Project 7 - Jamboree Education

August 13, 2022

[1]:
```
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,Lasso,Ridge
from sklearn.pipeline import make_pipeline
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.preprocessing import PolynomialFeatures
```

0.1 Context

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.

How can you help here? Your analysis will help Jamboree in understanding what factors are important in graduate admissions and how these factors are interrelated among themselves. It will also help predict one's chances of admission given the rest of the variables.

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)

Concept Used:

- Exploratory Data Analysis
- Linear Regression

[2]:
```
df=pd.read_csv('https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/
↪001/839/original/Jamboree_Admission.csv')
#First 5 rows
df.head()
```

[2]:
```
   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

   Research  Chance of Admit
0         1              0.92
1         1              0.76
2         1              0.72
3         1              0.80
4         0              0.65
```

[3]:
```
#Number of Rows and Columns
df.shape
#500 Rows and 9 Columns
```

[3]:
```
(500, 9)
```

[4]:
```
#Different Columns
df.columns.tolist()
```

[4]:
```
['Serial No.',
 'GRE Score',
 'TOEFL Score',
 'University Rating',
 'SOP',
 'LOR ',
 'CGPA',
 'Research',
 'Chance of Admit ']
```

[5]:
```
#Changing Column Name from "Chance of Admit " to "Chance of Admit" and "LOR "␣
↪to "LOR"
df.rename(columns={'Chance of Admit ':'Chance of Admit',"LOR ":
↪"LOR"},inplace=True)
df.head(3)
```

[5]:
```
   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

   Research  Chance of Admit
0         1             0.92
1         1             0.76
2         1             0.72
```

[6]:
```
#Checking for Null Values
df.isna().sum()
#There are no null values.
```

[6]:
```
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
```

[7]:
```
#Checking for duplicate rows
df[df.duplicated()]
#There are no duplicate rows
```

[7]:
```
Empty DataFrame
Columns: [Serial No., GRE Score, TOEFL Score, University Rating, SOP, LOR, CGPA,
Research, Chance of Admit]
Index: []
```

Checking for number of Unique values for every column.

[8]:
```
for value in df.columns:
    print(value,'=',df[value].nunique())
```

```
Serial No. = 500
GRE Score = 49
TOEFL Score = 29
University Rating = 5
SOP = 9
LOR = 9
CGPA = 184
Research = 2
Chance of Admit = 61
```

[9]:
```
#We can drop "Serial No." column, as it is a unique row identifier.
df.drop(columns='Serial No.',inplace=True)
#Checking the updated DataFrame
df.head(3)
```

[9]:
```
   GRE Score  TOEFL Score  University Rating  SOP  LOR  CGPA  Research  \
0        337          118                  4  4.5  4.5  9.65         1
1        324          107                  4  4.0  4.5  8.87         1
2        316          104                  3  3.0  3.5  8.00         1

   Chance of Admit
0             0.92
1             0.76
2             0.72
```

