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GRIP - The Spark Foundation

Data Science & Business Analytics Internship

Task 1 Predict the percentage of marks of an student based on the number of study hours

Prediction

To predict the score of a student who studies for 9.25 hrs/ day .We will predict the marks of that a student is expected to score based upon the number of hours they studied.

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
```

```
print("Reading the CSV file.")
data=pd.read_csv('student_scores.csv')
```

```
Reading the CSV file.
```

```
print("Displaying the top 5 rows")
data.head()
```

```
Displaying the top 5 rows
```

	Hours	Scores
0	2.5	21
1	5.1	47
2	3.2	27
3	8.5	75
4	3.5	30

```
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
```

```
print('Data has {} number of rows and {} columns'.format(data.shape[0],data.shape[1]))
```

```
Data has 25 number of rows and 2 columns
```

```
data.isna().sum()
```

```
Hours     0
Scores    0
dtype: int64
```

```
data.duplicated().sum()
```

```
0
```

```
data.describe()
```

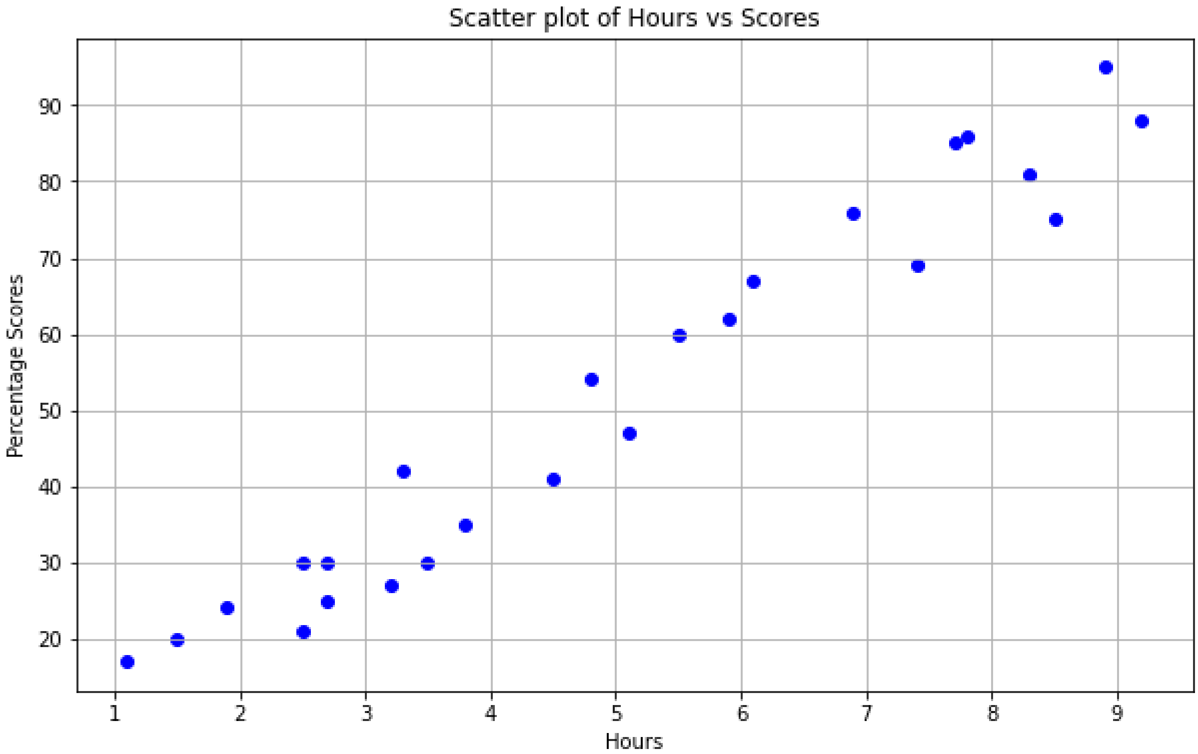
	Hours	Scores
count	25.000000	25.000000
mean	5.012000	51.480000
std	2.525094	25.286887
min	1.100000	17.000000
25%	2.700000	30.000000
50%	4.800000	47.000000
75%	7.400000	75.000000
max	9.200000	95.000000

```
data.groupby('Hours')['Scores'].mean()
```

```
Hours
1.1    17.0
1.5    20.0
1.9    24.0
2.5    25.5
2.7    27.5
3.2    27.0
3.3    42.0
3.5    30.0
3.8    35.0
4.5    41.0
4.8    54.0
5.1    47.0
5.5    60.0
5.9    62.0
6.1    67.0
6.9    76.0
7.4    69.0
7.7    85.0
7.8    86.0
8.3    81.0
8.5    75.0
8.9    95.0
```

