SRM University

- AP,Amaravathi

Department Of Computer Science And Engineering.

PROJECT REPORT ON

STUDENT RESULT PREDICTION USING LINEAR REGRESSION

Course Name :Data and Web Mining.
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Abstract:

In every educational institution analyzing the performance of students and predicting the result is important to understand the capability and performance of every student. Predicting student performance can help the teachers to take steps in developing strategy for improving performances at early stages. With the help of data mining supervised and unsupervised techniques developing these kinds of applications are helping teachers to analyse students in a better way compared to existing performance. In these student result predictions using linear regression algorithms taking input as previously how many hours a student studied for the exam and their results. Based on that calculating pass and fail percentage of students.

Introduction:

Prediction of student results helps the instructors or teachers develop a good understanding of how well or how poorly the students in their class are performing whether they are able to pass or not or they are failed. So based on that result the instructors can take proactive steps to improve student learning and getting them pass and getting good marks. Based on a dataset collected from students of their hours studied and their marks using a linear regression model to predict student performance.

Prediction of student academic performance has long been regarded as an important research topic in many academic disciplines because it benefits both teaching and learning. Instructors can use the predicted results to identify the number of students who will perform well, averagely, or poorly in a class, so instructors can be proactive. For instance, if the predicted results show that some students in the class would be “academically at risk,” instructors may consider taking certain proactive measures to help those students achieve better in the study. Representative examples of proactive measures include adding recitation sessions, adding more working hours, using computer simulations and animations to improve student problem solving, adopting a variety of active and cooperative learning strategies, to name a few. A variety of mathematical techniques, such as linear regression have been employed to develop various models to predict student academic performance/result.

Problem Survey:

Currently, the process of declaring and managing the students’ results at the S R M University, is performed manually with extensive human intervention. The students’ results are generated through a spreadsheet application and then printed on a paper, attached to a wall for declaration and then stored. Despite having an application that generates the result, it is not very effective as the system consumes a lot of time and human resources in performing various tasks, it is costly, it lacks data security and efficiency. And at present, the institution needs an

advanced and computerized environment. And once implemented, it will minimize all the problems mentioned.

DataSet Description:

We used our own dataset consisting of hours a student studied for exams and how many marks a student got. Based on that we will implement whether students passed or failed according to cutoff marks. It helps the instructors to develop the education of students and to motivate how to get good marks in upcoming exams.

Data Preprocessing:

It is a data mining technique that transforms raw data into an understandable format. Raw data(real world data) is always incomplete and that data cannot be sent through a model. That would cause certain errors. That is why we need to preprocess data before sending through a model.
For the data preprocessing techniques and algorithms, we used **Scikit-learn** libraries.

Steps in Data Preprocessing

Here are the steps I have followed;

1. Import libraries - We used pandas and numpy to import libraries

2. Read data

3. Checking for missing values

4. Checking for categorical data

5. Standardize the data

6. PCA transformation

7. Data splitting

Pre-Processed Data:

	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

Implementation of Code and the respective outputs and graphs:

STUDENT RESULT PREDICTION USING LINEAR REGRESSION

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
import statsmodels.formula.api as smf
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
```

In [3]:
```
df = pd.read_csv('C:/Users/HP/OneDrive/Desktop/DWM_Project/Sturesult.csv')
```

In [5]:
```
print("Loading Data")
df
```

```
Loading Data
```

Out[5]:

	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

In [6]:
```
##Analysing the data
```

In [7]:
```
df.shape
```

Out[7]:
```
(25, 2)
```

In [8]:
```
df.columns
```

Out[8]:
```
Index(['Hours', 'Scores'], dtype='object')
```

In [9]:
```
df.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
```

In [10]:
```
df.describe()
```

Out[10]:

	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 [11]:
```
df.corr()
```

Out[11]:

	Hours	Scores
Hours	1.000000	0.976191
Scores	0.976191	1.000000

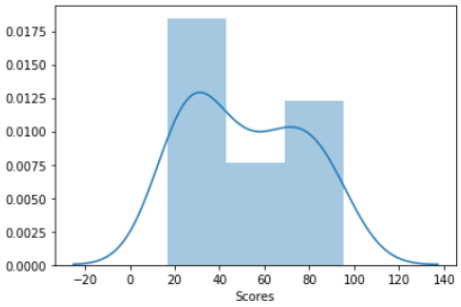
In [12]:
```
df.isnull()
```

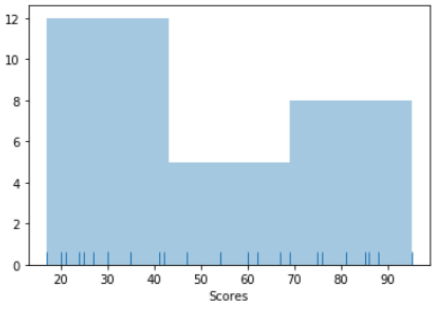
Out[12]:

	Hours	Scores
0	False	False
1	False	False
2	False	False
3	False	False
4	False	False
5	False	False
6	False	False
7	False	False
8	False	False
9	False	False
10	False	False
11	False	False
12	False	False
13	False	False
14	False	False
15	False	False
16	False	False
17	False	False
18	False	False
19	False	False
20	False	False

In [13]:
```
##From above analysis we came to know that there is no null value so no need to remove any outliers
##Lets do some analysis by visualization
```

In [14]:
```
sns.distplot(df["Scores"])
plt.show()