[10]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 8 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   GRE Score          500 non-null    int64
 1   TOEFL Score        500 non-null    int64
 2   University Rating  500 non-null    int64
 3   SOP                500 non-null    float64
 4   LOR                500 non-null    float64
 5   CGPA               500 non-null    float64
 6   Research           500 non-null    int64
 7   Chance of Admit    500 non-null    float64
dtypes: float64(4), int64(4)
memory usage: 31.4 KB
```

0.2 UNIVARIATE ANALYSIS

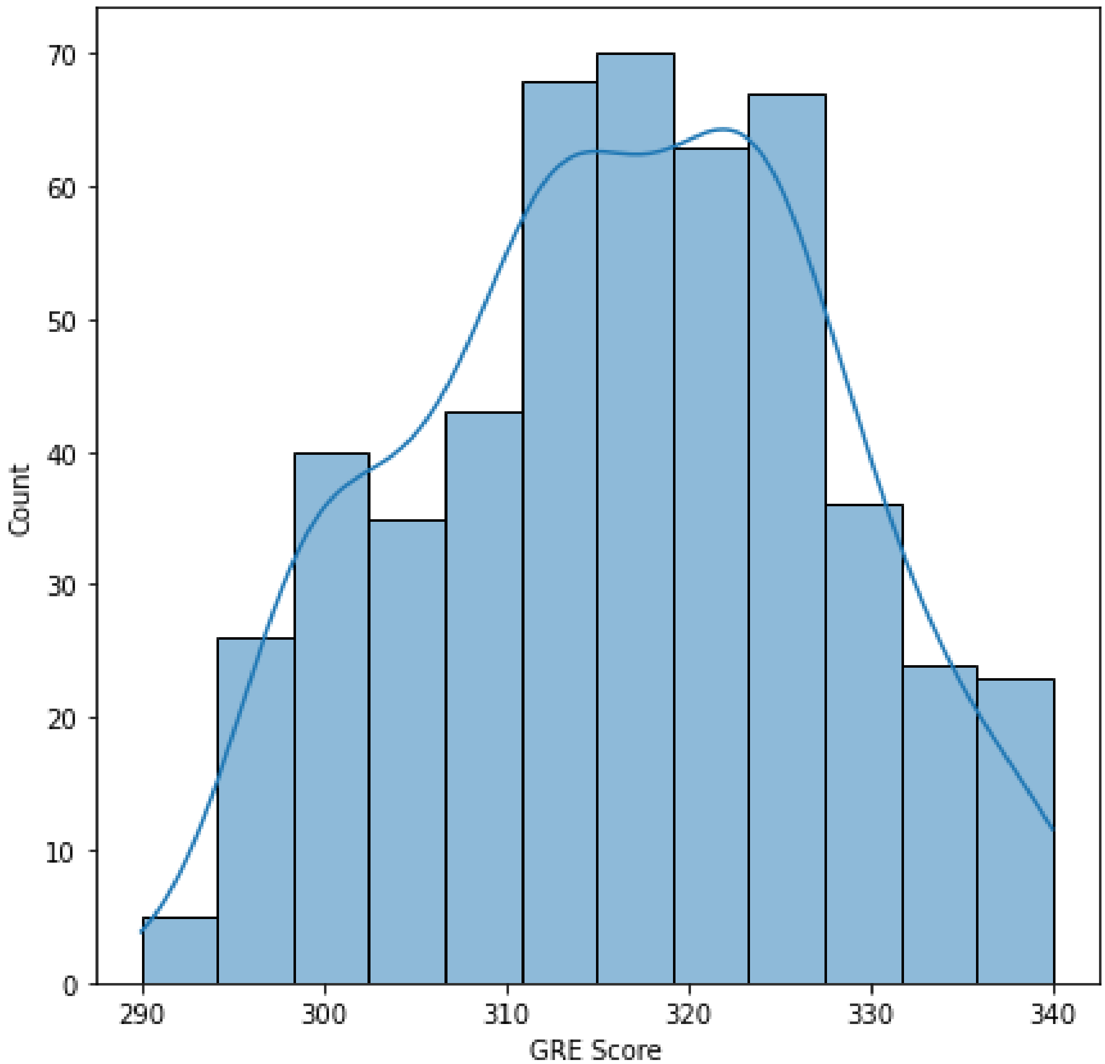
-

0.2.1 GRE Score

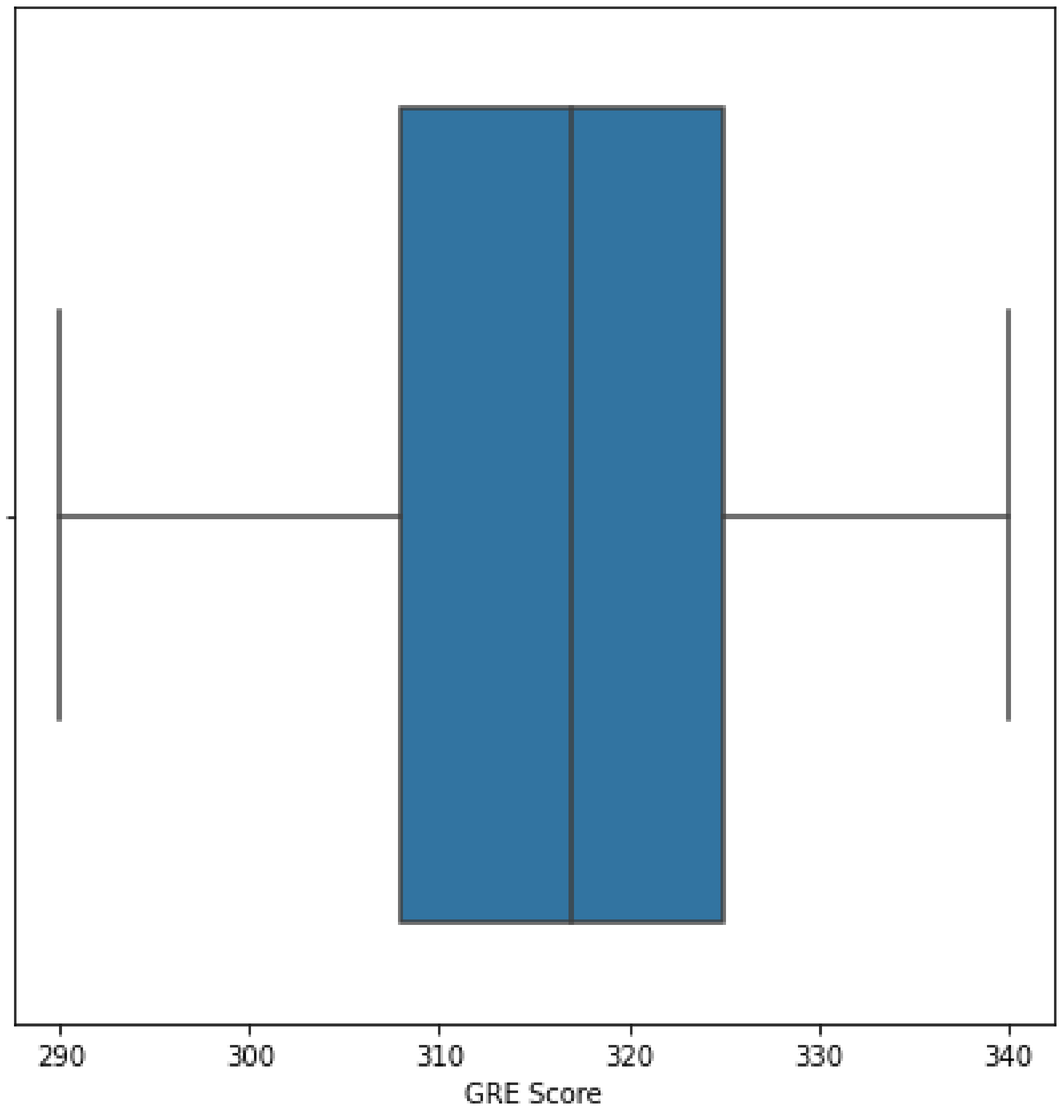
[11]:
```
#Number of Unique Values
df['GRE Score'].nunique()
```

[11]:
```
49
```

[12]:
```
plt.figure(figsize=(7,7))
sns.histplot(data=df,x='GRE Score',kde=True)
plt.show()
#The distribution looks similar to a normal distribution.
```



[13]:
```
plt.figure(figsize=(7,7))
sns.boxplot(data=df,x='GRE Score')
plt.show()
#There are no outliers
```



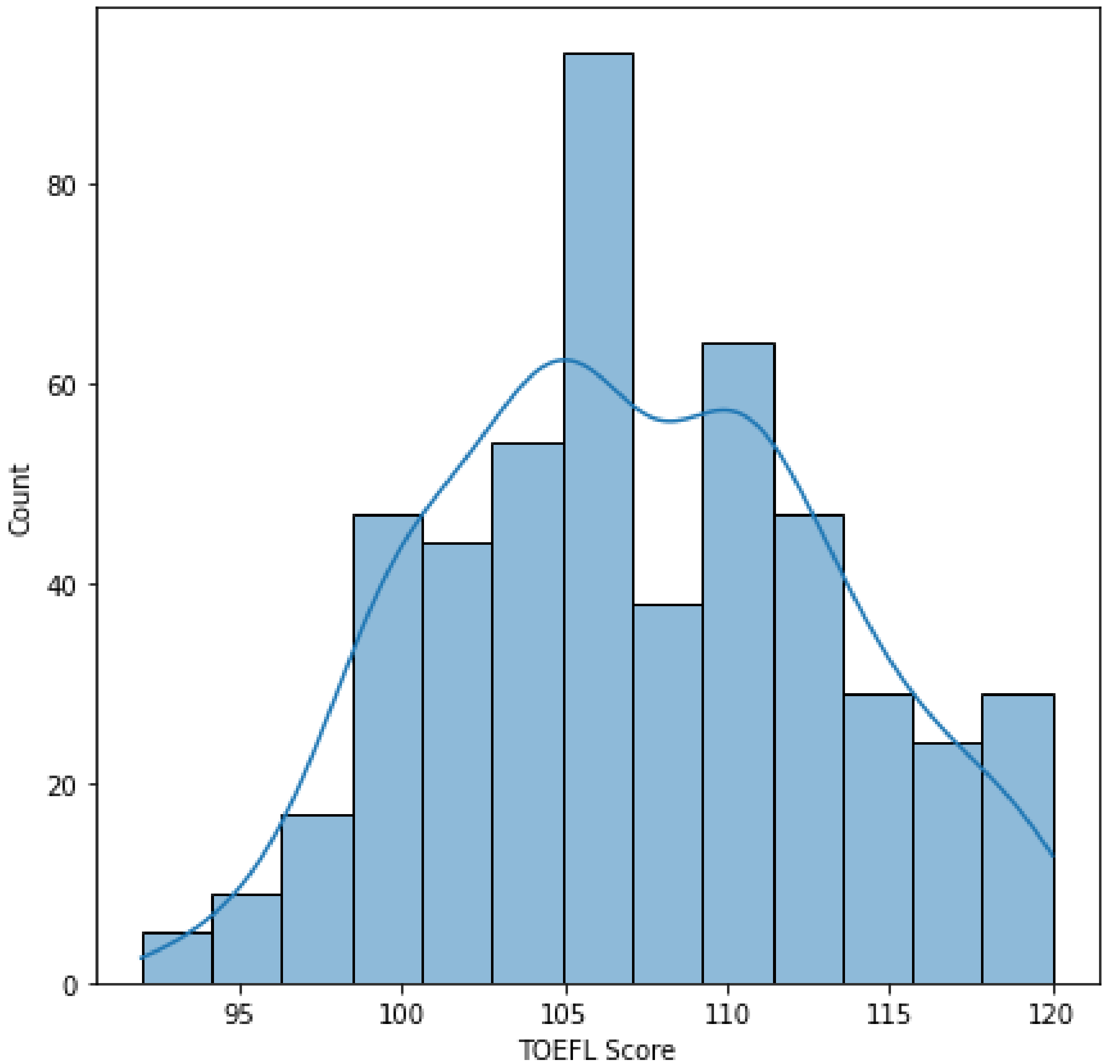
•

0.2.2 TOEFL Score

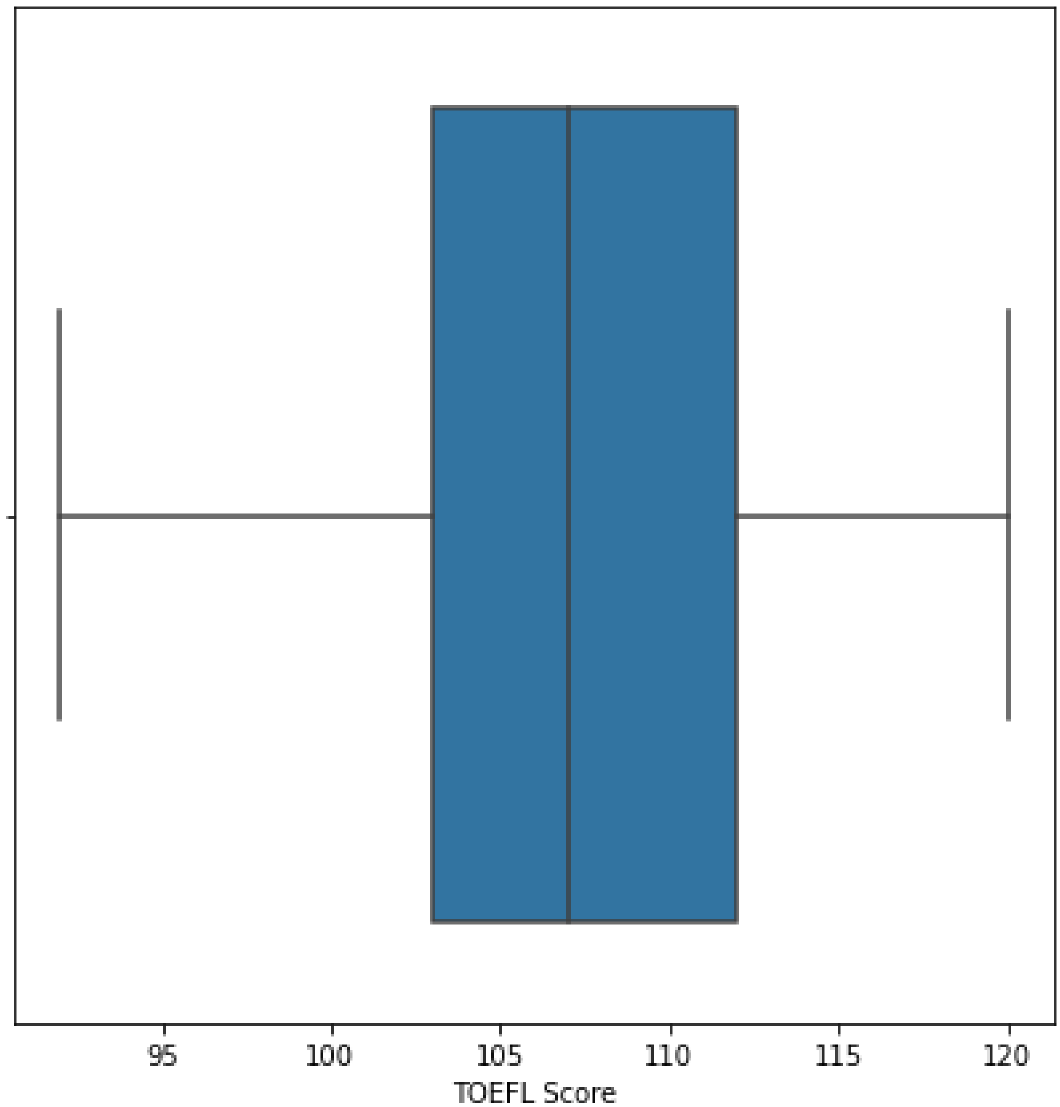
[14]:
```
#Number of Unique Values
df['TOEFL Score'].nunique()
```

[14]: 29

[15]:
```
plt.figure(figsize=(7,7))
sns.histplot(data=df,x='TOEFL Score',kde=True)
plt.show()
#The distribution looks similar to a normal distribution.
```



[16]:
```
plt.figure(figsize=(7,7))
sns.boxplot(data=df,x='TOEFL Score')
plt.show()
#There are no outliers
```

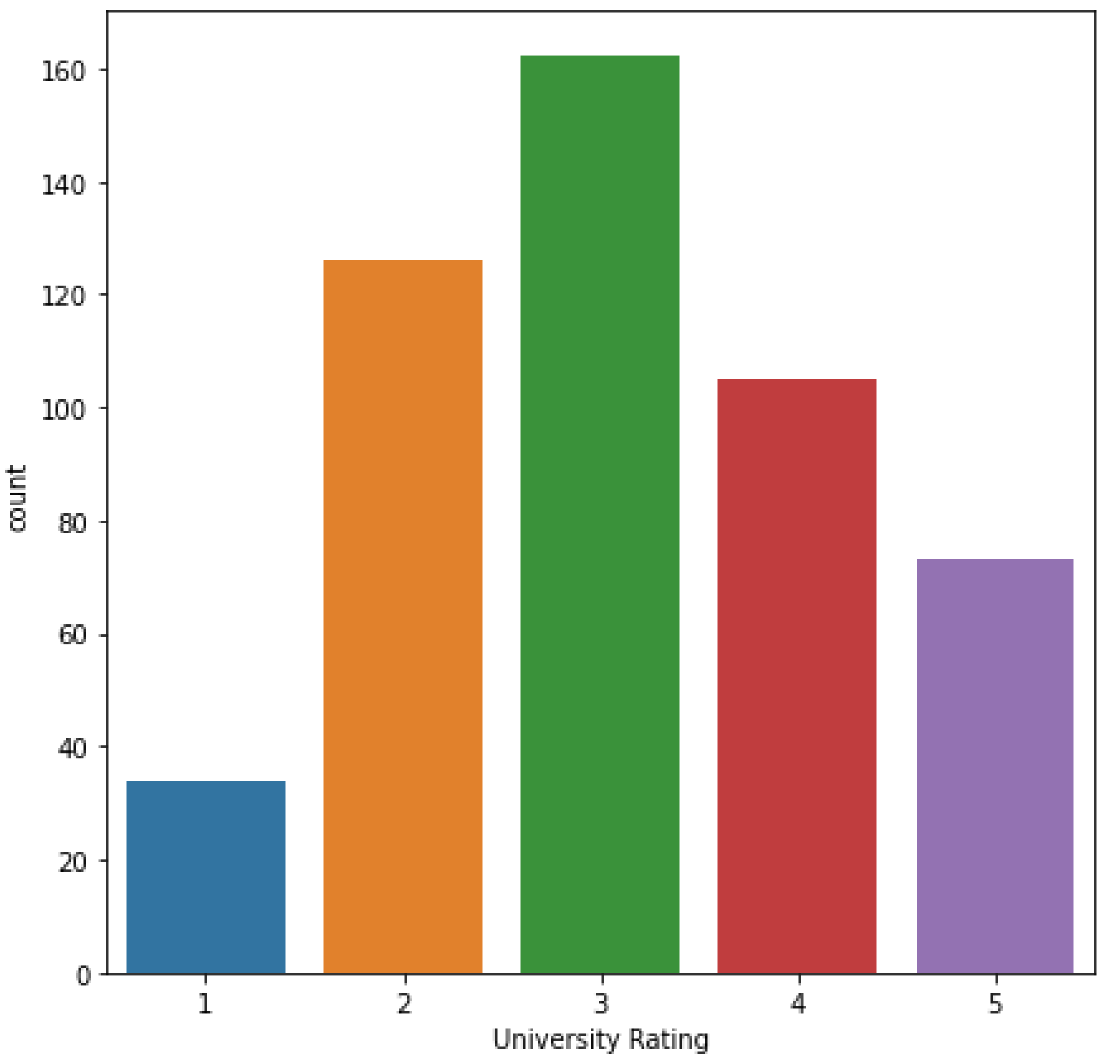


0.2.3 University Rating

[17]:
```
#Number of Unique Values