```
9.2    88.0
Name: Scores, dtype: float64
```

```
plt.figure(figsize=(10,6))
plt.scatter(data['Hours'],data['Scores'],color='b',marker='o')
plt.grid()
plt.xlabel("Hours")
plt.ylabel("Percentage Scores")
plt.title('Scatter plot of Hours vs Scores')
plt.show()
```

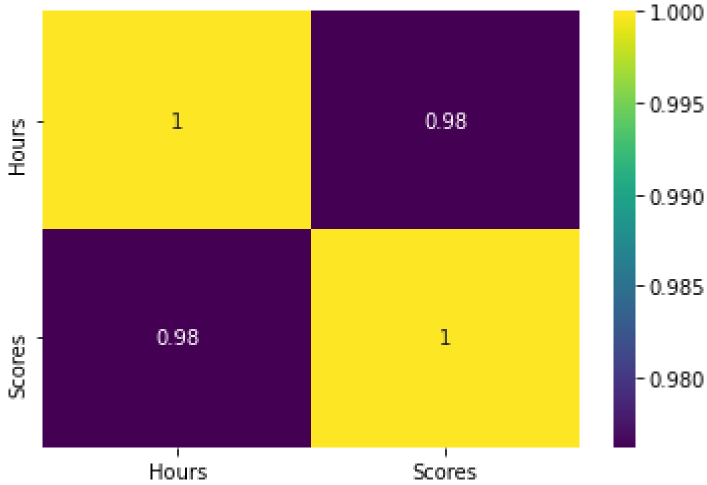



```
data.hist(figsize=(14,8))
plt.show()
```

A histogram gives us an idea about nature of distribution of data i.e. whether the data is normally distributed or it is skewed either positively or negetively. In the above histogram, we can observe for both Hours and Scores, there is a very minor skew in the positive side because many of the data points lies in this region though this very slight skew does not indicate that outliers are present in the data.


```
sns.heatmap(data.corr(),annot=True,fmt='.2g',cmap='viridis')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f011788f0b8>
```




```
data.corr()
```

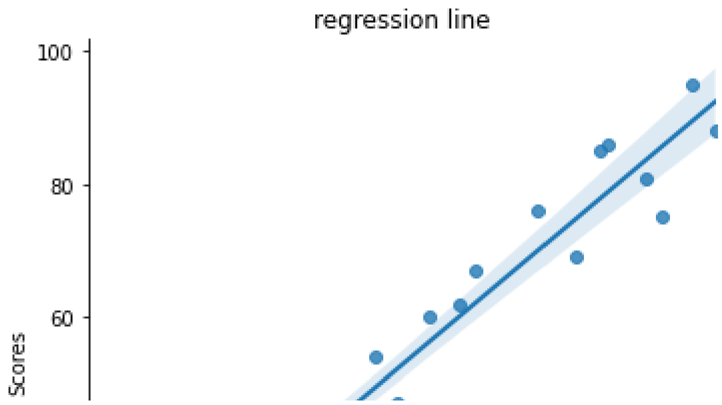
	Hours	Scores
Hours	1.000000	0.976191
Scores	0.976191	1.000000

- Hours and Scores are highly Positively correlated to each other

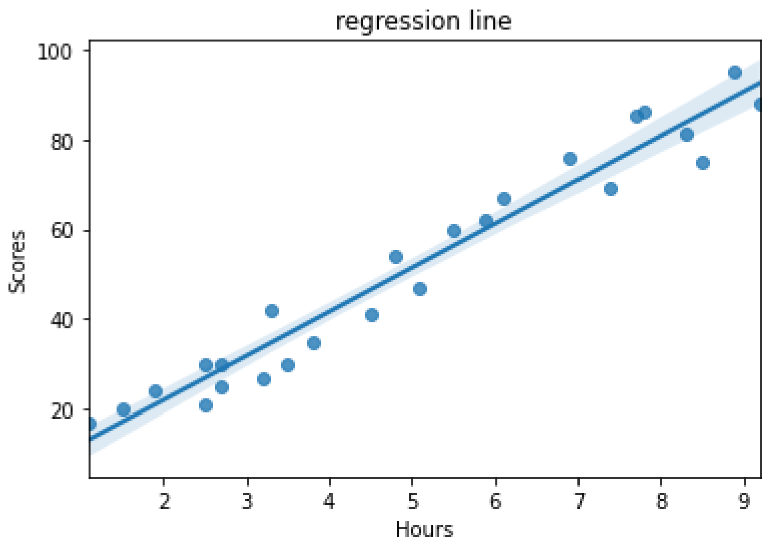
Implot

Implot() is one of the most widely used function to quickly plot the Linear Relationship between 2 variables

