Jamboree Education - Linear Regression

Jamboree Education

Jamboree has helped thousands of students like you make it to top colleges abroad. Be it GMAT, GRE or SAT, their unique problem-solving methods ensure maximum scores with minimum effort. They recently launched a feature where students/learners can come to their website and check their probability of getting into the IVY league college. This feature estimates the chances of graduate admission from an Indian perspective.

Column Profiling:

- Serial No. (Unique row ID)
- GRE Scores (out of 340)
- TOEFL Scores (out of 120)
- University Rating (out of 5)
- Statement of Purpose and Letter of Recommendation Strength (out of 5)
- Undergraduate GPA (out of 10)
- Research Experience (either 0 or 1)
- Chance of Admit (ranging from 0 to 1)

Problem Statment: Predict the chances of graduate admission based on the given features.

Import Libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score, mean_squared_error,
mean_absolute_error

from statsmodels.stats.outliers_influence import
variance_inflation_factor

import scipy as sp
```

Load The DataSet

```
ds = pd.read_csv("Jamboree_Admission_dataset.csv")
ds
```

```
     Serial No.  GRE Score  TOEFL Score  University Rating  SOP  LOR
CGPA  \
0             1        337          118                  4  4.5   4.5
9.65
1             2        324          107                  4  4.0   4.5
8.87
2             3        316          104                  3  3.0   3.5
8.00
3             4        322          110                  3  3.5   2.5
8.67
4             5        314          103                  2  2.0   3.0
8.21
..          ...        ...          ...                ...  ...   ...
...
495         496        332          108                  5  4.5   4.0
9.02
496         497        337          117                  5  5.0   5.0
9.87
497         498        330          120                  5  4.5   5.0
9.56
498         499        312          103                  4  4.0   5.0
8.43
499         500        327          113                  4  4.5   4.5
9.04

     Research  Chance of Admit
0           1             0.92
1           1             0.76
2           1             0.72
3           1             0.80
4           0             0.65
..        ...              ...
495         1             0.87
496         1             0.96
497         1             0.93
498         0             0.73
499         0             0.84

[500 rows x 9 columns]
```

Observations On DataSet

```
# shape of data set
ds.shape
```

```
(500, 9)
```

```
# data types of attributes of the data set
ds.dtypes
```

```
Serial No.              int64
GRE Score               int64
TOEFL Score             int64
University Rating       int64
SOP                   float64
LOR                   float64
CGPA                  float64
Research                int64
Chance of Admit       float64
dtype: object
```

```
# check for missing values
ds.isnull()
```

```
     Serial No.  GRE Score  TOEFL Score  University Rating    SOP
LOR   \
0         False      False        False              False  False
False
1         False      False        False              False  False
False
2         False      False        False              False  False
False
3         False      False        False              False  False
False
4         False      False        False              False  False
False
..          ...        ...          ...                ...    ...     .
..
495       False      False        False              False  False
False
496       False      False        False              False  False
False
497       False      False        False              False  False
False
498       False      False        False              False  False
False
499       False      False        False              False  False
False

      CGPA  Research  Chance of Admit
0    False     False            False
1    False     False            False
2    False     False            False
3    False     False            False
4    False     False            False
..     ...       ...              ...
495  False     False            False
496  False     False            False
497  False     False            False
498  False     False            False
```

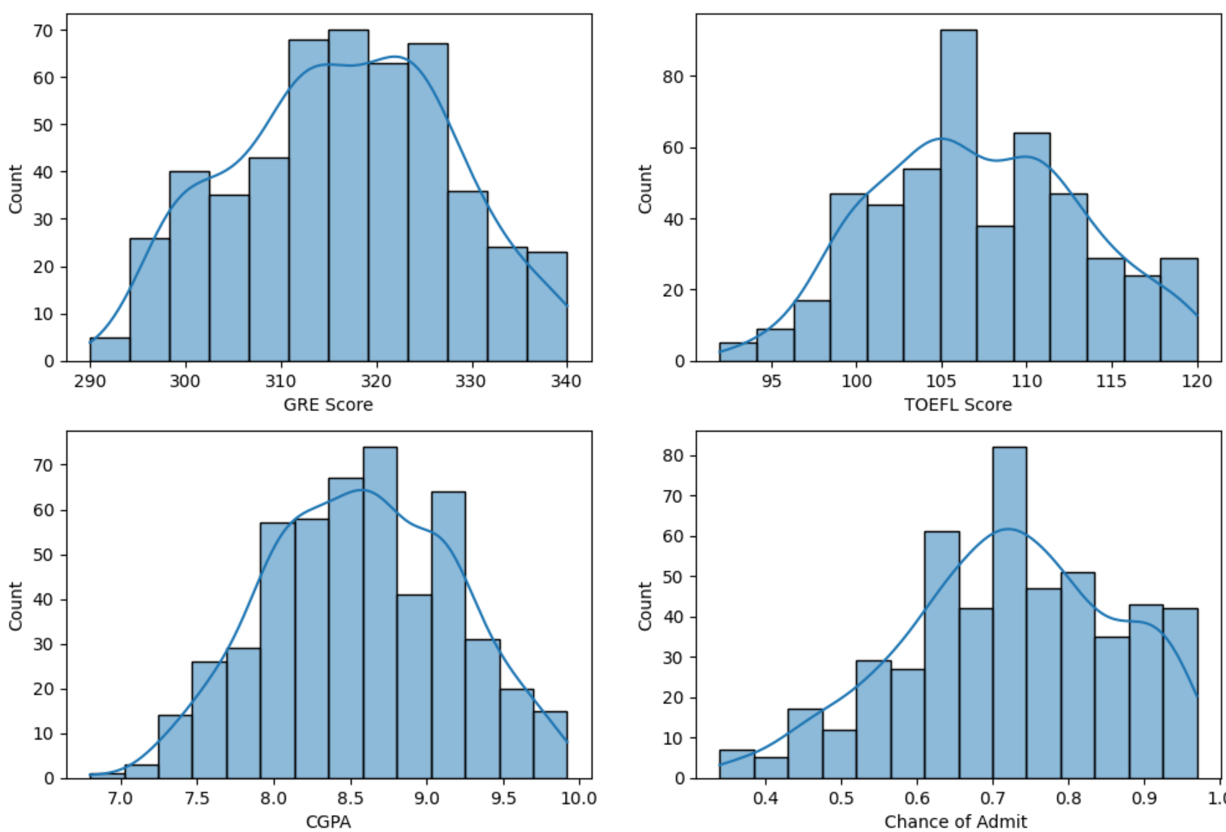
```
499   False     False             False

[500 rows x 9 columns]

# check for missing values
ds.isnull().sum()

Serial No.           0
GRE Score            0
TOEFL Score          0
University Rating    0
SOP                  0
LOR                  0
CGPA                 0
Research             0
Chance of Admit      0
dtype: int64