df['University Rating'].nunique()
```

[17]: 5

[18]:
```
plt.figure(figsize=(7,7))
sns.countplot(data=df,x='University Rating')
plt.show()
#University Rating 3 and 2 have the highest no. of occurences.
```



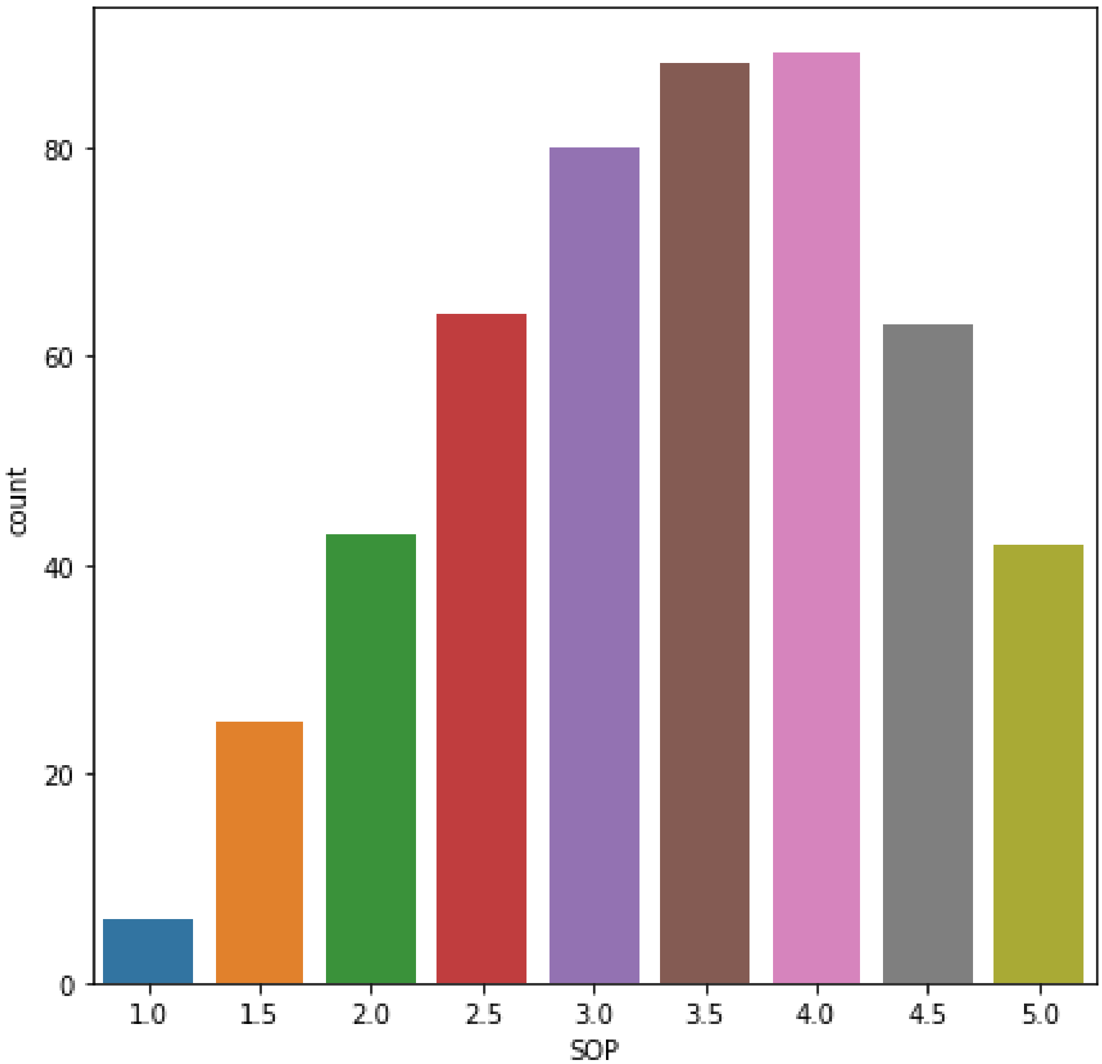
-

0.2.4 SOP

[19]:
```
#Number of Unique Values
df['SOP'].nunique()
```

[19]: 9

[20]:
```
plt.figure(figsize=(7,7))
sns.countplot(data=df,x='SOP')
plt.show()
#SOP 4,3.5,3 have the highest no. of occurences.
```



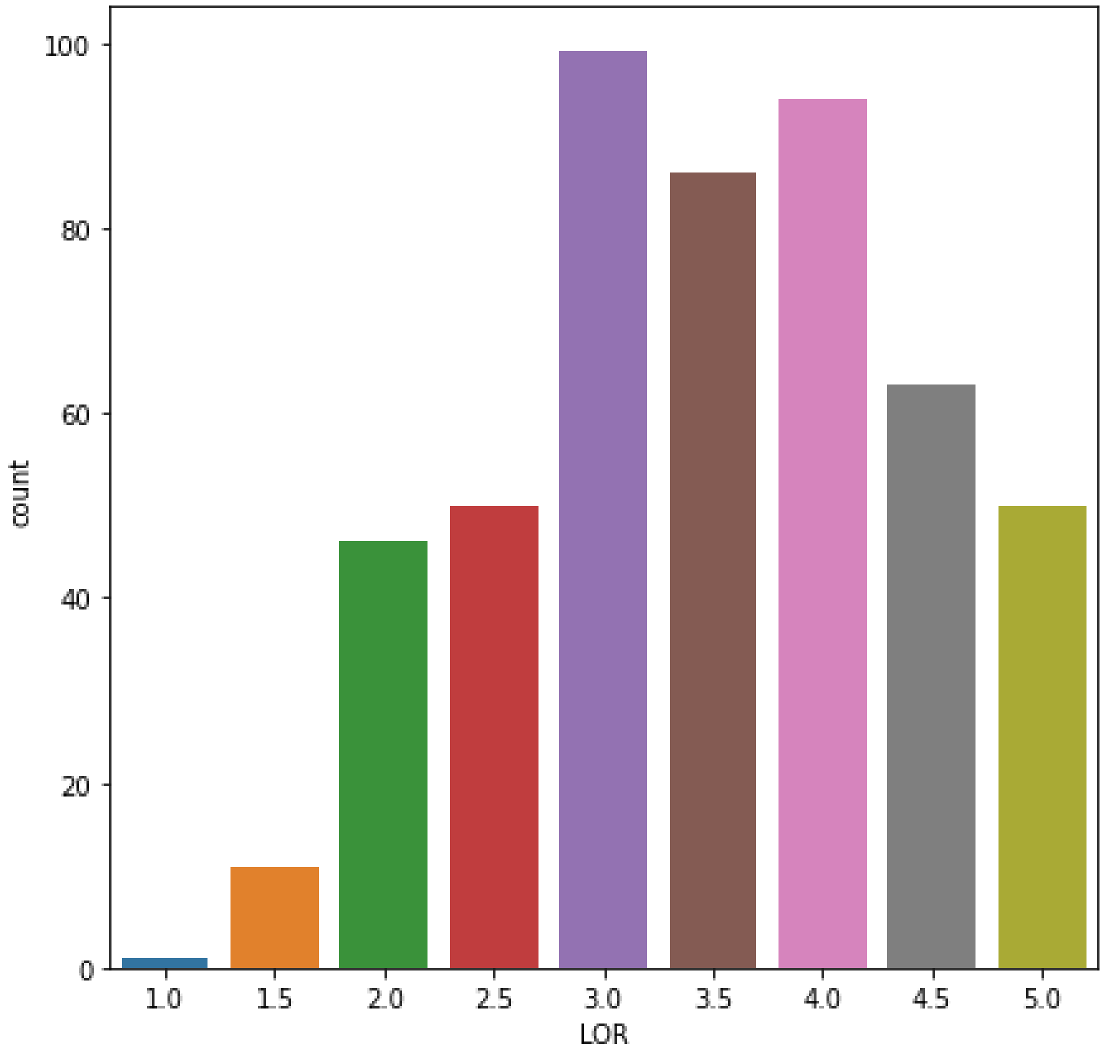
•

0.2.5 LOR

[21]:
```
#Number of Unique Values
df['LOR'].nunique()
```

[21]: 9

[22]:
```
plt.figure(figsize=(7,7))
sns.countplot(data=df,x='LOR')
plt.show()
#LOR 3,4,3.5 have the highest no. of occurences.
```



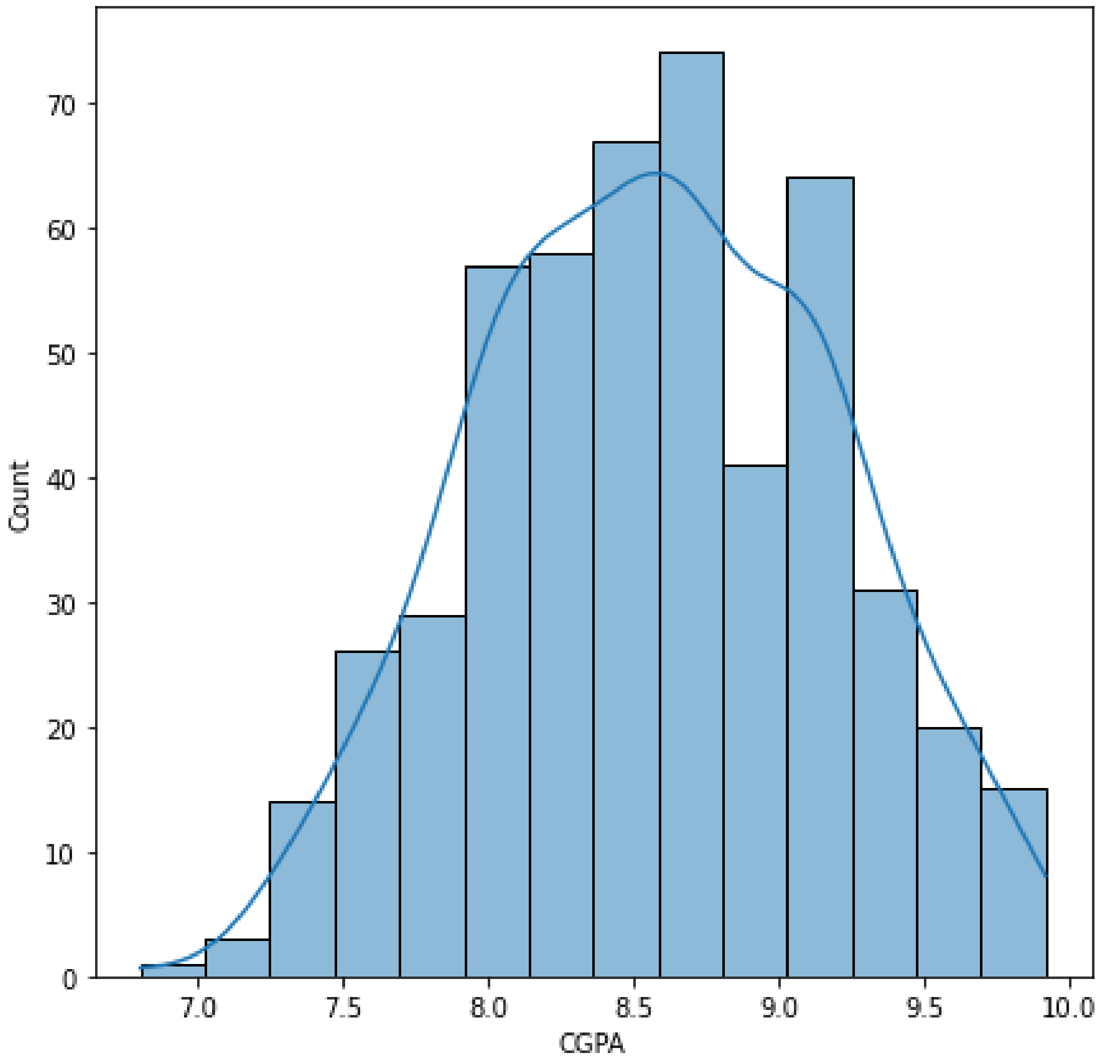
•

0.2.6 CGPA

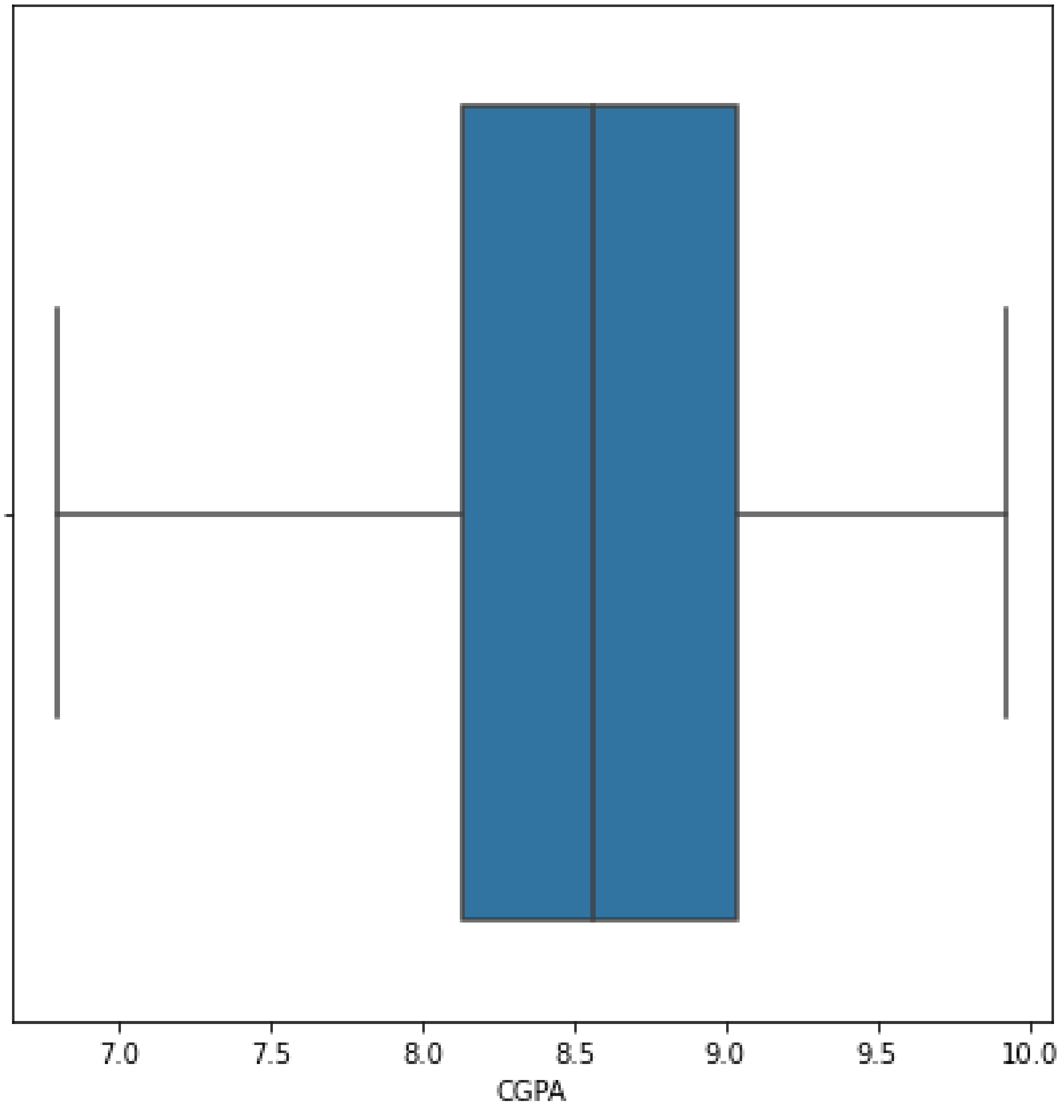
[23]:
```
#Number of Unique Values
df['CGPA'].nunique()
```

[23]: 184

[24]:
```
plt.figure(figsize=(7,7))
sns.histplot(data=df,x='CGPA',kde=True)
plt.show()
#The distribution looks similar to a normal distribution.
```



[25]:
```
plt.figure(figsize=(7,7))
sns.boxplot(data=df,x='CGPA')
plt.show()
#There are no outliers
```



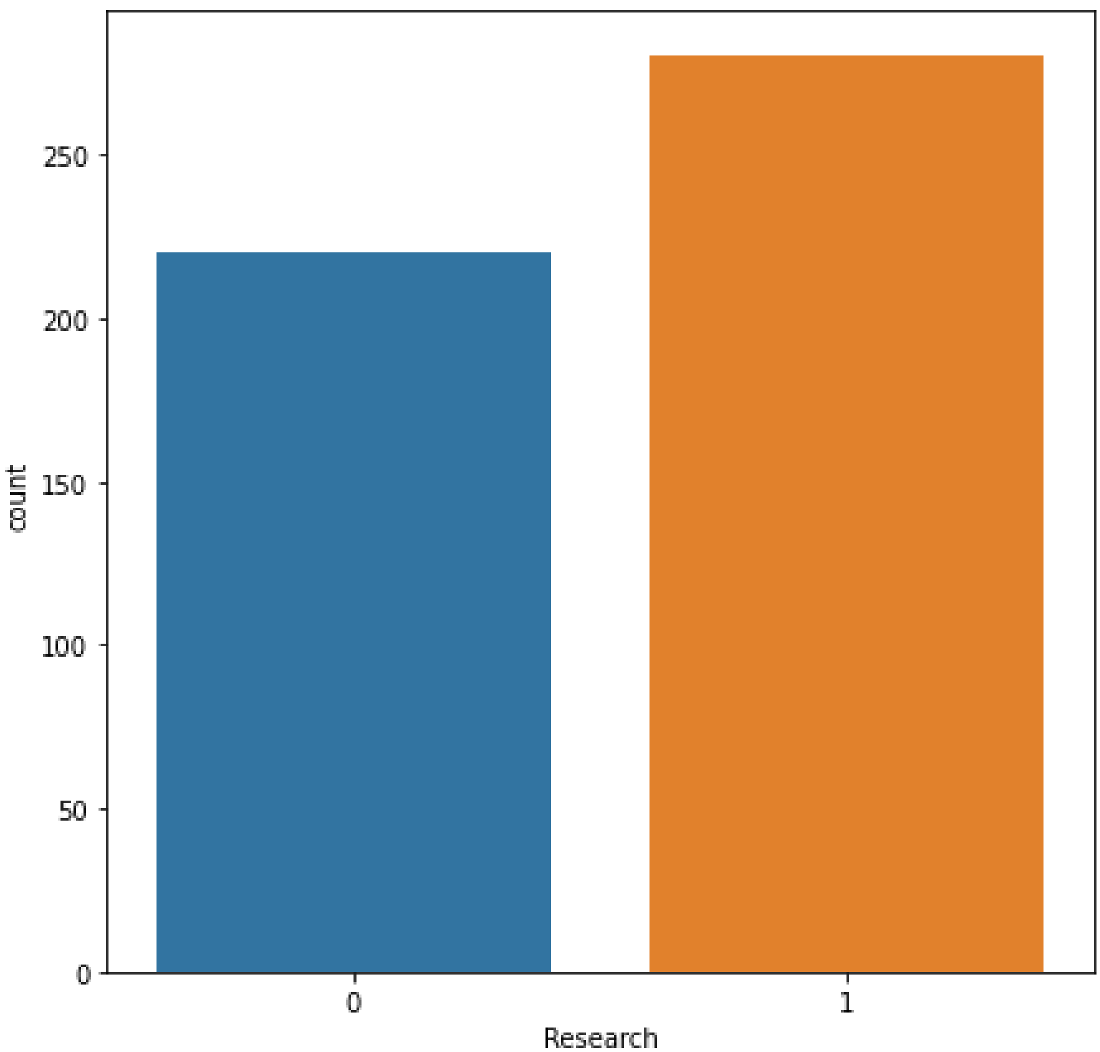
•

0.2.7 Research

[26]:
```
#Number of Unique Values
df['Research'].nunique()
```

[26]: 2

[27]:
```
plt.figure(figsize=(7,7))
sns.countplot(data=df,x='Research')
plt.show()
#There are more people who have done research.
```



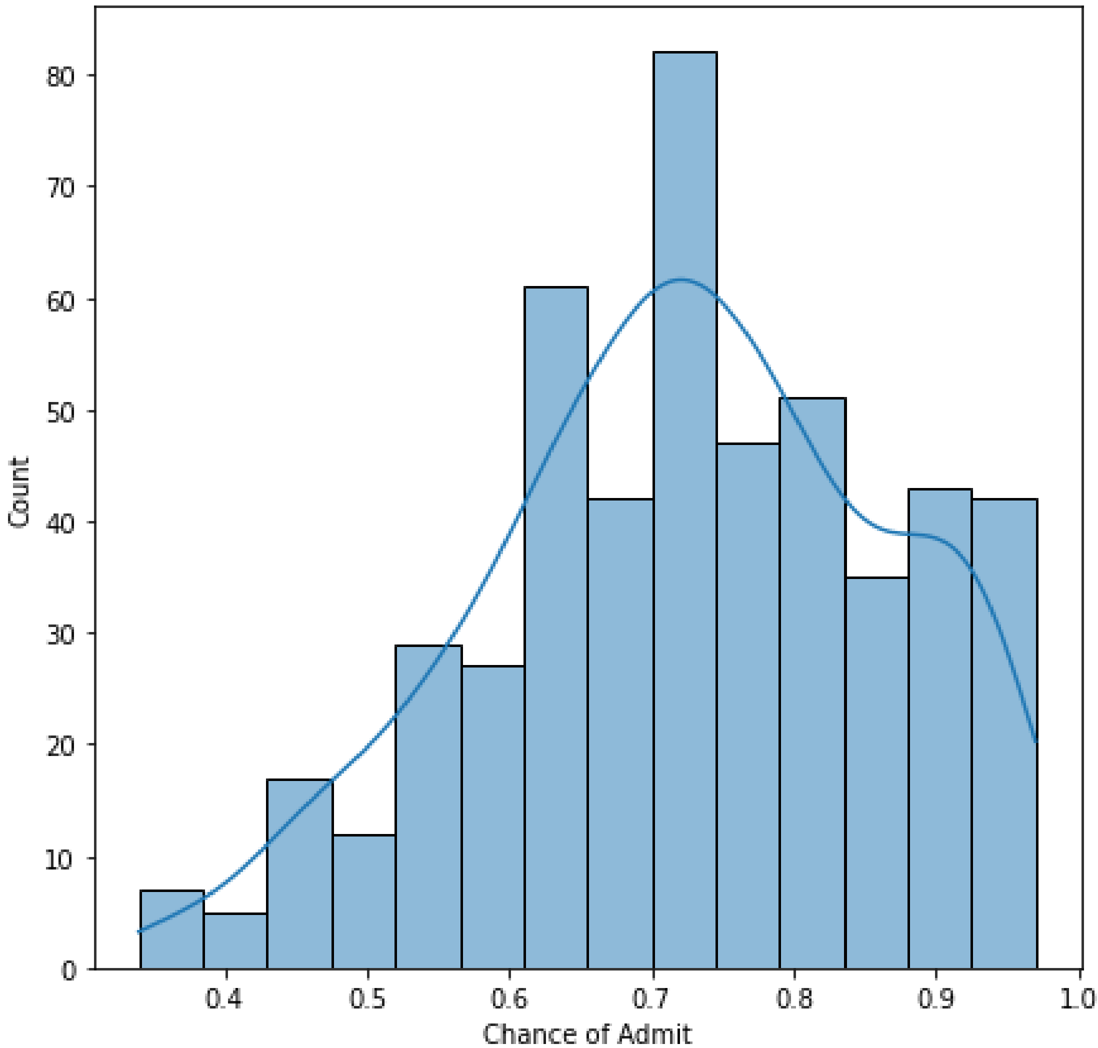
-

0.2.8 Chance of Admit

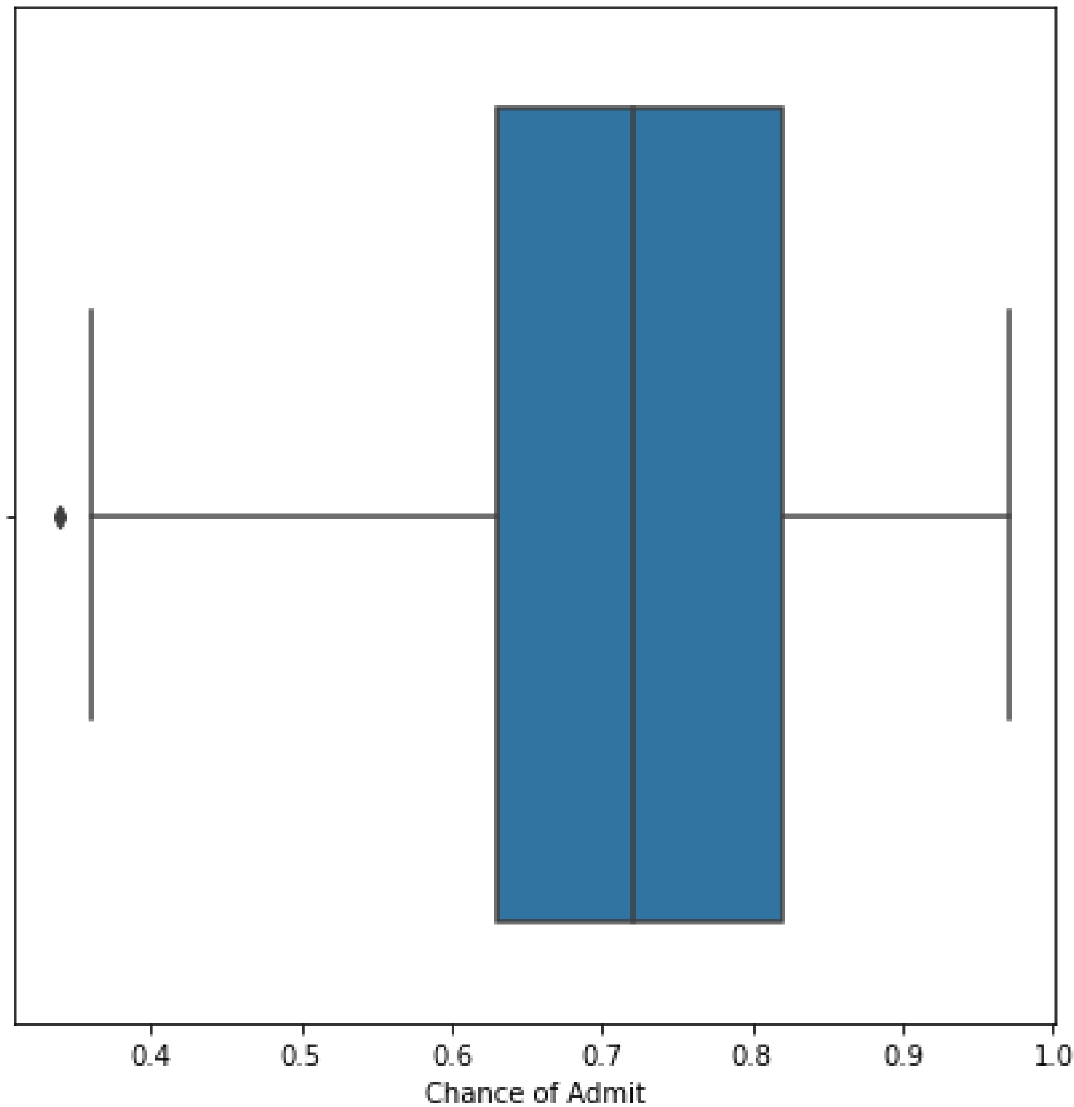
[28]:
```
#Number of Unique Values
df['Chance of Admit'].nunique()
