Business Case: Jamboree Education - Linear Regression

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.

Objective:

The goal is to provide insights into the graduate admissions process, particularly for Ivy League colleges, and to develop a predictive model that can estimate an individual's probability of admission based on various factors such as test scores (e.g., GMAT, GRE, SAT), academic performance, extracurricular activities, letters of recommendation, statement of purpose, and possibly other demographic or background information.

Overall, the goal is to provide Jamboree with actionable insights and a predictive tool that can assist students in assessing their chances of admission to Ivy League colleges and guide them in their college application process.

Importing Required Libraries

In [542...

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

import statsmodels.api as sm
```

Loading the given data-set

In [543...

```
df = pd.read_csv('D:\\Scaler\\Scaler\\Intro to ML\\Business Case\\Jamboree_Admission.csv')
```

In [544...

```
df
```

Out[544]:

	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
0	1	337	118	4	4.5	4.5	9.65	1	0.92
1	2	324	107	4	4.0	4.5	8.87	1	0.76
2	3	316	104	3	3.0	3.5	8.00	1	0.72
3	4	322	110	3	3.5	2.5	8.67	1	0.80
4	5	314	103	2	2.0	3.0	8.21	0	0.65
...	...	...	...	...	...	...	...	...	...
495	496	332	108	5	4.5	4.0	9.02	1	0.87
496	497	337	117	5	5.0	5.0	9.87	1	0.96
497	498	330	120	5	4.5	5.0	9.56	1	0.93
498	499	312	103	4	4.0	5.0	8.43	0	0.73
499	500	327	113	4	4.5	4.5	9.04	0	0.84

500 rows × 9 columns

Exploratory data analysis (EDA):

- shape of data, data types, Identify & convert to categorical attributes, missing value detection, statistical summary

In [545…

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 9 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Serial No.         500 non-null    int64  
 1   GRE Score          500 non-null    int64  
 2   TOEFL Score        500 non-null    int64  
 3   University Rating  500 non-null    int64  
 4   SOP                500 non-null    float64
 5   LOR                500 non-null    float64
 6   CGPA               500 non-null    float64
 7   Research           500 non-null    int64  
 8   Chance of Admit    500 non-null    float64
dtypes: float64(4), int64(5)
memory usage: 35.3 KB
```

In [546…

```
df.shape
```

Out[546]:

```
(500, 9)
```

In [547…

```
df.drop(["Serial No."],axis=1,inplace=True)
```

In [548…

```
df.columns
```

Out[548]:

```
Index(['GRE Score', 'TOEFL Score', 'University Rating', 'SOP', 'LOR ', 'CGPA',
       'Research', 'Chance of Admit '],
      dtype='object')
```

In [549…

```
# Rename the column
df = df.rename(columns={'Chance of Admit ': 'Chance of Admit'})
```

As 'Chance of Admit ' consistes a spce at the end of word, Renamed it by removing the space

In [550…

```
#checking for duplicates row
duplicate_rows = df[df.duplicated()]
duplicate_rows
```

Out[550]:

GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit

Observation: No duplicate rows/records observed

In [551…

```
# check for missing values
df.isnull().sum()
```

Out[551]:

```
GRE Score            0
TOEFL Score          0
University Rating    0
SOP                  0
LOR                  0
CGPA                 0
Research             0
Chance of Admit      0
dtype: int64
```

Oservation: No missing value observed

In [552…

```
df.nunique()
```

Out[552]:

```
GRE Score             49
TOEFL Score           29
University Rating      5
SOP                    9
LOR                    9
CGPA                 184
Research               2
Chance of Admit       61
dtype: int64
```

Observation:

- University Rating,SOP,LOR,Research seems to be categorical variables as the number of unique values are very small.
- rest of the features are numeric and ordinal
- University Rating, SOP, LOR, Research are discrete and rest are continuous
- SOP, University rating, LOR and research can be considered as numeric ordinal data.

In [553…

```
df.describe()
```

Out[553]:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
count	500.000000	500.000000	500.000000	500.000000	500.00000	500.000000	500.000000	500.00000
mean	316.472000	107.192000	3.114000	3.374000	3.48400	8.576440	0.560000	0.72174
std	11.295148	6.081868	1.143512	0.991004	0.92545	0.604813	0.496884	0.14114
min	290.000000	92.000000	1.000000	1.000000	1.00000	6.800000	0.000000	0.34000
25%	308.000000	103.000000	2.000000	2.500000	3.00000	8.127500	0.000000	0.63000
50%	317.000000	107.000000	3.000000	3.500000	3.50000	8.560000	1.000000	0.72000
75%	325.000000	112.000000	4.000000	4.000000	4.00000	9.040000	1.000000	0.82000
max	340.000000	120.000000	5.000000	5.000000	5.00000	9.920000	1.000000	0.97000

Observation:

- Chances of admit is a probability measure , which is within 0 to 1 which is good (no outliers or missleading data in column).
- Range of GRE score looks like between 290 to 340.
- Range of TOEFL score is between 92 to 120.
- University rating , SOP and LOR are distributed between range of 1 to 5.
- CGPA range is between 6.8 to 9.92.

Identifying continous (numerical), categorical and target variable(s)

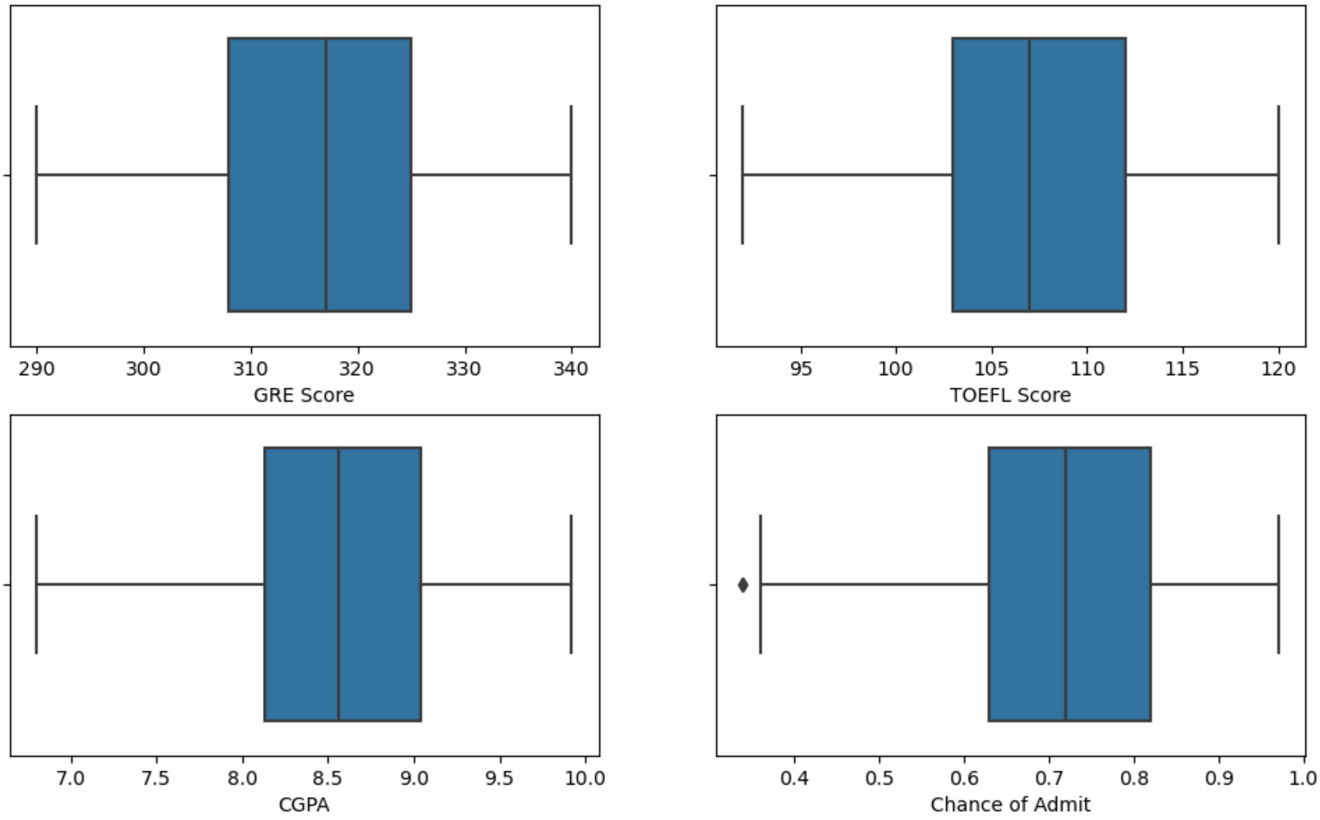
In [554…

```
cat_var = ['University Rating', 'SOP', 'LOR ', 'Research']
num_var = ['GRE Score', 'TOEFL Score', 'CGPA']
target_var = 'Chance of Admit'
```

