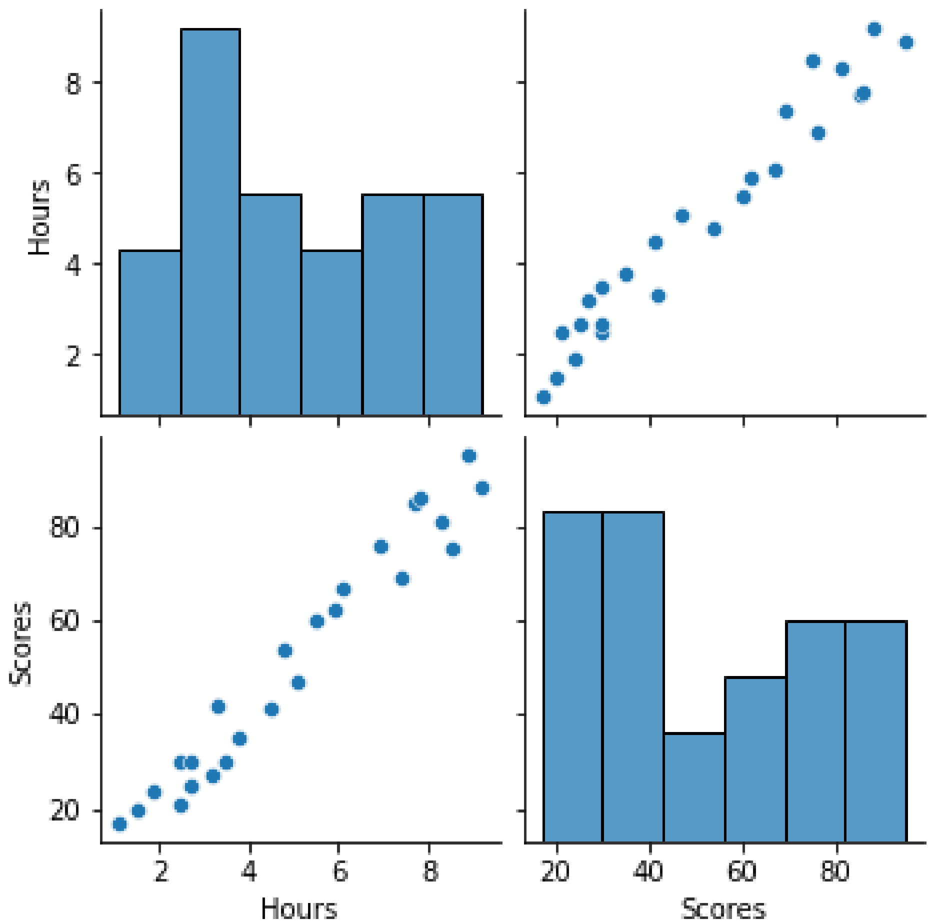
[33]:
```python
student_data.describe()
```

[33]:

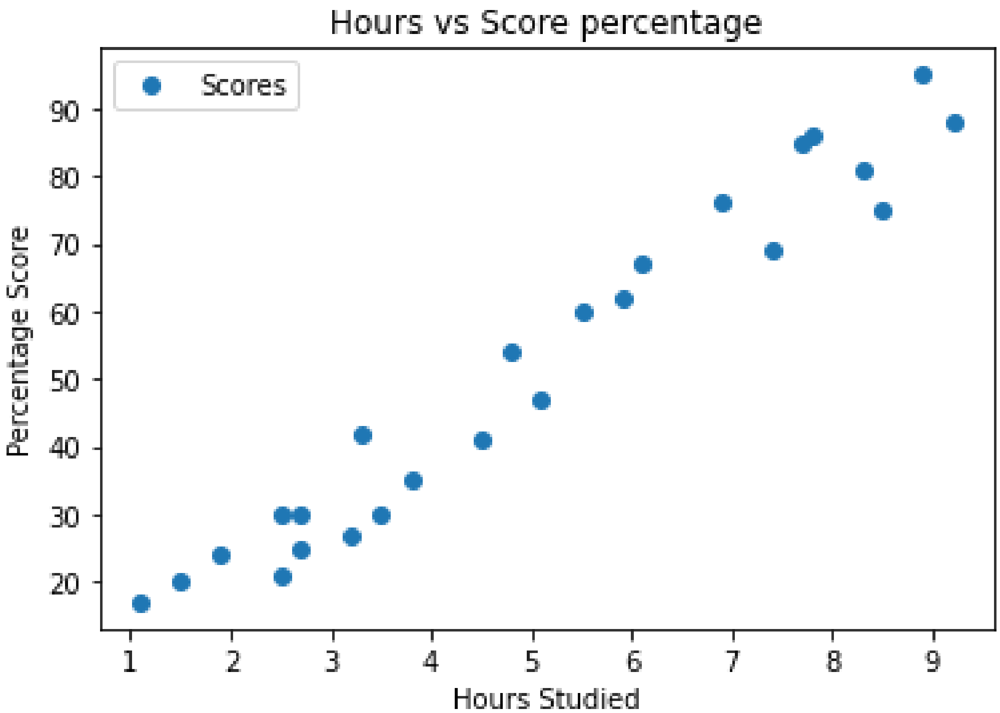
	Hours	Scores
count	25.000000	25.000000
mean	5.012000	51.480000
std	2.525094	25.286887
min	1.100000	17.000000
25%	2.700000	30.000000
50%	4.800000	47.000000
75%	7.400000	75.000000
max	9.200000	95.000000

