Spark-1

November 9, 2020

1 TASK-1

1.1 Prediction using Supervised ML

Here 2 varaibles given, based on which need to predict the percentage of an student based on the number of study hours.

1.1.1 Author- Sunny Kumar Tripathi

1.2 Step 1: Importing necessary python package

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

import warnings
warnings.filterwarnings('ignore')
```

1.3 Step 2: Importing dataset

[2]:
```
# Importing here dataset from url
url= "https://raw.githubusercontent.com/AdiPersonalWorks/Random/master/
 ↪student_scores%20-%20student_scores.csv"
df= pd.read_csv(url)
df.head()

df=pd.read_csv('student_scores - student_scores.csv')
```

[3]:
```
#Data with null values
df.isnull().sum()

#NO null values
```

[3]:
```
Hours     0
Scores    0
dtype: int64
```

[4]:
```
# data shape and size and other information
print('Shape of Data is:',df.shape)
print('Size of Data is:',df.size)
print('Dimension of Data is:',df.ndim)
print('Various Insights of Data:\n')
df.info()
```

```
Shape of Data is: (25, 2)
Size of Data is: 50
Dimension of Data is: 2
Various Insights of Data:

<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
```

[5]:
```
# Data Columns
print('Columns in Data ----',df.columns)
```

```
Columns in Data ---- Index(['Hours', 'Scores'], dtype='object')
```

[6]:
```
#Correlation Between data