Detecting for Outliers:

In [555…

```
# Graphical Approach
# check for outliers using boxplots ()
rows, cols = 2, 2
fig, axs = plt.subplots(rows, cols, figsize=(12, 7))

index = 0
for col in range(cols):
    sns.boxplot(x=num_var[index], data=df, ax=axs[0,index])
    index += 1

sns.boxplot(x=num_var[-1], data=df, ax=axs[1,0])
sns.boxplot(x=target_var, data=df, ax=axs[1,1])
plt.show()
```



In [556…

```
# Non-Graphical Approach
# Check for Outliers

def detect_outliers(data):
    length_before = len(data)
    Q1 = np.percentile(data,25)
    Q3 = np.percentile(data,75)
    IQR = Q3-Q1
    upperbound = Q3+1.5*IQR
    lowerbound = Q1-1.5*IQR
    if lowerbound < 0:
        lowerbound = 0

    length_after = len(data[(data>lowerbound)&(data<upperbound)])
    return f"{np.round((length_before-length_after)/length_before,4)} % Outliers data from in

for col in df.columns:
    print(col," : ",detect_outliers(df[col]))

detect_outliers(df)
```

```
GRE Score  :  0.0 % Outliers data from input data found
TOEFL Score  :  0.0 % Outliers data from input data found
University Rating  :  0.0 % Outliers data from input data found
SOP  :  0.0 % Outliers data from input data found
LOR   :  0.024 % Outliers data from input data found
CGPA  :  0.0 % Outliers data from input data found
Research  :  0.44 % Outliers data from input data found
Chance of Admit  :  0.004 % Outliers data from input data found
```

Out[556]:

```
'0.0 % Outliers data from input data found'
```

Observation:

There are no outliers present in the dataset.

Univariate Analysis

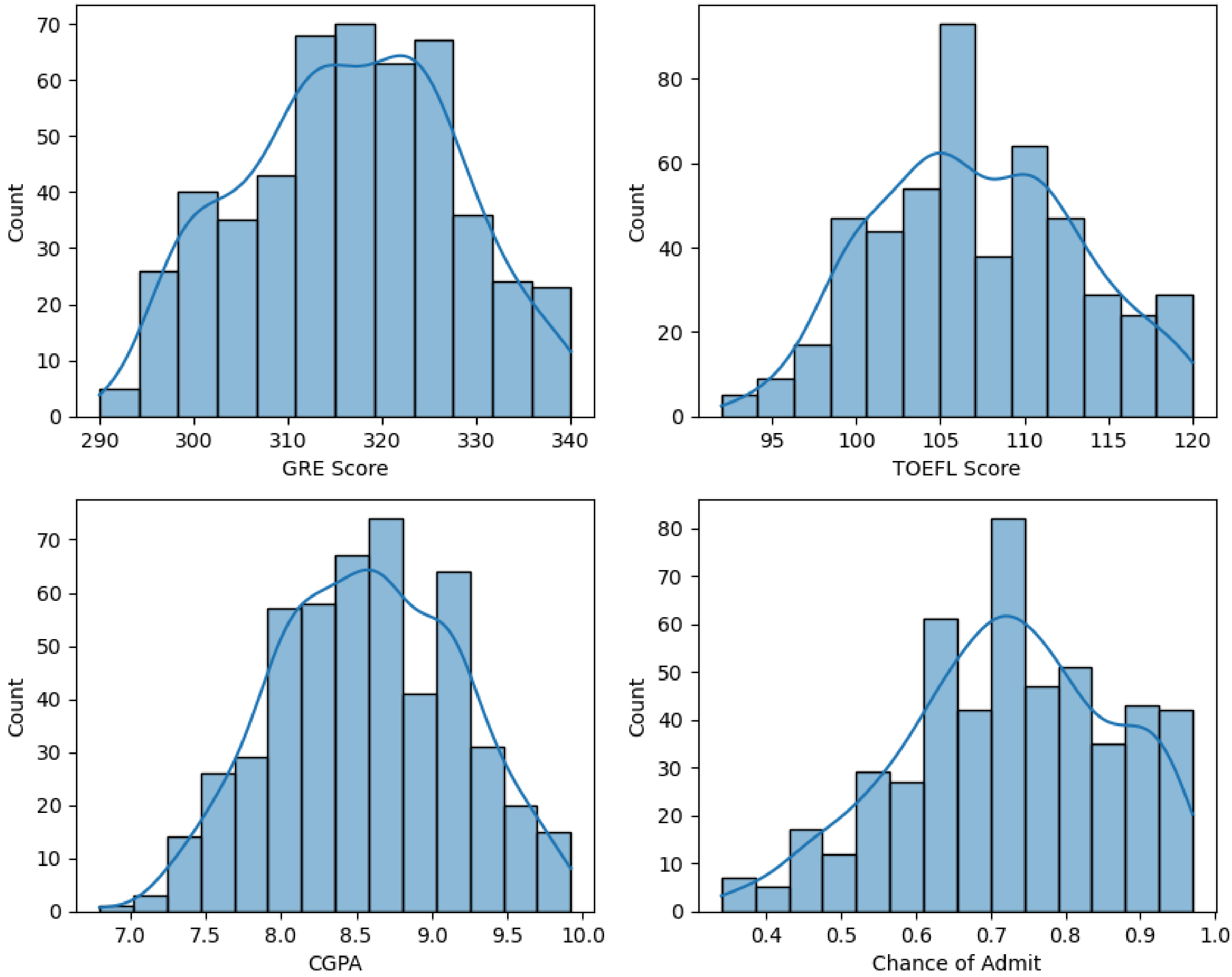
- Distribution plots of all the continuous variable(s)

- Barplots/countplots of all the categorical variables

Distribution plots of all the continuous variable(s)

In [557…

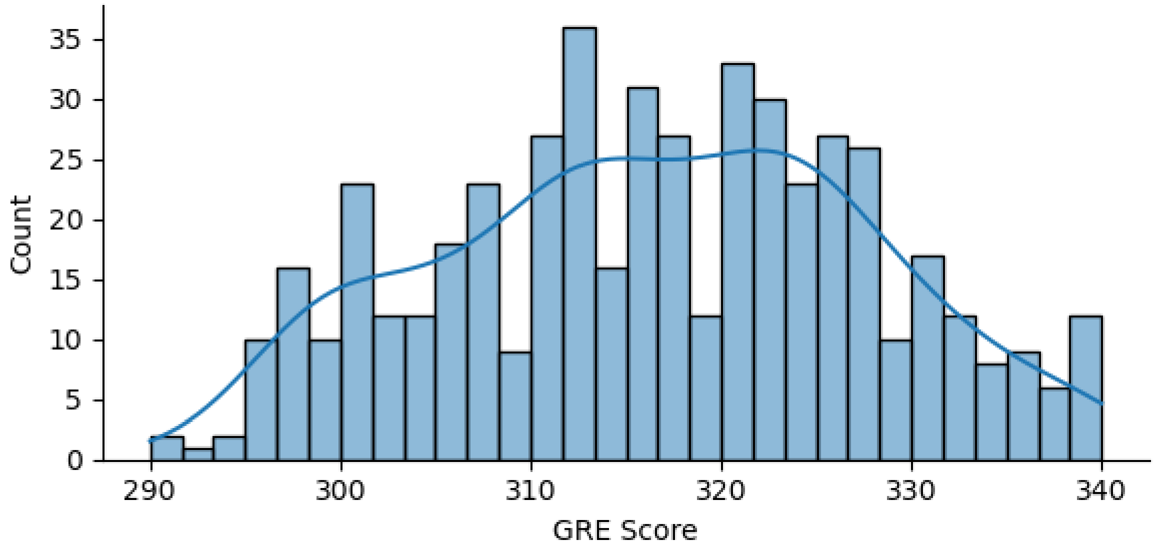
```
# check distribution of each continuous (numerical) variable
rows, cols = 2, 2
fig, axs = plt.subplots(rows,cols, figsize=(10, 8))
index = 0
for row in range(rows):
    for col in range(cols):
        sns.histplot(df[num_var[index]], kde=True, ax=axs[row,col])
        index += 1
    break

sns.histplot(df[num_var[-1]], kde=True, ax=axs[1,0])
sns.histplot(df[target_var], kde=True, ax=axs[1,1])
plt.show()
```

