```
#Basic libraries

import os
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
sns.set()

import warnings
warnings.filterwarnings("ignore")

dataset = pd.read_csv("Student_Performance.csv")
dataset.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
```

```
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 6 columns):
 #   Column                            Non-Null Count  Dtype
---  ------                            --------------  -----
 0   Hours Studied                     10000 non-null  int64
 1   Previous Scores                   10000 non-null  int64
 2   Extracurricular Activities        10000 non-null  object
 3   Sleep Hours                       10000 non-null  int64
 4   Sample Question Papers Practiced  10000 non-null  int64
 5   Performance Index                 10000 non-null  float64
```

```
dtypes: float64(1), int64(4), object(1)
memory usage: 468.9+ KB
```

```
dataset.describe()
```

```
       Hours Studied  Previous Scores   Sleep Hours  \
count   10000.000000     10000.000000  10000.000000
mean        4.992900        69.445700      6.530600
std         2.589309        17.343152      1.695863
min         1.000000        40.000000      4.000000
25%         3.000000        54.000000      5.000000
50%         5.000000        69.000000      7.000000
75%         7.000000        85.000000      8.000000
max         9.000000        99.000000      9.000000

       Sample Question Papers Practiced  Performance Index
count                      10000.000000       10000.000000
mean                           4.583300          55.224800
std                            2.867348          19.212558
min                            0.000000          10.000000
25%                            2.000000          40.000000
50%                            5.000000          55.000000
75%                            7.000000          71.000000
max                            9.000000         100.000000
```

```
dataset.isnull().sum()
```

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

```
# Cheking outlier
```

```
dataset.isnull().sum()/len(dataset)*100
```

```
Hours Studied                       0.0
Previous Scores                     0.0
Extracurricular Activities          0.0
Sleep Hours                         0.0
Sample Question Papers Practiced    0.0
Performance Index                   0.0
dtype: float64
```