df.corr()
```

[6]:

	Hours	Scores
Hours	1.000000	0.976191
Scores	0.976191	1.000000

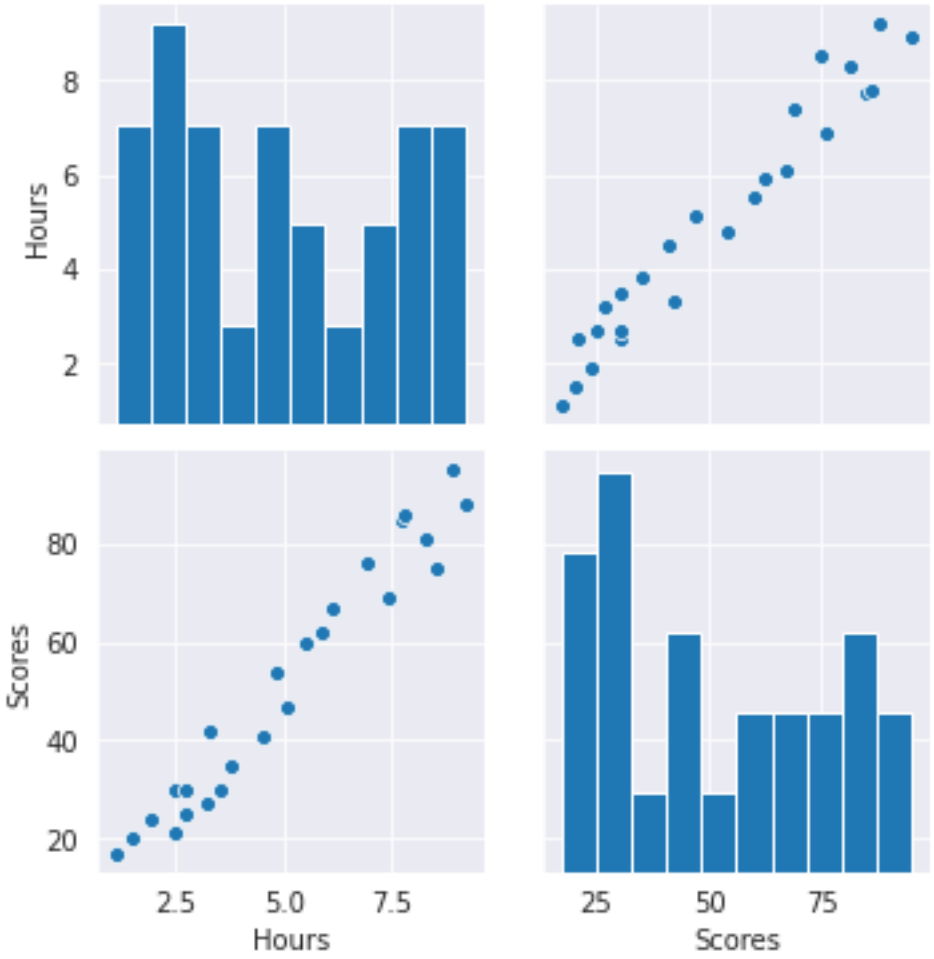
[7]:
```
# Data Description
df.describe()
```

[7]:

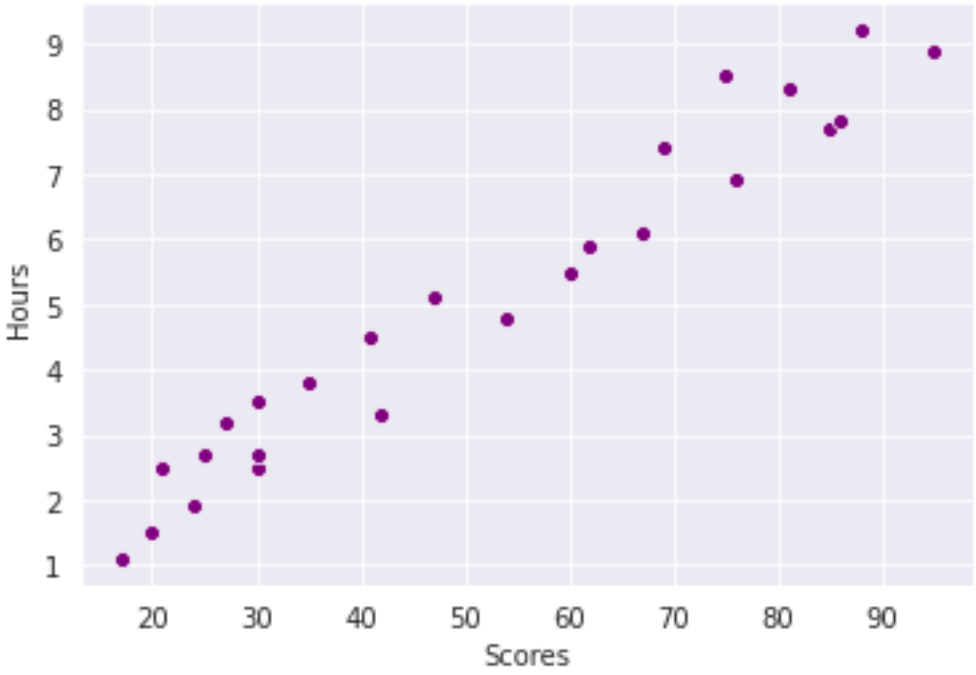
	Hours	Scores
count	25.000000	25.000000
mean	5.012000	51.480000
std	2.525094	25.286887
min	1.100000	17.000000
25%	2.700000	30.000000
50%	4.800000	47.000000
75%	7.400000	75.000000
max	9.200000	95.000000

2 Step 3: Plot & Visualization

[8]:
```
#Using Scatter/pair plot relationship between variables
sns.set_style('darkgrid')
sns.pairplot(df)
plt.show()
```