```

[28]: 61

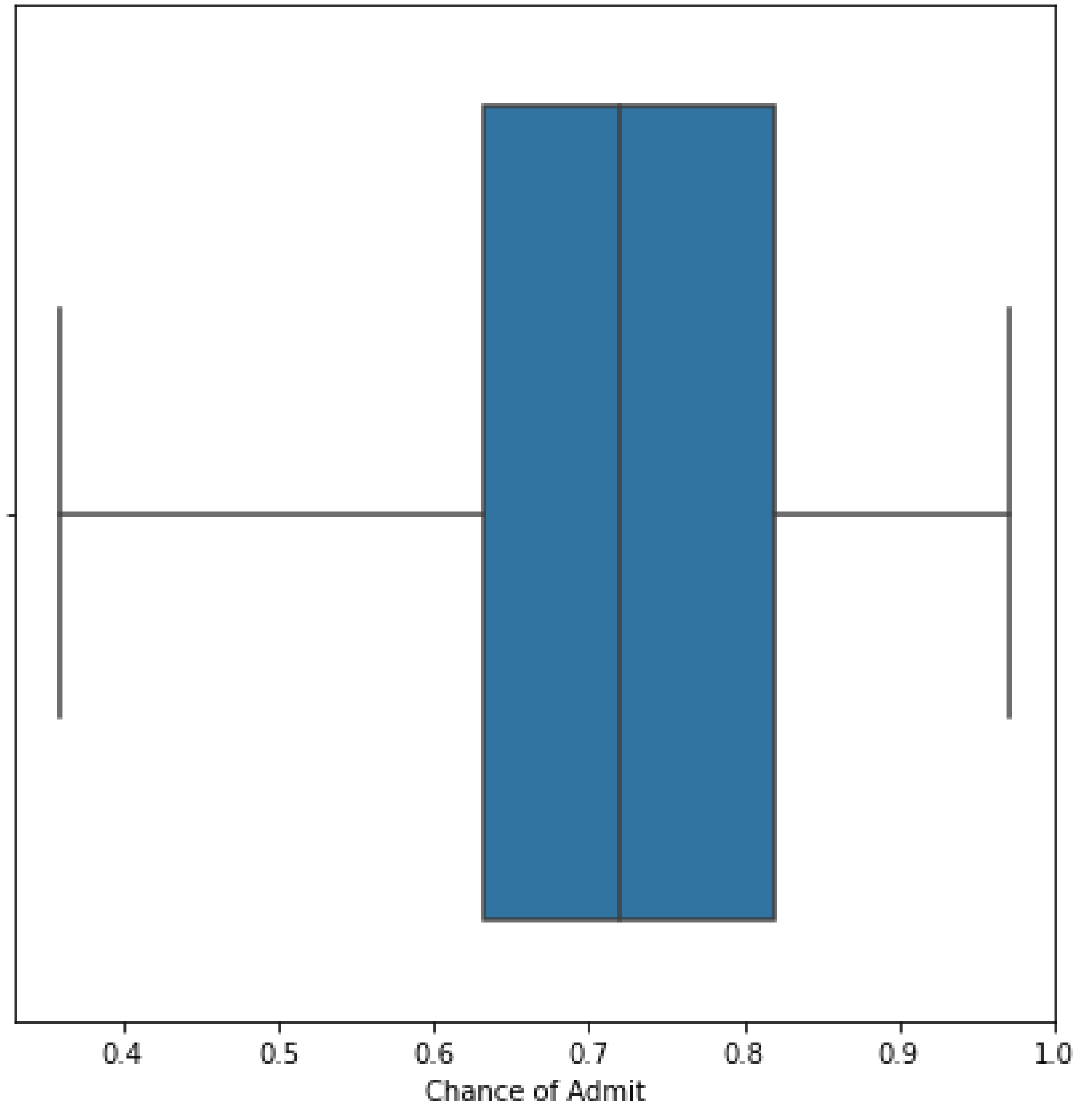
[29]:
```
plt.figure(figsize=(7,7))
sns.histplot(data=df,x='Chance of Admit',kde=True)
plt.show()
#The distribution does not look similar to a normal distribution.
```



[30]:
```
plt.figure(figsize=(7,7))
sns.boxplot(data=df,x='Chance of Admit')
plt.show()
#There is only 1 outlier.
```



[31]:
```
#Outlier Treatment for "Chance of Admit" variable.
#We can remove this outlier.
q25=np.quantile(df['Chance of Admit'],.25)
q75=np.quantile(df['Chance of Admit'],.75)
iqr=q75-q25
lower_whisker=q25-(1.5*iqr)
df=df[df['Chance of Admit']>lower_whisker]
plt.figure(figsize=(7,7))
sns.boxplot(data=df,x='Chance of Admit')
plt.show()
```



[32]:
```
#Updated Dataset Shape
df.shape
#2 outliers were removed
```

[32]: (498, 8)

[ ]:
```

```

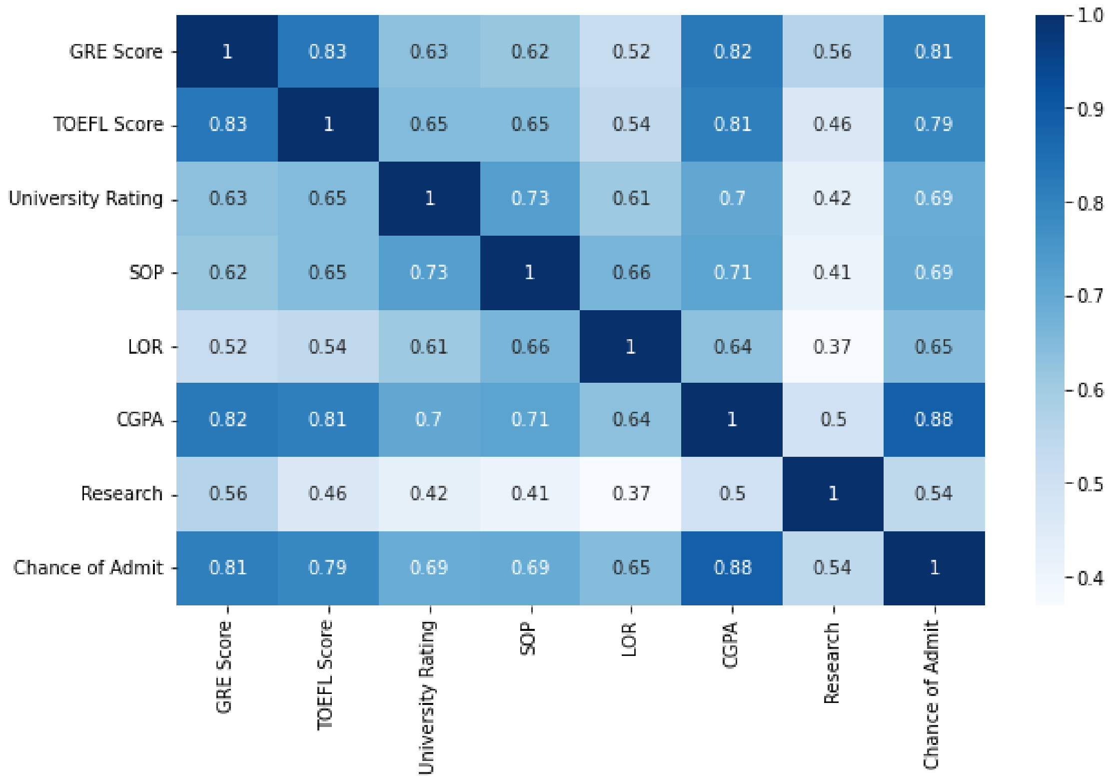
[33]:
```
#Checking the descriptive measures
df.describe()
```

[33]:
```
             GRE Score  TOEFL Score  University Rating         SOP         LOR  \
count   498.000000   498.000000         498.000000  498.000000  498.000000
mean    316.548193   107.232932           3.118474    3.374498    3.487952
std      11.253378     6.059228           1.143620    0.991824    0.924654
min     290.000000    92.000000           1.000000    1.000000    1.000000
25%     308.000000   103.000000           2.000000    2.500000    3.000000
50%     317.000000   107.000000           3.000000    3.500000    3.500000
75%     325.000000   112.000000           4.000000    4.000000    4.000000
max     340.000000   120.000000           5.000000    5.000000    5.000000