sns.distplot(df["Scores"], kde=False, rug=True)
plt.show()
```

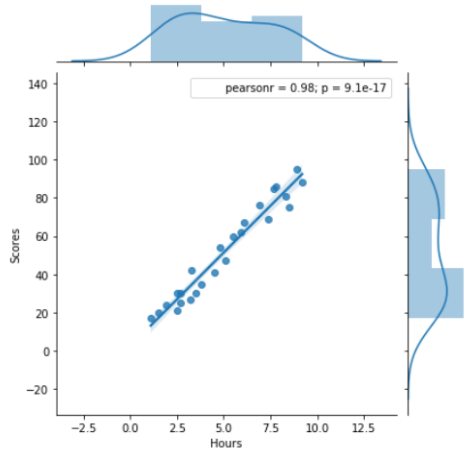




In [15]:
```
##Drawing a joint plot between scores and hours.
```

In [16]:
```
sns.jointplot(df['Hours'], df['Scores'], kind = "reg").annotate(stats.pearsonr)
plt.show()
```

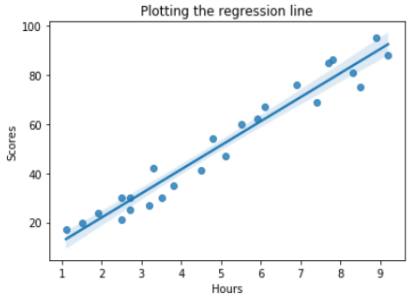
```
C:\Users\HP\anaconda4\lib\site-packages\seaborn\axisgrid.py:1848: UserWarning: JointGrid annotation is deprecated and
will be removed in a future release.
  warnings.warn(UserWarning(msg))
```



In [17]:
```
##Visualizing how much scores and hours are correlated to each other
```

In [18]:
```
sns.regplot(x="Hours", y="Scores", data=df)
plt.title("Plotting the regression line")
```

Out[18]:
```
Text(0.5, 1.0, 'Plotting the regression line')
```



In [19]:
```
##From the above analysis we came to the conclusion that scores and hours are strongly correlated .
##Using Simple linear regression to predict the data as we only have two columns.
```

In [20]:
```
X = df.iloc[:, :-1].values
y = df.iloc[:, -1].values
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.30, random_state = 0)

from sklearn.linear_model import LinearRegression
regressor = LinearRegression()
regressor.fit(X_train, y_train)
```

Out[20]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

In [21]:
```
y_pred = regressor.predict(X_test)