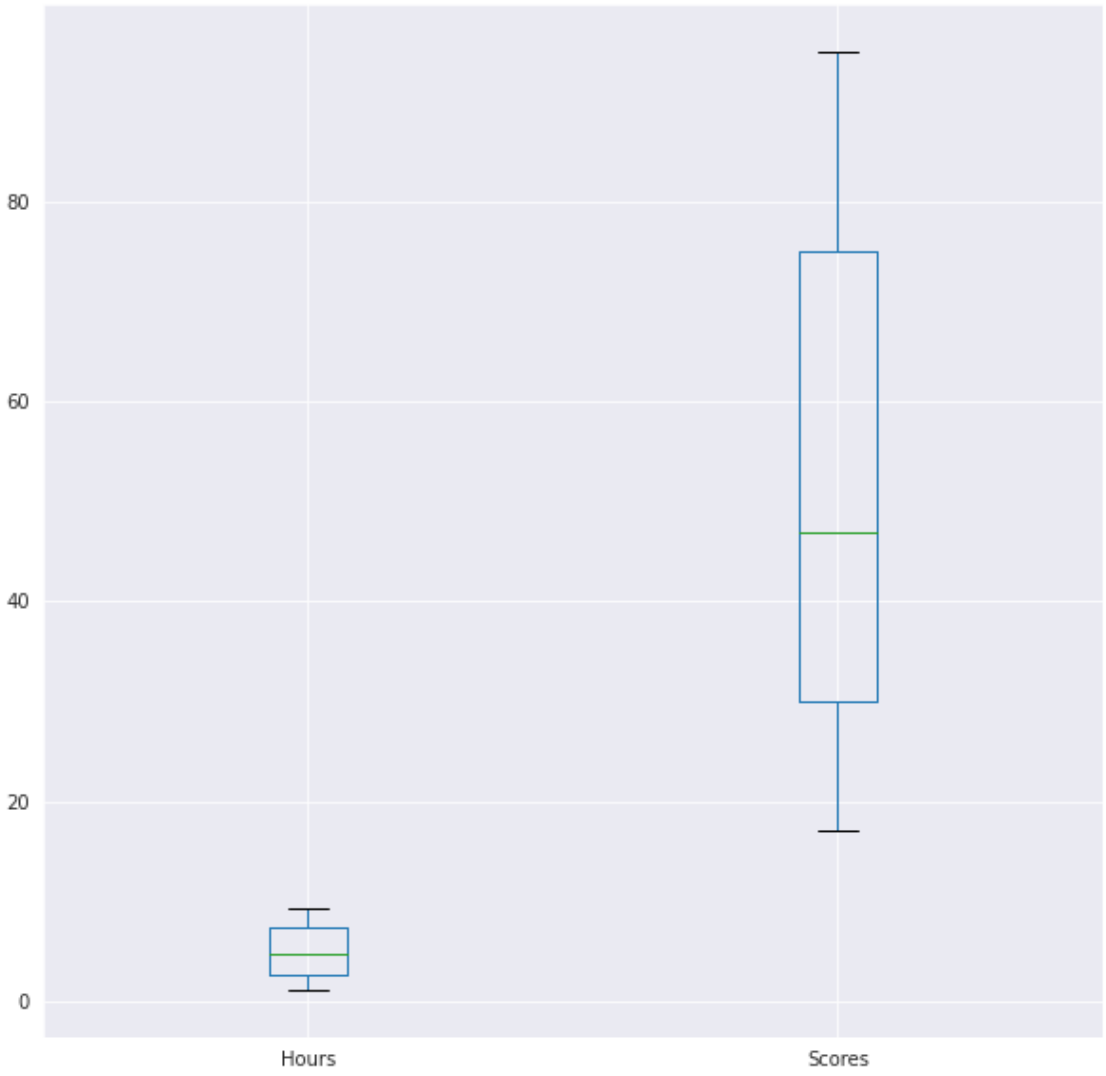


[9]:
```
sns.scatterplot(x=df.Scores,y=df.Hours,color='purple',marker='o')
plt.show()
```



Plot shows Positive Linear Relationship

[10]:
```
#From scatter plot we found no outliers , again cross Checking Outliers,no
 ↪value found
plt.figure(figsize=(10,10))
df.boxplot()
plt.show()
```



2.1 Step 4: Organizing data into training & testing sets

[11]:
```
#Defining Features n Label
X = df.drop("Scores",axis=1) #Independent variables aka Feature
y = df['Scores'] #Dependent variables aka Label
print(X.shape)
print(y.shape)
```