             CGPA    Research  Chance of Admit
count  498.000000  498.000000       498.000000
mean     8.579839    0.562249         0.723273
std      0.603335    0.496609         0.139327
min      6.800000    0.000000         0.360000
25%      8.130000    0.000000         0.632500
50%      8.560000    1.000000         0.720000
75%      9.040000    1.000000         0.820000
max      9.920000    1.000000         0.970000
```

[ ]:

[34]:
```
#Checking for correlation between various possible pairs of variables.
plt.figure(figsize=(10,6))
sns.heatmap(df.corr(),annot=True,cmap='Blues')
plt.show()
```



0.2.9 Observations

There is very strong correlation between: - "GRE Score" and "TOEFL Score" - "CGPA" and "TOEFL Score" - "GRE Score" and "CGPA" - "Chance of Admit" and "TOEFL Score" - "GRE Score" and "Chance of Admit" - "CGPA" and "Chance of Admit"

[ ]:

```

```

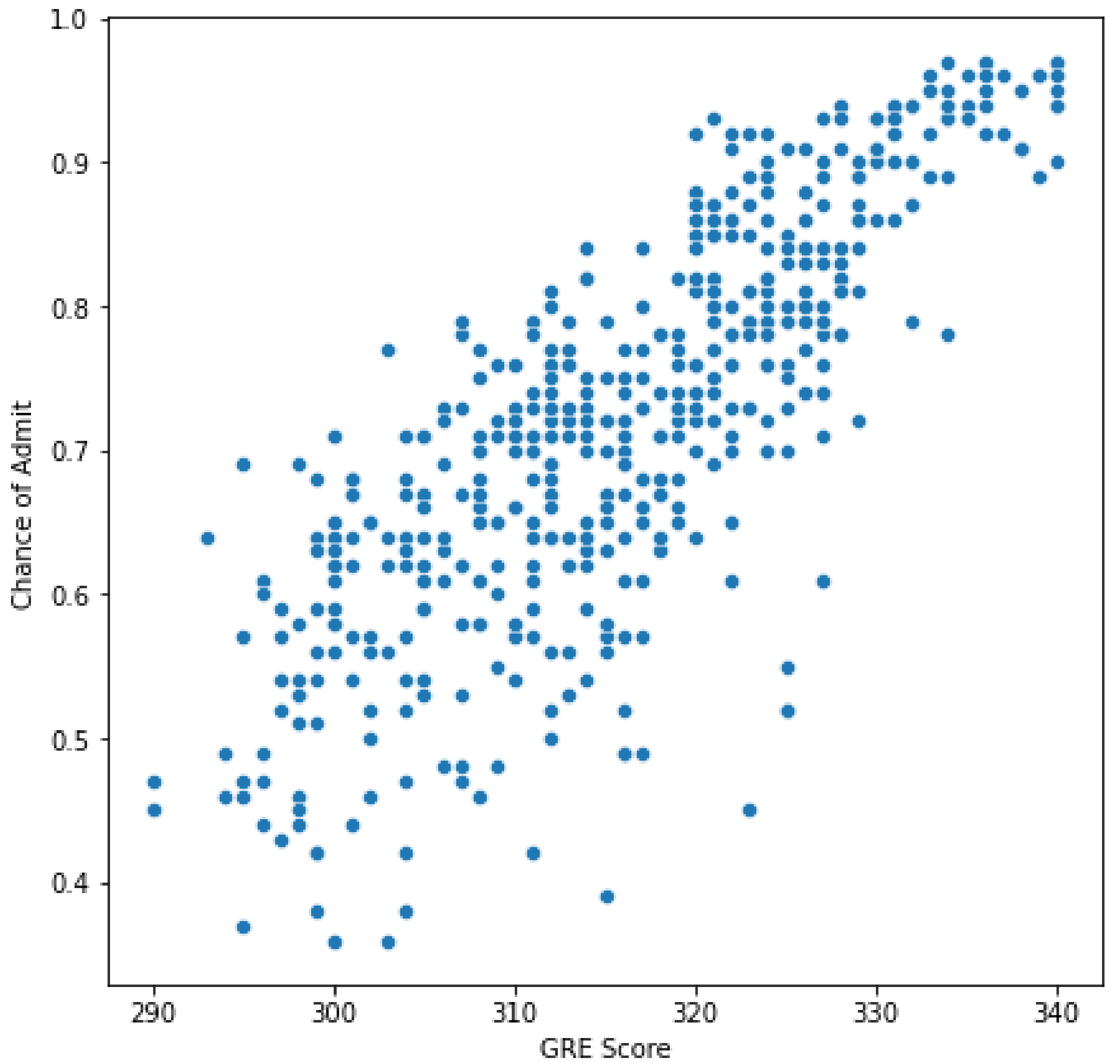
0.3 BIVARIATE ANALYSIS

-

0.3.1 Chance of Admit vs GRE Score

[35]:

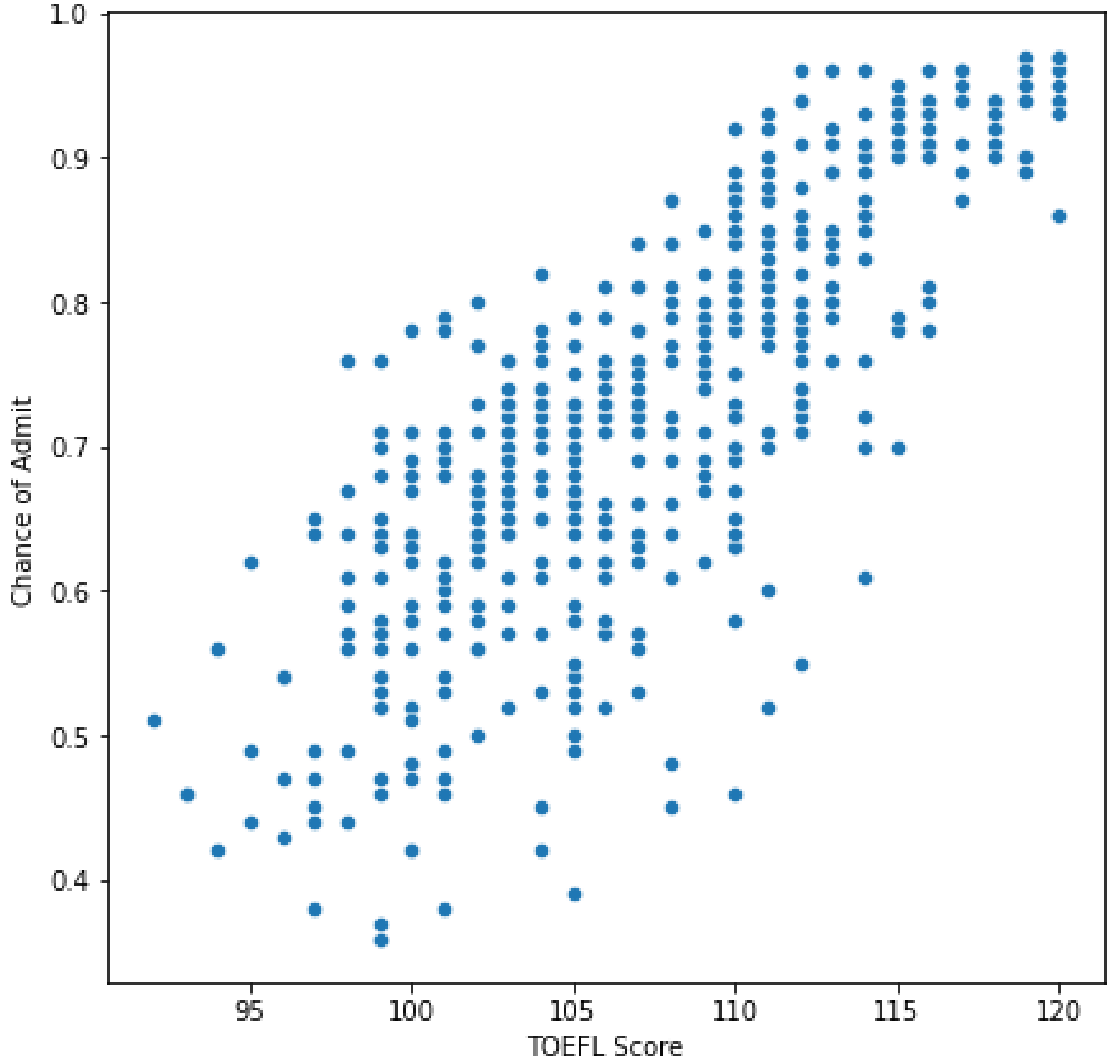
```
plt.figure(figsize=(7,7))
sns.scatterplot(data=df,x='GRE Score',y='Chance of Admit')
plt.show()
#There seems to be a positive relationship.
```



•

0.3.2 Chance of Admit vs TOEFL Score

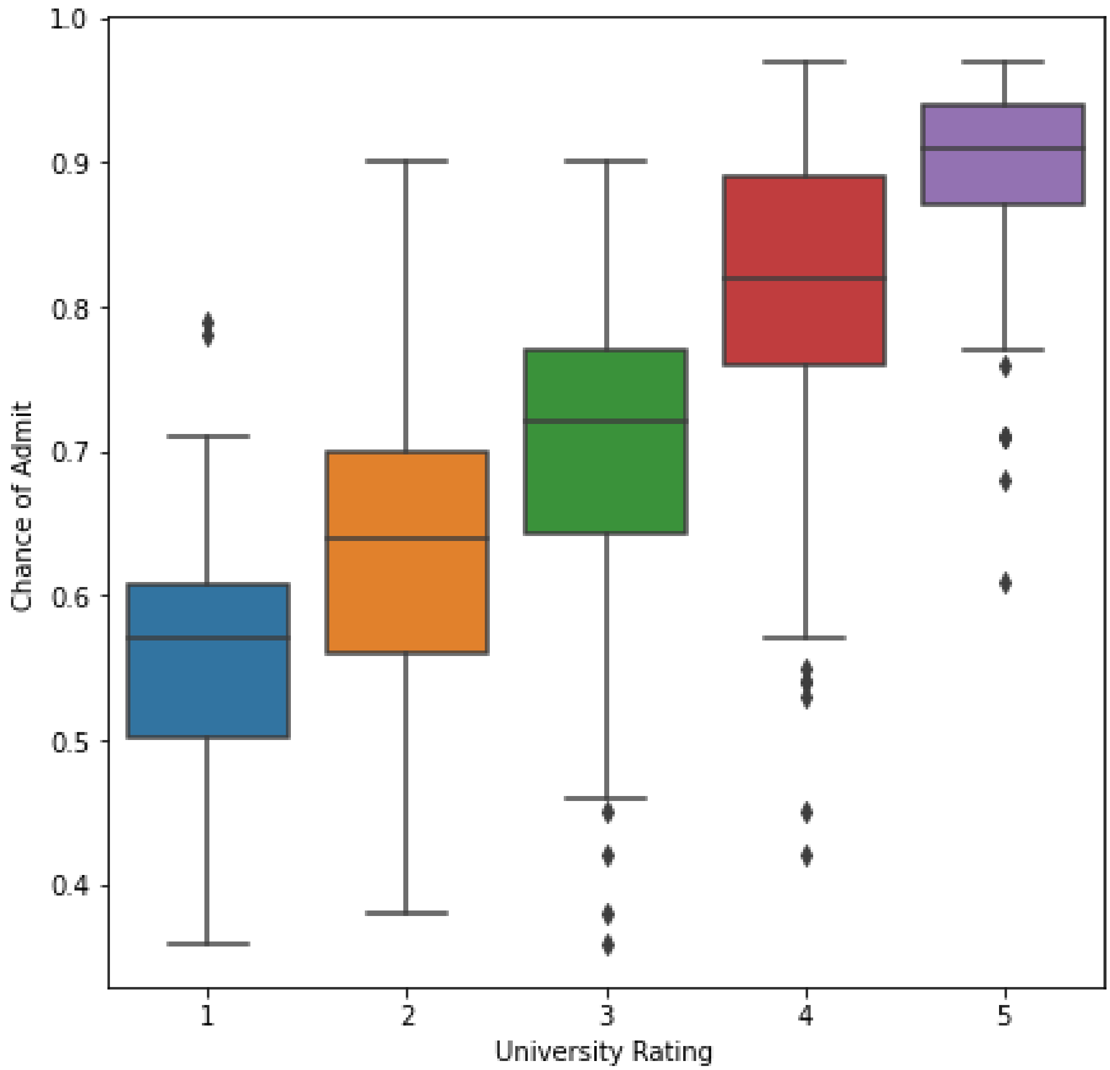
[36]:
```
plt.figure(figsize=(7,7))
sns.scatterplot(data=df,x='TOEFL Score',y='Chance of Admit')
plt.show()
#There seems to be a positive relationship.
```



•

0.3.3 Chance of Admit vs University Rating

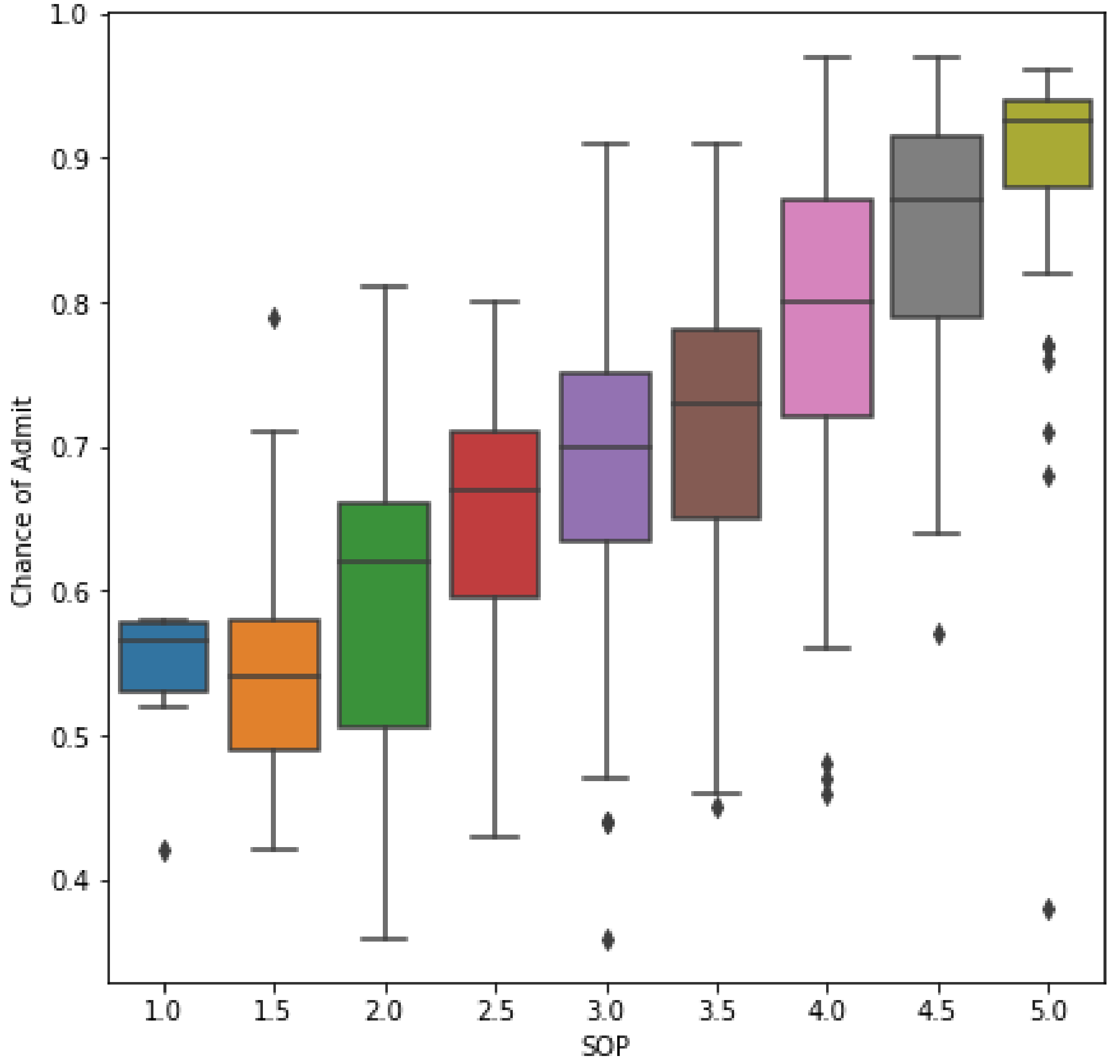
[37]:
```
plt.figure(figsize=(7,7))
sns.boxplot(data=df,x='University Rating',y='Chance of Admit')
plt.show()
#People having higher university ratings have higher median chance of admit.
```



•

0.3.4 Chance of Admit vs SOP

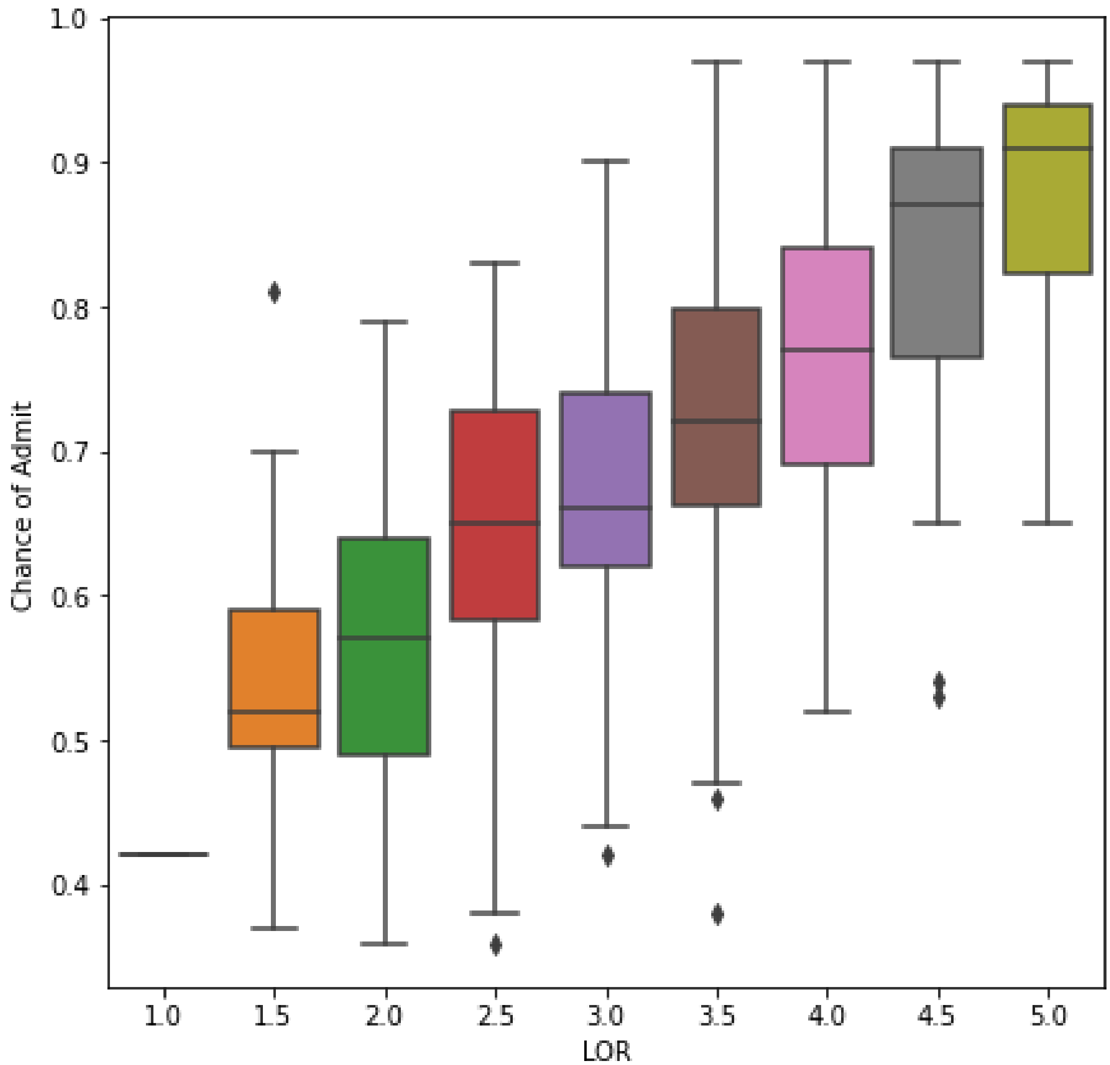
[38]:
```
plt.figure(figsize=(7,7))
sns.boxplot(data=df,x='SOP',y='Chance of Admit')
plt.show()
#People having higher SOP have higher median chance of admit.
```



•

0.3.5 Chance of Admit vs LOR

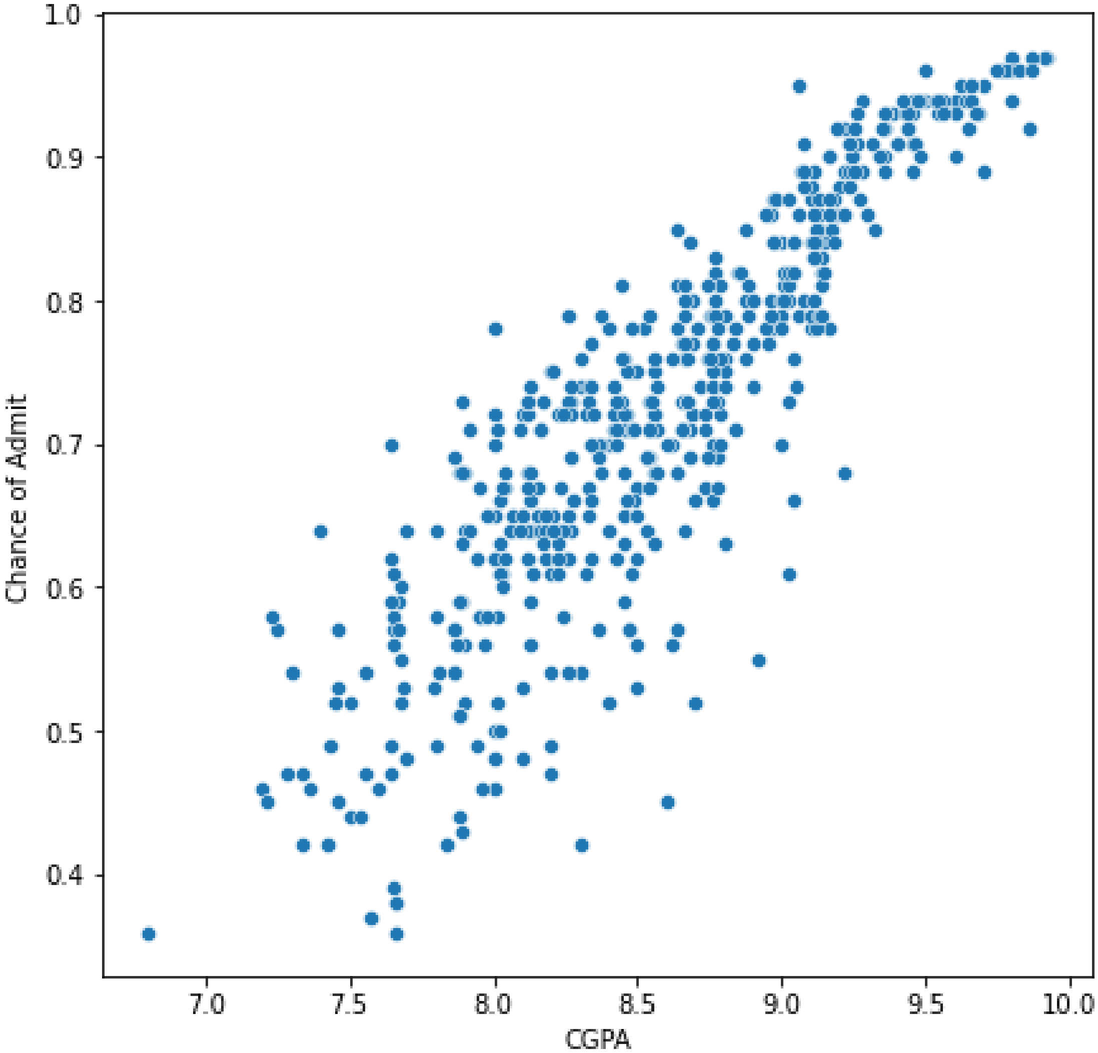
[39]:
```
plt.figure(figsize=(7,7))
sns.boxplot(data=df,x='LOR',y='Chance of Admit')
plt.show()
#People having higher LOR have higher median chance of admit.
```



•

0.3.6 Chance of Admit vs CGPA

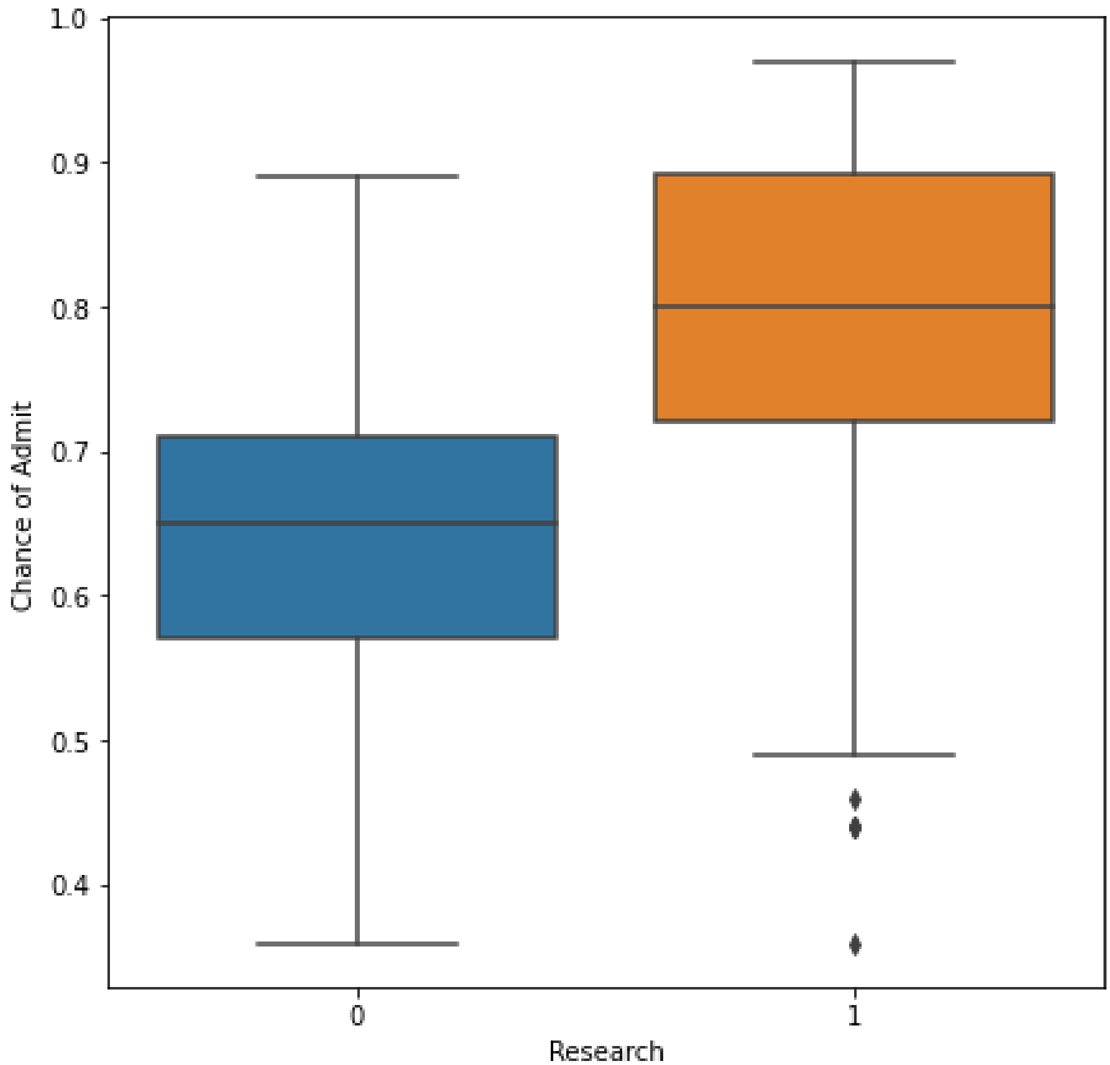
[40]:
```
plt.figure(figsize=(7,7))
sns.scatterplot(data=df,x='CGPA',y='Chance of Admit')
plt.show()
#There seems to be a positive relationship.
```



-

0.3.7 Chance of Admit vs Research

[41]:
```
plt.figure(figsize=(7,7))
sns.boxplot(data=df,x='Research',y='Chance of Admit')
plt.show()
#People who have done research have a higher median chance of admit.
```



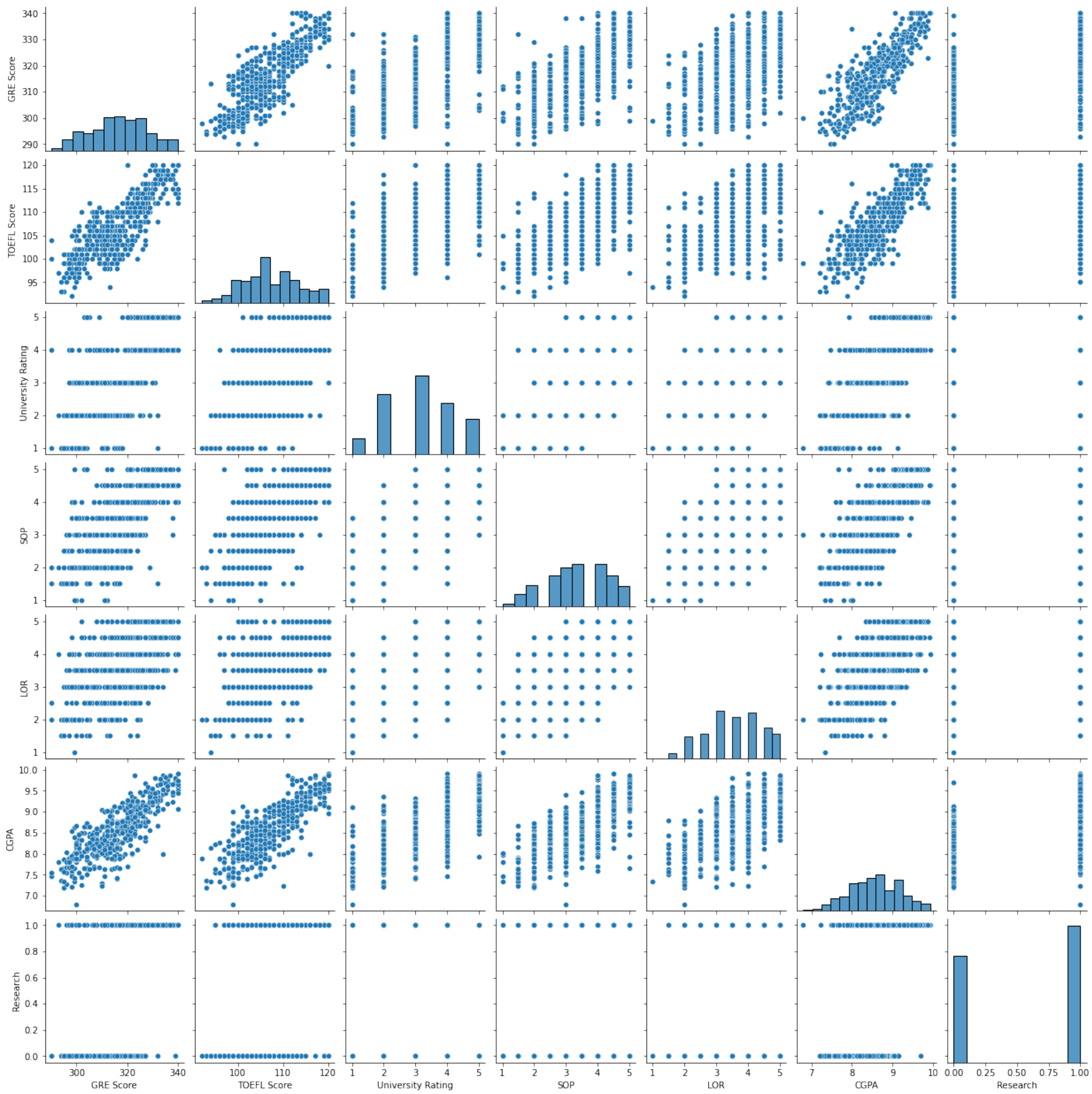
[ ]:

```
```

0.3.8 Pair-Plot between pairs of independent variables

[42]:

```
sns.pairplot(df.iloc[:,:-1])
plt.show()
```



0.3.9 Observations

We have the same obervations from the pariplot as from the Correlation Coefficient. There is very strong correlation between: - "GRE Score" and "TOEFL Score" - "CGPA" and "TOEFL Score" - "GRE Score" and "CGPA"

[43]:
```
#Splitting the dataset into X and y.
X=df.iloc[:,:-1]
display(X.head())
y=df.iloc[:,-1]
display(y.head())
```

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research
0	337	118	4	4.5	4.5	9.65	1

```
1        324          107                    4  4.0  4.5  8.87          1
2        316          104                    3  3.0  3.5  8.00          1
3        322          110                    3  3.5  2.5  8.67          1
4        314          103                    2  2.0  3.0  8.21          0
```

```
0    0.92
1    0.76
2    0.72
3    0.80
4    0.65
Name: Chance of Admit, dtype: float64
```

[ ]:

0.3.10 We will try 3 different models and compare which one gives the best performance and finally select that model.

[ ]:

0.4 1) Linear Regression without Regularization

Checking Assumption-1 : Multicollinearity check by VIF score

[44]:
```
#Splitting into Train and Test Data
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.
↪2,random_state=1)
```

[45]:
```
#No of observations in Train,Val and Test Dataset
print(X_train.shape)
print(X_test.shape)
```

```
(398, 7)
(100, 7)
```

[46]:
```
model=LinearRegression()
model.fit(X_train,y_train)
```

[46]:
```
LinearRegression()
```

[47]:
```
values=[list(model.coef_)+[model.intercept_]]
columns=list(model.feature_names_in_)+['intercept']
coefficients_df=pd.DataFrame(data=values,columns=columns)
coefficients_df
```

[47]:
```
   GRE Score  TOEFL Score  University Rating       SOP       LOR      CGPA  \
0   0.001892     0.002922           0.004863  0.004369  0.018484  0.115601

   Research  intercept
```

```
0  0.021924  -1.288234
```

[48]:
```
#Details of the model.
print(model.score(X_train,y_train))
print(model.score(X_test,y_test))
```

```
0.8252701604118984
0.8162154474443224
```

#R square is good. But can be better.

[49]:
```
vif = pd.DataFrame()
vif['Features'] = X_train.columns
vif['VIF'] = [variance_inflation_factor(X.values, i) for i in range(X_train.
 ↪shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

[49]:

	Features	VIF
0	GRE Score	1309.62
1	TOEFL Score	1215.27
5	CGPA	949.15
3	SOP	35.54
4	LOR	30.92
2	University Rating	21.00
6	Research	2.88

[50]:
```
#Lets remove the "GRE Score" variable since it has the highest VIF score.
X_train.drop(columns='GRE Score',inplace=True)
X_test.drop(columns='GRE Score',inplace=True)
```

[ ]:
```

```

[51]:
```
#No of observations in Train,Val and Test Dataset
print(X_train.shape)
print(X_test.shape)
```

```
(398, 6)
(100, 6)
```

[52]:
```
model=LinearRegression()
model.fit(X_train,y_train)
```

[52]: `LinearRegression()`

[53]:
```
values=[list(model.coef_)+[model.intercept_]]
columns=list(model.feature_names_in_)+['intercept']
```

```
coefficients_df=pd.DataFrame(data=values,columns=columns)
coefficients_df
```