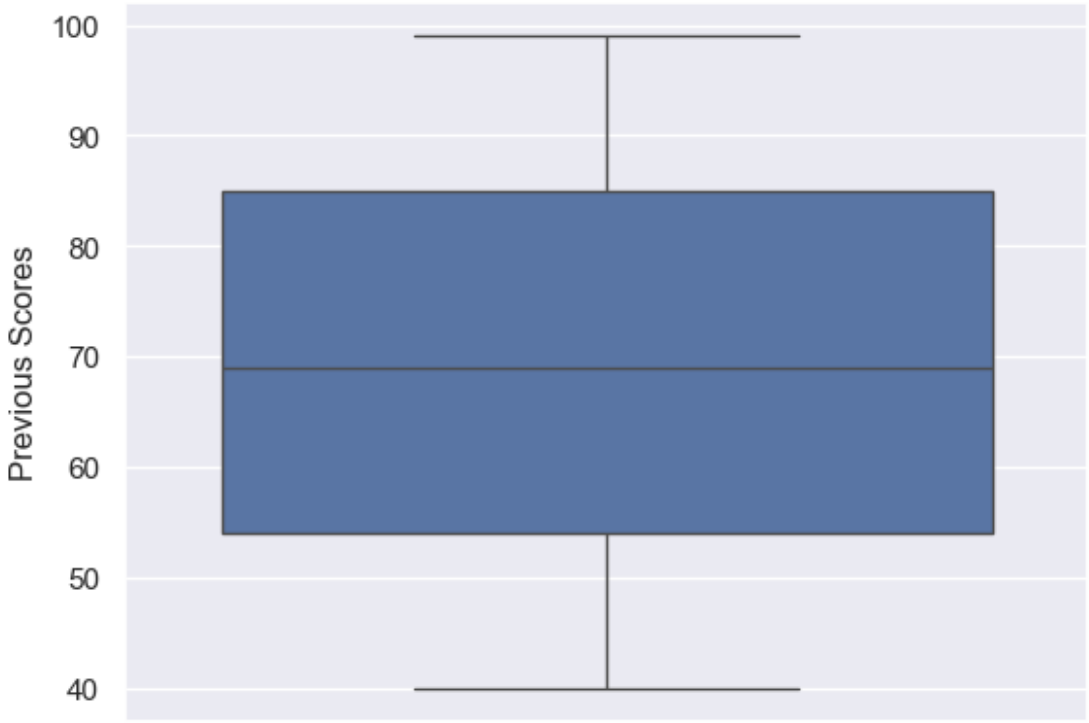
```
dataset.duplicated().sum()
```

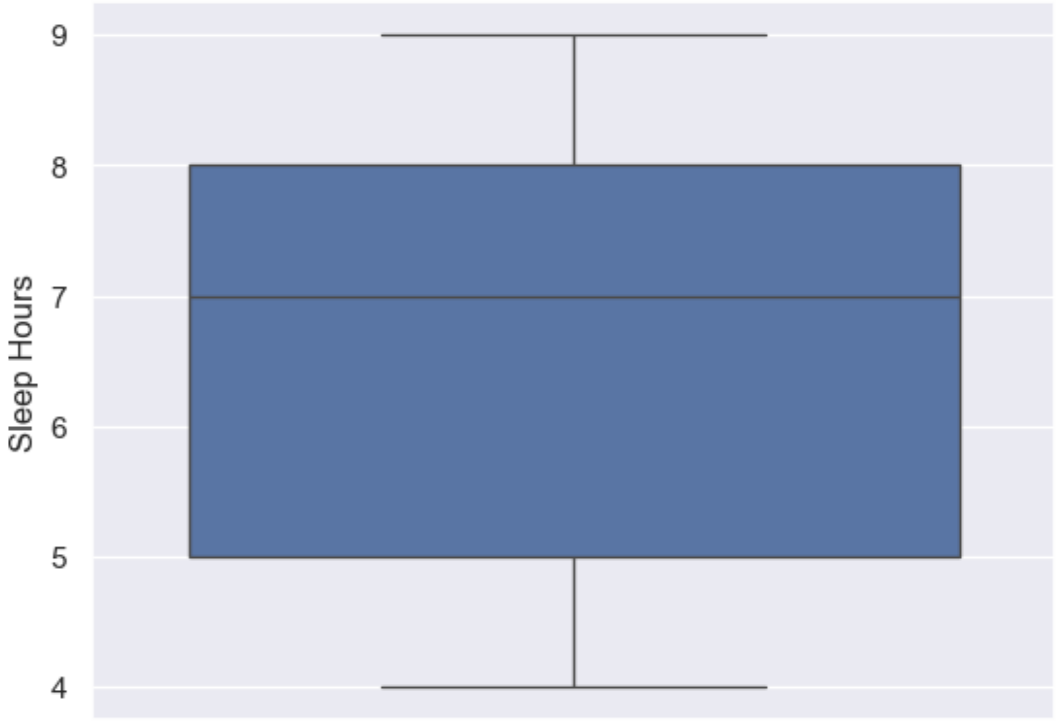
```
127
```

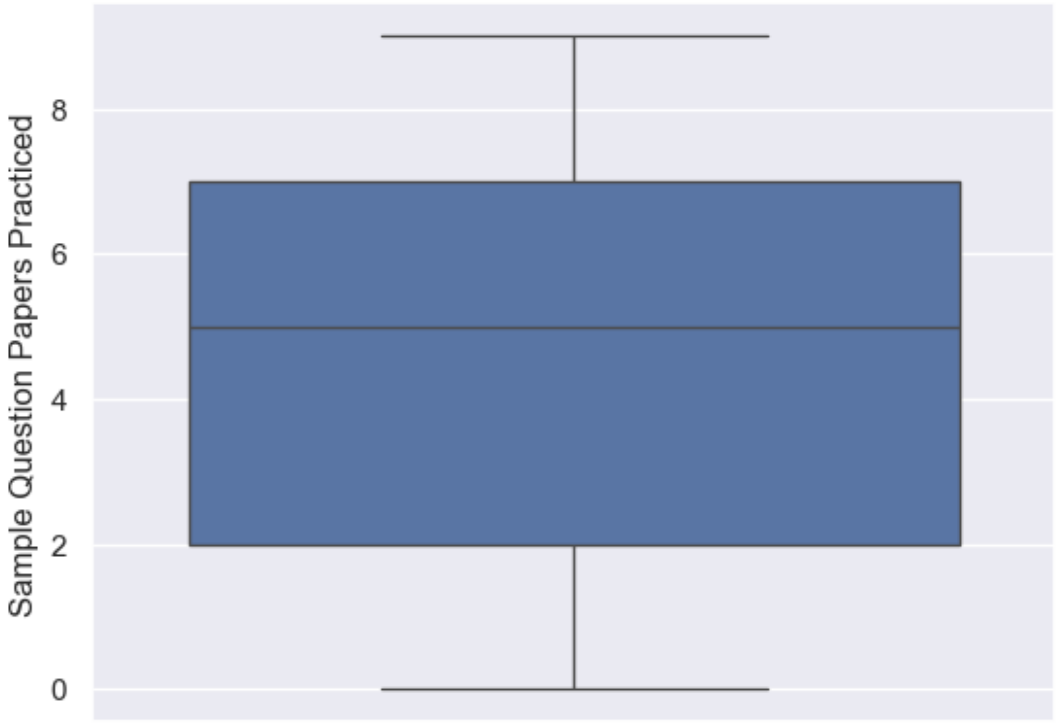
```
dataset = dataset.drop_duplicates()
dataset.duplicated().sum()
```

```
0
```

```
def boxplots(col):
    sns.boxplot(dataset[col])
    plt.show()

for i in list(dataset.select_dtypes(exclude =['object']).columns)[0:]:
    boxplots(i)
```


Previous Scores
100
90
80
70
60
50
40


Sleep Hours
9
8
7
6
5
4



Encoding the cat. variable

```
dataset['Extracurricular Activities'].value_counts()
```

```
Extracurricular Activities
No     4986
Yes    4887
Name: count, dtype: int64
```

```
dataset['Extracurricular Activities'] = dataset['Extracurricular
Activities'].astype('category')
dataset['Extracurricular Activities'] = dataset['Extracurricular
Activities'].cat.codes
```

```
dataset['Extracurricular Activities'].value_counts()
```

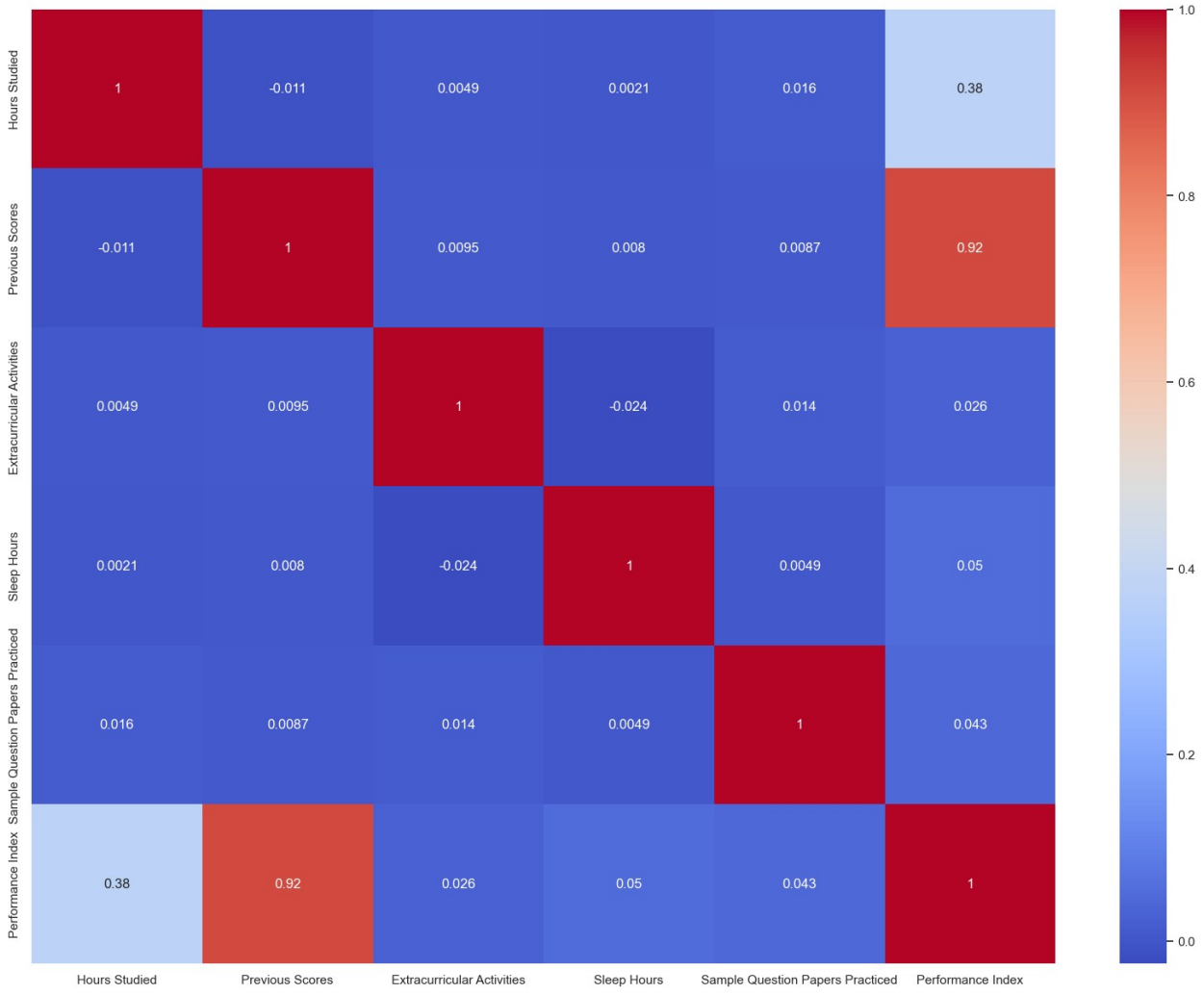
```
Extracurricular Activities
0    4986
1    4887
Name: count, dtype: int64
```

```
dataset.head()
```