[34]:
```python
#Investigating the correlation between the columns

sns.pairplot(student_data)
```

[34]:
```
<seaborn.axisgrid.PairGrid at 0x1f89cf95cd0>
```

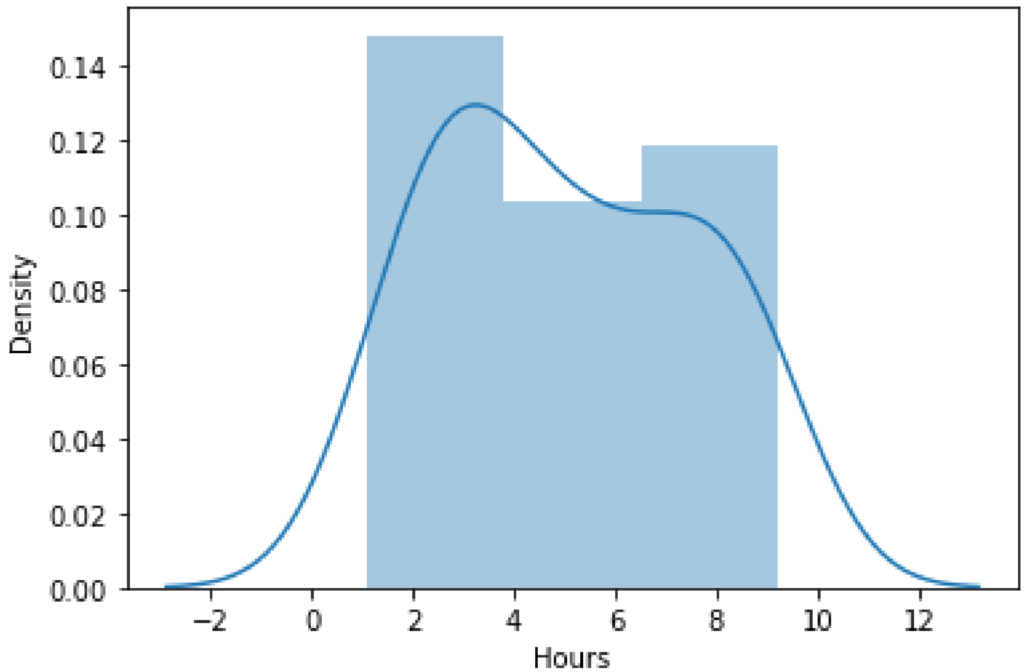


[35]:
```
# Scatter plot

student_data.plot(x='Hours', y='Scores' , style='o')
plt.title('Hours vs Score percentage')
plt.xlabel('Hours Studied')
plt.ylabel('Percentage Score')
plt.show()
```



[36]:
```
#Checking the column to be predicted on how its is distributed

sns.distplot(student_data['Hours'])
```