[53]:

```
   TOEFL Score  University Rating       SOP       LOR      CGPA  Research  \
0     0.004554           0.005914  0.002987  0.017442  0.129298  0.029314

   intercept
0  -0.981256
```

[54]:

```
#Details of the model.
print(model.score(X_train,y_train))
print(model.score(X_test,y_test))
```

```
0.8200275993029533
0.8138400528146292
```

[55]:

```
vif = pd.DataFrame()
vif['Features'] = X_train.columns
vif['VIF'] = [variance_inflation_factor(X.values, i) for i in range(X_train.
 ↪shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

[55]:

```
            Features      VIF
0        TOEFL Score  1309.62
1  University Rating  1215.27
5           Research   949.15
3                LOR    35.54
4               CGPA    30.92
2                SOP    21.00
```

[ ]:

[56]:

```
#Lets remove the "TOEFL Score" variable since it has the highest VIF score.
X_train.drop(columns='TOEFL Score',inplace=True)
X_test.drop(columns='TOEFL Score',inplace=True)
```

[57]:

```
#No of observations in Train,Val and Test Dataset
print(X_train.shape)
print(X_test.shape)
```

```
(398, 5)
(100, 5)
```

[58]:

```
model=LinearRegression()
model.fit(X_train,y_train)
```

[58]: LinearRegression()

[59]:
```
values=[list(model.coef_)+[model.intercept_]]
columns=list(model.feature_names_in_)+['intercept']
coefficients_df=pd.DataFrame(data=values,columns=columns)
coefficients_df
```

[59]:

	University Rating	SOP	LOR	CGPA	Research	intercept
0	0.007416	0.006367	0.017241	0.158417	0.033636	-0.760462

[60]:
```
#Details of the model.
print(model.score(X_train,y_train))
print(model.score(X_test,y_test))
```

```
0.8066241977645116
0.8189603044540663
```

[61]:
```
vif = pd.DataFrame()
vif['Features'] = X_train.columns
vif['VIF'] = [variance_inflation_factor(X.values, i) for i in range(X_train.
 ↪shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

[61]:

	Features	VIF
0	University Rating	1309.62
1	SOP	1215.27
3	CGPA	35.54
4	Research	30.92
2	LOR	21.00

[ ]:

[62]:
```
#Lets first remove the "University Rating" variable since it has the highest␣
 ↪VIF score.
X_train.drop(columns='University Rating',inplace=True)
X_test.drop(columns='University Rating',inplace=True)
```

[63]:
```
#No of observations in Train,Val and Test Dataset
print(X_train.shape)
print(X_test.shape)
```

```
(398, 4)
(100, 4)
```

[64]:
```
model=LinearRegression()
model.fit(X_train,y_train)
```

[64]: LinearRegression()

[65]:
```
values=[list(model.coef_)+[model.intercept_]]
columns=list(model.feature_names_in_)+['intercept']
coefficients_df=pd.DataFrame(data=values,columns=columns)
coefficients_df
```

[65]:

	SOP	LOR	CGPA	Research	intercept
0	0.00992	0.018396	0.162313	0.035068	-0.787588

[66]:
```
#Details of the model.
print(model.score(X_train,y_train))
print(model.score(X_test,y_test))
```

```
0.80513097994306
0.8157198077244471
```

[67]:
```
vif = pd.DataFrame()
vif['Features'] = X_train.columns
vif['VIF'] = [variance_inflation_factor(X.values, i) for i in range(X_train.
↪shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

[67]:

	Features	VIF
0	SOP	1309.62
1	LOR	1215.27
3	Research	35.54
2	CGPA	21.00

[ ]:
```

```

[68]:
```
#Lets first remove the "SOP" variable since it has the highest VIF score.
X_train.drop(columns='SOP',inplace=True)
X_test.drop(columns='SOP',inplace=True)
```

[69]:
```
#No of observations in Train,Val and Test Dataset
print(X_train.shape)
print(X_test.shape)
```

```
(398, 3)
(100, 3)
```

[70]:
```
model=LinearRegression()
model.fit(X_train,y_train)
```

[70]: LinearRegression()

[71]:
```
values=[list(model.coef_)+[model.intercept_]]
columns=list(model.feature_names_in_)+['intercept']
coefficients_df=pd.DataFrame(data=values,columns=columns)
coefficients_df
```

[71]:

	LOR	CGPA	Research	intercept
0	0.021959	0.169973	0.035916	-0.832748

[72]:
```
#Details of the model.
print(model.score(X_train,y_train))
print(model.score(X_test,y_test))
```

```
0.8029230132754355
0.814834553731494
```

[73]:
```
vif = pd.DataFrame()
vif['Features'] = X_train.columns
vif['VIF'] = [variance_inflation_factor(X.values, i) for i in range(X_train.
 ↪shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

[73]:

	Features	VIF
0	LOR	1309.62
1	CGPA	1215.27
2	Research	21.00

[ ]:
```

```

[74]:
```
#Lets first remove the "LOR" variable since it has the highest VIF score.
X_train.drop(columns='LOR',inplace=True)
X_test.drop(columns='LOR',inplace=True)
```

[75]:
```
#No of observations in Train,Val and Test Dataset
print(X_train.shape)
print(X_test.shape)
```

```
(398, 2)
(100, 2)
```

[76]:
```
model=LinearRegression()
model.fit(X_train,y_train)
```

[76]: LinearRegression()

[77]:
```
values=[list(model.coef_)+[model.intercept_]]
columns=list(model.feature_names_in_)+['intercept']
coefficients_df=pd.DataFrame(data=values,columns=columns)
coefficients_df
```

[77]:

	CGPA	Research	intercept
0	0.190978	0.037811	-0.937678

[78]:
```
#Details of the model.
print(model.score(X_train,y_train))
print(model.score(X_test,y_test))
```

```
0.7902034821610344
0.8173819376498599
```

[79]:
```
vif = pd.DataFrame()
vif['Features'] = X_train.columns
vif['VIF'] = [variance_inflation_factor(X.values, i) for i in range(X_train.
 ↪shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

[79]:

	Features	VIF
0	CGPA	1309.62
1	Research	1215.27

[ ]:
```

```

[80]:
```
#Lets first remove the "CGPA" variable since it has the highest VIF score.
X_train.drop(columns='CGPA',inplace=True)
X_test.drop(columns='CGPA',inplace=True)
```

[81]:
```
#No of observations in Train,Val and Test Dataset
print(X_train.shape)
print(X_test.shape)
```

```
(398, 1)
(100, 1)
```

[82]:
```
model=LinearRegression()
model.fit(X_train,y_train)
```

[82]: LinearRegression()

[83]:
```
values=[list(model.coef_)+[model.intercept_]]
columns=list(model.feature_names_in_)+['intercept']
coefficients_df=pd.DataFrame(data=values,columns=columns)
coefficients_df
```

[83]:

	Research	intercept
0	0.155353	0.634913

[84]:
```
#Details of the model.
print(model.score(X_train,y_train))
print(model.score(X_test,y_test))
```

```
0.30379585070109627
0.2568948508579596
```

[85]:
```
vif = pd.DataFrame()
vif['Features'] = X_train.columns
vif['VIF'] = [variance_inflation_factor(X.values, i) for i in range(X_train.
 ↪shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

[85]:

	Features	VIF
0	Research	1309.62

[ ]:

0.4.1 Observation:

We observed that as we kept removing features, the model score kept on decreasing. So instead we can rely on statistical tests to select the important features.

[ ]:

[86]:
```
import statsmodels.api as sm
```

[87]:
```
#Splitting into Train and Test Data
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.
 ↪2,random_state=1)
#No of observations in Train,Val and Test Dataset
print(X_train.shape)
print(X_test.shape)
```

```
(398, 7)
(100, 7)
```

[88]:
```
X_train_sm=sm.add_constant(X_train)
X_train_sm.head(3)
```

```
C:\Users\kiit\anaconda3\lib\site-packages\statsmodels\tsa\tsatools.py:142:
FutureWarning: In a future version of pandas all arguments of concat except for
the argument 'objs' will be keyword-only
  x = pd.concat(x[::order], 1)
```

[88]:
```
     const  GRE Score  TOEFL Score  University Rating  SOP  LOR  CGPA  \
438    1.0        318          110                  1  2.5  3.5  8.54
274    1.0        315          100                  1  2.0  2.5  7.95
58     1.0        300           99                  1  3.0  2.0  6.80

     Research
438         1
274         0
58          1
```

[89]:
```
model=sm.OLS(y_train,X_train).fit()
```

[90]:
```
model.summary()
```

[90]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                                 OLS Regression Results
================================================================================
=======
Dep. Variable:        Chance of Admit   R-squared (uncentered):
0.992
Model:                            OLS   Adj. R-squared (uncentered):
0.991
Method:                 Least Squares   F-statistic:
6630.
Date:                Sat, 13 Aug 2022   Prob (F-statistic):
0.00
Time:                        23:55:38   Log-Likelihood:
509.39
No. Observations:                 398   AIC:
-1005.
Df Residuals:                     391   BIC:
-976.9
Df Model:                           7
Covariance Type:            nonrobust
================================================================================
=====
                        coef    std err          t      P>|t|      [0.025
0.975]
```

```
-----------------------------------------------------------------------------
-----
GRE Score           -0.0030      0.000     -7.705      0.000      -0.004
-0.002
TOEFL Score          0.0038      0.001      3.485      0.001       0.002
0.006
University Rating    0.0147      0.005      3.196      0.002       0.006
0.024
SOP                  0.0094      0.006      1.662      0.097      -0.002
0.020
LOR                  0.0195      0.005      3.786      0.000       0.009
0.030
CGPA                 0.1273      0.012     10.602      0.000       0.104
0.151
Research             0.0565      0.008      7.318      0.000       0.041
0.072
==============================================================================
Omnibus:                       51.250   Durbin-Watson:                   1.846
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               74.181
Skew:                          -0.855   Prob(JB):                     7.80e-17
Kurtosis:                       4.244   Cond. No.                     1.20e+03
==============================================================================

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.
[3] The condition number is large, 1.2e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

- From the p-values we can observe that "SOP" feature is not significant. So we can remove it, and then proceed with building our model.

[ ]:
```

```

[91]:
```
X_train.drop(columns="SOP",inplace=True)
X_test.drop(columns="SOP",inplace=True)
```

[92]:
```
features=X_train.columns
features
```

[92]:
```
Index(['GRE Score', 'TOEFL Score', 'University Rating', 'LOR', 'CGPA',
       'Research'],
      dtype='object')
```

[93]:
```
scaler=StandardScaler()
X_train=scaler.fit_transform(X_train)
X_test=scaler.transform(X_test)
model=LinearRegression()
model.fit(X_train,y_train)
```

[93]:
```
LinearRegression()
```

[94]:
```
print("Train Score",model.score(X_train,y_train))
print("Test Score",model.score(X_test,y_test))
```

```
Train Score 0.8249183132096353
Test Score 0.816345586231225
```

[95]:
```
values=[list(model.coef_)+[model.intercept_]]
columns=list(features)+['intercept']
coefficients_df=pd.DataFrame(data=values,columns=columns)
coefficients_df
```

[95]:
```
   GRE Score  TOEFL Score  University Rating       LOR      CGPA  Research  \
0   0.020654      0.01836           0.007198  0.018169  0.069751  0.010918

   intercept
0   0.722739
```

From the coefficients, we can conclude that CGPA and GRE Score have the highest importance.

[96]:
```
y_pred=model.predict(X_test)
```

[97]:
```
#Train Score
model.score(X_train,y_train)
```

[97]:
```
0.8249183132096353
```

[98]:
```
#Test R2 Score
r2=model.score(X_test,y_test)
r2
```

[98]:
```
0.816345586231225
```

[99]:
```
#Adjusted test r2 score:
num=(1-r2)*(X_test.shape[0]-1)
den=X_test.shape[0] - X_test.shape[1] -1
print(1-(num/den))
#Adjusted r2 score is good
```

```
0.804496914375175
```

[100]:
```
def rmse(y_pred, y_test):
    return sum((y_pred-y_test) ** 2)/X_test.shape[0]
```

[101]:
```
def mae(y_pred, y_test):
    return sum(abs(y_pred-y_test))/X_test.shape[0]
```

[102]:
```
#Root Mean Square Error
rmse(y_pred,y_test)
#RMSE error is pretty low
```

[102]:
```
0.0034480822338025462
```

[103]:
```
#Mean Absolute Error
mae(y_pred,y_test)
#MAE error is pretty low
```

[103]:
```
0.04104574540762105
```

#There is scope for improvement of the model, if we use Polynomial Features maybe along with Regularization, which can negate both overfitting and multicollinearity effects.

[ ]:
```

```

Checking Assumption-2 : The mean of residuals is nearly zero

[104]:
```
residuals=y_test-y_pred
print(np.mean(residuals))
#We see that the mean of residuals is almost 0.
```

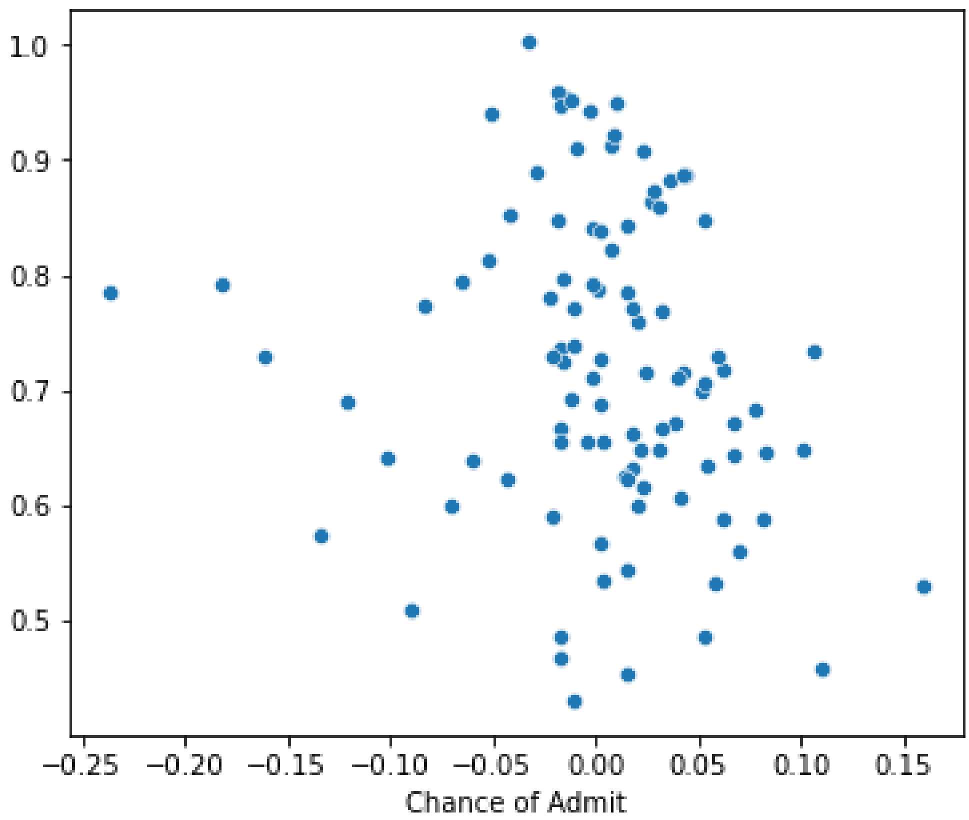
```
0.0035551209418732007
```

[ ]:
```

```

Checking Assumption-3 : Linearity of variables

[105]:
```
plt.figure(figsize=(6,5))
sns.scatterplot(x=residuals,y=y_pred)
plt.show()
#There is no pattern.
```