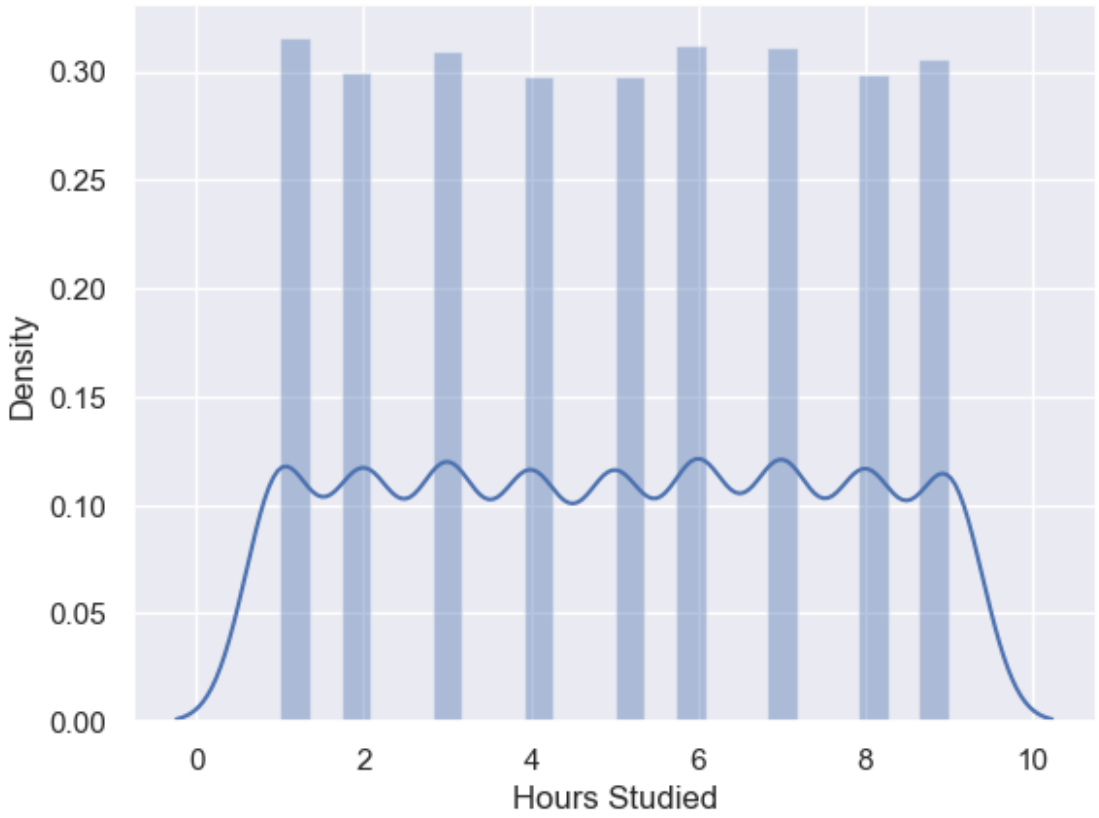
```
   Hours Studied  Previous Scores  Extracurricular Activities  Sleep
Hours  \
0              7               99                           1
9
1              4               82                           0
4
2              8               51                           1
7
3              5               52                           1
5
4              7               75                           0
8

   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
```

