```
#This is a Student Performance Dataset designed to examine the factors
influencing academic student performance.
#In this notebook, I have implemented multiple linear regression from
stratch.

import pandas as pd
import numpy as np
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
import seaborn as sns
from sklearn import linear_model
import matplotlib.pyplot as plt

data=pd.read_csv(r"C:\Users\shamzkha\Documents\
Student_Performance.csv")

data.shape

(10000, 6)

data.head()

   Hours Studied  Previous Scores Extracurricular Activities  Sleep
Hours  \
0              7               99                        Yes
9
1              4               82                         No
4
2              8               51                        Yes
7
3              5               52                        Yes
5
4              7               75                         No
8

   Sample Question Papers Practiced  Performance Index
0                                 1               91.0
1                                 2               65.0
2                                 2               45.0
3                                 2               36.0
4                                 5               66.0

data.isnull().sum()

Hours Studied                       0
Previous Scores                     0
Extracurricular Activities          0
Sleep Hours                         0
Sample Question Papers Practiced    0
Performance Index                   0
dtype: int64
```

```
#No missing values found

#Renaming the columns

data=data.rename(columns={"Hours Studied":"Hours_Studied"})

data=data.rename(columns={"Previous Scores":"Previous_Scores"})

data=data.rename(columns={"Extracurricular
Activities":"Extracurricular_Activities"})

data=data.rename(columns={"Sleep Hours":"Sleep_Hours"})

data=data.rename(columns={"Sample Question Papers Practiced":"SQPP"})

data=data.rename(columns={"Performance Index":"Performance_Index"})

data.dtypes

Hours_Studied                  int64
Previous_Scores                int64
Extracurricular_Activities    object
Sleep_Hours                    int64
SQPP                           int64
Performance_Index            float64
dtype: object
```

Converting categorical value to numerical value

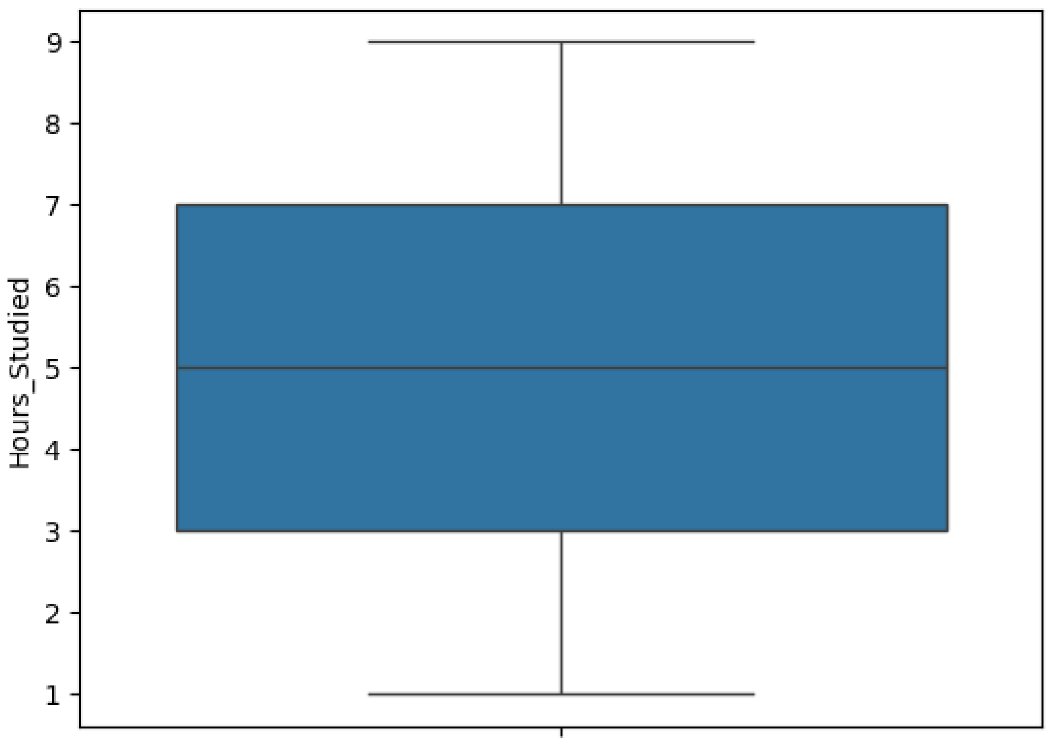
```
data.Extracurricular_Activities=le.fit_transform(data.Extracurricular_
Activities)

#data.dtypes
```

EDA

```
#The target column performance index is numerical so no class
imbalance treatment is required
```