y_pred
```

Out[21]:
```
array([17.05366541, 33.69422878, 74.80620886, 26.8422321 , 60.12335883,
       39.56736879, 20.96909209, 78.72163554])
```

In [22]:
```
##Comparing Actual vs Predicted Value
```

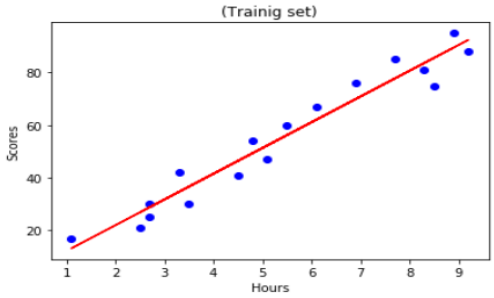
In [23]:
```
df1 = pd.DataFrame({'Actual': y_test, 'Predicted_Score': y_pred})
```

Out[23]:

	Actual	Predicted_Score
0	20	17.053665
1	27	33.694229
2	69	74.806209
3	30	26.842232
4	62	60.123359
5	35	39.567369
6	24	20.969092
7	86	78.721636

In [24]:
```
##Visualizing Actual scores and predected scores
```

In [25]:
```
# PLotting the training set
plt.scatter(X_train,y_train, color='blue')
plt.plot(X_train,regressor.predict(X_train),color='red')
plt.title('(Trainig set)')
plt.xlabel('Hours')
plt.ylabel('Scores')
plt.show()
```



In [26]:
```
##Calculating the coeffeciants of the simple linear regression equation: y = C0 +
ercept)
```

In [26]:
```
##Calculating the coeffeciants of the simple linear regression equation: y = C0 + C1.x (C1: Is the Slope, C0:Is the Intercept)
```

In [27]:
```
mean_x = np.mean(df['Hours'])
mean_y = np.mean(df['Scores'])
num = 0
den = 0
x = list(df['Hours'])
y = list(df['Scores'])
for i in range(len(df)):
    num += (x[i]-mean_x)*(y[i]-mean_y)
    den += (x[i]-mean_x)**2
B1 = num/den
```

In [28]:
```
B0 = mean_y - B1*mean_x
```

In [29]:
```
df['predicted_Scores'] = B0 + B1*df['Hours']
```

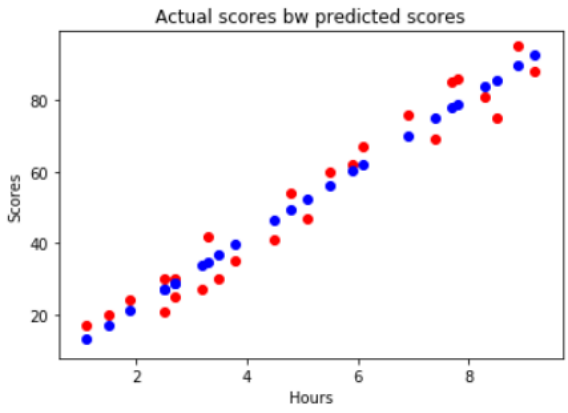
In [30]:
```
df.head()
```

Out[30]:

	Hours	Scores	predicted_Scores
0	2.5	21	26.923182
1	5.1	47	52.340271
2	3.2	27	33.766244
3	8.5	75	85.578002
4	3.5	30	36.698985

In [31]:
```
plt.scatter(df['Hours'], df['Scores'], c='red', label='Aactual Marks')
plt.scatter(df['Hours'], df['predicted_Scores'], c='blue', label='Predected Marks')
plt.title('Actual scores bw predicted scores')
plt.xlabel('Hours')
plt.ylabel('Scores')
plt.plot()
```

Out[31]:
```
[]
```



In [32]:
```
y = B0 + B1*9.25
print("Marks scored by the student who study 9.25 hours a day is ",y)
```

```
Marks scored by the student who study 9.25 hours a day is  92.90985477015732
```

In [33]:
```
##Categorising the students who passed or failed .
```

In [34]:
```
# Lets the cut of be 40 marks
cut_off = 40