# statistical summary
ds.describe()

       Serial No.   GRE Score  TOEFL Score  University Rating
SOP  \
count  500.000000  500.000000   500.000000         500.000000
500.000000
mean   250.500000  316.472000   107.192000           3.114000
3.374000
std    144.481833   11.295148     6.081868           1.143512
0.991004
min      1.000000  290.000000    92.000000           1.000000
1.000000
25%    125.750000  308.000000   103.000000           2.000000
2.500000
50%    250.500000  317.000000   107.000000           3.000000
3.500000
75%    375.250000  325.000000   112.000000           4.000000
4.000000
max    500.000000  340.000000   120.000000           5.000000
5.000000

             LOR         CGPA    Research  Chance of Admit
count  500.00000  500.000000  500.000000        500.00000
mean     3.48400    8.576440    0.560000          0.72174
std      0.92545    0.604813    0.496884          0.14114
min      1.00000    6.800000    0.000000          0.34000
25%      3.00000    8.127500    0.000000          0.63000
50%      3.50000    8.560000    1.000000          0.72000
75%      4.00000    9.040000    1.000000          0.82000
max      5.00000    9.920000    1.000000          0.97000
```

Exploratory Data Analysis

```
cat_cols = ['University Rating', 'SOP', 'LOR ', 'Research']
num_cols = ['GRE Score', 'TOEFL Score', 'CGPA']
target = 'Chance of Admit '
```

Univariate Analysis

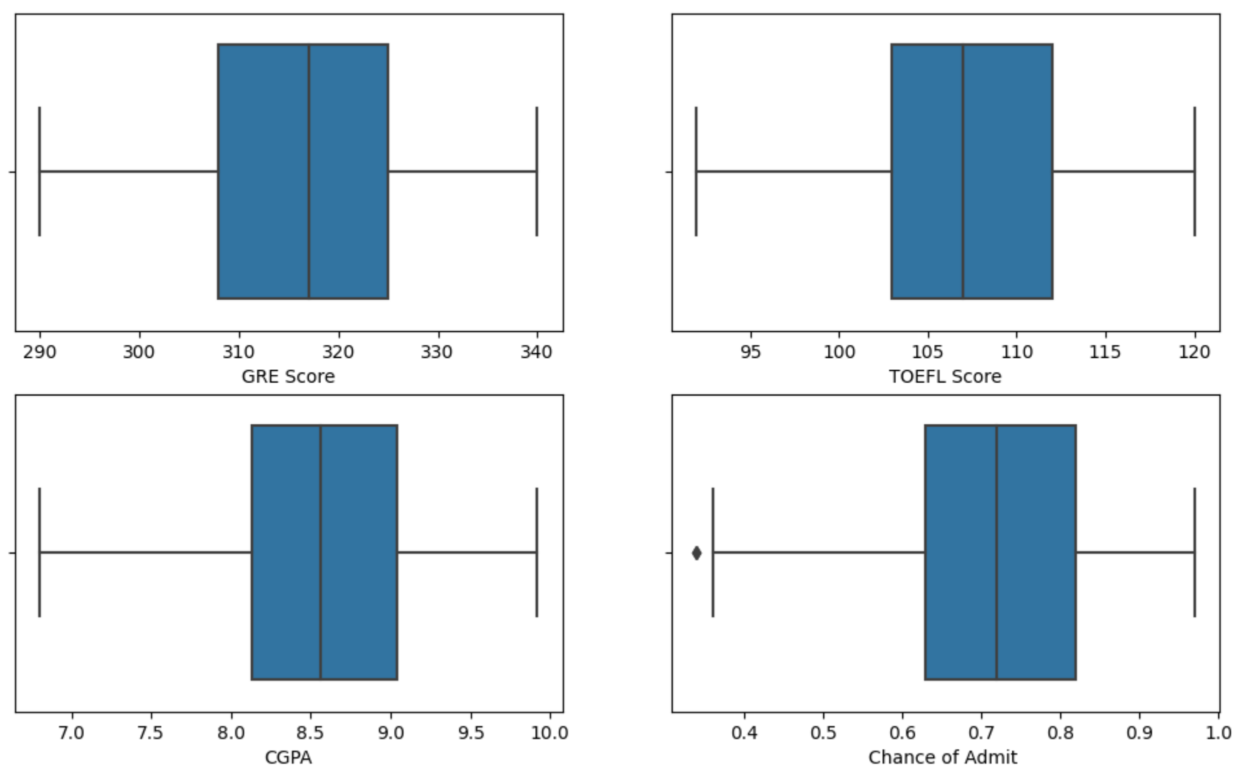
```
# check distribution of each numerical variable

rows, cols = 2, 2

fig, axs = plt.subplots(rows,cols, figsize=(12, 8))

sns.histplot(ds[num_cols[0]],kde=True, ax = axs[0,0])

sns.histplot(ds[num_cols[1]],kde=True, ax = axs[0,1])

sns.histplot(ds[num_cols[-1]], kde=True, ax=axs[1,0])

sns.histplot(ds[target], kde=True, ax=axs[1,1])

plt.show()
```



Insights

- from the above graph analysis we can check that how many students got the GRE Scores, TOEFL Scores, CGPA, and Chance of Admit

```
# Checking Outliers Using BoxPlots

rows, cols = 2, 2

fig, axs = plt.subplots(rows,cols, figsize=(12, 7))

sns.boxplot(x=num_cols[0], data = ds, ax = axs[0,0])

sns.boxplot(x=num_cols[1], data = ds, ax = axs[0,1])

sns.boxplot(x=num_cols[2], data = ds, ax = axs[1,0])

sns.boxplot(x= target, data = ds, ax = axs[1,1])