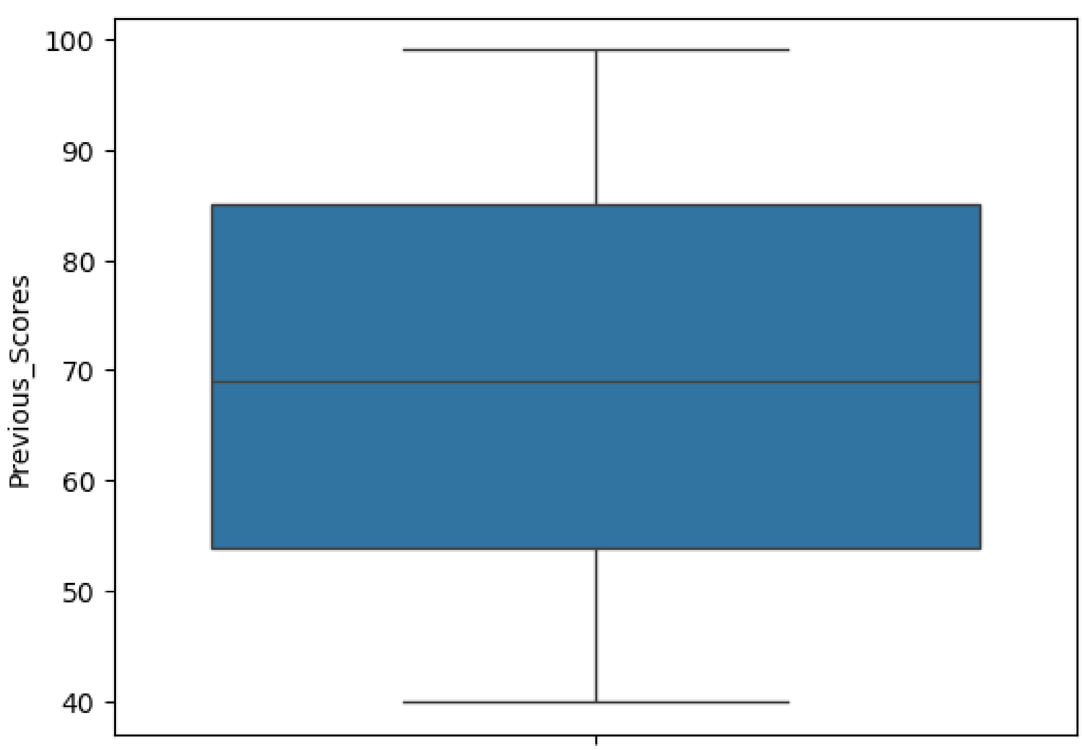
Outlier Treatment

```
sns.boxplot(data=data,y="Hours_Studied")

<Axes: ylabel='Hours_Studied'>
```



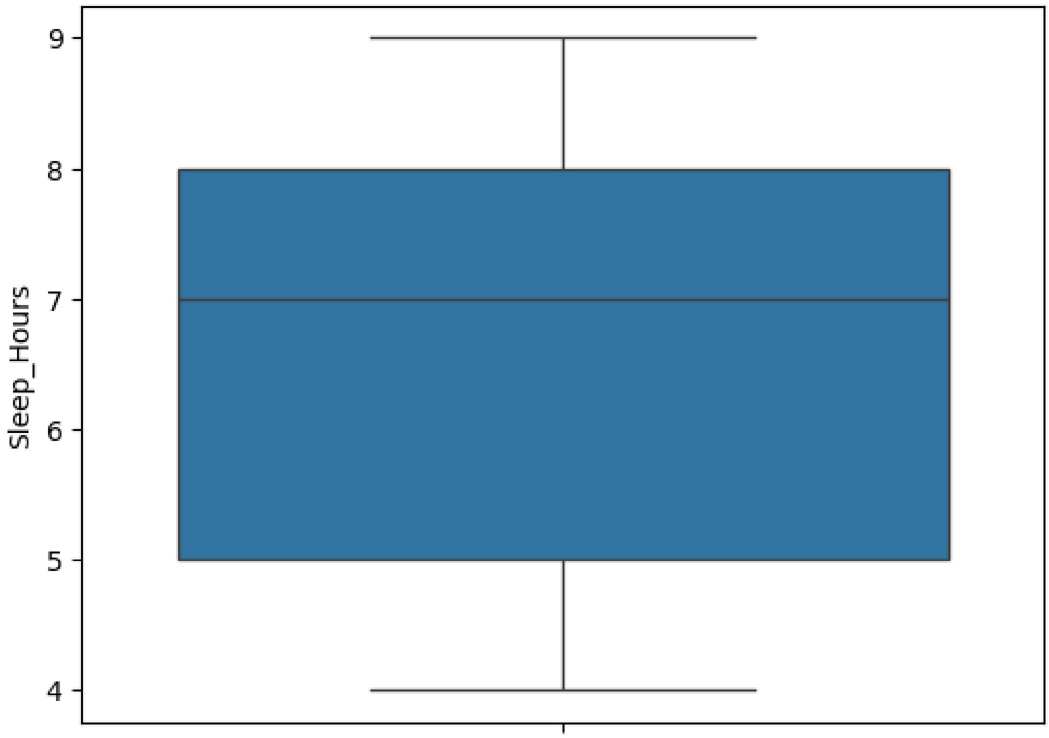

```
sns.boxplot(data=data,y="Previous_Scores")
```

```
<Axes: ylabel='Previous_Scores'>
```