```
(25, 1)
(25,)
```

[12]:
```
#Train test split
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)
print('X Train Shape:',X_train.shape)
print('X Test Shape:',X_test.shape)
print('y Train Shape:',y_train.shape)
print('X Test Shape:',y_test.shape)
```

```
X Train Shape: (20, 1)
X Test Shape: (5, 1)
y Train Shape: (20,)
X Test Shape: (5,)
```

2.2 Step 5: Model evaluation & prediction

2.3 Fit the train data into Model

[13]:
```
from sklearn.linear_model import LinearRegression
lr1=LinearRegression()
lr1.fit(X_train,y_train)
```

[13]:
```
LinearRegression()
```

[14]:
```
print(lr1.coef_)
print(lr1.intercept_)
```

```
[9.91065648]
2.018160041434683
```

[15]:
```
#Predicting the scores
y_pred=lr1.predict(X_test)
y_pred
```

[15]:
```
array([16.88414476, 33.73226078, 75.357018  , 26.79480124, 60.49103328])
```

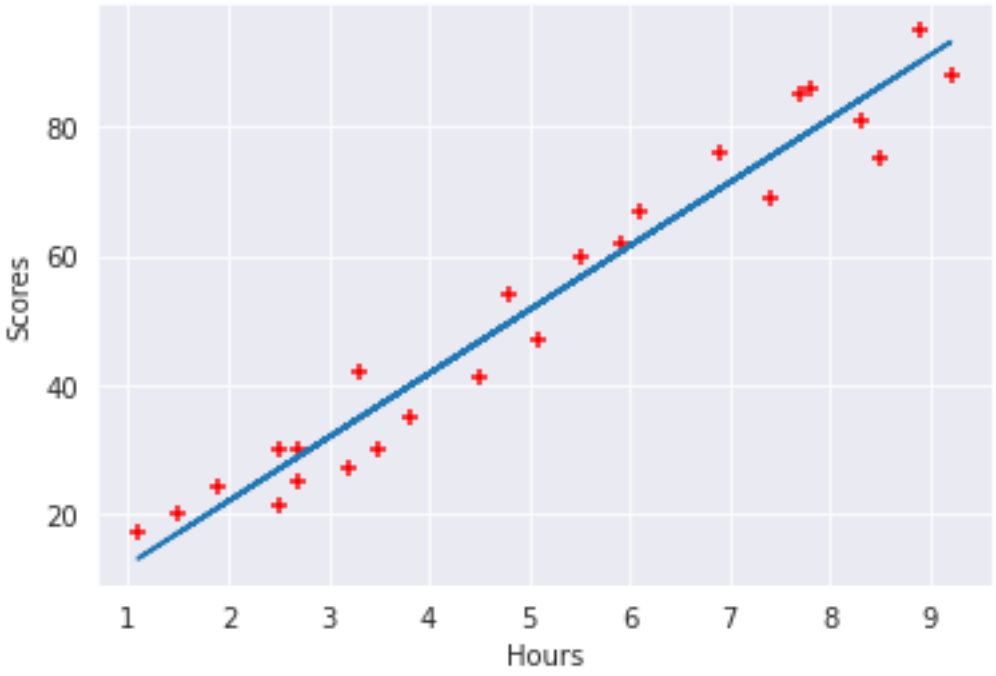
[16]:
```
# Comparing Actual vs Predicted
df_predicted = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})
df_predicted
```

[16]:

	Actual	Predicted
5	20	16.884145
2	27	33.732261
19	69	75.357018
16	30	26.794801
11	62	60.491033

[17]:
```
# Plotting the regression line
reg_line = lr1.coef_*X+lr1.intercept_
```