plt.show()
```

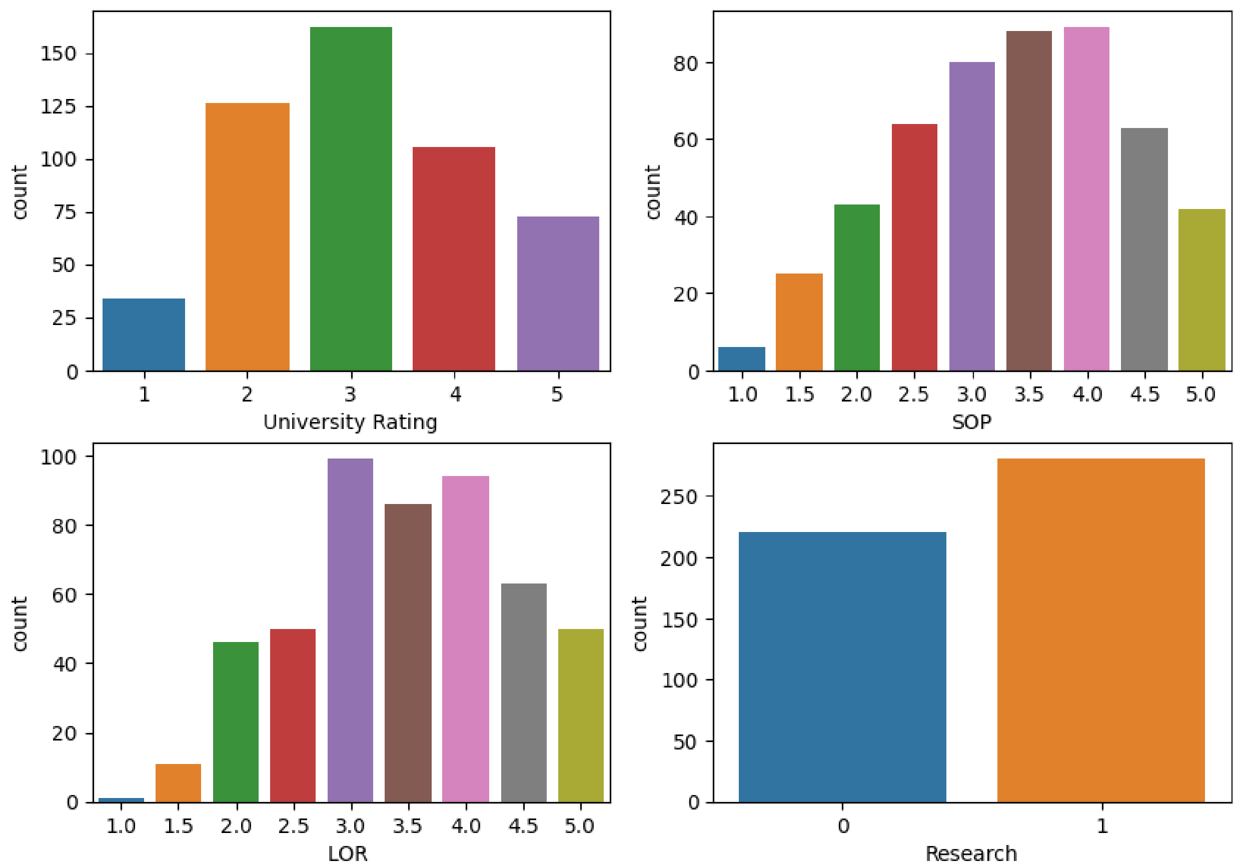


Insights

- We can see clearly that there are no outliers in the above features or independent variables

```
# Countplots for categorical variables
```

```
cols, rows = 2, 2

fig, axs = plt.subplots(rows, cols, figsize=(10, 7))

index = 0

for row in range(rows):
    for col in range(cols):
        sns.countplot(x=cat_cols[index], data=ds, ax=axs[row, col], 
alpha=1)
        index += 1

plt.show()
```



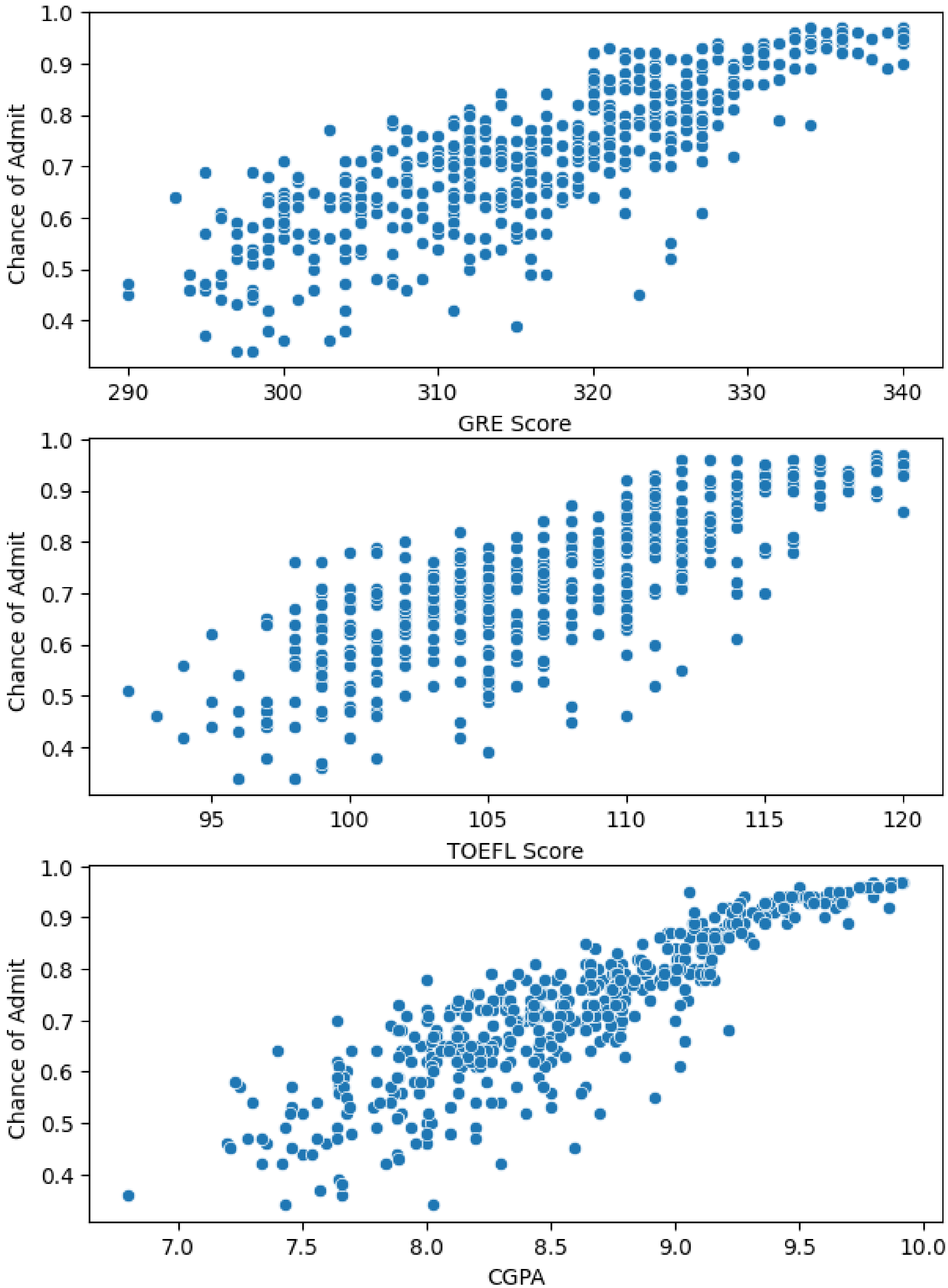
Insights

- from the above graph analysis we can check that how many students opted according to university rating, SOP, LOR, Research

Bivariate Analysis