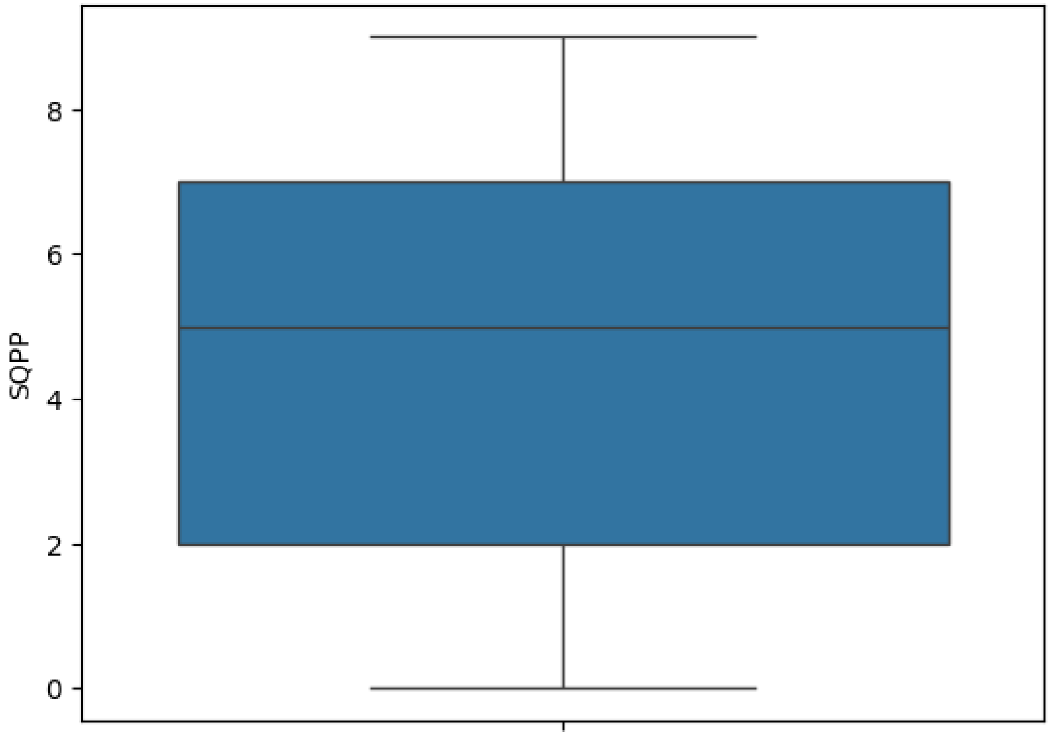
```
sns.boxplot(data=data,y="Sleep_Hours")
```

```
<Axes: ylabel='Sleep_Hours'>
```




```
sns.boxplot(data=data,y="SQPP")
```

```
<Axes: ylabel='SQPP'>
```




```
#extracurricular activities not checked as it is categorical column

#No outlier ,so no treatment is required
```

Correlation

```
data1=data.corr()
data1
```

```
                            Hours_Studied  Previous_Scores  \
Hours_Studied                    1.000000        -0.012390
Previous_Scores                 -0.012390         1.000000
Extracurricular_Activities       0.003873         0.008369
Sleep_Hours                      0.001245         0.005944
SQPP                             0.017463         0.007888
Performance_Index                0.373730         0.915189

                            Extracurricular_Activities  Sleep_Hours
SQPP  \
Hours_Studied                                 0.003873     0.001245
0.017463
Previous_Scores                               0.008369     0.005944
0.007888
Extracurricular_Activities                    1.000000    -0.023284
0.013103
```

```
Sleep_Hours                                        -0.023284     1.000000
0.003990
SQPP                                                0.013103     0.003990
1.000000
Performance_Index                                   0.024525     0.048106
0.043268

                            Performance_Index
Hours_Studied                        0.373730
Previous_Scores                      0.915189
Extracurricular_Activities           0.024525
Sleep_Hours                          0.048106
SQPP                                 0.043268
Performance_Index                    1.000000

#Conclusion:

#Performance Index is most strongly correlated with Previous Scores
(0.915).
#Hours Studied has a moderate, positive correlation with Performance
Index (0.374).
#Extracurricular Activities, Sleep Hours, and SQPP show weak
correlations with performance.
```