```
sns.lmplot(x='Hours',y='Scores',data=data)
plt.title('regression line')
plt.show()
```




```
sns.regplot(x='Hours',y='Scores',data=data)
plt.title('regression line')
plt.show()
```

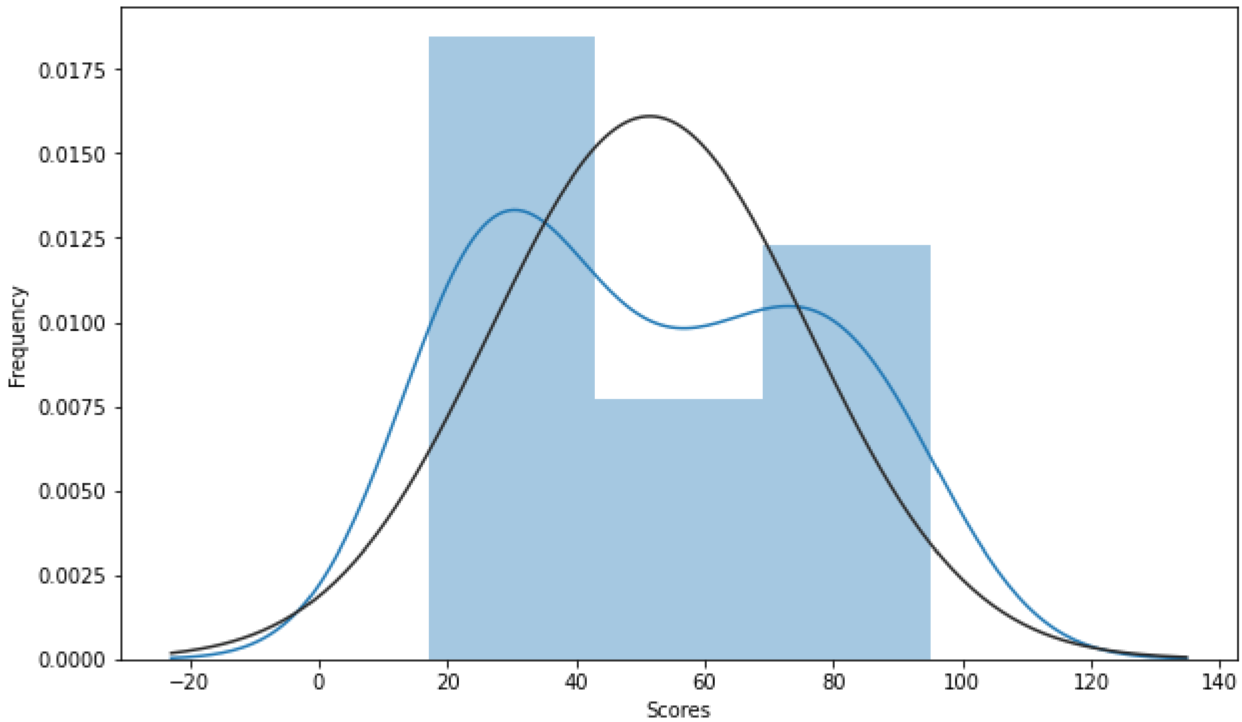


From the graph above, we can clearly observe that there is a positive linear relationship between the number of hours studied and the scores obtained. We can say that with the increase of Hours studied(x), there is an increase in the scores obtained(y).

```
plt.figure(figsize=(10,6))
sns.kdeplot(data['Hours'],legend='Hours')
sns.kdeplot(data['Scores'],legend='Scores')
plt.show()
```


```
from scipy import stats
from scipy.stats import norm, skew #for some statistics
print("skewness of scores is :", data['Scores'].skew())
plt.figure(figsize=(10,6))
sns.distplot(data['Scores'],fit=norm)
mu,sigma=norm.fit(data['Scores'])
plt.ylabel('Frequency')
plt.show()
print('mu:',str(mu),'sigma:',str(sigma))
```

```
skewness of scores is : 0.2339646665397317
```




```
mu: 51.48 sigma: 24.775988375844868
```

The most convenient way to take a quick look at a univariate distribution in seaborn is the distplot() function. By default, this will draw a histogram and fit a kernel density estimate (KDE).