```
# check relation bw continuous variables & target variable
```

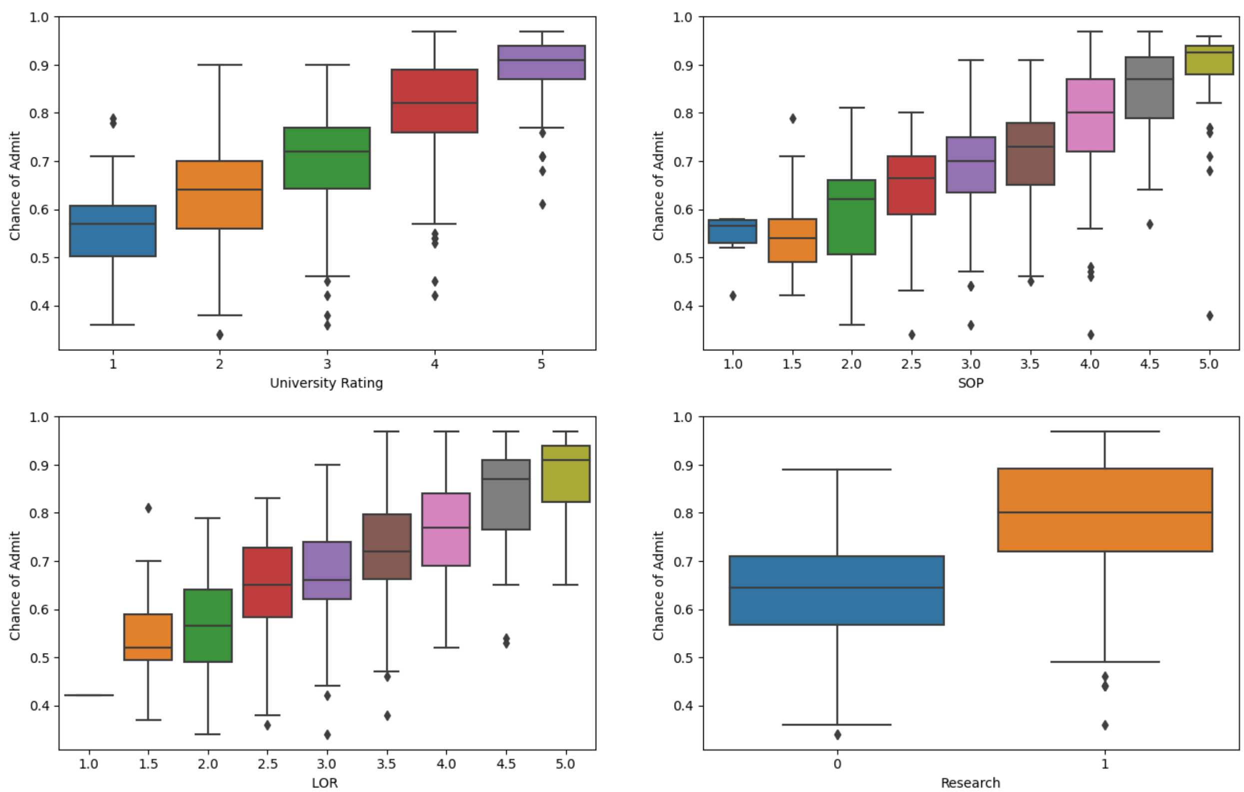
```
fig, axs = plt.subplots(3,1, figsize=(7,10))

sns.scatterplot(x=num_cols[0], y=target, data=ds, ax=axs[0])

sns.scatterplot(x=num_cols[1], y=target, data=ds, ax=axs[1])

sns.scatterplot(x=num_cols[2], y=target, data=ds, ax=axs[2])

plt.show()
```


Chance of Admit
1.0
0.9
0.8
0.7
0.6
0.5
0.4
290
300
310
320
330
340
GRE Score
Chance of Admit
1.0
0.9
0.8
0.7
0.6
0.5
0.4
95
100
105
110
115
120
TOEFL Score
Chance of Admit
1.0
0.9
0.8
0.7
0.6
0.5
0.4
7.0
7.5
8.0
8.5
9.0
9.5
10.0
CGPA

Insights

- We can say that the continuos variables and target variables are linearly correalted.
- It generally indicates a strong relationship between the predictors and the outcome.
- Strong Predictive Power: Linear correlation between independent variables and the target variable means that the predictors are informative in predicting the outcome.

```
# check relation b/1w Categorical variables & target variable
rows, cols = 2,2
fig, axs = plt.subplots(rows, cols, figsize=(16,10))

index = 0
for row in range(rows):
    for col in range(cols):
        sns.boxplot(x=cat_cols[index], y=target, data=ds, 
ax=axs[row,col])
        index += 1
```

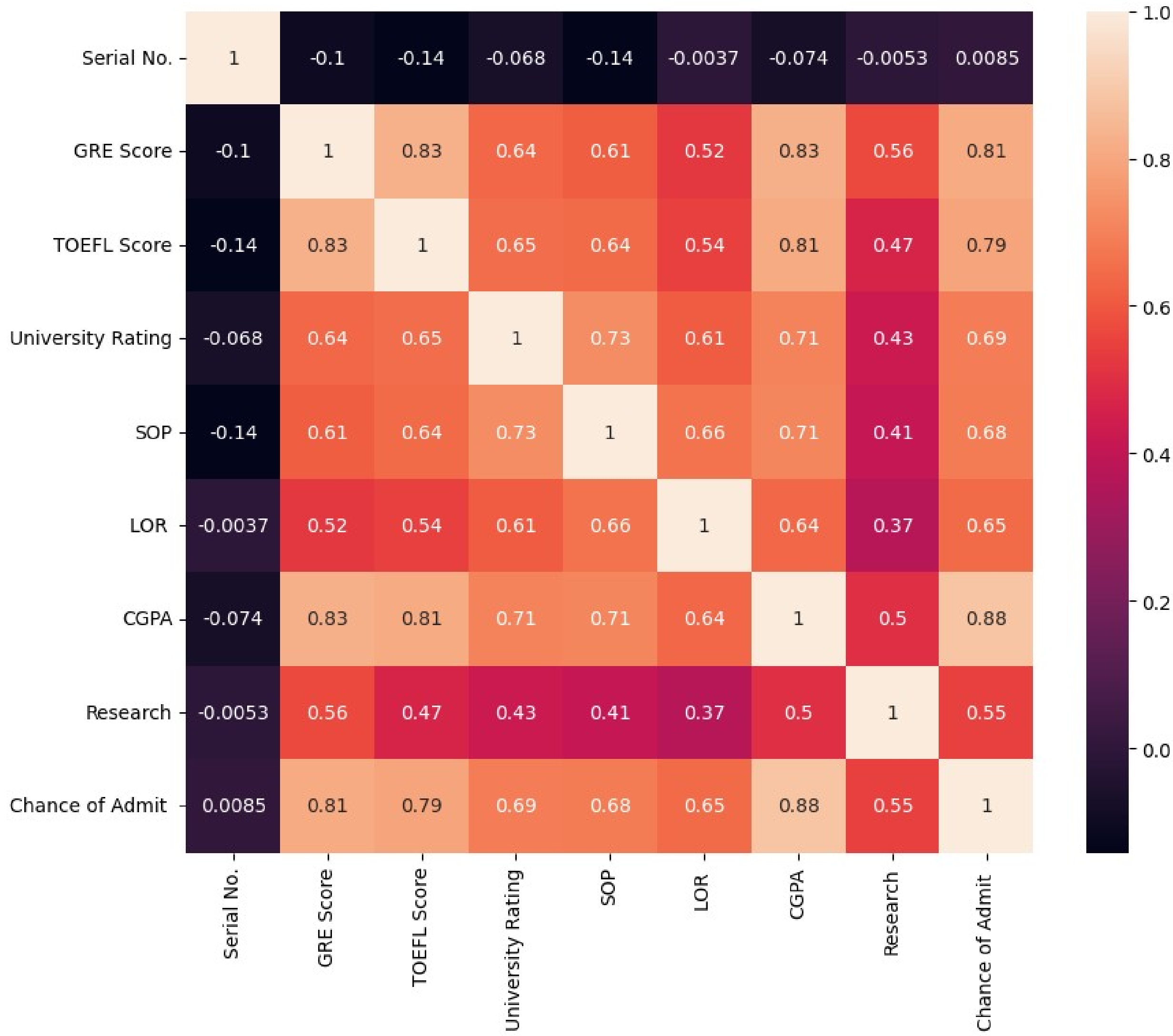


Insights

- From this, we can that as the rating increases the chance of getting an admission also increases.
- Students who have the research experience have more chances of getting an admission as compared to other students who don't have the research experience.