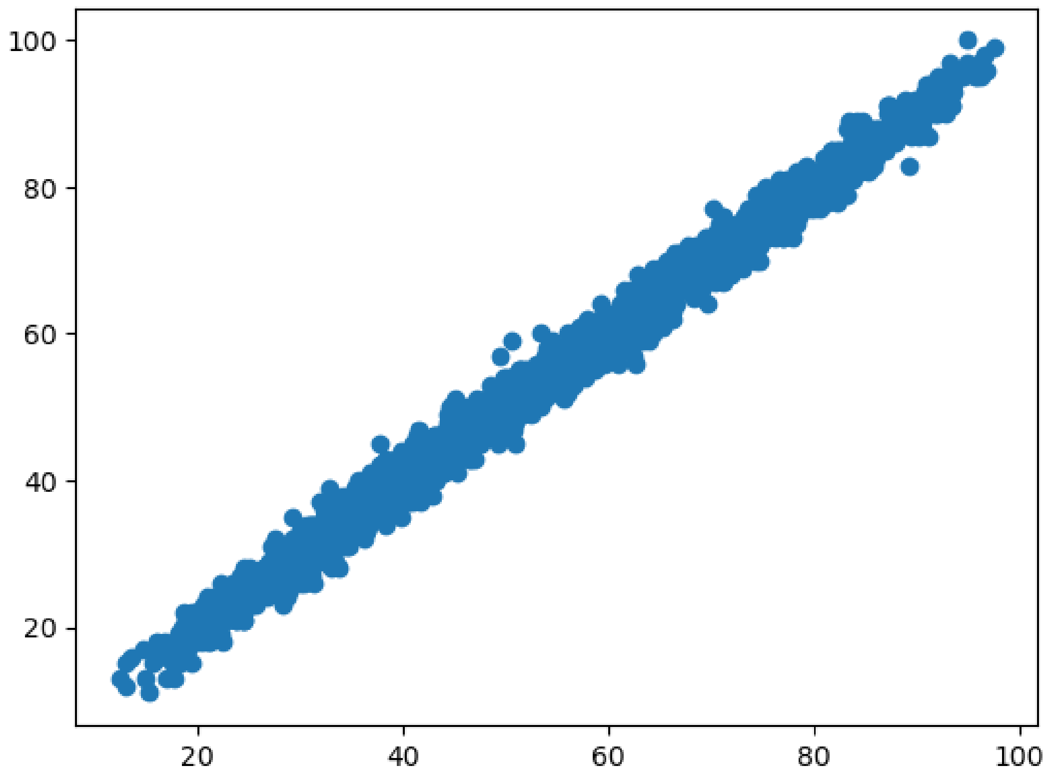
Linear Regression

```
data.head()

   Hours_Studied  Previous_Scores  Extracurricular_Activities
Sleep_Hours  \
0              7               99                           1
9
1              4               82                           0
4
2              8               51                           1
7
3              5               52                           1
5
4              7               75                           0
8

   SQPP  Performance_Index
0     1               91.0
1     2               65.0
2     2               45.0
3     2               36.0
4     5               66.0
```