```
X=data.iloc[:,:-1].values
y=data.iloc[:,-1].values
```

- Splitting the dataset into the Training set and Test set

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_state = 95)
```

Training the Simple Linear Regression model on the Training set

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

```
lr.fit(X_train,y_train)
```

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

```
y_pred=lr.predict(X_test)
```

```
y_pred
```

```
array([45.29073881, 76.53669095, 68.72520291, 25.76201873, 48.22004683,
       33.57350676, 58.96084287, 91.18323101])
```

```
# Comparing Actual vs Predicted
df1=pd.DataFrame({'actual':y_test,'predicted':y_pred})
df1
```

	actual	predicted
0	41	45.290739
1	85	76.536691
2	76	68.725203
3	30	25.762019
4	54	48.220047
5	42	33.573507
6	62	58.960843
7	88	91.183231

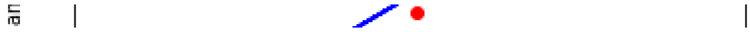
```
def visualize(x,y,model,title):
  plt.scatter(x,y,color='red',marker='o')
  plt.plot(x,model.predict(x),color='blue')
  plt.title(title)
  plt.xlabel('X_Plane - Hours')

  plt.ylabel('Y_Plane - Scores')
  plt.show()
```

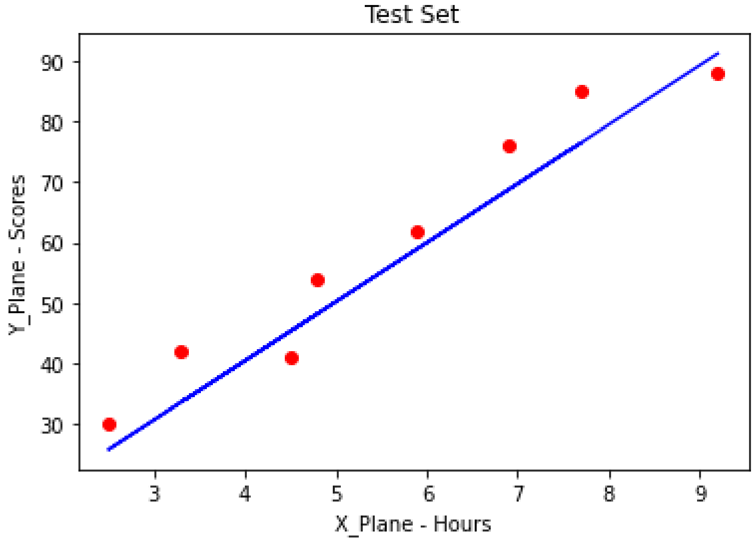
Visualising the Training set results

```
visualize(X_train,y_train,lr,'Training Set')
```

Visualising the Test set results



```
visualize(X_test,y_test,lr,'Test Set')
```




```
##Evaluating the model - to check its perfomance
from sklearn.metrics import mean_squared_error,mean_squared_log_error,r2_score
```

R-squared is a goodness-of-fit measure for linear regression models. As we can see that R-squared value is approx 0.955. r squared value basically tells us how much variance is explaned by dependent variable is explained by independent variables. In this case, around 95.5% of variance is explained which is a very good score as per industry standards.

The mean squared error tells you how close a regression line is to a set of points. It does this by taking the distances from the points to the regression line (these distances are the “errors”) and squaring them. The squaring is necessary to remove any negative signs

```
print('mean_squared_error :',mean_squared_error(y_test,y_pred))

print('mean_squared_log_error :',mean_squared_log_error(y_test,y_pred))

print('r2_score :',r2_score(y_test,y_pred))
```