```
# Correlation
ds.corr()
```

```
                   Serial No.  GRE Score  TOEFL Score  University
Rating  \
Serial No.           1.000000  -0.103839    -0.141696           -
0.067641
GRE Score           -0.103839   1.000000     0.827200
0.635376
TOEFL Score         -0.141696   0.827200     1.000000
0.649799
University Rating   -0.067641   0.635376     0.649799
1.000000
SOP                 -0.137352   0.613498     0.644410
0.728024
LOR                 -0.003694   0.524679     0.541563
0.608651
CGPA                -0.074289   0.825878     0.810574
0.705254
Research            -0.005332   0.563398     0.467012
0.427047
Chance of Admit      0.008505   0.810351     0.792228
0.690132

                        SOP       LOR      CGPA  Research  Chance of
Admit
Serial No.        -0.137352 -0.003694 -0.074289 -0.005332
0.008505
GRE Score          0.613498  0.524679  0.825878  0.563398
0.810351
TOEFL Score        0.644410  0.541563  0.810574  0.467012
0.792228
University Rating  0.728024  0.608651  0.705254  0.427047
0.690132
SOP                1.000000  0.663707  0.712154  0.408116
0.684137
LOR                0.663707  1.000000  0.637469  0.372526
0.645365
CGPA               0.712154  0.637469  1.000000  0.501311
0.882413
Research           0.408116  0.372526  0.501311  1.000000
0.545871
Chance of Admit    0.684137  0.645365  0.882413  0.545871
1.000000

# Heatmap
plt.figure(figsize=(10,8))
sns.heatmap(ds.corr(), annot=True)
plt.show()
```



Insights

- we can see that the CGPA and Chance of Admit are highly related to each other which means the cgpa plays a major role in getting an admission in foreign universities.
- And next GRE and TOEFL Scores are closely related to the chance of admit

Data Preprocessing

```
# dropping unnecessary column

ds = ds.drop(columns=['Serial No.'], axis=1)

ds.columns

Index(['GRE Score', 'TOEFL Score', 'University Rating', 'SOP', 'LOR ',
'CGPA',
```

```
       'Research', 'Chance of Admit '],
      dtype='object')
```

```
# checking the duplicates

ds.duplicated().sum()
```

```
0
```

Data Preparation for model building

```
x = ds.drop(columns=[target])
y = ds[target]

# standardize the dataset
sc = StandardScaler()
x = sc.fit_transform(x)

# train test split
x_train, x_test, y_train, y_test = train_test_split(x, y,
test_size=0.3, random_state=1)

print(x_train.shape, y_train.shape)
print(x_test.shape, y_test.shape)
```

```
(350, 7) (350,)
(150, 7) (150,)
```

Model Building

LINEAR REGRESSION

Linear regression

y = (w1x1) + (w2x2) .... (wnxn) + w0

x represents the independent variables.

y represents the dependent variable.

```
# calling the linear regression function
li_reg = LinearRegression()
li_reg.fit(x_train,y_train)
```

```
LinearRegression()
```

```
# Model Coefficients
```

```
print(f'The coefficient for linear regression: {li_reg.coef_}')
print()
print(f'The intercept for linear regression: {li_reg.intercept_}')
```

```
The coefficient for linear regression: [ 0.01865693  0.02317626
0.01156475 -0.00099944  0.01249708  0.06467088
  0.01396816]

The intercept for linear regression: 0.724978121476996
```

Insights

- CGPA feature has a high Positive influence on the predicted output over the remaining features.
- SOP feature has a negative influence on the predicted output.

Checking MAE, RSME, R^2 and Adjusted R^2 for Linear Regression

```
y_predict = li_reg.predict(x_test)

print('The score of Linear Regression for Training
Data:',li_reg.score(x_train,y_train))

print('The score of Linear Regression for Test
Data:',li_reg.score(x_test,y_test))

print('Mean Absolute
error:',mean_absolute_error(y_true=y_test,y_pred=y_predict))

print('Root Mean Squared
Error:',mean_squared_error(y_true=y_test,y_pred=y_predict,squared=Fals
e))

print('R^2:',r2_score(y_test,y_predict))

print('Adjusted R^2: ',(1 - (1-(r2_score(y_test,y_predict)))*(len(y)-
1)/(len(y)-x.shape[1]-1)))
```

```
The score of Linear Regression for Training Data: 0.8209843725364347
The score of Linear Regression for Test Data: 0.8157672116057979
Mean Absolute error: 0.043975442403392
Root Mean Squared Error: 0.06423343550447695
R^2: 0.8157672116057979
Adjusted R^2:  0.8131460133969373
```

REGULARIZATION(L2) - RIDGE REGRESSION

Ridge regression performs ‘L2 regularization‘, i.e. it adds a factor of sum of squares of coefficients in the optimization objective. Thus, ridge regression optimizes the following:

Objective = RSS + α * (sum of square of coefficients)

Here, α (alpha) is the parameter which balances the amount of emphasis given to minimizing RSS vs minimizing sum of square of coefficients.