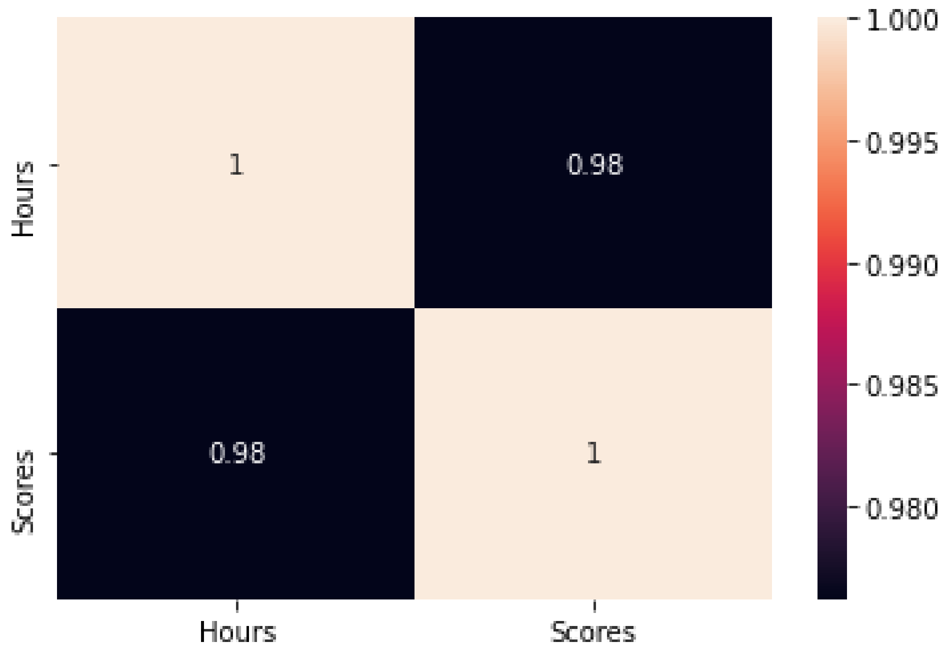
[36]:
```
<AxesSubplot:xlabel='Hours', ylabel='Density'>
```



From the above plot we can see the average distribution is around 1 to 3 hours and the second highest is between 7 to 9

[37]:
```
#check the correlation between each columns using a heat map

sns.heatmap(student_data.corr(), annot = True )
```

[37]: <AxesSubplot:>



2 Assigning Test and Training sets

[38]:
```
#lets assign X label

X = student_data.iloc[:, :-1].values

#Lets assign the target variable 'Hours' for the Y label

y = student_data.iloc[:, 1].values
```

[39]:
```
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=0)
```

3 Training the model

[40]:
```
from sklearn.linear_model import LinearRegression

LM = LinearRegression()

LM.fit(X_train, y_train)
```

[40]:
```
LinearRegression()
```

4 Making Predictions

[41]:
```
print(X_test) # Testing data - In Hours
```

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

[42]:
```
Pred = LM.predict(X_test) # giving the model an unexpexted data to predict
```

[43]:
```
Pred #this shows the prediction made by the model for the X_test data
```

[43]:
```
array([16.88414476, 33.73226078, 75.357018  , 26.79480124, 60.49103328])
```

[44]:
```
# Comparing Actual vs Predicted

new_df = pd.DataFrame({'Actual': y_test, 'Predicted': Pred})
new_df
```

[44]:

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

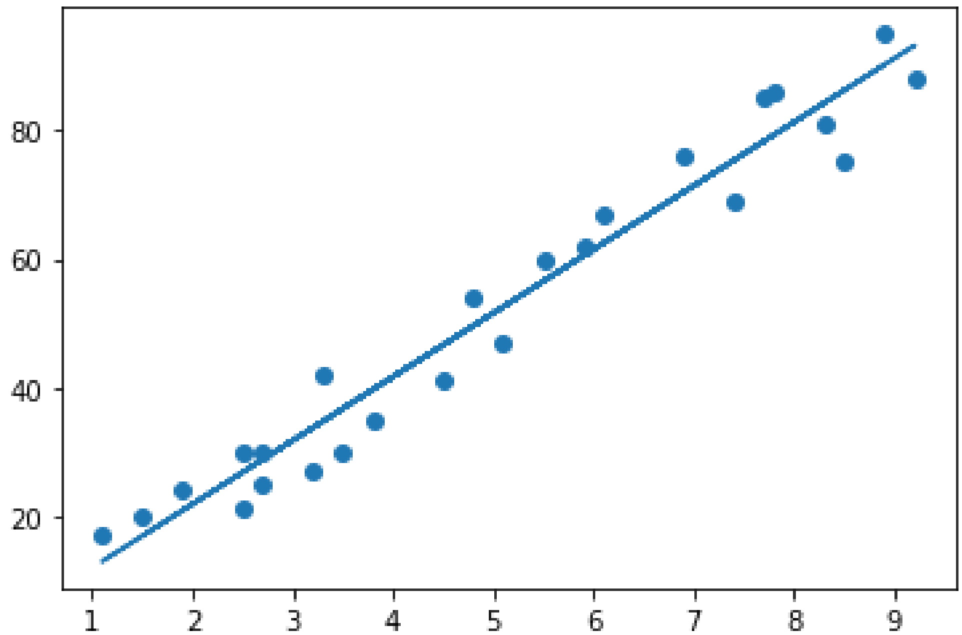
[45]:
```
#now lets check the intercepts by calling the model

print(LM.intercept_)
```

```
2.018160041434683
```