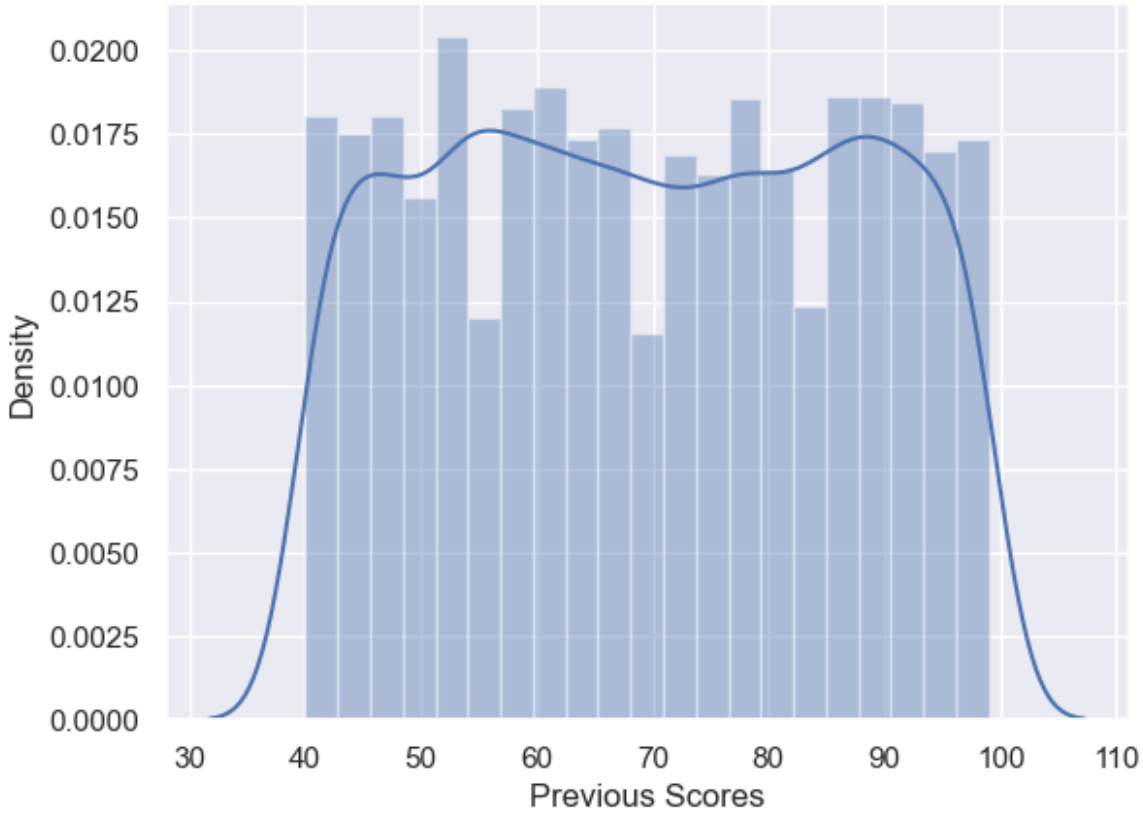
Finding correlation

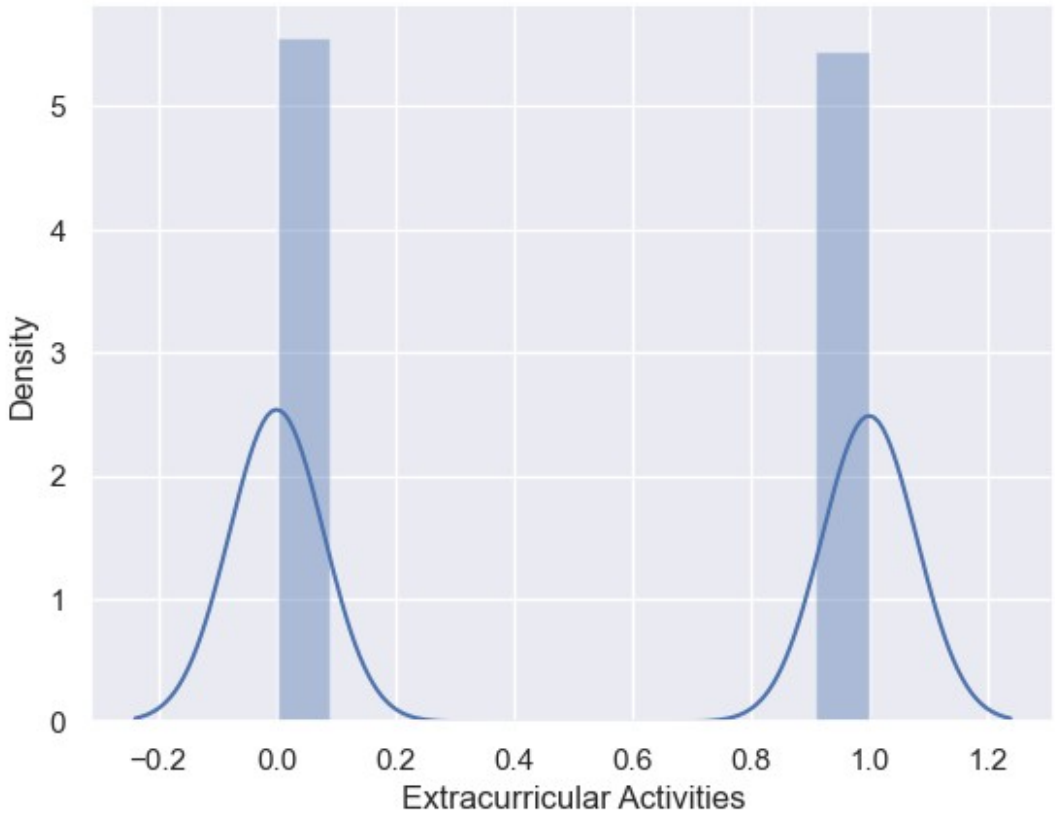
```
plt.figure(figsize=(20,15))
#corr = dataset.corr()
sns.heatmap(dataset.corr(), annot=True, cmap='coolwarm')
plt.show()
```