```
# import the Ridge and Lasso
from sklearn.linear_model import Lasso
from sklearn.linear_model import Ridge

reg = Ridge(alpha=0)
reg.fit(x_train,y_train)
reg.coef_

array([ 0.01865693,  0.02317626,  0.01156475, -0.00099944,
0.01249708,
        0.06467088,  0.01396816])
```

if α = 0:

- The objective becomes same as simple linear regression.
- ## Coefficeints will be the same coefficients as simple linear regression

```
reg = Ridge(alpha=1)
reg.fit(x_train,y_train)
reg.coef_

array([ 0.01890168,  0.02325201,  0.01159441, -0.00079808,
0.01253884,
        0.06400375,  0.01399031])

reg = Ridge(alpha=2)
reg.fit(x_train,y_train)
reg.coef_
```

```
array([ 0.0191347 ,  0.02332466,  0.01162418, -0.0006022 ,
0.01257856,
        0.06335834,  0.01401208])
```

---

if 0 < α < ∞:

- The magnitude of α will decide the weightage given to different parts of objective.
- The coefficients will be somewhere between 0 and ones for simple linear regression.

  Will work with aplha = 3

```
reg = Ridge(alpha=3)
reg.fit(x_train,y_train)

Ridge(alpha=3)

print('Coefficients:',reg.coef_)
print()
print('Intercept:',reg.intercept_)

Coefficients: [ 0.01935669  0.02339431  0.01165402 -0.00041155
0.01261636  0.06273356
  0.01403346]

Intercept: 0.7249904774750751
```

when compared with aplha values 1,2 the coefficients for aplha 3 is increased

```
reg = Ridge(alpha=4)
reg.fit(x_train,y_train)
reg.coef_

array([ 0.01956827,  0.02346108,  0.0116839 , -0.0002259 ,
0.01265237,
        0.06212839,  0.01405444])
```

we can say that the coefficients are decreased for aplha value = 4

The Best aplha value for ridge regression is 3

Insights

- CGPA feature has a Positive influence on the predicted output

- SOP feature has a negative influence on the predicted output

```
reg_pred = reg.predict(x_test)
```

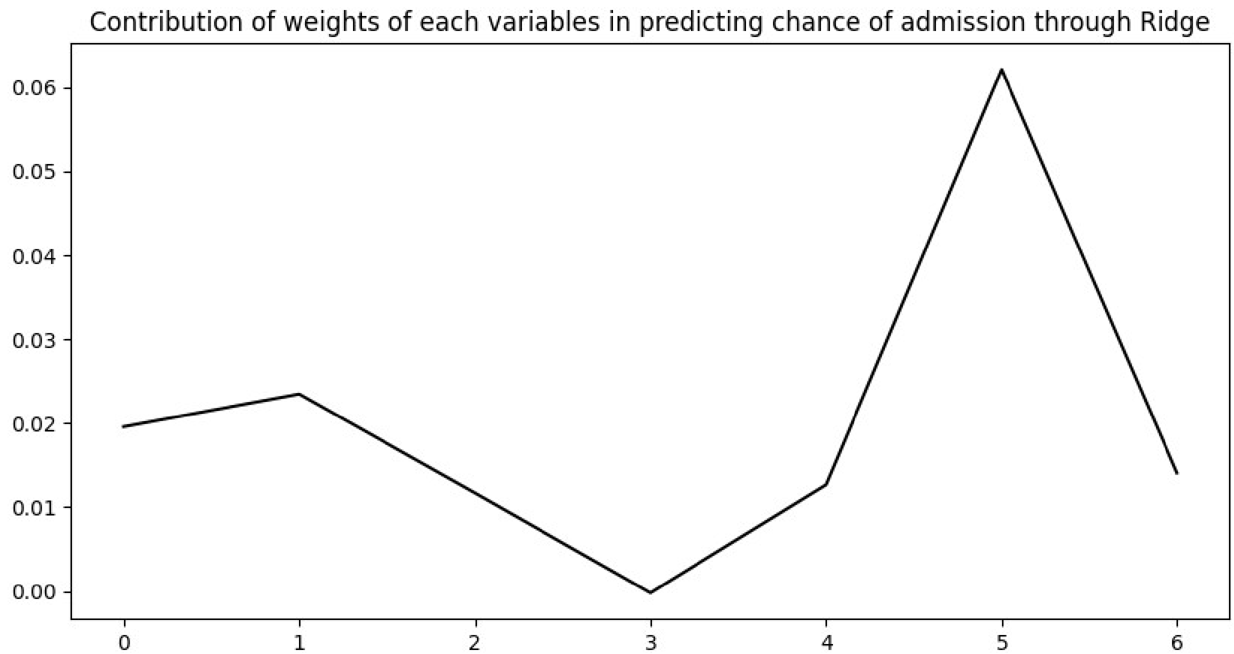
Checking MAE, Score, RSME, R^2 and Adjusted R^2 for Ridge Regression

```
print('The score of Ridge Regression for Training
Data:',reg.score(x_train,y_train),'.')

print('The score of Ridge Regression for Test
Data:',reg.score(x_test,y_test),'.')

print('Mean Absolute
error:',mean_absolute_error(y_true=y_test,y_pred=reg_pred),'.')
# defailt squared =True

print('Root Mean Squared
Error:',mean_squared_error(y_true=y_test,y_pred=reg_pred,squared=False
),'.')

print('R^2:',r2_score(y_test,reg_pred),'.')

print('Adjusted R^2: ',(1 - (1-(r2_score(y_test,reg_pred)))*(len(y)-
1)/(len(y)-x.shape[1]-1)),'.')

The score of Ridge Regression for Training Data: 0.820905769011983 .
The score of Ridge Regression for Test Data: 0.8146197401744573 .
Mean Absolute error: 0.04411094194771019 .
Root Mean Squared Error: 0.06443316005292868 .
R^2: 0.8146197401744573 .
Adjusted R^2:  0.8119822161525492 .
```

Insights

- There is a small increase in all these metrics comapared to linear regression

```
plt.figure(figsize=(10,5))
plt.plot(reg.coef_, color='black')
plt.title('Contribution of weights of each variables in predicting
chance of admission through Ridge')
print({'0':'GRE score','1':'TOEFL score','2':'University
Rating','3':'SOP','4':'LOR','5':'CGPA','6':'Research'})
plt.show()

{'0': 'GRE score', '1': 'TOEFL score', '2': 'University Rating', '3':
'SOP', '4': 'LOR', '5': 'CGPA', '6': 'Research'}
```



Insights:

- CGPA holds the highest Weightage in coeffieints among all variable during Ridge Regularization.

LASSO REGRESSION

LASSO stands for Least Absolute Shrinkage and Selection Operator. I know it doesn't give much of an idea but there are 2 key words here – 'absolute' and 'selection'.

Lasso regression performs L1 regularization, i.e. it adds a factor of sum of absolute value of coefficients in the optimization objective. Thus, lasso regression optimizes the following:

Objective = RSS + α * (sum of absolute value of coefficients)

Here, α (alpha) works similar to that of ridge and provides a trade-off between balancing RSS and magnitude of coefficients.

---

if $\alpha = 0$:

- Coefficeints will be the same coefficients as simple linear regression

if $\alpha = \infty$:

- All coefficients zero (same logic as before)

$0 < \alpha < \infty$:

- Coefficients between 0 and that of simple linear regression

---

```
laso = Lasso(alpha=0.01)
laso.fit(x_train,y_train)
laso.coef_

array([0.01775501, 0.02058363, 0.00895251, 0.        , 0.0073064 ,
       0.06473126, 0.00817853])
```

Here we can see that one of the coefficient is zero , it means that the predicted outcome remains unchanged regardless of whether the value of that feature increases or decreases.