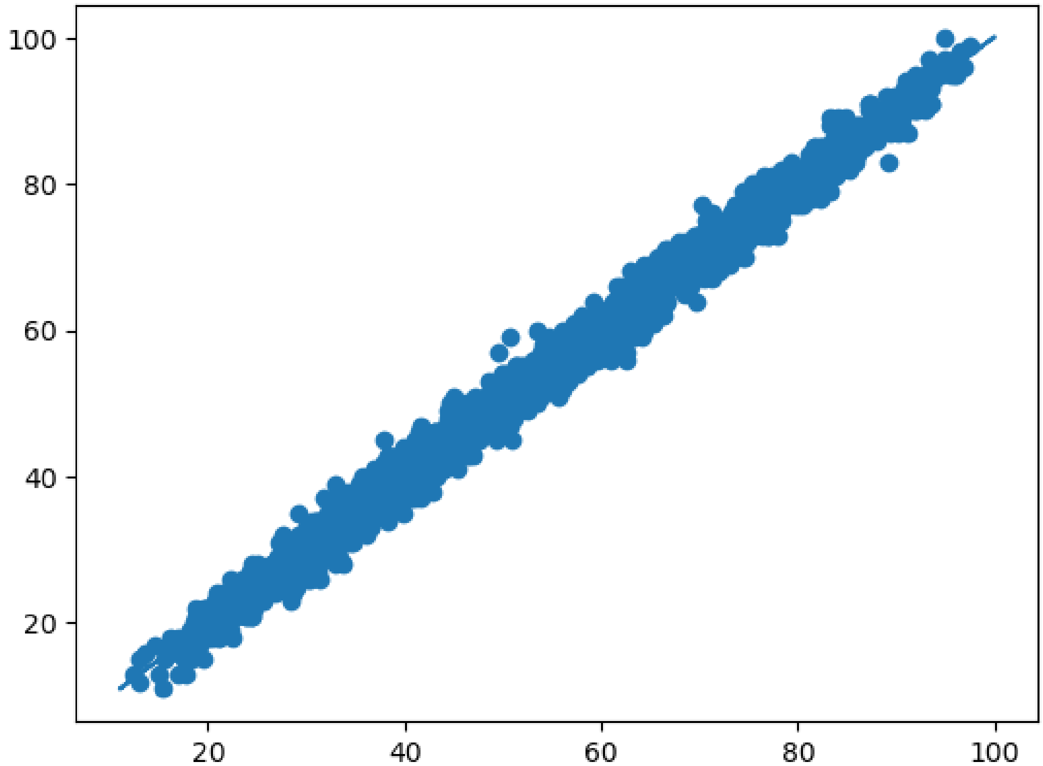
```
#Separating features from target

x=data.iloc[:,0:5]
#x.head()

y=data.iloc[:,5]
#y.head()

import sklearn
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,rando
m_state=101)

x_train.shape,x_test.shape,y_train.shape,y_test.shape

((8000, 5), (2000, 5), (8000,), (2000,))

from sklearn import linear_model

linear=linear_model.LinearRegression()

linear.fit(x_train,y_train)

LinearRegression()

pred=linear.predict(x_test)
pred

array([44.38891422, 96.15853705, 30.52422606, ..., 45.9649391 ,
       59.64558417, 16.80314704])

linear.coef_

array([2.85283863, 1.01817717, 0.63290609, 0.48524068, 0.19369907])

linear.intercept_

-34.10276056362111

R2=linear.score(x_train,y_train) #Rsquare vale
R2

0.9887109739552409

Adj_R2=1-(((1-R2)*(8000-1))/(8000-5-1)) #adjusted Rsquare value
Adj_R2

0.9887039130182602

pred_train=linear.predict(x_train)
#pred_train
pred_train.shape
```

```
(8000,)

mean_y=y_train.mean()
mean_y

55.260625

SSE=np.sum(np.square(pred_train-y_train))
SSE

33333.5316344614

SSR=np.sum(np.square(pred_train-mean_y))
SSR

2919404.0652405405

Rsq=SSR/(SSR+SSE) #Rsquare value by formula
Rsq

0.9887109739552408

from sklearn import metrics

#MAE=mean absolute error

MSE=metrics.mean_squared_error(pred,y_test)
MSE

4.091042932500655

RMSE=np.sqrt(MSE)
RMSE

2.0226326736460716

#MAPE=Mean absolute Percentage Error

error=pred-y_test
error
error_abs=np.abs(error)
#error_abs

MAPE=np.mean(error_abs/y_test)*100
MAPE

3.512131434073932

Accuracy=(100-MAPE)
Accuracy

96.48786856592606
```

```
plt.scatter(pred,y_test)
plt.show()
```




```
from scipy import stats
slope,intercepts,r,p,std_err=stats.linregress(pred,y_test)
def myfunc(y_test):
    return slope*y_test+intercepts
mymodel=list(map(myfunc,y_test))

plt.scatter(pred,y_test)
plt.plot(y_test,mymodel)
plt.show()
```




```
#Conclusion:

#The linear regression model developed for predicting the dependent variable has demonstrated strong predictive performance, with an accuracy of 96.48%.
#This indicates that the model is highly effective at making predictions, with minimal error.
#The adjusted R-squared value of 0.988870 suggests that approximately 98.89% of the variance in the dependent variable can be explained by the independent variables in the model.
```

L1=Lasso

```
from sklearn.linear_model import Lasso
lasso=Lasso()

lasso.fit(x_train,y_train)

Lasso()

lasso.coef_

array([2.71029613, 1.01484602, 0.        , 0.13493396, 0.07585949])
```

```
l1_pred=lasso.predict(x_test)
l1_pred
```

```
array([45.53780956, 95.07744207, 31.42387377, ..., 45.41309159,
       60.24373499, 16.69862985])
```

```
l1_R2=lasso.score(x_train,y_train)
l1_R2
```

```
0.9867853232610752
```

```
l1_adj_R2=1-(((1-l1_R2)*(8000-1))/(8000-5-1))
l1_adj_R2
```

```
0.9867770578890843
```

```
df=pd.DataFrame({"Feature_importances":lasso.coef_,"columns":list(x)})
df
```

	Feature_importances	columns
0	2.710296	Hours_Studied
1	1.014846	Previous_Scores
2	0.000000	Extracurricular_Activities
3	0.134934	Sleep_Hours
4	0.075859	SQPP

```
df2=pd.DataFrame({"Actual":y_test,"Predictions":l1_pred})
df2
```

	Actual	Predictions
6676	43.0	45.537810
6421	95.0	95.077442
9834	29.0	31.423874
8492	48.0	51.069095
9982	44.0	44.171937
...	...	...
4441	38.0	39.997799
4166	42.0	39.652071
2567	46.0	45.413092
8527	61.0	60.243735
406	17.0	16.698630