Checking Assumption-4 : Test for Homoscedasticity (10 Points)

[106]:
```
import statsmodels.stats.api as sms
name = ['F statistic', 'p-value']
test = sms.het_goldfeldquandt(residuals, X_test)
```

[107]:
```
test
```

[107]: (0.4604397316780448, 0.9942459565716549, 'increasing')

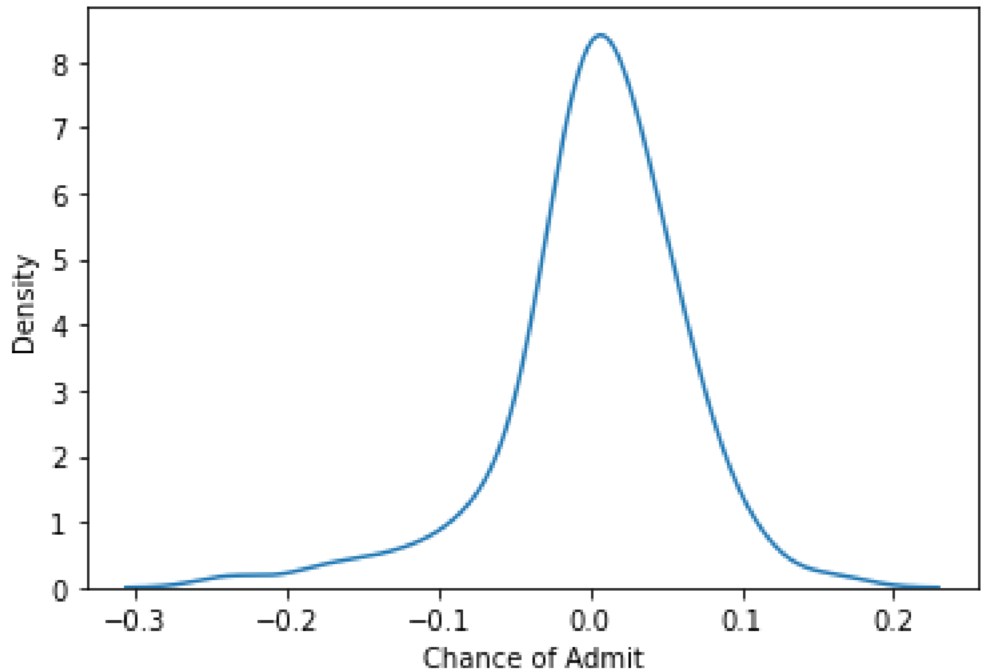
Since p-value is greater than 0.5, therefore there is homoscedasticity.

[ ]:
```

```

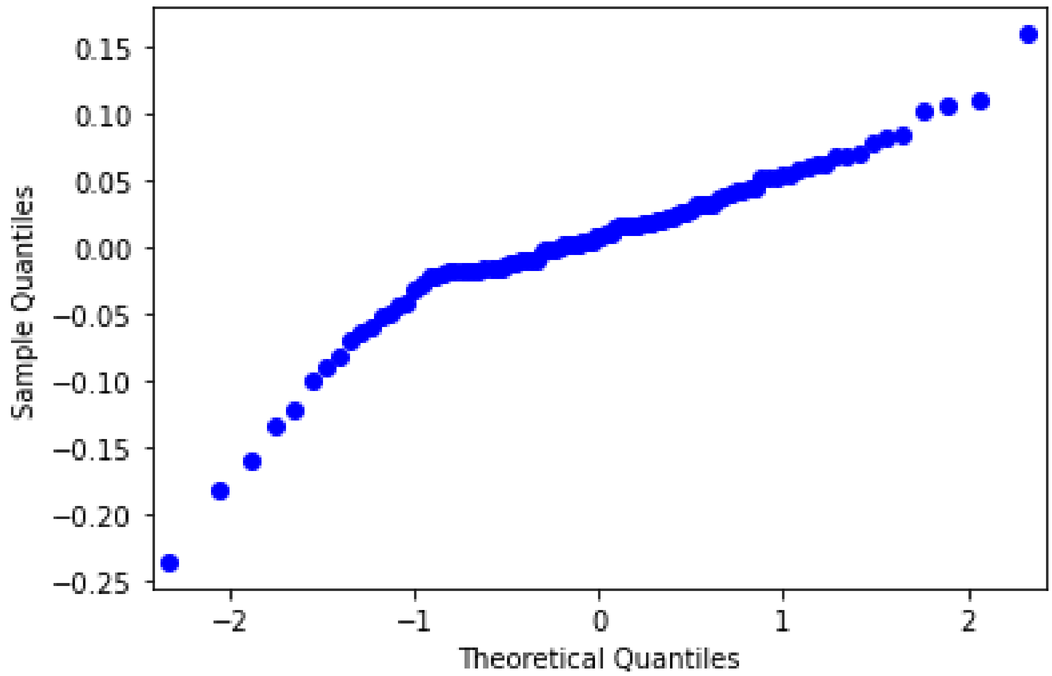
Checking Assumption-5 : Normality of residuals

[108]:
```
sns.kdeplot(residuals)
plt.show()
#It looks almost like a normal curve
```



[109]:
```
fig = sm.qqplot(residuals)
plt.show()
#It isnt a normal distribution.
```

```
C:\Users\kiit\anaconda3\lib\site-packages\statsmodels\graphics\gofplots.py:993:
UserWarning: marker is redundantly defined by the 'marker' keyword argument and
the fmt string "bo" (-> marker='o'). The keyword argument will take precedence.
  ax.plot(x, y, fmt, **plot_style)
```



[ ]:

```

```

0.5 2) Linear Regression using Ridge Regularization

For linear Regression using Regularization, the model weights will give appropriate weights to the features, and also take care of multicollinearity and weights assigned to the polynomial features.

[110]:

```
#Splitting into Train,Val and Test Data
X_train_cv,X_test,y_train_cv,y_test = train_test_split(X,y,test_size=0.
↪2,random_state=1)
X_train,X_val,y_train,y_val =␣
↪train_test_split(X_train_cv,y_train_cv,test_size=0.25,random_state=1)
```

[111]:

```
#No of observations in Train,Val and Test Dataset
print(X_train.shape)
print(X_val.shape)
print(X_test.shape)
```

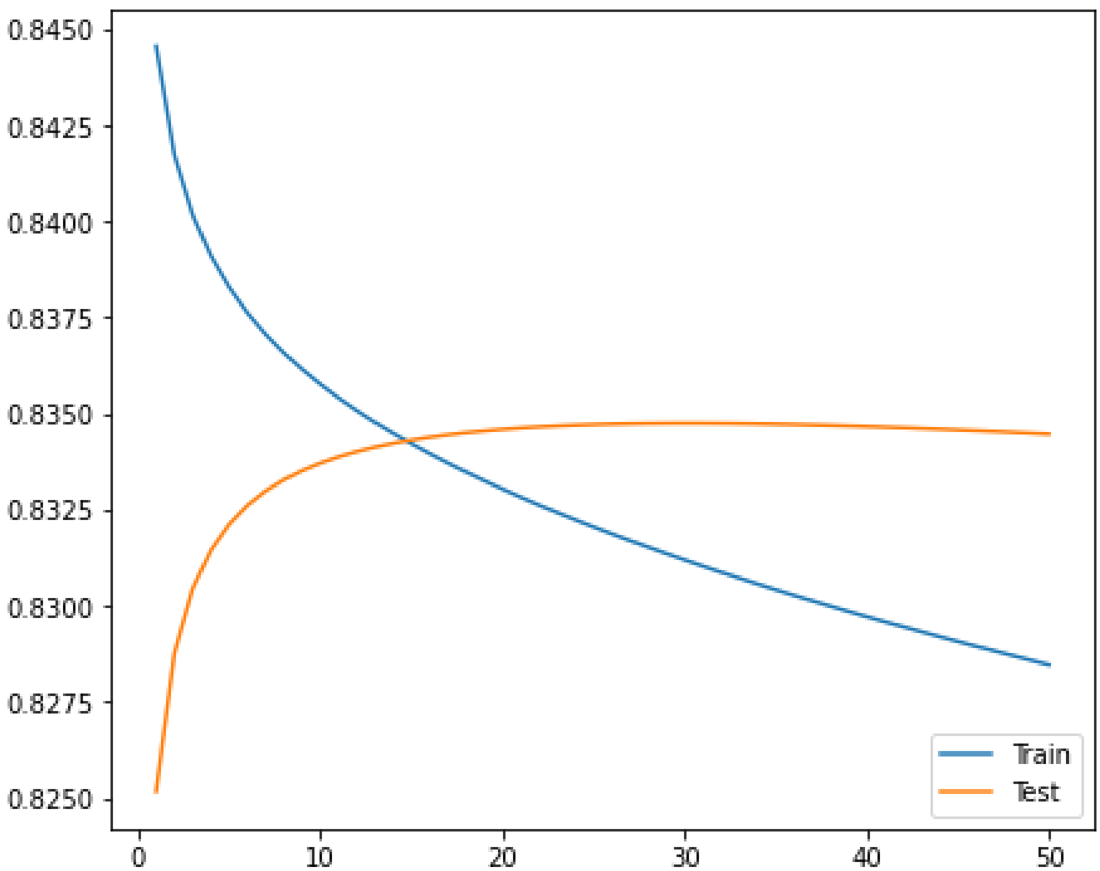
```
(298, 7)
(100, 7)
(100, 7)
```

[112]:

```
train_scores=[]
test_scores=[]
```

```
for value in range(1,51):
    model=make_pipeline(PolynomialFeatures(5),StandardScaler(),Ridge(alpha=value))
    model.fit(X_train,y_train)
    train_scores.append(model.score(X_train,y_train))
    test_scores.append(model.score(X_val,y_val))
```

[113]:
```
plt.figure(figsize=(7,6))
plt.plot(list(range(1,51)),train_scores,label='Train')
plt.plot(list(range(1,51)),test_scores,label='Test')
plt.legend(loc='lower right')
plt.show()
```



[114]:
```
np.argmax(test_scores)
```

[114]: 29

[115]:
```
#For lambda = 30, we are getting the best test score.
model=make_pipeline(PolynomialFeatures(5),StandardScaler(),Ridge(alpha=30))
```

```
model.fit(X_train,y_train)
print(model.score(X_train,y_train))
print(model.score(X_val,y_val))
```

```
0.8311866730455106
0.8347489168267126
```

#Observation : We get a better test score with Ridge Regularization than with normal Linear Regression.

[ ]:

```

```

0.6 3) Linear Regression using Lasso Regularization

For linear Regression using Regularization, the model weights will give appropriate weights to the features, and also take care of multicollinearity and weights assigned to the polynomial features.

[116]:

```
#Splitting into Train,Val and Test Data
X_train_cv,X_test,y_train_cv,y_test = train_test_split(X,y,test_size=0.
 ↪2,random_state=1)
X_train,X_val,y_train,y_val =␣
 ↪train_test_split(X_train_cv,y_train_cv,test_size=0.25,random_state=1)
```

[117]:

```
#No of observations in Train,Val and Test Dataset
print(X_train.shape)
print(X_val.shape)
print(X_test.shape)
```

```
(298, 7)
(100, 7)
(100, 7)
```

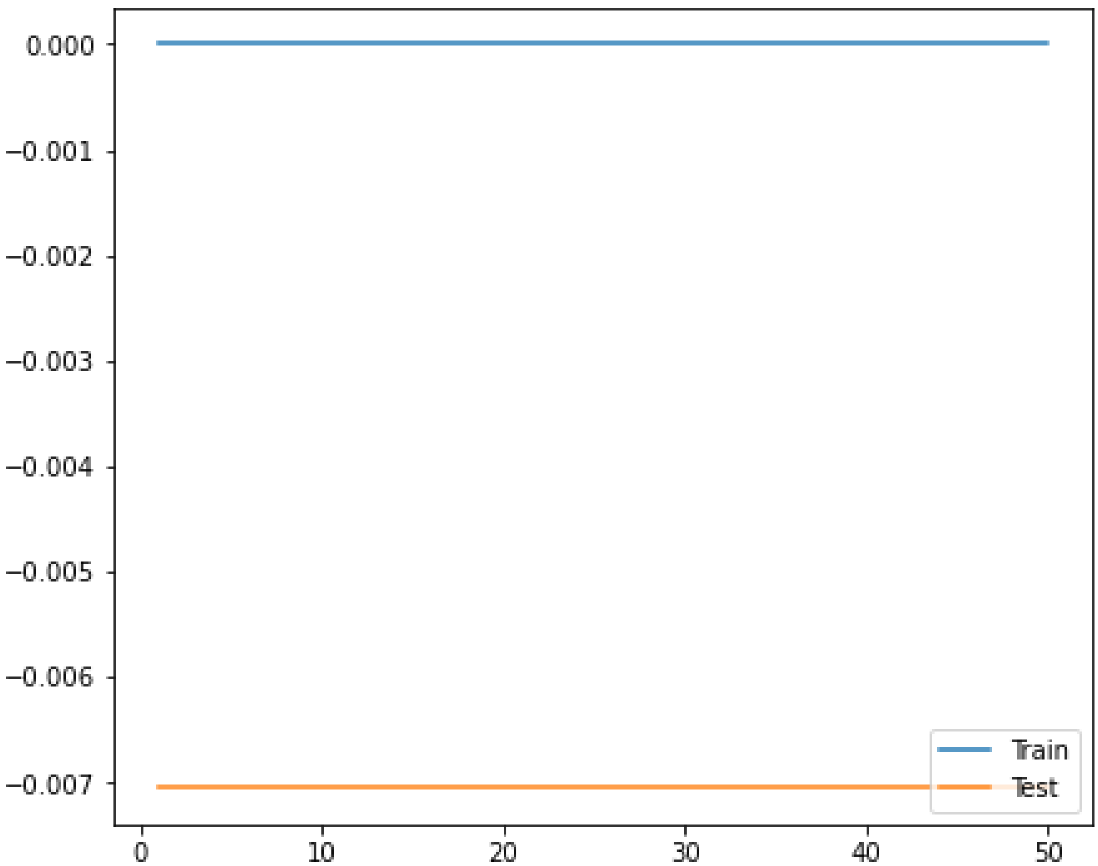
[118]:

```
train_scores=[]
test_scores=[]

for value in range(1,51):
    ␣
 ↪model=make_pipeline(PolynomialFeatures(5),StandardScaler(),Lasso(alpha=value))
    model.fit(X_train,y_train)
    train_scores.append(model.score(X_train,y_train))
    test_scores.append(model.score(X_val,y_val))
```

[119]:

```
plt.figure(figsize=(7,6))
plt.plot(list(range(1,51)),train_scores,label='Train')
plt.plot(list(range(1,51)),test_scores,label='Test')
plt.legend(loc='lower right')
plt.show()
```



#For the lasso regularization, since we do not have Polynomial features, therefore it is putting all the coefficients as 0. So, using Lasso regularization is not a good idea here.

[ ]:

```

```

0.7 Actionable Insights and Recommendations:

- From the Linear Regression model, we found that the most important variables are CGPA and GRE score.
- University rating and research are not so significant contributors to chance of admit.
- For better model performance, we can introduce Polynomial Features, which along with Regularization can give better results.
- By knowing the important features, for chances of admit, Jamboree can easily shortlist candidates who have higher CGPA and GRE score. It will save a lot of time and resources.
- Additionally, to save time and resources, Jamboree can declare a cut off for the important predictor variables, so that its employees do not go through the pain of an unsuccessful admit.
- We can also get data about the level of higher education(Bachelors, Masters, Phd) the candidates have, which can be a good predictor variable for chance of admit.
- We can also get data about the tier of college the candidates went to, which can be a good predictor variable for chance of admit.

- We can also get data about the work experience of candidates, which can be a good predictor variable for chance of admit.

[ ]:

```

```

[ ]:

```

```

[ ]:

```

```

[ ]:

```

```