```
plt.scatter(X, y,color='red',marker='+')
plt.plot(X,reg_line);
plt.xlabel('Hours')
plt.ylabel('Scores')
plt.show()
```



[18]:
```
#Accuracy
lr1.score(X_test,y_test)
```

[18]: 0.9454906892105356

[19]:
```
from sklearn.linear_model import Ridge,Lasso

#Ridge
rd=Ridge()
rd.fit(X_train,y_train)
rd.score(X_test,y_test)
```

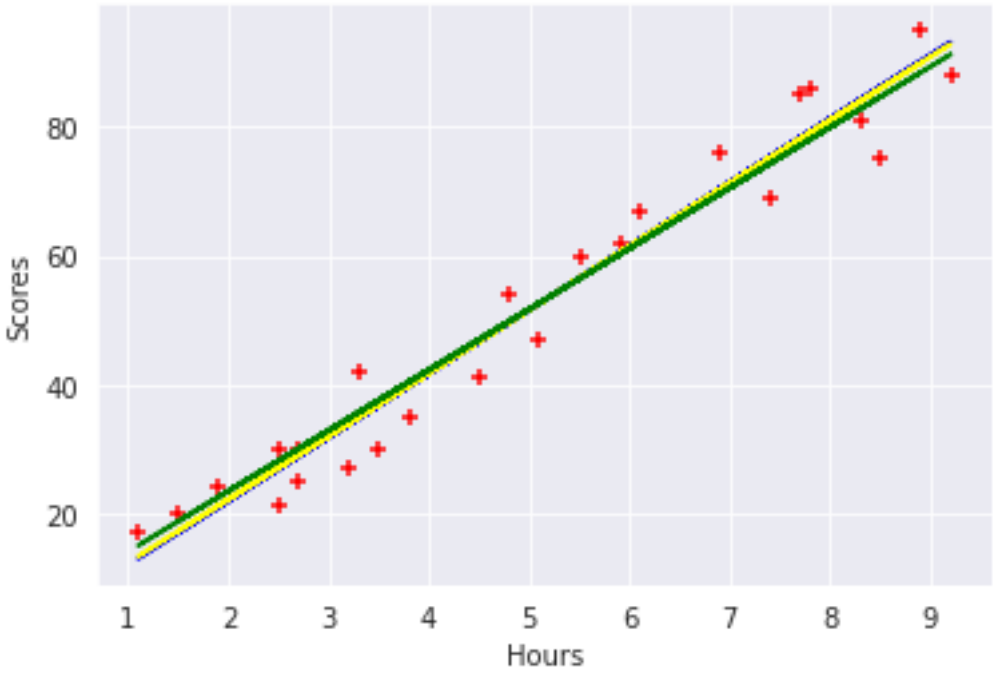
[19]: 0.9469535028586777

[20]:
```
#LASSO
ls=Lasso(alpha=3)
ls.fit(X_train,y_train)
ls.score(X_test,y_test)
```

[20]: 0.951357783797495

[21]:
```
# Plotting the regression line
reg_line = lr1.coef_*X+lr1.intercept_
rd_line = rd.coef_*X+rd.intercept_
ls_line = ls.coef_*X+ls.intercept_

plt.scatter(X, y,color='red',marker='+')
p1=plt.plot(X,reg_line,color='blue');
p2=plt.plot(X,rd_line,color='yellow');
p3=plt.plot(X,ls_line,color='green');
#plt.legend('p1','p2','p3')
plt.xlabel('Hours')
plt.ylabel('Scores')
plt.show()
```



2.4 Step 6: Performance computation

[22]:
```
from sklearn.metrics import mean_absolute_error,mean_squared_error,r2_score
print("Regressor model performance:")
print("MAE =", mean_absolute_error(y_test, y_pred))
print("MSE =", mean_squared_error(y_test, y_pred))
print("RMSE =", np.sqrt(mean_squared_error(y_test, y_pred)))
print("R2 score =",r2_score(y_test, y_pred))
```