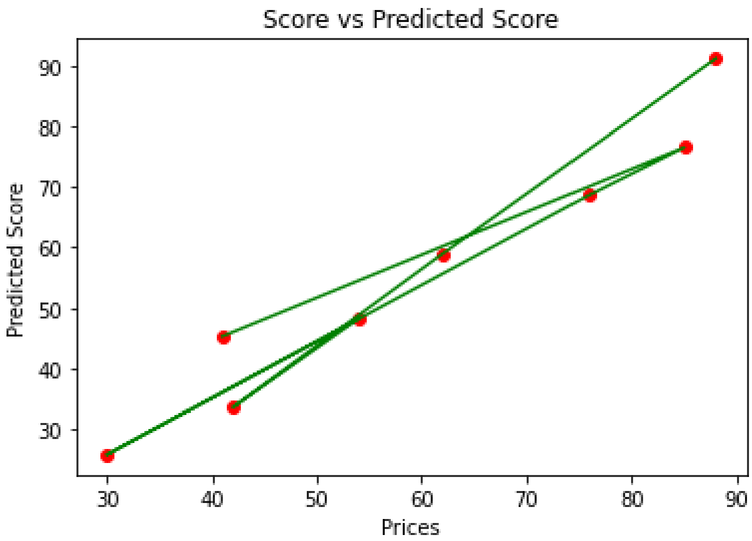
```
    mean_squared_error : 35.58803503032817
    mean_squared_log_error : 0.014404263100547189
    r2_score : 0.9134505912015123
```

```
#predicting the given data point:
data_1=np.array([[9.25]])
res=lr.predict(data_1)
```

```
print("Predicted Score = {}".format(res[0]))
```

```
Predicted Score = 91.67144901144641
```

```
plt.scatter(y_test,y_pred,c='r')
plt.plot(y_test,y_pred,c='g')
plt.xlabel("Prices")
plt.ylabel("Predicted Score")
plt.title("Score vs Predicted Score")
plt.show()
```



Feature Engineering:

```
#let us do some feature engineering on our data as we know that the dataset is very small so trying
```

```
data.head(3)
```

	Hours	Scores	Minutes	Seconds	Days
0	0.172840	21	0.172840	-0.135797	0.376315
1	0.493827	47	0.493827	-0.135786	1.327389
2	0.259259	27	0.259259	-0.135794	0.632373

```
#converting Hours to minutes ,seconds, days

data['Minutes']=data['Hours']*60
data['Seconds']=data['Hours']*60*60
data['Days']=data['Hours']/24.0
```

```
data.head()
```

	Hours	Scores	Minutes	Seconds	Days
0	2.5	21	150.0	9000.0	0.104167
1	5.1	47	306.0	18360.0	0.212500
3	8.5	75	510.0	30600.0	0.354167

Double-click (or enter) to edit

```
def scaler(x,col):
  min=data[col].min()
  max=data[col].max()
  if (max!=min):
    return (x-min)/(max-min)
  else:
    print('max and min values are same')
```

```
data['Minutes']=data['Minutes'].apply(lambda x: scaler(x,'Minutes'))
data['Hours']=data['Hours'].apply(lambda x: scaler(x,'Hours'))
data['Seconds']=data['Minutes'].apply(lambda x: scaler(x,'Seconds'))
data['Days']=data['Minutes'].apply(lambda x: scaler(x,'Days'))
```

```
data.head()
```

	Hours	Scores	Minutes	Seconds	Days
0	0.172840	21	0.172840	-0.135797	0.376315
1	0.493827	47	0.493827	-0.135786	1.327389
2	0.259259	27	0.259259	-0.135794	0.632373
3	0.913580	75	0.913580	-0.135771	2.571102
4	0.296296	30	0.296296	-0.135792	0.742112

```
y=data.Scores
X=data.drop('Scores',axis=1)
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.33, random_state = 95)
```

```
from sklearn.linear_model import LinearRegression
lr=LinearRegression()
lr.fit(X_train,y_train)
y_pred=lr.predict(X_test)
```

```
y_pred
```

```
array([45.875     , 78.34193878, 70.22520408, 25.58316327, 48.91877551,
       33.69989796, 60.07928571, 93.56081633, 86.45867347])
```

```
lr.coef_
```

```
array([7.62415797e+00, 7.62415797e+00, 2.61459464e-04, 2.25900977e+01])
```

```
lr.intercept
```

```
lr.intercept_
```

```
14.446704103698103
```

```
# Comparing Actual vs Predicted
df1=pd.DataFrame({'actual':y_test,'predicted':y_pred})
df1
```

	actual	predicted
12	41	45.875000
10	85	78.341939
23	76	70.225204
16	30	25.583163
21	54	48.918776
13	42	33.699898
11	62	60.079286
6	88	93.560816
3	75	86.458673

```
print('mean_squared_error :',mean_squared_error(y_test,y_pred))

print('mean_squared_log_error :',mean_squared_log_error(y_test,y_pred))

print('r2_score :',r2_score(y_test,y_pred))
```

```
mean_squared_error : 42.397297152806715
mean_squared_log_error : 0.014222328882571569
r2_score : 0.890860577468463
```

```
from sklearn.tree import DecisionTreeRegressor
dt=DecisionTreeRegressor()
dt.fit(X_train,y_train)
dt_pred=dt.predict(X_test)
```

```
dt_pred
```

```
array([47., 86., 69., 21., 47., 27., 67., 95., 81.])
```

```
# Comparing Actual vs Predicted
df1=pd.DataFrame({'actual':y_test,'predicted':dt_pred})
df1
```