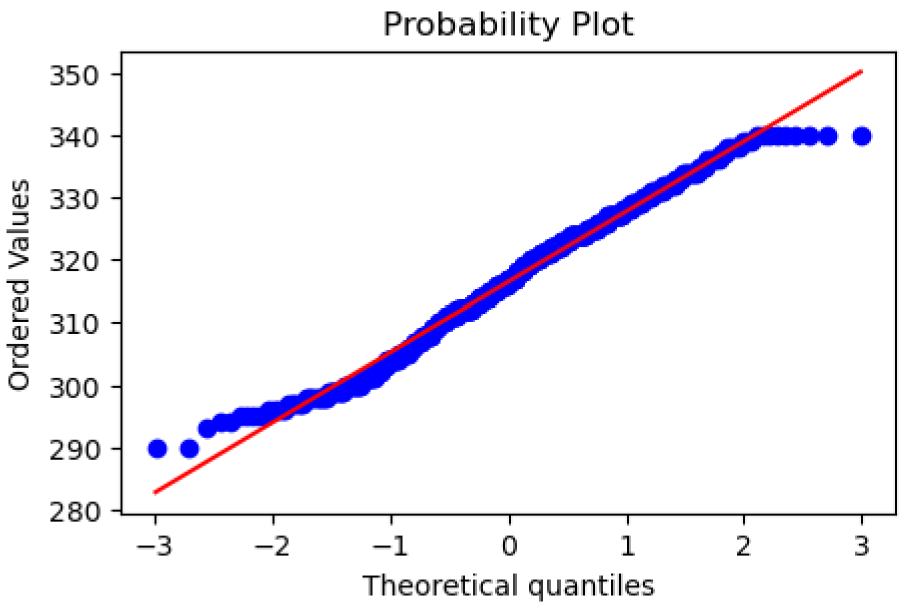


Chance_of_Admit

In [558…

```
# Plotting distribution
sns.displot(df['GRE Score'], bins=30, kde=True, height=3, aspect=2)

# Plotting QQ plot
fig, ax = plt.subplots(figsize=(5, 3))  # Adjust figsize as per your preference
stats.probplot(df['GRE Score'], dist="norm", plot=ax)
plt.show()
```

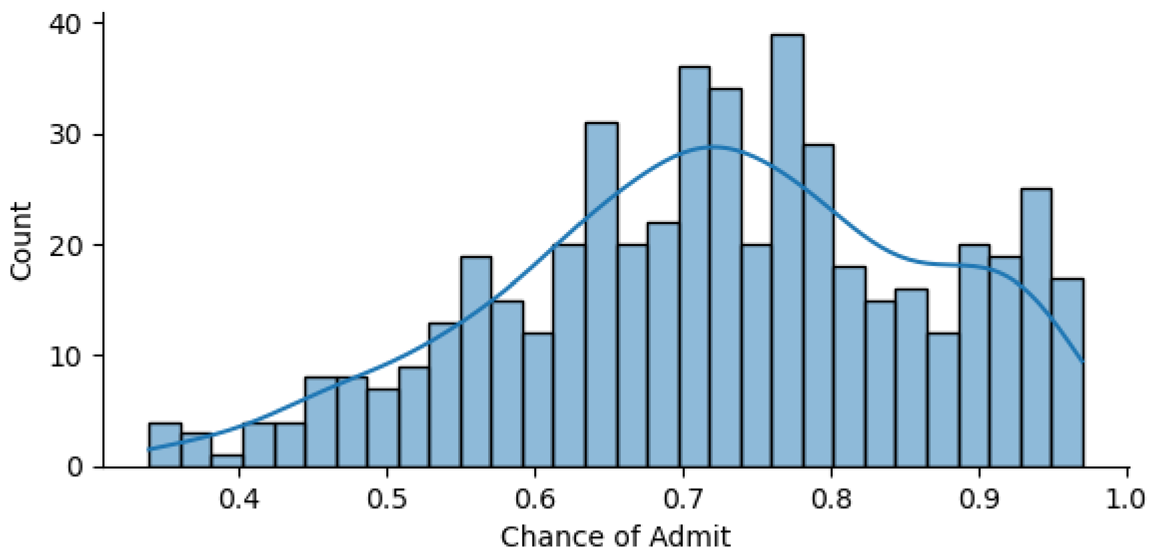


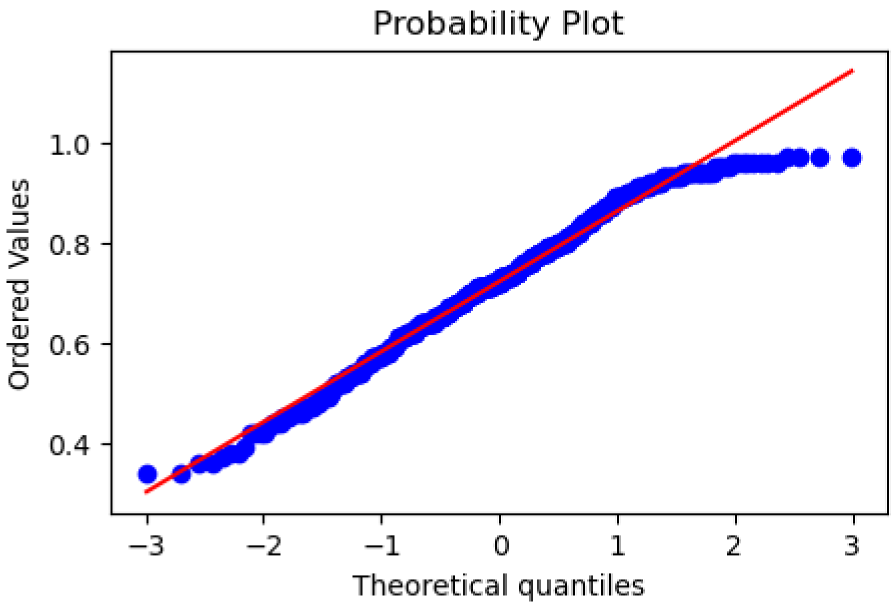


GRE_Score

In [559…

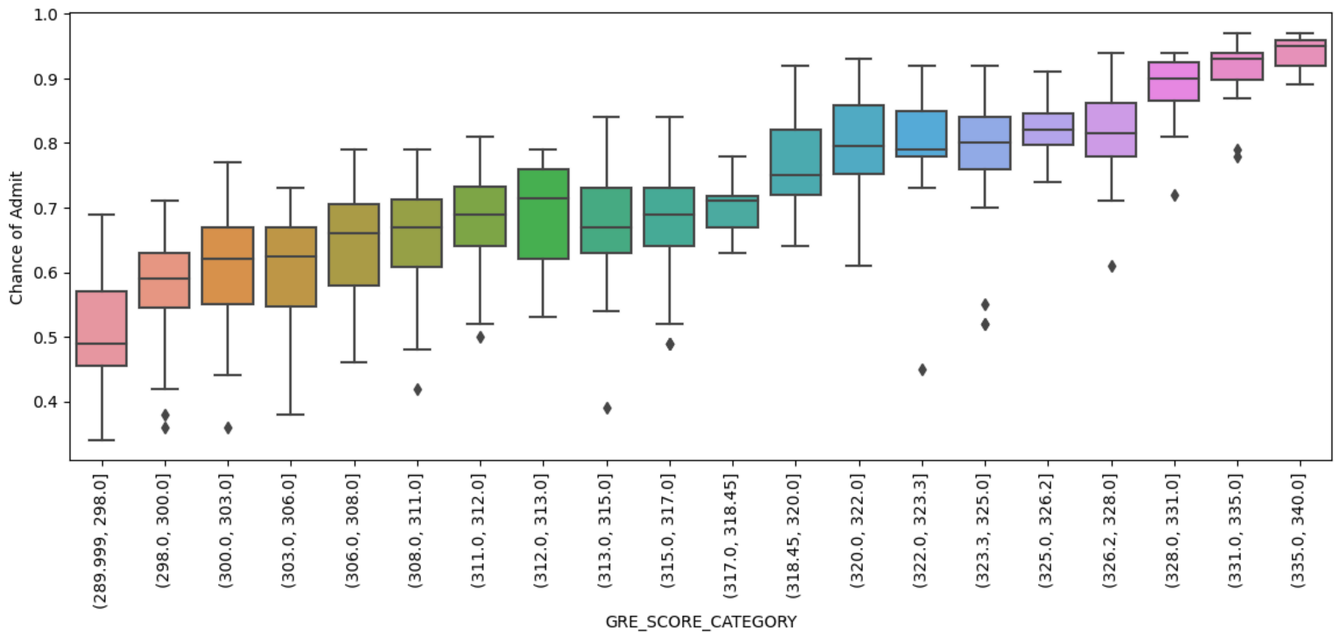
```
# Plotting distribution
sns.displot(df[target_var], bins=30, kde=True, height=3, aspect=2)

# Plotting QQ plot
fig, ax = plt.subplots(figsize=(5, 3))  # Adjust figsize as per your preference
stats.probplot(df[target_var], dist="norm", plot=ax)
plt.show()
```





In [560…
```
df1 = df.copy()
```

In [561…
```
df1["GRE_SCORE_CATEGORY"]=pd.qcut(df1["GRE Score"],20)
plt.figure(figsize=(14,5))
sns.boxplot(y = df1["Chance of Admit"], x = df1["GRE_SCORE_CATEGORY"])
plt.xticks(rotation = 90)
plt.show()
```