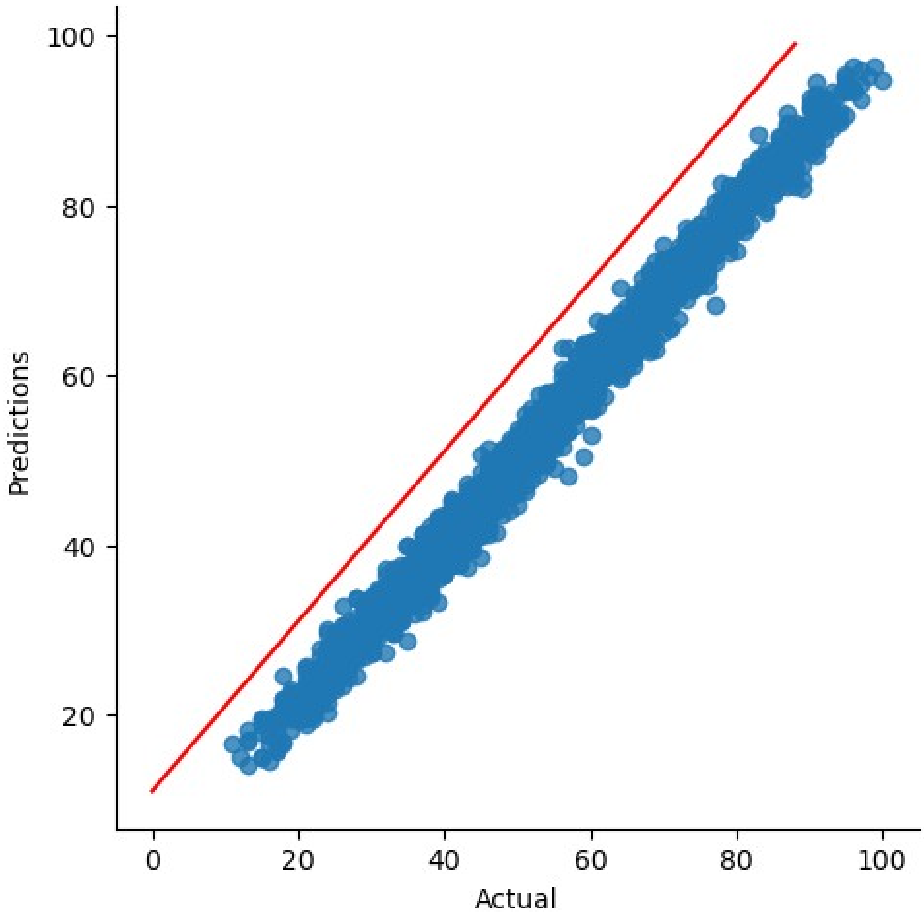
[2000 rows x 2 columns]

```
MSE_l1=metrics.mean_squared_error(l1_pred,y_test)
MSE_l1
```

```
4.718953466209578
```

```
sns.lmplot(x="Actual",y="Predictions",data=df2,fit_reg=False)
d_line=np.arange(df2.min().min(),df2.max().max())
```

```
plt.plot(d_line,color="red",linestyle="-")
plt.show()
```



L2=Ridge

```
from sklearn.linear_model import Ridge
rd=Ridge()

rd.fit(x_train,y_train)

Ridge()

rd_pred=rd.predict(x_test)
rd_pred

array([44.38903204, 96.15814176, 30.52429609, ..., 45.96509303,
       59.64559074, 16.80317541])

list(rd.coef_)
```

```
[2.8527862054001183,
 1.0181766862753776,
 0.6325885585926317,
 0.4852177273122147,
 0.1936980544421156]
```

```python
rd_R2=rd.score(x_train,y_train)
rd_R2
```

```
0.9887109738325554
```

```python
rd_adj_R2=1-(((1-rd_R2)*(8000-1))/(8000-5-1))
rd_adj_R2
```

```
0.9887039128954979
```

```python
df_1=pd.DataFrame({"Feature_importances":rd.coef_,"columns":list(x)})
df_1
```

	Feature_importances	columns
0	2.852786	Hours_Studied
1	1.018177	Previous_Scores
2	0.632589	Extracurricular_Activities
3	0.485218	Sleep_Hours
4	0.193698	SQPP

```python
df_2=pd.DataFrame({"Actual":y_test,"Predictions":rd_pred})
df_2
```

	Actual	Predictions
6676	43.0	44.389032
6421	95.0	96.158142
9834	29.0	30.524296
8492	48.0	49.753932
9982	44.0	43.266933
...	...	...
4441	38.0	39.831898
4166	42.0	38.667764
2567	46.0	45.965093
8527	61.0	59.645591
406	17.0	16.803175