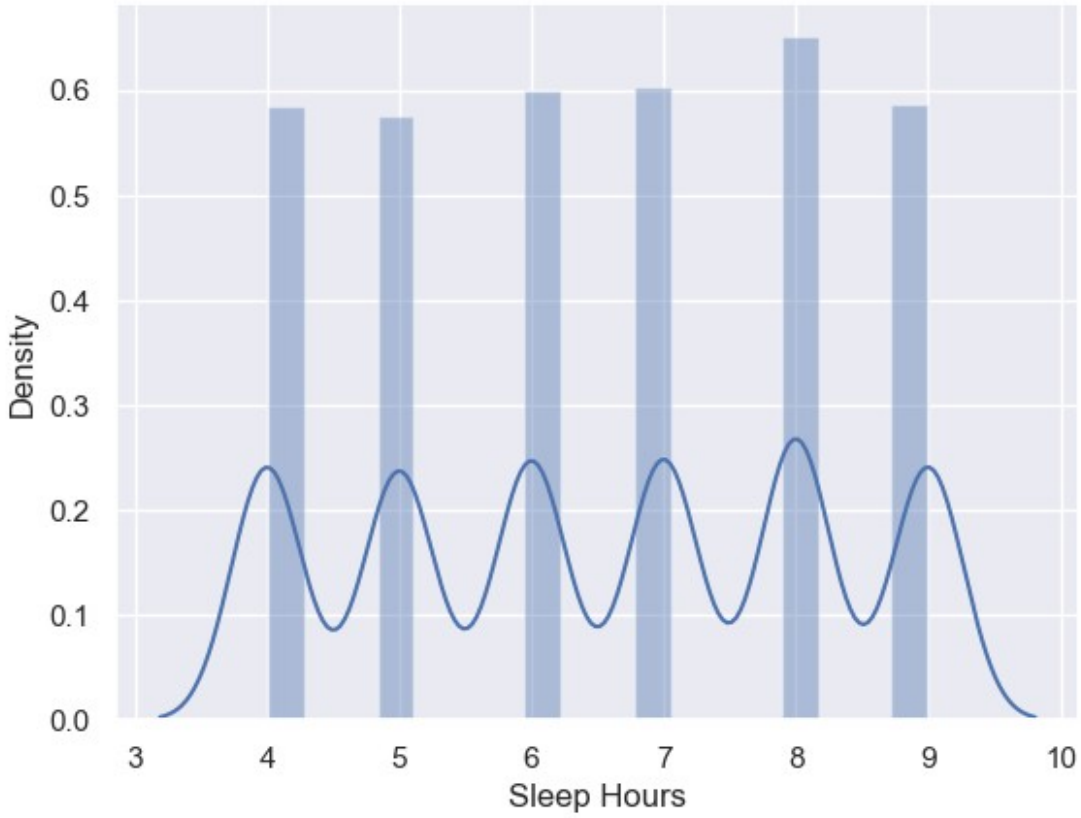


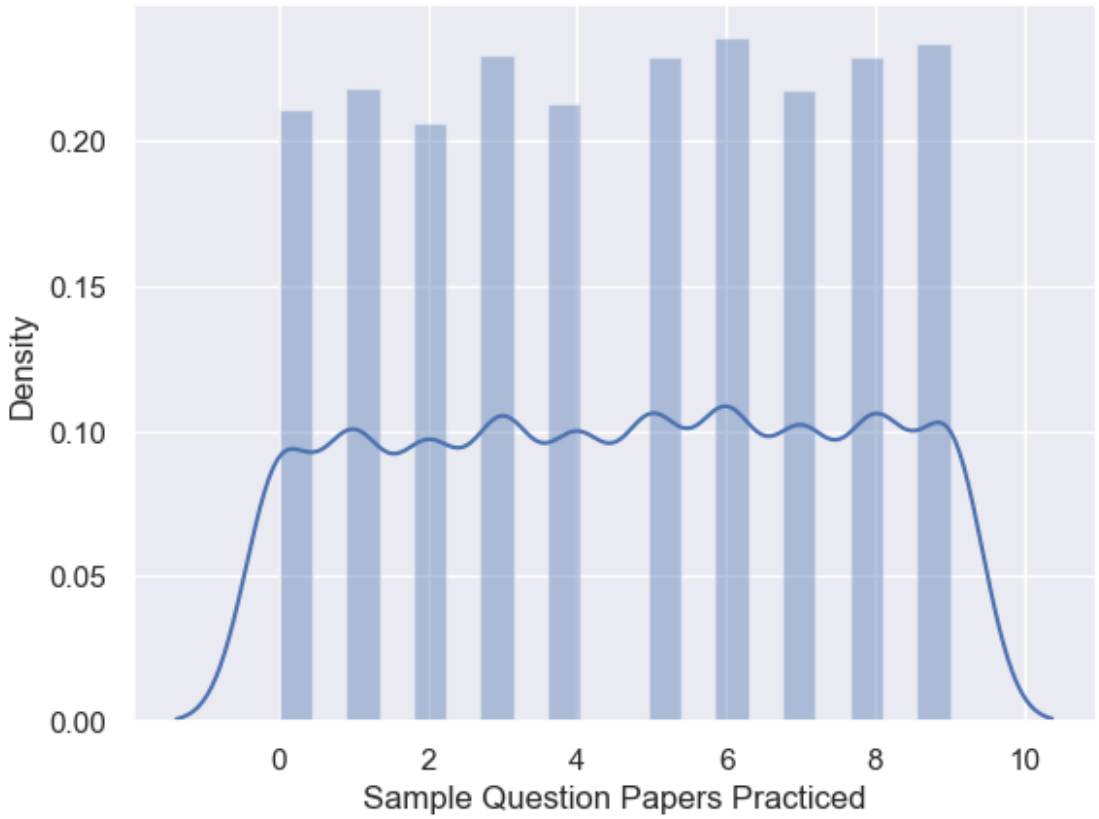

```
def distplots(col):
    sns.distplot(dataset[col])
    plt.show()

for i in list(dataset.columns)[0:]:
    distplots(i)
```

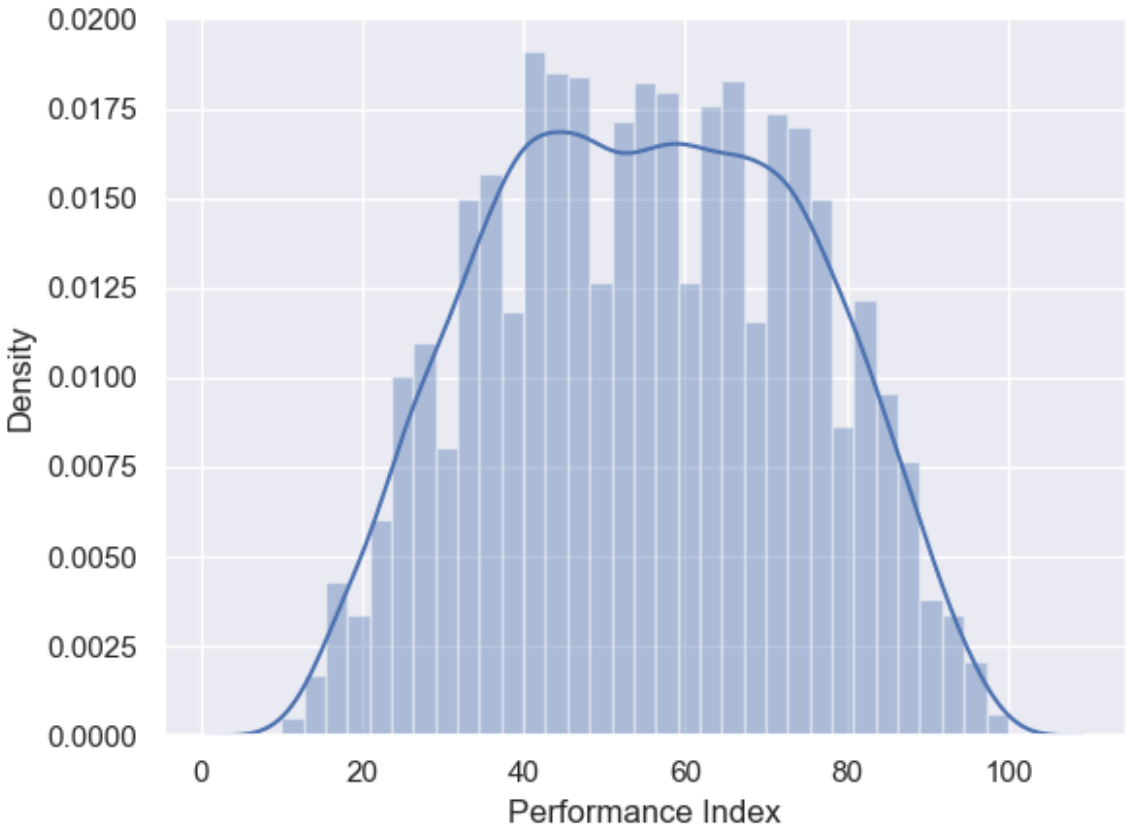

0.30
0.25
0.20
0.15
0.10
0.05
0.00
Density
0
2
4
6
8
10
Hours Studied


0.0200
0.0175
0.0150
0.0125
0.0100
0.0075
0.0050
0.0025
0.0000
Density
30
40
50
60
70
80
90
100
110
Previous Scores


Density
5
4
3
2
1
0
−0.2
0.0
0.2
0.4
0.6
0.8
1.0
1.2
Extracurricular Activities


Density
0.6
0.5
0.4
0.3
0.2
0.1
0.0
3
4
5
6
7
8
9
10
Sleep Hours


0.20
0.15
0.10
0.05
0.00
Density
0
2
4
6
8
10
Sample Question Papers Practiced




```
# Feature Scaling - split the data into indepednet and dependent
varialbe
x = dataset.iloc[:,0:-1] # Independent variable
y = dataset.iloc[:,-1] # Dependent variable

x.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

   Sample Question Papers Practiced
0                                 1
1                                 2
2                                 2
```

```
3                                   2
4                                   5
```

```
y.head()
```