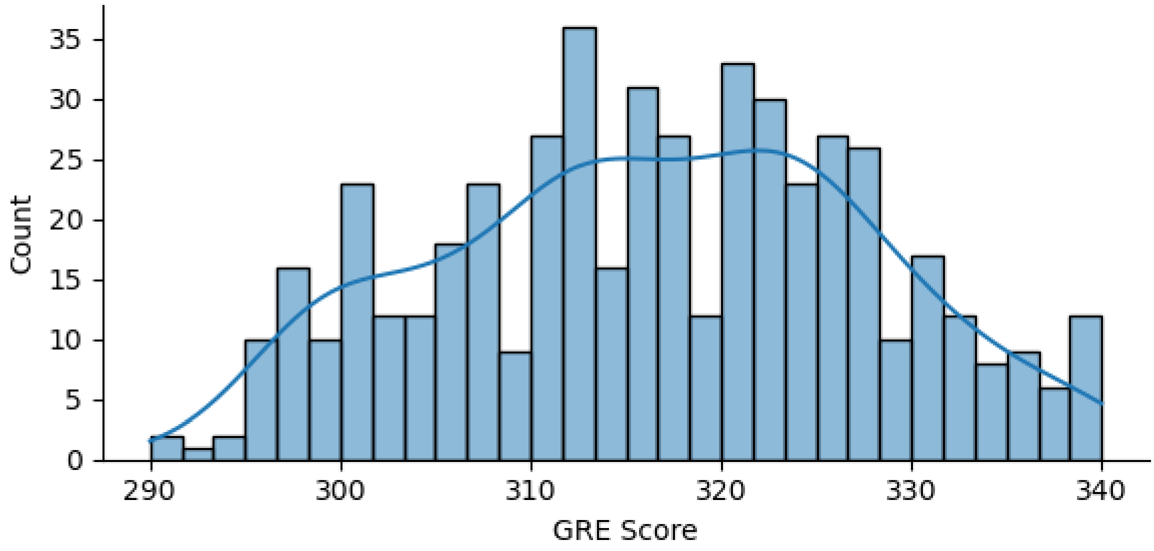


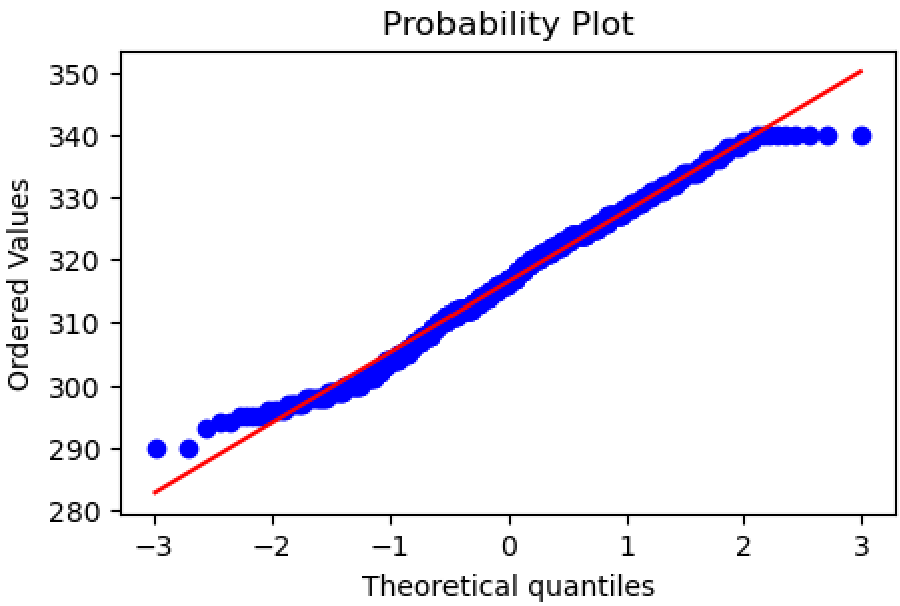
Observation:

From above boxplot (distribution of chance of admition (probability of getting admition) as per GRE score) : with higher GRE score , there is high probability of getting an admition .

TOEFL_Score

In [562…
```
# Plotting distribution
sns.displot(df['GRE Score'], bins=30, kde=True, height=3, aspect=2)

# Plotting QQ plot
fig, ax = plt.subplots(figsize=(5, 3))  # Adjust figsize as per your preference
stats.probplot(df['GRE Score'], dist="norm", plot=ax)
plt.show()
```



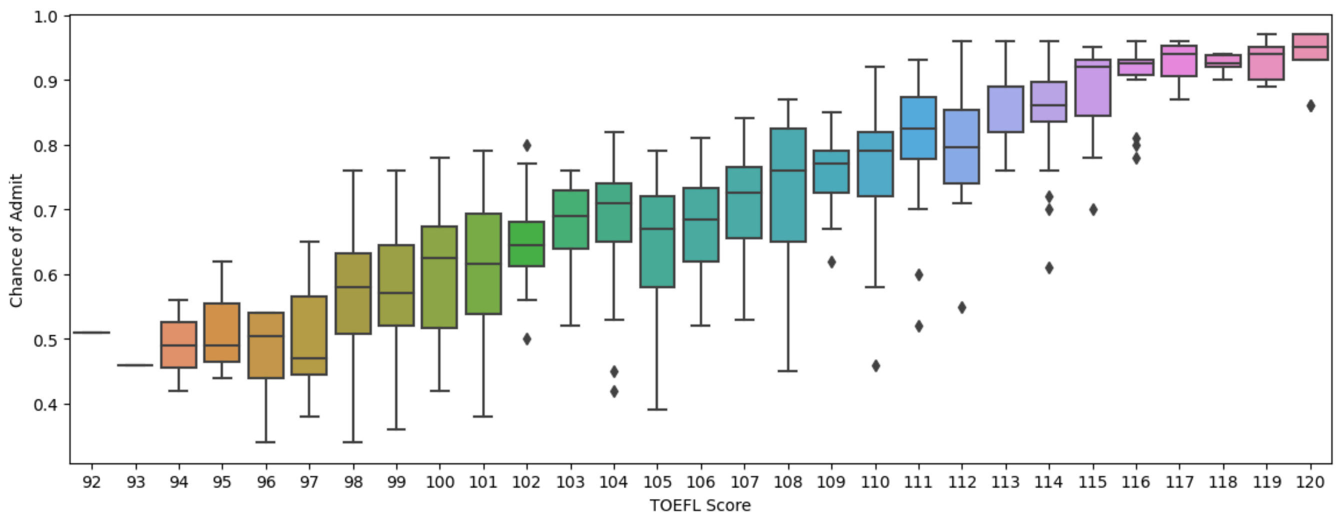


In [563…

```
plt.figure(figsize=(14,5))
sns.boxplot(y = df["Chance of Admit"], x = df["TOEFL Score"])
```

Out[563]:

```
<Axes: xlabel='TOEFL Score', ylabel='Chance of Admit'>
```



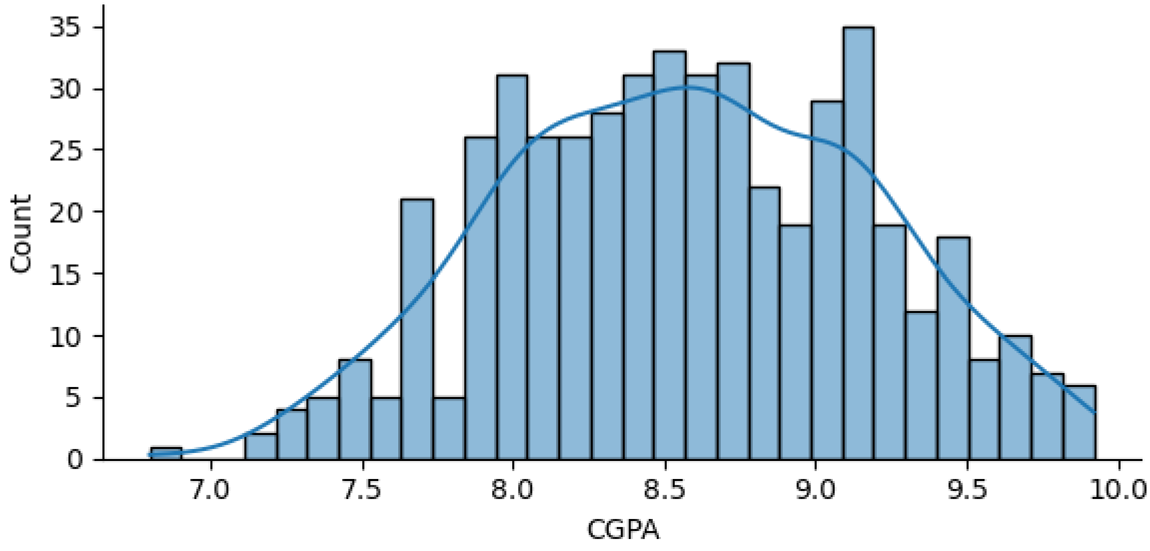
Observation:

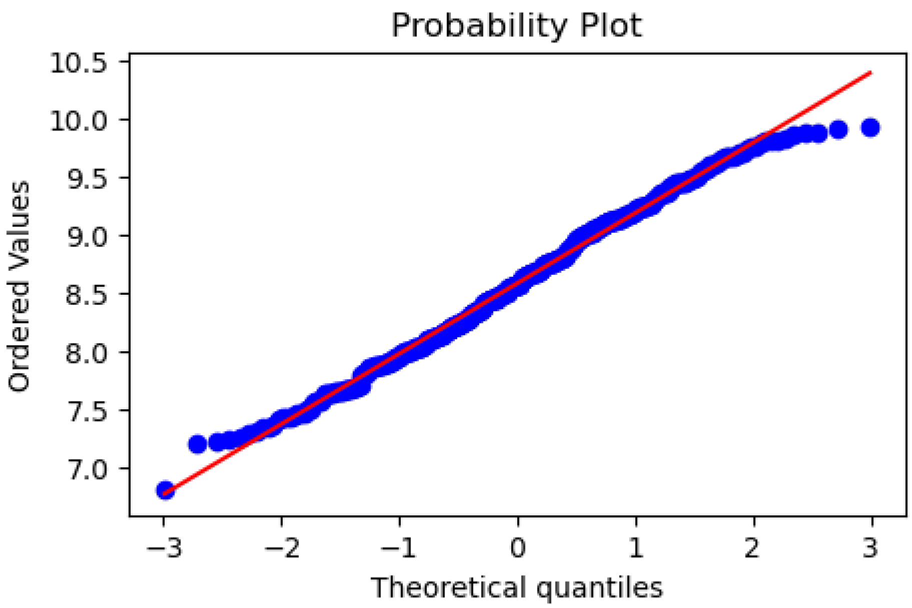
Students having high toefl score , has higher probability of getting admition .

CGPA

In [564…

```
# Plotting distribution
sns.displot(df['CGPA'], bins=30, kde=True, height=3, aspect=2)

# Plotting QQ plot
fig, ax = plt.subplots(figsize=(5, 3))  # Adjust figsize as per your preference
stats.probplot(df['CGPA'], dist="norm", plot=ax)
plt.show()
```



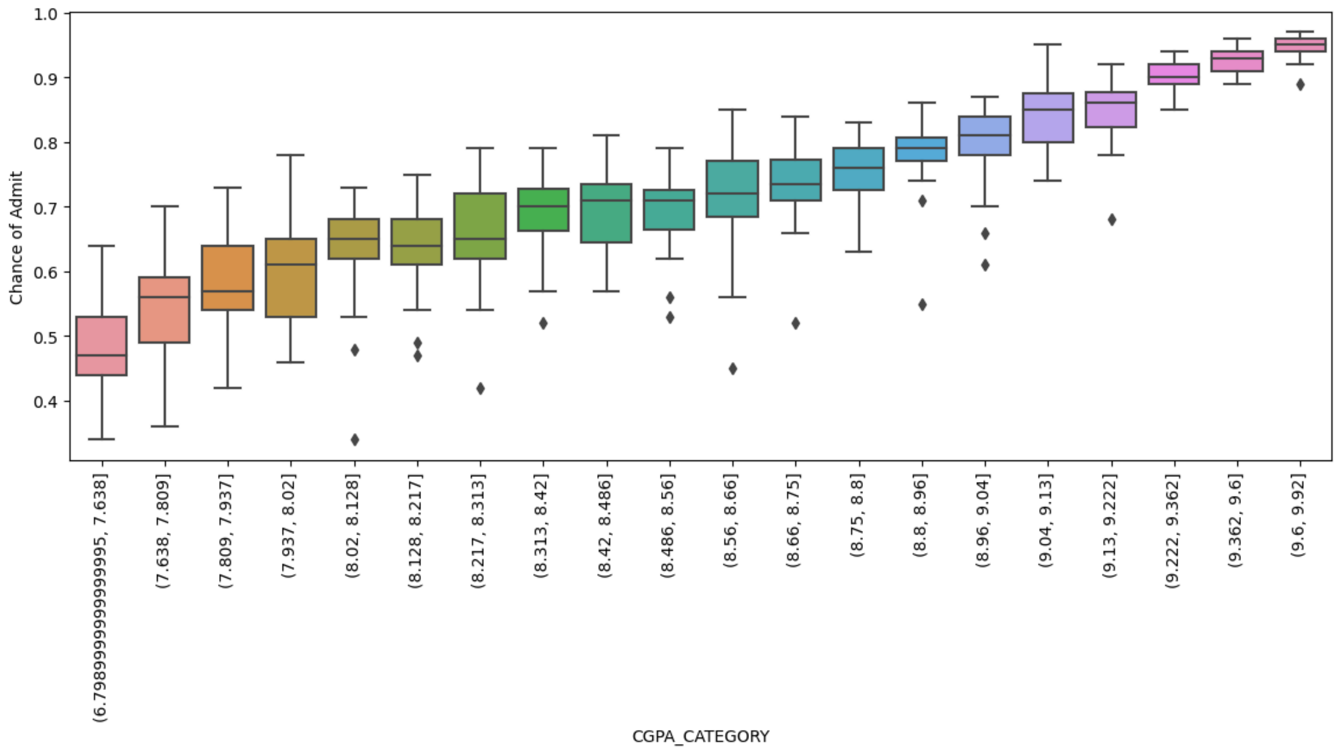


Observation:

Chance of admit and GRE score are nearly normally distrubted.

In [565…

```
#plt.figure(figsize=(14,5))
#sns.boxplot(y = df["Chance of Admit"], x = df["CGPA"])

df1["CGPA_CATEGORY"]=pd.qcut(df1["CGPA"],20)
plt.figure(figsize=(14,5))
sns.boxplot(y = df1["Chance of Admit"], x = df1["CGPA_CATEGORY"])
plt.xticks(rotation = 90)
plt.show()
```



Observation:

Students having high CGPA score , has higher probability of getting admition

Insight:

GRE score, TOEFL score and CGPA has a strong correlation with chance of addmission .

In [566…

```
df.columns
```

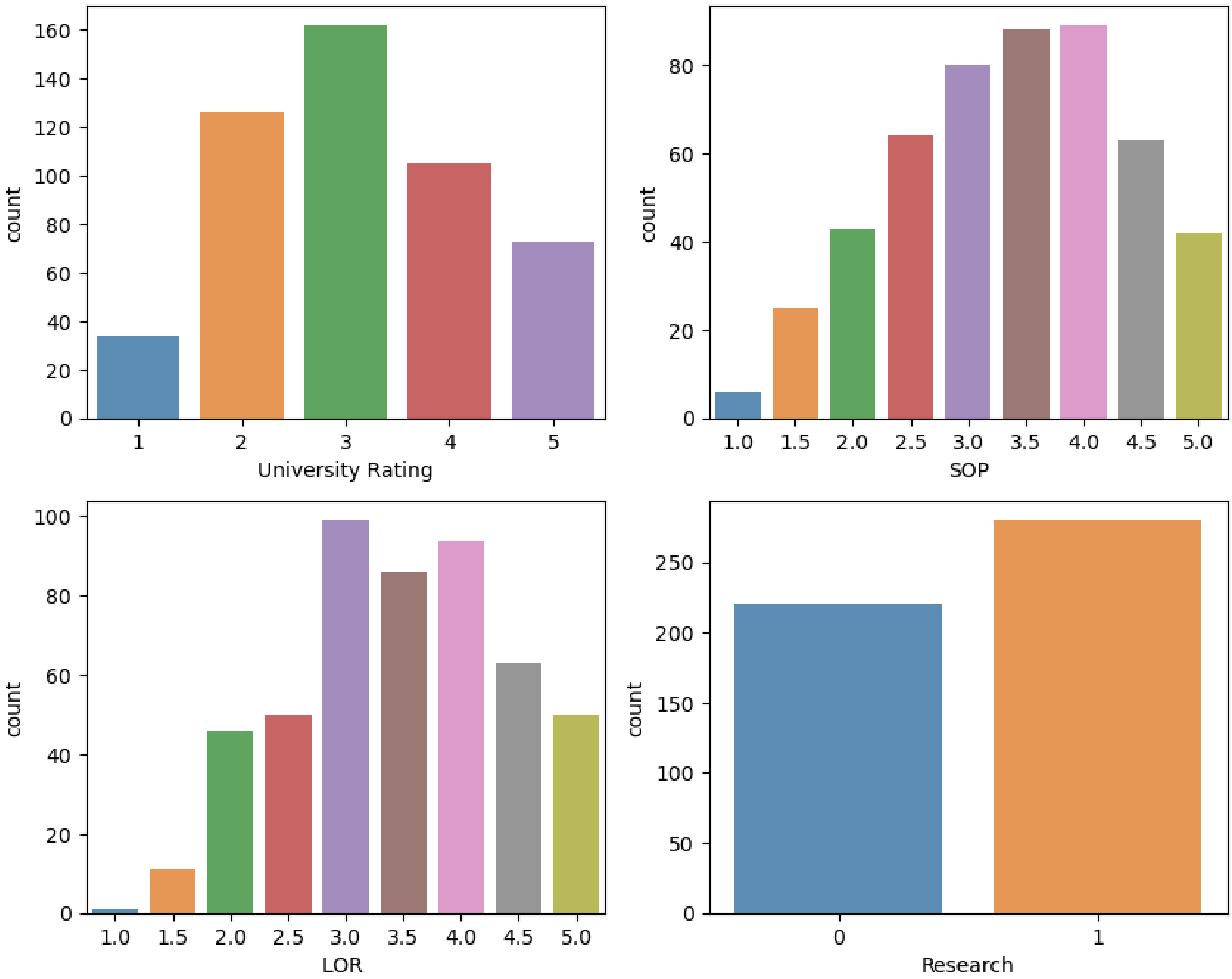
Out[566]:

```
Index(['GRE Score', 'TOEFL Score', 'University Rating', 'SOP', 'LOR ', 'CGPA',
       'Research', 'Chance of Admit'],
      dtype='object')
```