[46]:
```
 #the o/p coefficient will realate to each and every value in the datatset

LM.coef_
```

[46]:
```
array([9.91065648])
```

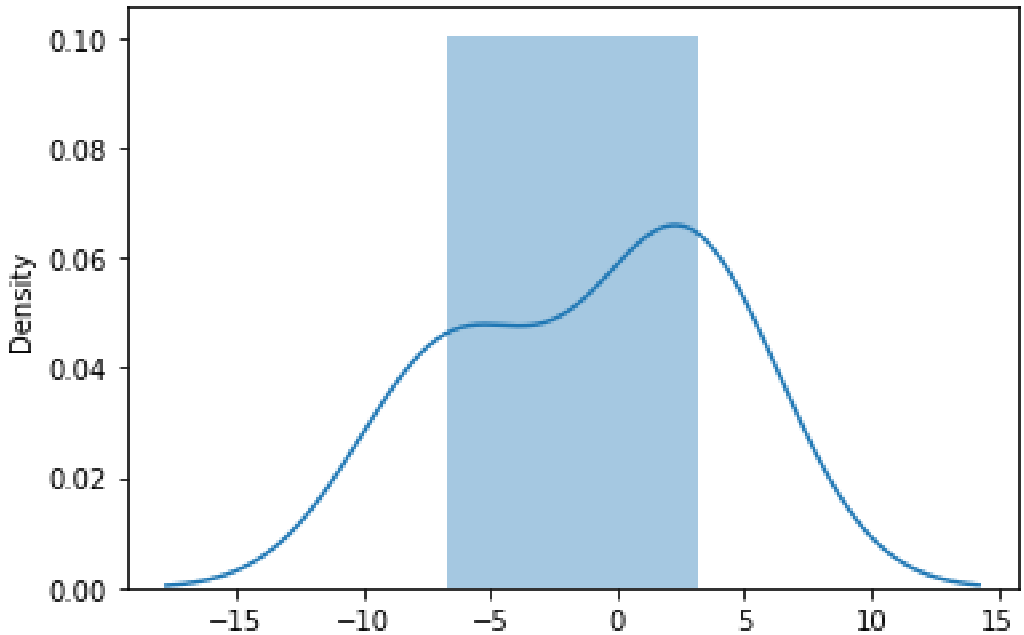
[47]:
```
# regression line

Reg_line = LM.coef_*X+LM.intercept_

#Lets check the above in visualization

plt.scatter(X, y)
plt.plot(X, Reg_line);
plt.show()
```



We can see that both the y_test data and the X_train data are more or less near the linear line

[48]:
```
#Let plot a histogram of the residuals if any

sns.distplot((y_test - Pred)) #Residual is the difference between the actual␣
↪value and the predicted value
```

[48]: `<AxesSubplot:ylabel='Density'>`



5 Evaluation of Regression

Now our goal is to minimise the error if any with various evaluation metrics

[49]:
```
from sklearn import metrics
```

[50]:
```
#Mean Average Error (MAE) - its the average of errors

print('Mean Average Error is :' , metrics.mean_absolute_error(y_test,Pred))
```

```
Mean Average Error is : 4.183859899002975
```

[51]:
```
#Mean Squared Error (MSE) - better cancellation of larger error compared to MAE␣
↪as it is squaring them

print('Mean Squared Error is :' , metrics.mean_squared_error(y_test,Pred))
```

```
Mean Squared Error is : 21.5987693072174
```

[52]:
```
#Root Mean Squared Error (RMSE) - Most accurate of all as it can be interpreted␣
↪in the 'y' units

print('Root Mean Squared Error is :' , np.sqrt(metrics.
↪mean_squared_error(y_test,Pred)))
```

```
Root Mean Squared Error is : 4.6474476121003665
```

We can consider RMSE evaluation metric for our model as its the most accurate out of the 3

6 Now Lets Test the Model with our own data to Predict the Score

[53]:

```
input_value = np.array(9.25).reshape(-1, 1)
Pred = LM.predict(input_value)
print("No of Hours = {}".format(input_value))
print("Predicted Score = {}".format(Pred[0]))
```

```
No of Hours = [[9.25]]
Predicted Score = 93.69173248737538
```

[ ]:

```

```