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

```
# Feature Scaling
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
sc_x = scaler.fit_transform(x)
pd.DataFrame(sc_x)
```

```
             0         1         2         3         4
0     0.775566  1.706168  1.010078  1.454025 -1.249715
1    -0.383205  0.724912 -0.990022 -1.491315 -0.900925
2     1.161822 -1.064438  1.010078  0.275889 -0.900925
3     0.003052 -1.006717  1.010078 -0.902247 -0.900925
4     0.775566  0.320865 -0.990022  0.864957  0.145444
...        ...       ...       ...       ...       ...
9868 -1.541976 -1.179880  1.010078 -1.491315 -0.900925
9869  0.775566 -0.314066  1.010078  0.864957  0.145444
9870  0.389309  0.782633  1.010078  0.864957  0.145444
9871  1.548079  1.590727  1.010078  0.275889 -1.598505
9872  0.775566  0.263144 -0.990022  0.864957 -1.249715

[9873 rows x 5 columns]
```

```
pd.DataFrame(sc_x).describe()
```

```
                  0             1             2             3
4
count  9.873000e+03  9.873000e+03  9.873000e+03  9.873000e+03
9.873000e+03
mean  -8.672177e-17 -8.348319e-17 -1.381791e-16  2.382150e-16 -
1.201870e-16
std    1.000051e+00  1.000051e+00  1.000051e+00  1.000051e+00
1.000051e+00
min   -1.541976e+00 -1.699369e+00 -9.900224e-01 -1.491315e+00 -
1.598505e+00
25%   -7.694624e-01 -8.912755e-01 -9.900224e-01 -9.022472e-01 -
9.009252e-01
50%    3.051559e-03 -2.546084e-02 -9.900224e-01  2.758888e-01
1.454439e-01
75%    7.755655e-01  8.980748e-01  1.010078e+00  8.649568e-01
8.430232e-01
```

```
max    1.548079e+00  1.706168e+00  1.010078e+00  1.454025e+00
1.540603e+00
```

```
# checking "Multicollinearity" since it's multiple linear regression.
variable = sc_x
variable.shape
```

```
(9873, 5)
```

To check Multicollinearity - VIF (Variance Inflation Factor)

```
# VIF value is more than 5 means there is a multicollinearity there in
the features
from statsmodels.stats.outliers_influence import
variance_inflation_factor
variable = sc_x
vif = pd.DataFrame()
vif['variance_inflation_factor'] =
[variance_inflation_factor(variable, i) for i in
range(variable.shape[1])]

vif['Features'] = x.columns

vif
```

```
   variance_inflation_factor                          Features
0                   1.000393                     Hours Studied
1                   1.000350                  Previous Scores
2                   1.000888       Extracurricular Activities
3                   1.000676                       Sleep Hours
4                   1.000540  Sample Question Papers Practiced
```

```
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)
print(x_test.shape)
```

```
(7898, 5)
(1975, 5)
```

```
print(y_train.shape)
print(y_test.shape)
```

```
(7898,)
(1975,)
```

```
x_test
```

```
      Hours Studied  Previous Scores  Extracurricular Activities
Sleep Hours  \
```

```
6244                7                  79                             1
9
334                 5                  44                             0
6
9900                5                  53                             1
7
3055                3                  88                             0
5
6555                6                  73                             1
7
...               ...                ...                           ...
...
6129                3                  40                             1
5
9484                7                  65                             0
6
3453                1                  69                             0
4
1961                8                  41                             1
5
9025                9                  74                             1
4
```

```
      Sample Question Papers Practiced
6244                                 9
334                                  0
9900                                 7
3055                                 3
6555                                 1
...                                ...
6129                                 4
9484                                 7
3453                                 8
1961                                 5
9025                                 5

[1975 rows x 5 columns]
```

Building Model - Linear Regression

```
from sklearn.linear_model import LinearRegression
lm = LinearRegression()
lm.fit(x_train, y_train)
```

```
LinearRegression()
```

```
print(lm.coef_)
```

```
[2.85807139 1.01779793 0.62057095 0.47811677 0.19466511]
```

```
print(lm.intercept_)
```

```
-34.03759919742531
```

```
x.columns
```

```
Index(['Hours Studied', 'Previous Scores', 'Extracurricular
Activities',
       'Sleep Hours', 'Sample Question Papers Practiced'],
      dtype='object')
```

```
x_test
```

```
      Hours Studied  Previous Scores  Extracurricular Activities
Sleep Hours  \
6244              7               79                           1
9
334               5               44                           0
6
9900              5               53                           1
7
3055              3               88                           0
5
6555              6               73                           1
7
...             ...              ...                         ...
...
6129              3               40                           1
5
9484              7               65                           0
6
3453              1               69                           0
4
1961              8               41                           1
5
9025              9               74                           1
4

      Sample Question Papers Practiced
6244                                 9
334                                  0
9900                                 7
3055                                 3
6555                                 1
...                                ...
6129                                 4
9484                                 7
3453                                 8
1961                                 5
9025                                 5
```

```
[1975 rows x 5 columns]
```

Predict test dataset with linear model

```
y_pred = lm.predict(x_test)
print(y_pred)
```

```
[73.05054486 27.90456729 39.52609214 ... 42.51831731 34.5411674
 70.50845371]
```

```
y_test
```

```
6244    74.0
334     30.0
9900    40.0
3055    68.0
6555    63.0
        ...
6129    19.0
9484    53.0
3453    43.0
1961    33.0
9025    67.0
Name: Performance Index, Length: 1975, dtype: float64
```

Evaluation

```
from sklearn.metrics import r2_score, mean_absolute_error,
mean_absolute_percentage_error
print("Accuracy :", r2_score(y_test, y_pred))
```

```
Accuracy : 0.9878120360079914
```

```
mae= mean_absolute_error(y_test, y_pred)
print(mae)
```

```
1.6911921606195806
```

```
mape= mean_absolute_percentage_error(y_test, y_pred)
print(mape)
```

```
0.03595106470817499
```

Using the OLS method

```
from statsmodels.regression.linear_model import OLS
import statsmodels.regression.linear_model as smf

reg_model = smf.OLS(endog = y_train, exog=x_train).fit()
```

```
reg_model = smf.OLS(endog = y_test, exog=x_test).fit()

reg_model.summary()
```

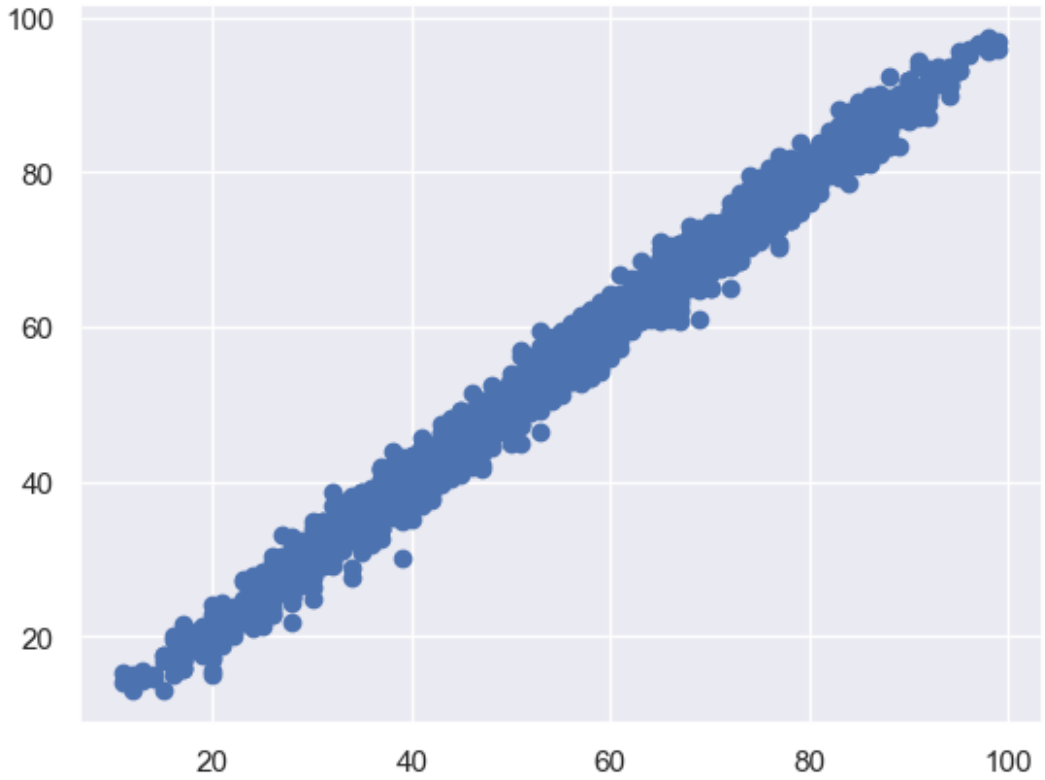
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                                 OLS Regression Results