Barplots/countplots of all the categorical variables

In [567…

```
cols, rows = 2, 2
fig, axs = plt.subplots(rows, cols, figsize=(10, 8))

index = 0
for row in range(rows):
    for col in range(cols):
        sns.countplot(x=cat_var[index], data=df, ax=axs[row, col], alpha=0.8)
        index += 1

plt.show()
```

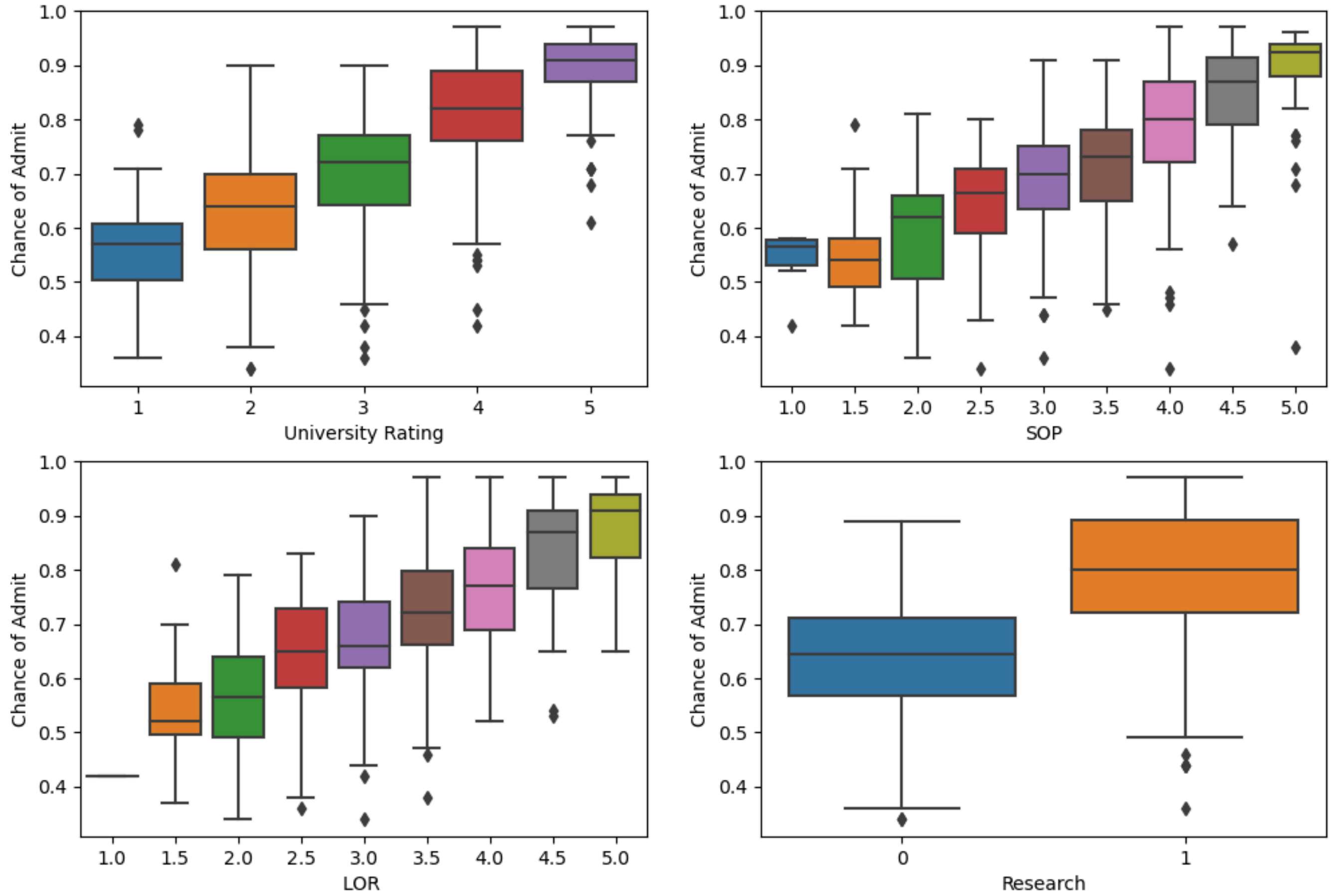


Bivariate Analysis

Categorical features vis-a-vis Target variable boxplot

In [568...

```
rows, cols = 2,2
fig, axs = plt.subplots(rows, cols, figsize=(12,8))

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



Observation:

- Upon examination of the preceding plots, it becomes evident that the strength of the Statement of Purpose (SOP) is positively associated with the Chance of Admission.
- Similarly, a comparable pattern emerges with both the strength of the Letter of Recommendation and University rating, indicating a positive correlation with the Chance of Admission.
- Students engaged in research demonstrate a higher likelihood of admission. However, it is worth noting the presence of outliers within this category.

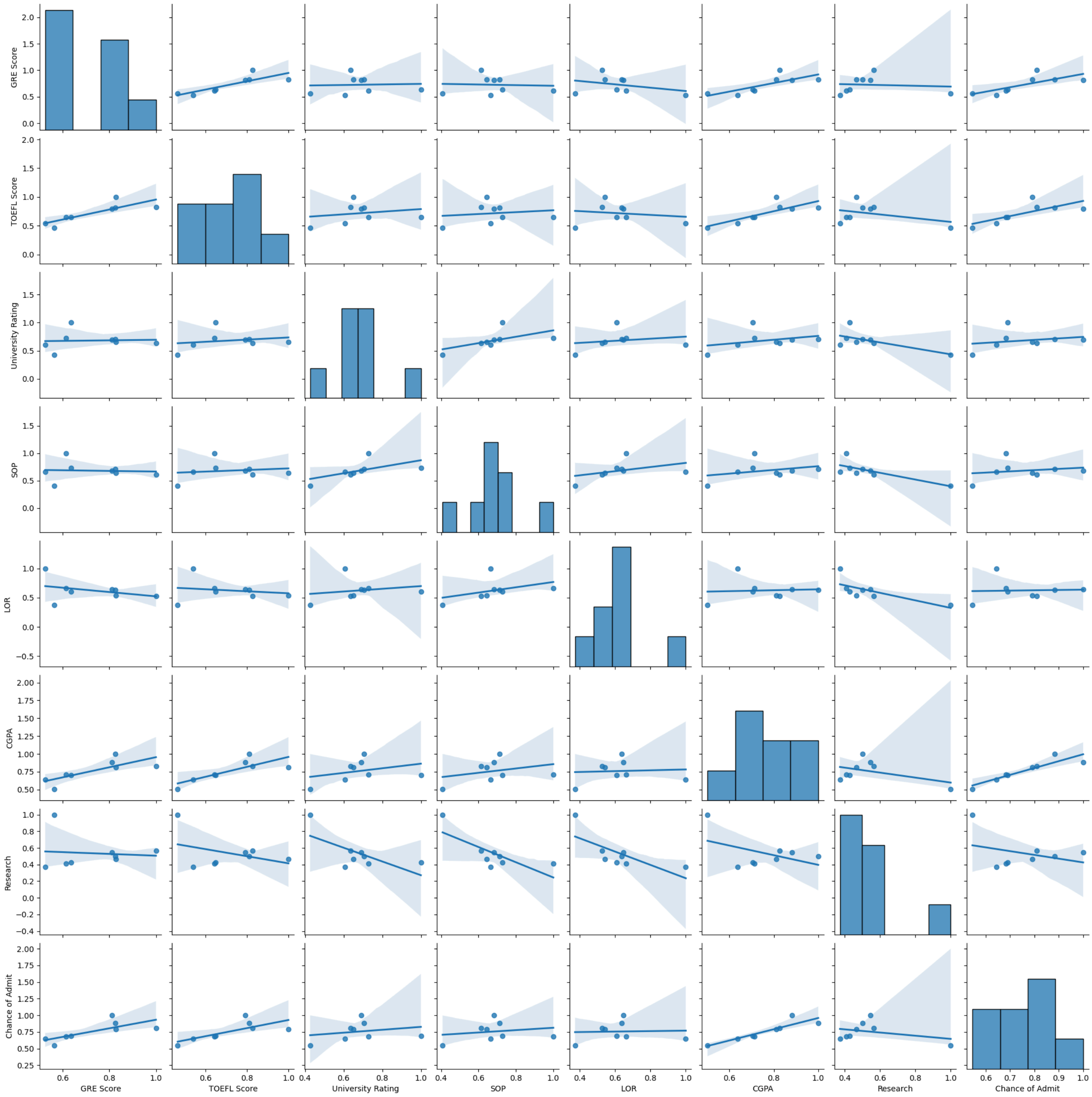
Checking the overall linearity and correlation among all features through a pairplot

In [569…