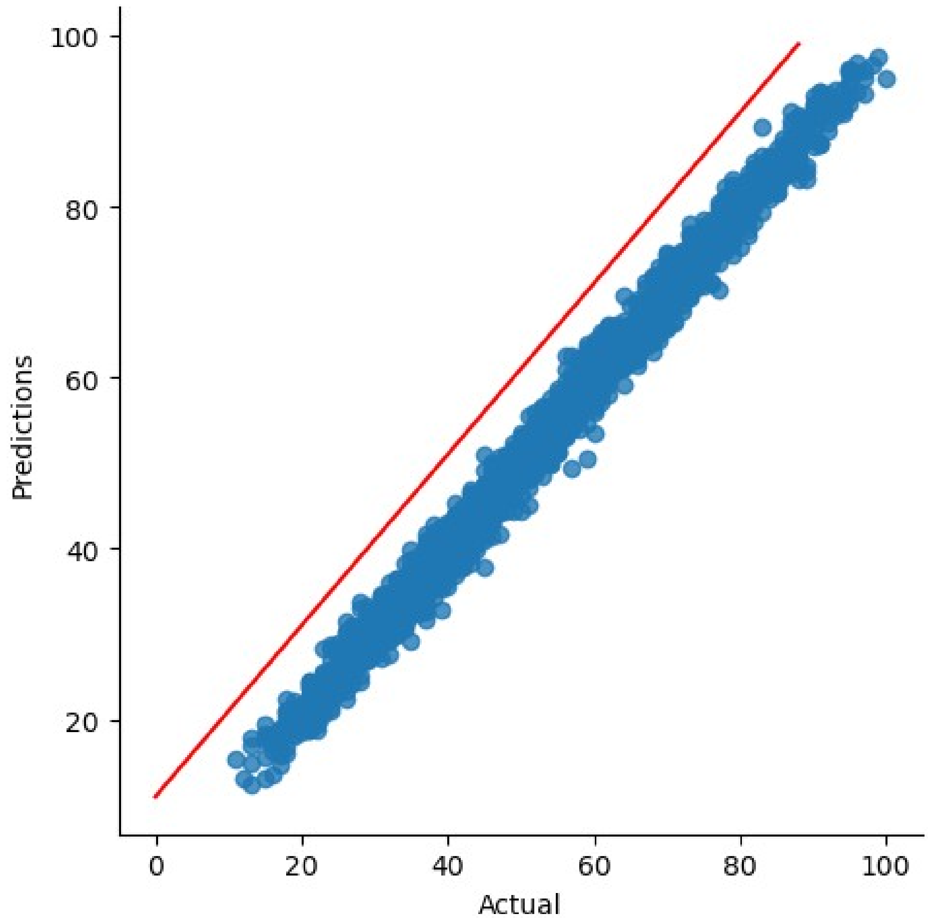
```
[2000 rows x 2 columns]
```

```python
MSE_rd=metrics.mean_squared_error(rd_pred,y_test)
MSE_rd
```

```
4.0910252511709615
```

```python
sns.lmplot(x="Actual",y="Predictions",data=df_2,fit_reg=False)
d_line=np.arange(df_2.min().min(),df_2.max().max())
```

```
plt.plot(d_line,color="red",linestyle="-")
plt.show()
```



Feature Selection

```
df
```

	Feature_importances	columns
0	2.710296	Hours_Studied
1	1.014846	Previous_Scores
2	0.000000	Extracurricular_Activities
3	0.134934	Sleep_Hours
4	0.075859	SQPP

```
data.shape
```

```
(10000, 6)
```

```
l_new=data.drop(["Extracurricular_Activities","SQPP"],axis=1)
#dropping the non-significant columns
l_new.shape
```

```
(10000, 4)
```

```
l_new.head()
```

```
   Hours_Studied  Previous_Scores  Sleep_Hours  Performance_Index
0              7               99            9               91.0
1              4               82            4               65.0
2              8               51            7               45.0
3              5               52            5               36.0
4              7               75            8               66.0
```

```
l_new.isnull().sum()
```

```
Hours_Studied        0
Previous_Scores      0
Sleep_Hours          0
Performance_Index    0
dtype: int64
```

```
l_new.dtypes
```

```
Hours_Studied          int64
Previous_Scores        int64
Sleep_Hours            int64
Performance_Index    float64
dtype: object
```

```
x1=l_new.iloc[:,0:3] #separating significant features from target
x1.head()
```

```
   Hours_Studied  Previous_Scores  Sleep_Hours
0              7               99            9
1              4               82            4
2              8               51            7
3              5               52            5
4              7               75            8
```

```
y1=l_new.iloc[:,3]
y1.head()
```

```
0    91.0
1    65.0
2    45.0
3    36.0
4    66.0
Name: Performance_Index, dtype: float64
```

```
x1_train,x1_test,y1_train,y1_test=train_test_split(x1,y1,test_size=0.2
,random_state=101)
x1_train.shape,x1_test.shape,y1_train.shape,y1_test.shape
```

```
((8000, 3), (2000, 3), (8000,), (2000,))
```

```
linear.fit(x1_train,y1_train)
```

```
LinearRegression()
```

```
linear_new_pred=linear.predict(x1_test)
linear_new_pred
```

```
array([45.03684486, 95.97802431, 30.87754813, ..., 45.97886901,
       59.91952586, 16.5575236 ])
```

```
new_R2=linear.score(x1_train,y1_train)
new_R2
```

```
0.9875902655142141
```

```
Anew_R2=1-(((1-new_R2)*(8000-1))/(8000-3-1))
Anew_R2
```

```
0.9875856095357928
```

```
new_MSE=metrics.mean_squared_error(linear_new_pred,y1_test)
new_MSE
```