==============================================================================
==================
Dep. Variable:      Performance Index   R-squared (uncentered):
0.990
Model:                            OLS   Adj. R-squared (uncentered):
0.990
Method:                 Least Squares   F-statistic:
3.808e+04
Date:                Sat, 12 Apr 2025   Prob (F-statistic):
0.00
Time:                        14:33:16   Log-Likelihood:
-6316.3
No. Observations:                1975   AIC:
1.264e+04
Df Residuals:                    1970   BIC:
1.267e+04
Df Model:                           5

Covariance Type:            nonrobust

==============================================================================
==============================
                                   coef    std err          t
P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
------------------------------
Hours Studied                      2.1477      0.049     44.039
0.000       2.052       2.243
Previous Scores                    0.8172      0.006    136.830
0.000       0.805       0.829
Extracurricular Activities        -1.1133      0.264     -4.210
0.000      -1.632      -0.595
Sleep Hours                       -1.4524      0.063    -23.209
0.000      -1.575      -1.330
Sample Question Papers Practiced  -0.2915      0.045     -6.449
0.000      -0.380      -0.203
==============================================================================
========
Omnibus:                        8.592   Durbin-Watson:
1.952
Prob(Omnibus):                  0.014   Jarque-Bera (JB):
6.642
```

```
Skew:                          0.020   Prob(JB):
0.0361
Kurtosis:                      2.719   Cond. No.
143.
================================================================================

Notes:
[1] R² is computed without centering (uncentered) since the model does
not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
"""
```

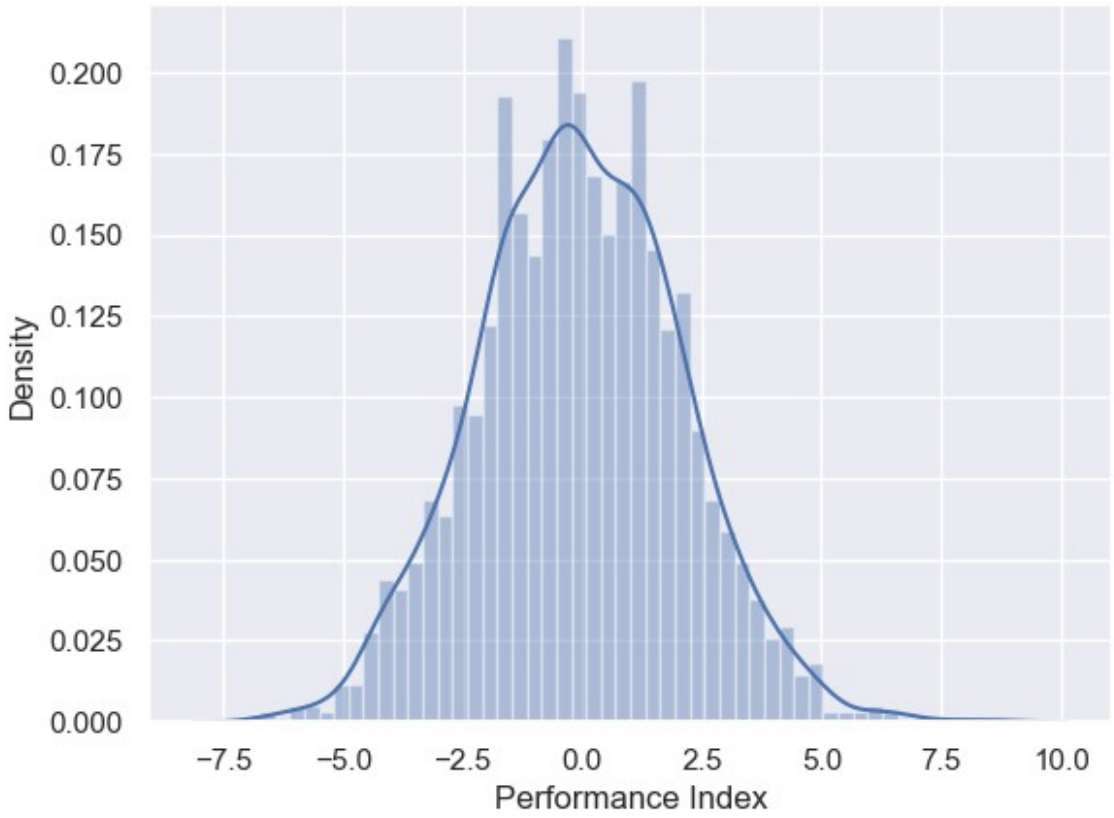
```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x,y,test_size=0.2,
random_state=0)

reg_model = smf.OLS(endog = y_train, exog=x_train).fit()
reg_model.summary()
```

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results

================================================================================
Dep. Variable:      Performance Index   R-squared (uncentered):
0.990
Model:                            OLS   Adj. R-squared (uncentered):
0.990
Method:                 Least Squares   F-statistic:
1.578e+05
Date:                Sat, 12 Apr 2025   Prob (F-statistic):
0.00
Time:                        14:39:18   Log-Likelihood:
-25113.
No. Observations:                7898   AIC:
5.024e+04
Df Residuals:                    7893   BIC:
5.027e+04
Df Model:                           5

Covariance Type:            nonrobust

================================================================================
                                 coef    std err          t
P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
```

```
------------------------------
Hours Studied                          2.2090      0.024     91.737
0.000       2.162       2.256
Previous Scores                        0.8167      0.003    281.114
0.000       0.811       0.822
Extracurricular Activities            -1.1753      0.129     -9.096
0.000      -1.429      -0.922
Sleep Hours                           -1.5118      0.030    -49.771
0.000      -1.571      -1.452
Sample Question Papers Practiced      -0.2597      0.022    -11.708
0.000      -0.303      -0.216
==============================================================================
Omnibus:                       37.617   Durbin-Watson:
1.967
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
27.600
Skew:                          -0.005   Prob(JB):
1.02e-06
Kurtosis:                       2.711   Cond. No.
142.
==============================================================================

Notes:
[1] R² is computed without centering (uncentered) since the model does
not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
"""

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