```
sns.pairplot(df.corr(),kind= 'reg')
```

Out[569]:

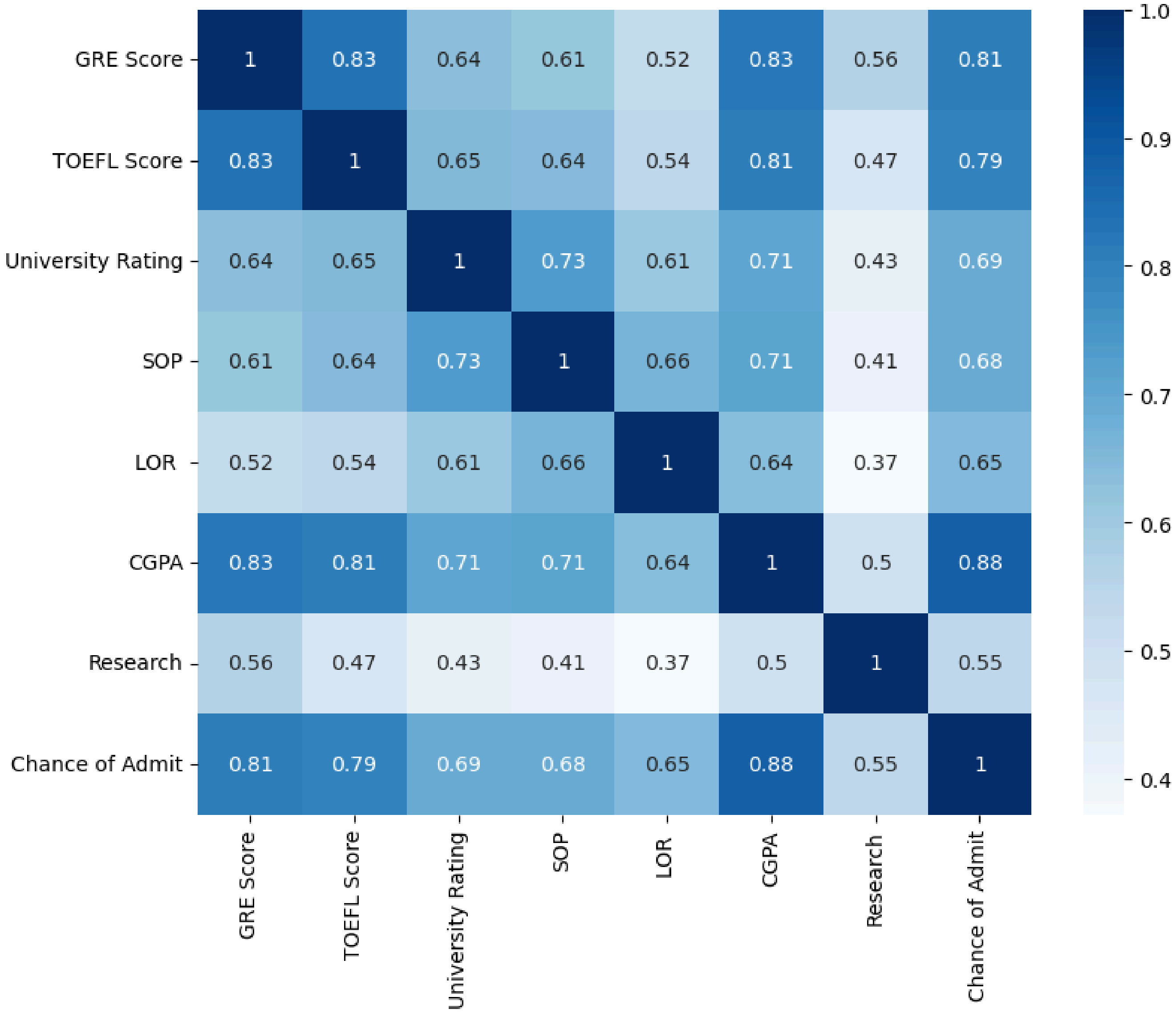
```
<seaborn.axisgrid.PairGrid at 0x1772aee92d0>
```



Overall look at correlation:

In [570…
```
plt.figure(figsize=(9,7))
sns.heatmap(df.corr(),annot=True,cmap = "Blues")
```

Out[570]: <Axes: >



Observation:

Independent Variables (Input data): GRE Score, TOEFL Score, University Rating, SOP, LOR, CGPA, Research

Target/Dependent Variable : Chance of Admit (the value we want to predict)

from above correlation heatmap , we can observe GRE score TOEFL score and CGPA have very high correlation with Change of admission.

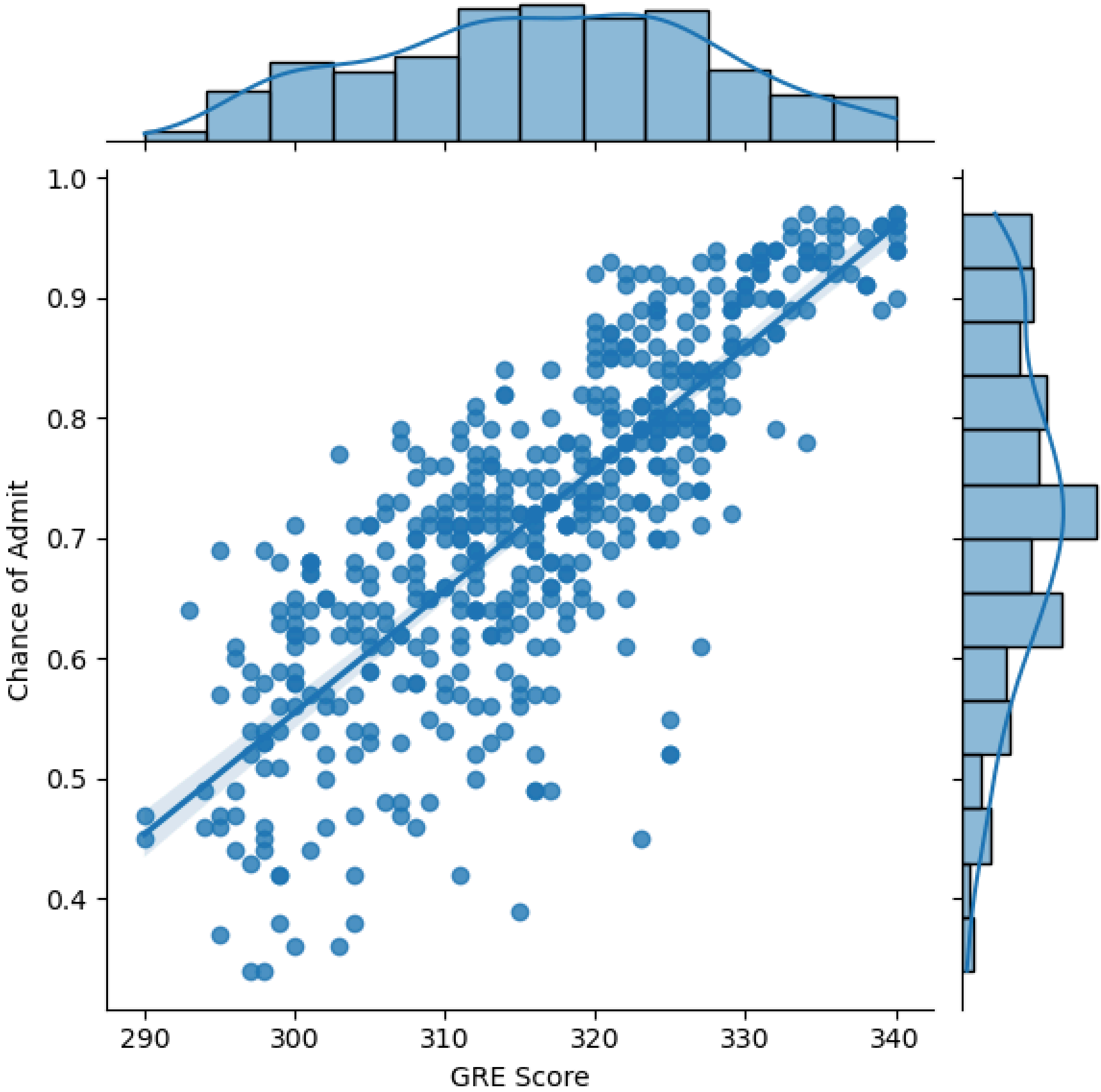
University rating, SOP ,LOR and Research have comparatively slightly less correlated than other features.

Checking Linearity of all the features/variables correlating with Target variable (chance of admit)

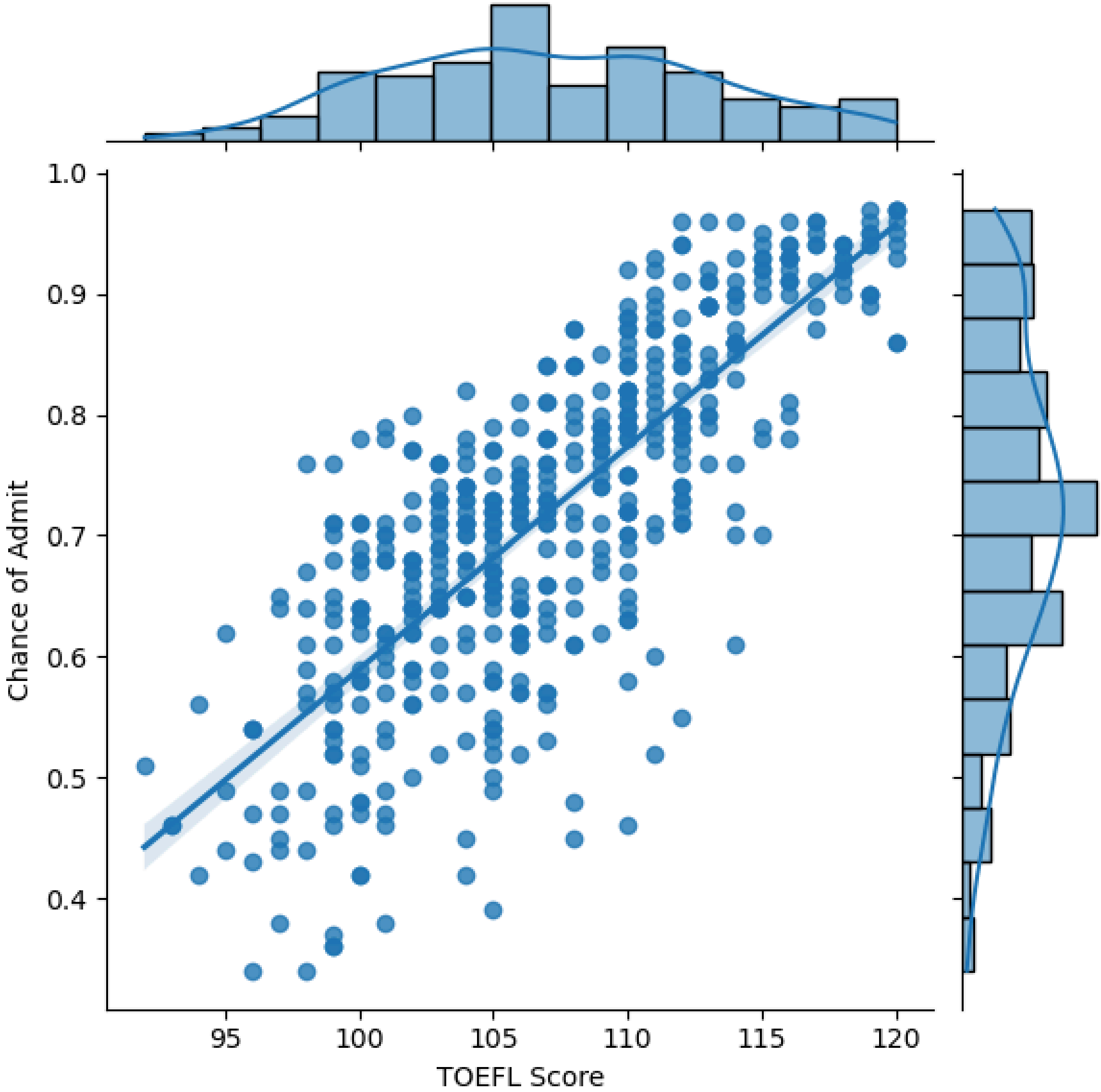
In [571…