```
laso = Lasso(alpha=1)
laso.fit(x_train,y_train)
laso.coef_

array([0., 0., 0., 0., 0., 0., 0.])
```

Here all coefficients are zero, it means that the corresponding features have no effect on the predicted outcome.

```
laso = Lasso(alpha=0.0001)
laso.fit(x_train,y_train)

Lasso(alpha=0.0001)

print('Coefficients:',laso.coef_)
print()
print('Intercept:',laso.intercept_)

Coefficients: [ 0.01870951  0.02306132  0.01130287 -0.00045029
0.01230956  0.06455643
```

```
 0.01391719]

Intercept: 0.7249727181128369
```

The best alpha value for lasso regression is 0.0001

Insights

- CGPA feature has a Positive influence on the predicted output
- SOP feature has a negative influence on the predicted output

```
laso_pred = laso.predict(x_test)
```

Checking MAE, Score, RSME, R^2 and Adjusted R^2 for Lasso Regression

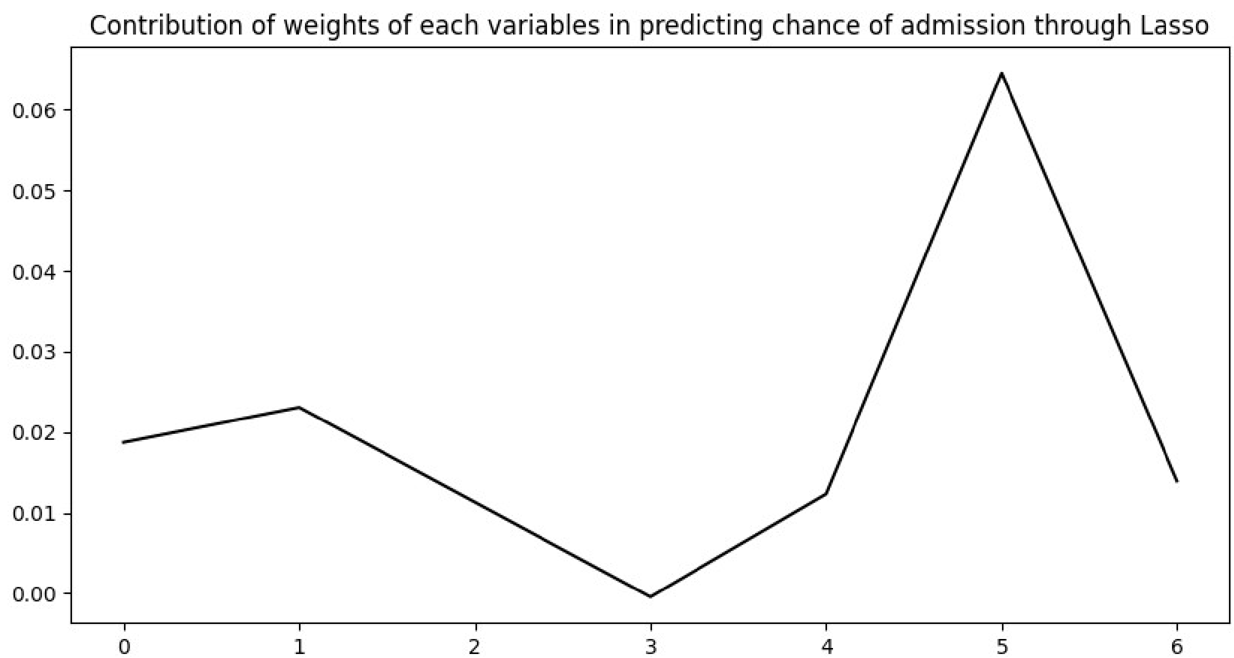
```
print('The score of Lasso Regression for Training 
Data:',laso.score(x_train,y_train),'.')
print()
print('The score of Lasso Regression for Test 
Data:',laso.score(x_test,y_test),'.')
print()
print('Mean Absolute 
error:',mean_absolute_error(y_true=y_test,y_pred=laso_pred),'.')
# default squared =True
print()
print('Root Mean Squared 
Error:',mean_squared_error(y_true=y_test,y_pred=laso_pred,squared=Fals
e),'.')
print()
print('R^2:',r2_score(y_test,laso_pred),'.')
print()
print('Adjusted R^2: ',(1 - (1-(r2_score(y_test,laso_pred)))*(len(y)-
1)/(len(y)-x.shape[1]-1)),'.')
print()

The score of Lasso Regression for Training Data: 0.8209778399606931 .

The score of Lasso Regression for Test Data: 0.8158806046861055 .

Mean Absolute error: 0.04394451781823835 .

Root Mean Squared Error: 0.06421366500579023 .

R^2: 0.8158806046861055 .

Adjusted R^2:  0.8132610197934281 .
```

Insights

- There is a small increase in all these metrics

```
x_ticks = list(x)
y_ticks = list(laso.coef_)
plt.figure(figsize=(10,5))
plt.plot(laso.coef_, color='black')
plt.title('Contribution of weights of each variables in predicting
chance of admission through Lasso')
print({'0':'GRE score','1':'TOEFL score','2':'University
Rating','3':'SOP','4':'LOR','5':'CGPA','6':'Research'})
plt.show()
```

```
{'0': 'GRE score', '1': 'TOEFL score', '2': 'University Rating', '3':
'SOP', '4': 'LOR', '5': 'CGPA', '6': 'Research'}
```



Insights:

- CGPA claims the highest Weightage in coeffieints among all variable during Lasso Regression.
- Since model is not overfitting, Results for Linear, Ridge and Lasso are the same.
- R2_score and Adjusted_r2 are almost the same. Hence there are no unnecessary independent variables in the data.

LINEAR REGRESSION ASSUMPTIONS TESTING

a) Multicollinearity check by VIF score (variables are dropped one-by-one till none has VIF>5)

```
col = ds[['GRE Score', 'TOEFL Score', 'University Rating', 'SOP', 'LOR
', 'CGPA','Research']]
x1 = np.array(x_train)
vif = []
for i in range(x1.shape[1]):
    vif.append(round(variance_inflation_factor(x1, i),2))
vif_score= pd.DataFrame({'Columns':['GRE Score', 'TOEFL Score',
'University Rating', 'SOP', 'LOR ', 'CGPA','Research'],
                         'VIF score':vif})


print(vif_score)
```

```
             Columns  VIF score
0          GRE Score       4.49
1        TOEFL Score       4.15
2  University Rating       2.99
3                SOP       2.96
4               LOR        2.03
5               CGPA       4.63
6           Research       1.53
```

Insights:-

```
It can be observed that every column has a VIF less than 5.
```

Hence, there is no multicollinearity among the independent variables.

- The 'Research' has the lowest VIF score of 1.53, indicating that it has the least correlation with the other predictor variables.
- This means that 'Research' provides unique information that is not highly correlated with the information provided by the other variables.
- 'CGPA' has the highest VIF score of 4.63, suggesting a relatively higher correlation with the other predictor variables compared to the rest.

b) The mean of residuals is nearly zero