```
sns.distplot((y_test - y_pred), bins=50)
plt.show()
```



Regularisation Method

```
# from sklearn.linear_model import LinearRegression
# lm = LinearRegression()
# lm.fit(x_train, y_train)
print("lm model", lm.coef_)
```

```
lm model [2.85807139 1.01779793 0.62057095 0.47811677 0.19466511]
```

```
y_pred_lm_train = lm.predict(x_train)
y_pred_lm_test = lm.predict(x_test)

print("LM_Train_ACCURACY :", r2_score(y_train, y_pred_lm_train))
print()
print("LM_Test_ACCURACY :", r2_score(y_test, y_pred_lm_test))
```

```
LM_Train_ACCURACY : 0.9888967225498639

LM_Test_ACCURACY : 0.9878120360079914
```

Lasso method (L1)

```
# Lasso method - exact zero or closed to zero (slope/coefficient)
from sklearn.linear_model import Lasso
lasso = Lasso(alpha=0.3)
```

```
lasso.fit(x_train, y_train)
print("Lasso Regularisation", lasso.coef_)
```

```
Lasso Regularisation [2.81526489 1.01697199 0.         0.36960318
0.15964043]
```

```
y_pred_lasso_train = lasso.predict(x_train)
y_pred_lasso_test = lasso.predict(x_test)

print("Lasso_Train_ACCURACY :", r2_score(y_train, y_pred_lasso_train))
print()
print("Lasso_Test_ACCURACY :", r2_score(y_test, y_pred_lasso_test))
```

```
Lasso_Train_ACCURACY : 0.9884863216492178

Lasso_Test_ACCURACY : 0.9874370304228809
```

Ridge Regularization (L2)

```
from sklearn.linear_model import Ridge
ridge = Ridge(alpha=0.3)
ridge.fit(x_train, y_train)
print("Ridge Model :", ridge.coef_)
```

```
Ridge Model : [2.85805535 1.0177978  0.62047692 0.47810979 0.1946646 ]
```

```
y_pred_ridge_train = ridge.predict(x_train)
y_pred_ridge_test = ridge.predict(x_test)

print("Ridge_Train_ACCURACY :", r2_score(y_train, y_pred_ridge_train))
print()
print("Ridge_Test_ACCURACY :", r2_score(y_test, y_pred_ridge_test))
```

```
Ridge_Train_ACCURACY : 0.9888967225387757

Ridge_Test_ACCURACY : 0.9878120526807271
```

ElasticNet Regularization (L1 + L2)

```
from sklearn.linear_model import ElasticNet
elasticnet = ElasticNet(alpha=0.3, l1_ratio=0.1)
elasticnet.fit(x_train, y_train)
```

```
ElasticNet(alpha=0.3, l1_ratio=0.1)
```

```
print("ElasticNet Model :", elasticnet.coef_)
```

```
ElasticNet Model : [2.74376579 1.01672792 0.24143725 0.42512968
0.18761367]
```

```
y_pred_elasticNet_train = elasticnet.predict(x_train)
y_pred_elasticNet_test = elasticnet.predict(x_test)
```

```
print("ElasticNet_Train_ACCURACY :", r2_score(y_train,
y_pred_elasticNet_train))
print()
print("ElasticNet_Test_ACCURACY :", r2_score(y_test,
y_pred_elasticNet_test))
```

```
ElasticNet_Train_ACCURACY : 0.9885369885439956

ElasticNet_Test_ACCURACY : 0.9875655539539913
```

Gradient Descent

```
from sklearn.model_selection import train_test_split
x_train1, x_test1, y_train1, y_test1 =
train_test_split(sc_x,y,test_size=0.2, random_state=0)

from sklearn.linear_model import SGDRegressor
gdmodel = SGDRegressor()
gdmodel.fit(x_train1, y_train1)
```

```
SGDRegressor()
```

```
y_pred_sgd_train = gdmodel.predict(x_train1)
y_pred_sgd_test = gdmodel.predict(x_test1)

y_test
```

```
6244    74.0
334     30.0
9900    40.0
3055    68.0
6555    63.0
        ...
6129    19.0
9484    53.0
3453    43.0
1961    33.0
9025    67.0
Name: Performance Index, Length: 1975, dtype: float64
```

```
print(y_pred_sgd_test)
```

```
[72.9475822  27.81140631 39.42517154 ... 42.50199303 34.49515402
 70.54012115]
```

```
print("GD Model Training Accuracy :", r2_score(y_train,
y_pred_sgd_train))
print()
print("GD Model Test Accuracy :", r2_score(y_test, y_pred_sgd_test))
```

```
GD Model Training Accuracy : 0.9888760949958205

GD Model Test Accuracy : 0.987809036929611
```

TO Ensure that our model is absolutely fine we will carryout

Cross Validation Score - K-Fold method

```
from sklearn.model_selection import cross_val_score
training_accuracy = cross_val_score(lm, x_train, y_train, cv=10)

print('training_accuracy for all 10 individual :', training_accuracy)
print()
print("training_accuracy with mean value :", training_accuracy.mean())
print()
print("training_accuracy max value :", training_accuracy.max())
```

```
training_accuracy for all 10 individual : [0.98945562 0.98891322
0.98861269 0.98785487 0.98999143 0.98949854
 0.98760861 0.98857868 0.98954505 0.98851622]

training_accuracy with mean value : 0.9888574924996106

training_accuracy max value : 0.9899914296093275
```

Performance matrix

```
## Mean Absolute Error - MAE
from sklearn import metrics

print("MAE :",metrics.mean_absolute_error(y_test, y_pred_lm_test))
```

```
MAE : 1.6911921606195806
```

```
# Mean Absolute Percent Error
print("MAPE :", metrics.mean_absolute_error(y_test,
y_pred_lm_test)/y_test*100)
```

```
MAPE : 6244    2.285395
334     5.637307
9900    4.227980
3055    2.487047
6555    2.684432
          ...
6129    8.901011
9484    3.190929
3453    3.933005
1961    5.124825
```

```
9025    2.524167
Name: Performance Index, Length: 1975, dtype: float64
```

```
# Mean Squared Error
print("MSE :", metrics.mean_squared_error(y_test, y_pred_lm_test))
```

```
MSE : 4.490041091497724
```

```
# Root Mean Squared Error
print("RMSE :", np.sqrt(metrics.mean_squared_error(y_test,
y_pred_lm_test)))
```

```
RMSE : 2.1189717061579003
```