df['Result'] = df['Scores']>=40
df
```

Out[34]:

	Hours	Scores	predicted_Scores	Result
0	2.5	21	26.923182	False
1	5.1	47	52.340271	True
2	3.2	27	33.766244	False
3	8.5	75	85.578002	True
4	3.5	30	36.698985	False
5	1.5	20	17.147378	False
6	9.2	88	92.421065	True
7	5.5	60	56.250592	True
8	8.3	81	83.622842	True
9	2.7	25	28.878343	False
10	7.7	85	77.757360	True
11	5.9	62	60.160913	True
12	4.5	41	46.474789	True
13	3.3	42	34.743825	True
14	1.1	17	13.237057	False
15	8.9	95	89.488324	True
16	2.5	30	26.923182	False
17	1.9	24	21.057700	False
18	6.1	67	62.116074	True
19	7.4	69	74.824618	True
20	2.7	30	28.878343	False
21	4.8	54	49.407530	True
22	3.8	35	39.631726	False
23	6.9	76	69.936717	True
24	7.8	86	78.734940	True

In [35]:
```
df["Result"] = df["Result"].astype(str)
```

In [36]:
```
df.Result = df.Result.replace({"True": "Passed", "False": "Failed"})
```

In [37]:
```
df
```

Out[37]:

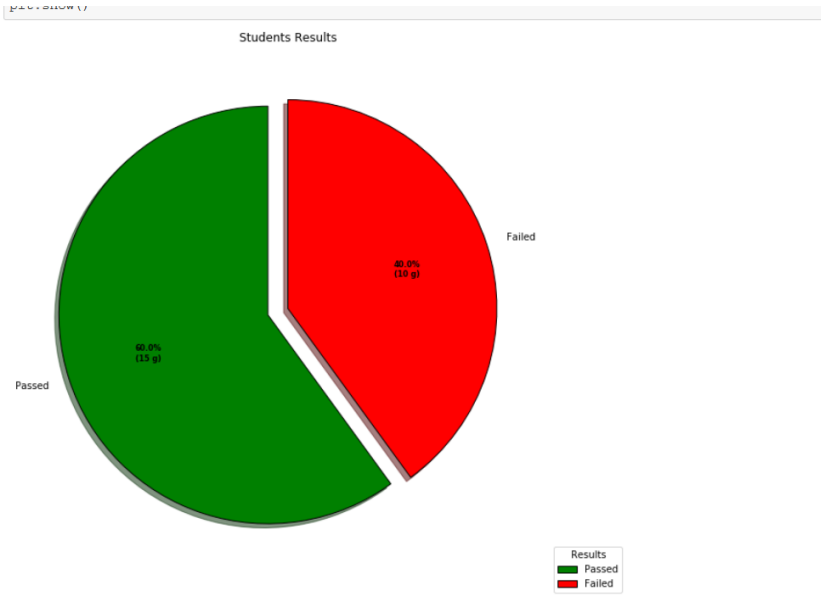
Out[37]:

	Hours	Scores	predicted_Scores	Result
0	2.5	21	26.923182	Failed
1	5.1	47	52.340271	Passed
2	3.2	27	33.766244	Failed
3	8.5	75	85.578002	Passed
4	3.5	30	36.698985	Failed
5	1.5	20	17.147378	Failed
6	9.2	88	92.421065	Passed
7	5.5	60	56.250592	Passed
8	8.3	81	83.622842	Passed
9	2.7	25	28.878343	Failed
10	7.7	85	77.757360	Passed
11	5.9	62	60.160913	Passed
12	4.5	41	46.474789	Passed
13	3.3	42	34.743825	Passed
14	1.1	17	13.237057	Failed
15	8.9	95	89.488324	Passed
16	2.5	30	26.923182	Failed
17	1.9	24	21.057700	Failed
18	6.1	67	62.116074	Passed
19	7.4	69	74.824618	Passed
20	2.7	30	28.878343	Failed
21	4.8	54	49.407530	Passed
22	3.8	35	39.631726	Failed
23	6.9	76	69.936717	Passed
24	7.8	86	78.734940	Passed

In [38]:
```
df["Result"].value_counts()
```

Out[38]:
```
Passed    15
Failed    10
Name: Result, dtype: int64
```

In [41]:
```
Results = ['Passed', 'Failed']
data = [15,10]
explode = (0.1, 0.0)
colors = ( "Green", "Red")


wp = { 'linewidth' : 1, 'edgecolor' : "black" }
# Creating autocpt arguments
def func(pct, allvalues):
    absolute = int(pct / 100.*np.sum(allvalues))
    return "{:.1f}%\n({:d} g)".format(pct, absolute)

# Creating plot
fig, ax = plt.subplots(figsize =(15, 10))
wedges, texts, autotexts = ax.pie(data,
                                  autopct = lambda pct: func(pct, data),
                                  explode = explode,
                                  labels = Results,
                                  shadow = True,
                                  colors = colors,
                                  startangle = 90,
                                  wedgeprops = wp,
                                  textprops = dict(color ="black"))

# Adding legend
ax.legend(wedges, Results,
          title ="Results",
          loc ="center left",
          bbox_to_anchor =(1, 0))

plt.setp(autotexts, size = 8, weight ="bold")
ax.set_title("Students Results")

# show plot
plt.show()
```



In [ ]:
```
#So by our analysis we came to the conclusion that 60% of the students passed while 40% failed
```

Conclusion:

Predicting a student’s performance would boost the results of a student's grades and gives the teachers a better approach for teaching the students who are at risk of failure. Regression models,tree based models are created to make the best predictions with high accuracy. The basic idea is to increase the efficiency of the prediction results using various algorithms. Thus by finding the student grade whether he/she has passed or failed using a linear regression model gives optimal results.