	actual	predicted
12	41	47.0
10	85	86.0
23	76	69.0
16	30	21.0
21	54	47.0

```
print('mean_squared_error :',mean_squared_error(y_test,dt_pred))

print('mean_squared_log_error :',mean_squared_log_error(y_test,dt_pred))

print('r2_score :',r2_score(y_test,dt_pred))
```

```
mean_squared_error : 61.22222222222222
mean_squared_log_error : 0.04050750960769281
r2_score : 0.8424013220619081
```

```
from sklearn.svm import LinearSVR
svr=LinearSVR()
svr.fit(X_train,y_train)
svr_pred=svc.predict(X_test)
```

```
# Comparing Actual vs Predicted
df1=pd.DataFrame({'actual':y_test,'predicted':svr_pred})
df1
```

	actual	predicted
12	41	36.796299
10	85	60.910266
23	76	54.881774
16	30	21.725070
21	54	39.056983
13	42	27.753561
11	62	47.346159
6	88	72.213688
3	75	66.938757

```
print('mean_squared_error :',mean_squared_error(y_test,svr_pred))

print('mean_squared_log_error :',mean_squared_log_error(y_test,svr_pred))

print('r2_score :',r2_score(y_test,svr_pred))
```

```
mean_squared_error : 229.73571324566197
mean_squared_log_error : 0.07795306396550865
r2_score : 0.4086127002828889
```

```
from sklearn.naive_bayes import GaussianNB
nb=GaussianNB()
nb.fit(X_train,y_train)
nb_pred=svc.predict(X_test)
```

```
nb_pred
```

```
array([36.796299  , 60.91026578, 54.88177408, 21.72506977, 39.05698339,
       27.75356146, 47.34615947, 72.2136877 , 66.93875747])
```

```
# Comparing Actual vs Predicted
df1=pd.DataFrame({'actual':y_test,'predicted':nb_pred})
df1
```

	actual	predicted
12	41	36.796299
10	85	60.910266
23	76	54.881774
16	30	21.725070
21	54	39.056983
13	42	27.753561
11	62	47.346159
6	88	72.213688
3	75	66.938757

```
print('mean_squared_error :',mean_squared_error(y_test,svr_pred))

print('mean_squared_log_error :',mean_squared_log_error(y_test,svr_pred))

print('r2_score :',r2_score(y_test,svr_pred))
```

```
mean_squared_error : 229.73571324566197
mean_squared_log_error : 0.07795306396550865
r2_score : 0.4086127002828889
```

Results and conclusions:

```
#for results table:
from prettytable import PrettyTable
x = PrettyTable()

x.field_names = ["model", "mean_squared_error","mean_squared_log_error" ,"r2_score"]
```

```
x.add_row(["LinearRegression without new features","35.58803503032817","0.014404263100547189","0.913


x.add_row(["LinearRegression ","42.397297152806715"," 0.014222328882571569","0.890860577468463"])

x.add_row(["DecisionTreeRegressor ","61.22222222222222"," 0.04050750960769281"," 0.8424013220619081"
x.add_row(["GaussianNB:","229.73571324566197 ","0.07795306396550865 ","  0.4086127002828889"])

x.add_row(["LinearSVR ","229.73571324566197 "," 0.07795306396550865"," 0.4086127002828889 "])



print(x)
```

```
+----------------------------------------+---------------------+-------------------------+------
|                 model                  |  mean_squared_error | mean_squared_log_error  |
+----------------------------------------+---------------------+-------------------------+------
| LinearRegression without new features  |  35.58803503032817  |  0.014404263100547189   |  0.91
|           LinearRegression             |  42.397297152806715 |  0.014222328882571569   |  0.89
|         DecisionTreeRegressor          |  61.22222222222222  |   0.04050750960769281   |  0.84
|              GaussianNB:               | 229.73571324566197  |  0.07795306396550865    |   0.4
|               LinearSVR                | 229.73571324566197  |   0.07795306396550865   |  0.40
+----------------------------------------+---------------------+-------------------------+------
```