```
normal = y_test - y_predict
print('Mean of Residuals:',(sum(np.array(normal)/len(normal))))

Mean of Residuals: -0.010793738256654518
```

Insights

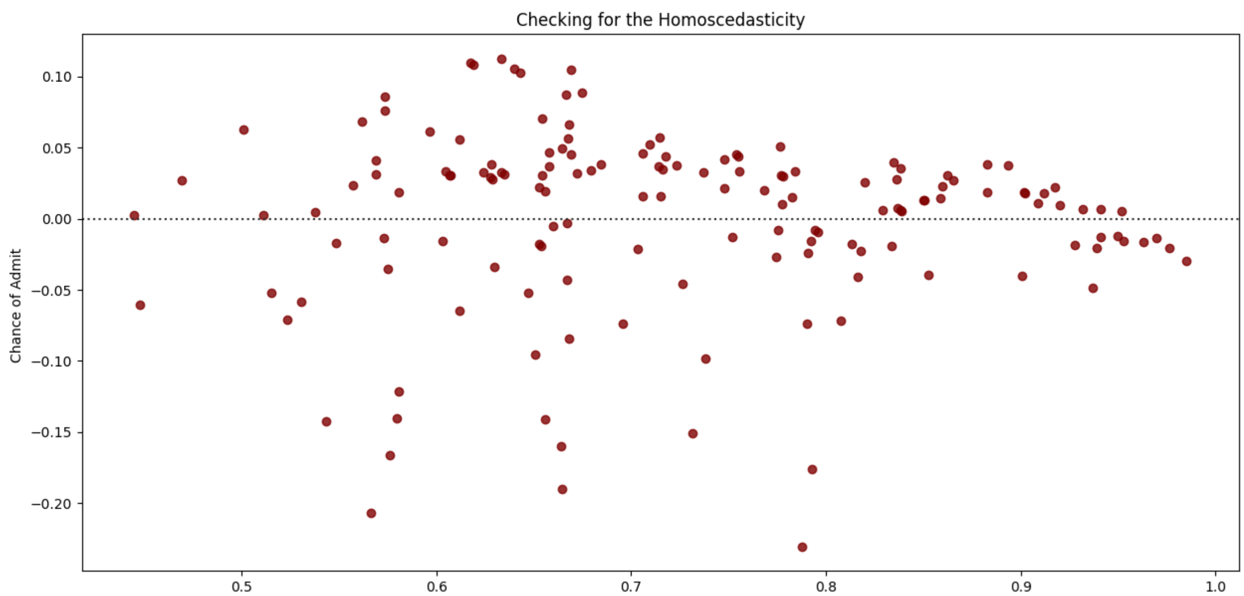
- suggests a slight underestimation in the model's predictions on average. While this indicates a generally unbiased model.

c) Linearity of variables

- It is quite clear from EDA that independent variables are linearly dependent on the target variables

d) Test for Homoscedasticity

```
plt.figure(figsize=(15,7))
sns.residplot(x=y_predict,y=normal,color='maroon')
plt.title('Checking for the Homoscedasticity')
plt.show()
```



Insights

- No discernible pattern at y=0 in the residual plot indicates homoscedasticity, ensuring the model's errors have a consistent spread across predicted values, implying stable and reliable performance.

e) Normality of residuals (almost bell-shaped curve in residuals distribution, points in QQ plot are almost all on the line)

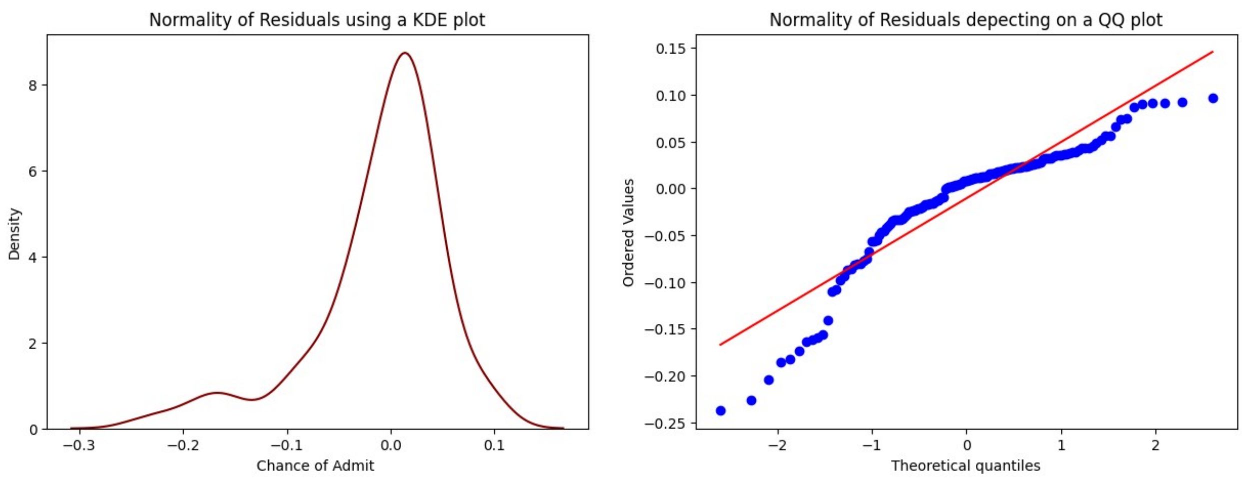
```
normal = y_test - y_predict
normal.head()

304   -0.032803
340    0.040549
47    -0.046701
67    -0.161461
```

```
479   -0.028033
Name: Chance of Admit , dtype: float64
```

Insights

- In summary, the output will be the residuals, which indicate how much the model's predictions deviate from the actual observed values for the first few data points.

```
# qq-plot and kde plot of residuals
fig = plt.figure(figsize=(15,5))
ax = fig.add_subplot(1,2,1)
sns.kdeplot(x=normal,color='maroon')
plt.title('Normality of Residuals using a KDE plot')

ax = fig.add_subplot(1,2,2)
sp.stats.probplot(normal,plot=plt)
plt.title('Normality of Residuals depecting on a QQ plot')
plt.show()
```



Insights

- The KDE plot resembles a bell-shaped curve (i.e., approximately normal distribution), it suggests that the residuals follow a normal distribution.
- Area of high density(i.e., CGPA) indicate where the majority of residuals are clustered.
- The points in a QQ plot lie approximately along the diagonal line, it indicates that the data closely follows the normal distribution.
- The QQ plot confirms the normality of residuals, as the majority of points are aligned with the diagonal line.

Recommendations

- After analysing the all features, to get a chance of admit in the universities we understood that the feature "CGPA" is showing more impact.
- CGPA and Research are the only two variables which are important in making the prediction for Chance of Admit.
- CGPA is the most important varibale in making the prediction for the Chance of Admit.
- Following are the final model results on the test data:
- Mean Absolute error: 0.04394451781823835 .
- Root Mean Squared Error: 0.06421366500579023 .
- R^2: 0.8158806046861055 .
- Adjusted R^2: 0.8132610197934281 .