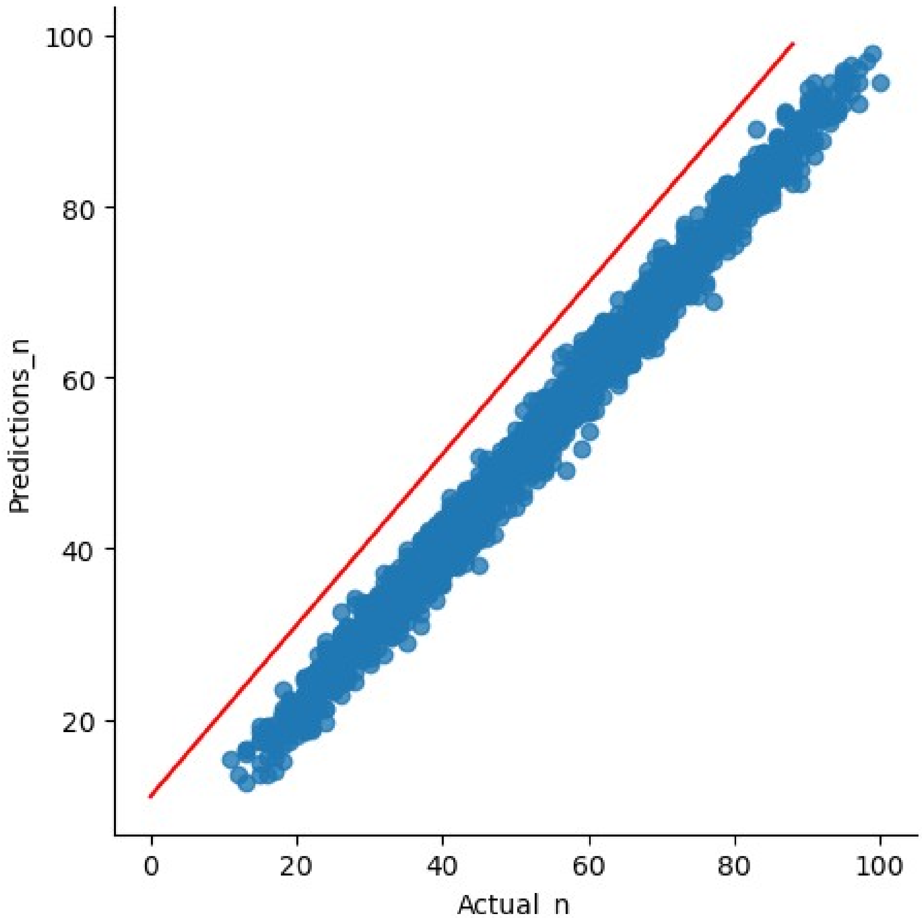
```
4.470622176935699
```

```
df_new=pd.DataFrame({"Actual_n":y1_test,"Predictions_n":linear_new_pre
d})
df_new
```

```
      Actual_n  Predictions_n
6676      43.0      45.036845
6421      95.0      95.978024
9834      29.0      30.877548
8492      48.0      50.374289
9982      44.0      44.299792
...        ...            ...
4441      38.0      39.024597
4166      42.0      38.068905
2567      46.0      45.978869
8527      61.0      59.919526
406       17.0      16.557524

[2000 rows x 2 columns]
```

```
sns.lmplot(x="Actual_n",y="Predictions_n",data=df_new,fit_reg=False)
d_line=np.arange(df_new.min().min(),df_new.max().max())
```

```
plt.plot(d_line,color="red",linestyle="-")
plt.show()
```




```
list1=["Linear Regression","Lasso","Ridge","Feature_SelectionModel"]
list2=[R2,l1_R2,rd_R2,new_R2]
list3=[Adj_R2,l1_adj_R2,rd_adj_R2,Anew_R2]
list4=[MSE,MSE_l1,MSE_rd,new_MSE]

Final_Result=pd.DataFrame({"Model_Name":list1,"R2_value":list2,"Adj_R2
":list3,"MSE":list4})
Final_Result
```

	Model_Name	R2_value	Adj_R2	MSE
0	Linear Regression	0.988711	0.988704	4.091043
1	Lasso	0.986785	0.986777	4.718953
2	Ridge	0.988711	0.988704	4.091025
3	Feature_SelectionModel	0.987590	0.987586	4.470622

```
#Conclusion:

#The Linear Regression and Ridge models are the best, showing
```

```
identical Rsquare, adjusted Rsquare, and MSE values.
#In comparison, the Lasso and Feature Selection Model show slightly
lower performance with R-squared values of 0.986785 and 0.987590, as
well as higher MSEs.
#In summary, the high accuracy and adjusted R-squared value confirm
that the linear regression model and Ridge is both reliable and
capable of providing meaningful insights for prediction.
```