```
Regressor model performance:
MAE = 4.183859899002975
MSE = 21.5987693072174
RMSE = 4.6474476121003665
R2 score = 0.9454906892105356
```

2.5 As per questioned

[23]:
```
ls.predict([[9.25]])
```

[23]:
```
array([91.74462644])
```

3 CROSS VALIDATION

[24]:
```
from sklearn.model_selection import cross_val_score,cross_val_predict #for␣
↪various model

X = df.drop("Scores",axis=1) #Independent variables aka Feature
y = df['Scores'] #Dependent variables aka Label
print(X.shape)
print(y.shape)
```

```
(25, 1)
(25,)
```

[25]:
```
#Creating Different Model-Technique object

#LinearRegression
from sklearn.linear_model import LinearRegression
lr=LinearRegression()

#Applying Decission Tree Regressor
from sklearn.tree import DecisionTreeRegressor
dtr = DecisionTreeRegressor(criterion='mse',max_depth=7)

#Applying Ensemble Technique-Random Forest Regressor
from sklearn.ensemble import RandomForestRegressor
rf = RandomForestRegressor(n_estimators=7)

#Support Vector Regressor
from sklearn.svm import SVR
sv = SVR(kernel='rbf',gamma='auto')
```

[26]:
```
#LinearRegression
print(cross_val_score(lr,X,y,cv=3))
print(cross_val_score(lr,X,y,cv=3).mean()*100)
```

```
[0.90059648 0.95290326 0.93422769]
92.92424775400274
```

[27]:
```
#Applying DecissionTreeRegressor
print(cross_val_score(dtr,X,y))
print(cross_val_score(dtr,X,y).mean()*100)
```

```
[0.71901261 0.92643302 0.83507612 0.87820878 0.9384501 ]
85.94361262471449
```

[28]:
```
#Applying Ensemble Technique-RandomForestRegressor
print(cross_val_score(rf,X,y))
print(cross_val_score(rf,X,y).mean()*100)
```

```
[0.76541599 0.97513361 0.84136835 0.85866923 0.90133132]
88.64668750961468
```

[29]:
```
#Applying SupportVectorRegressor
print(cross_val_score(sv,X,y))
print(cross_val_score(sv,X,y).mean()*100)
```

```
[-0.27473578  0.10569138  0.1913754   0.0570679   0.04710908]
2.5301596162142936
```

Best Model Accuracy is by Linear Regression

[30]:
```
# Cross validated predictions
predict = cross_val_predict(ls, X, y, cv=5)
sns.scatterplot(y, predict,color='orange',s=100,)
plt.show()
```

[31]:
```
# Comparing Actual vs Predicted
df_predict = pd.DataFrame({'Actual': y, 'Predicted': predict})
df_predict
```

[31]:

	Actual	Predicted
0	21	29.991497
1	47	54.118014
2	27	36.487098
3	75	85.668075
4	30	39.270927
5	20	18.423807
6	88	91.299485
7	60	56.281302
8	81	82.781549
9	25	29.781056
10	85	75.912511
11	62	59.099027
12	41	46.021872
13	42	34.812882
14	17	14.263068
15	95	86.991003
16	30	27.594168
17	24	22.025714
18	67	61.004888
19	69	73.069870

```
20      30  29.744594
21      54  48.802586
22      35  39.727352
23      76  67.860578
24      86  76.028289
```

[32]:
```
#Accuracy measures
import sklearn.metrics as metrics
from sklearn.metrics import r2_score,mean_squared_error
accuracy = metrics.mean_squared_error(y, predict)
rmse=np.sqrt(accuracy)
print('Cross Predicted MSE:', accuracy)
print('Cross Predicted RMSE:', rmse)
print("R2 score =",r2_score(y, predict))
```

```
Cross Predicted MSE: 39.65269613897749
Cross Predicted RMSE: 6.297038680123975
R2 score = 0.9354032386125567
```