```
for col in df.columns:
    print(col)
    plt.figure(figsize=(2, 2))  # Adjust width and height as per your preference
    sns.jointplot(x=col, y=target_var, data=df, kind="reg")
    plt.show()
```

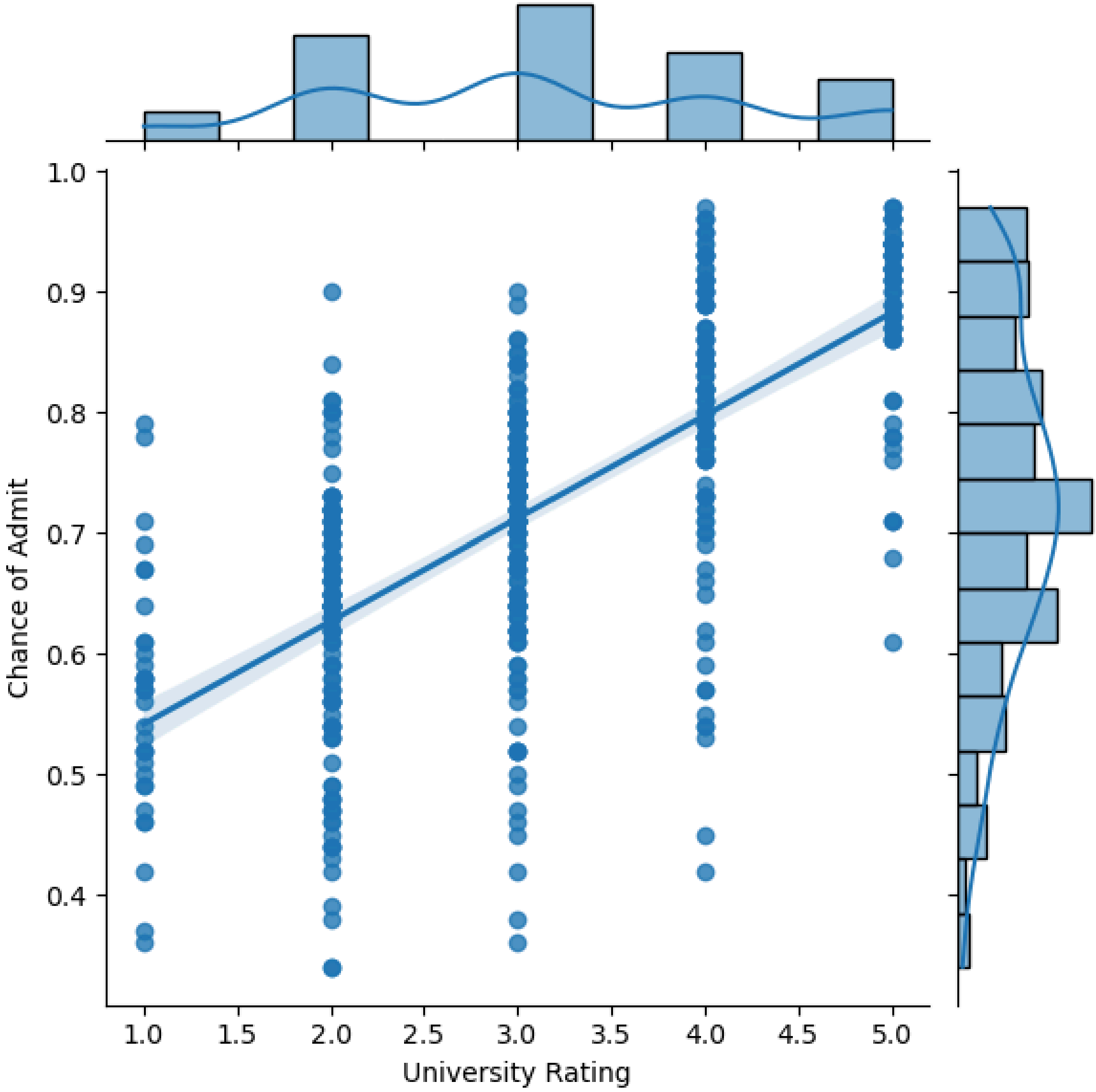
```
GRE Score
<Figure size 200x200 with 0 Axes>
```



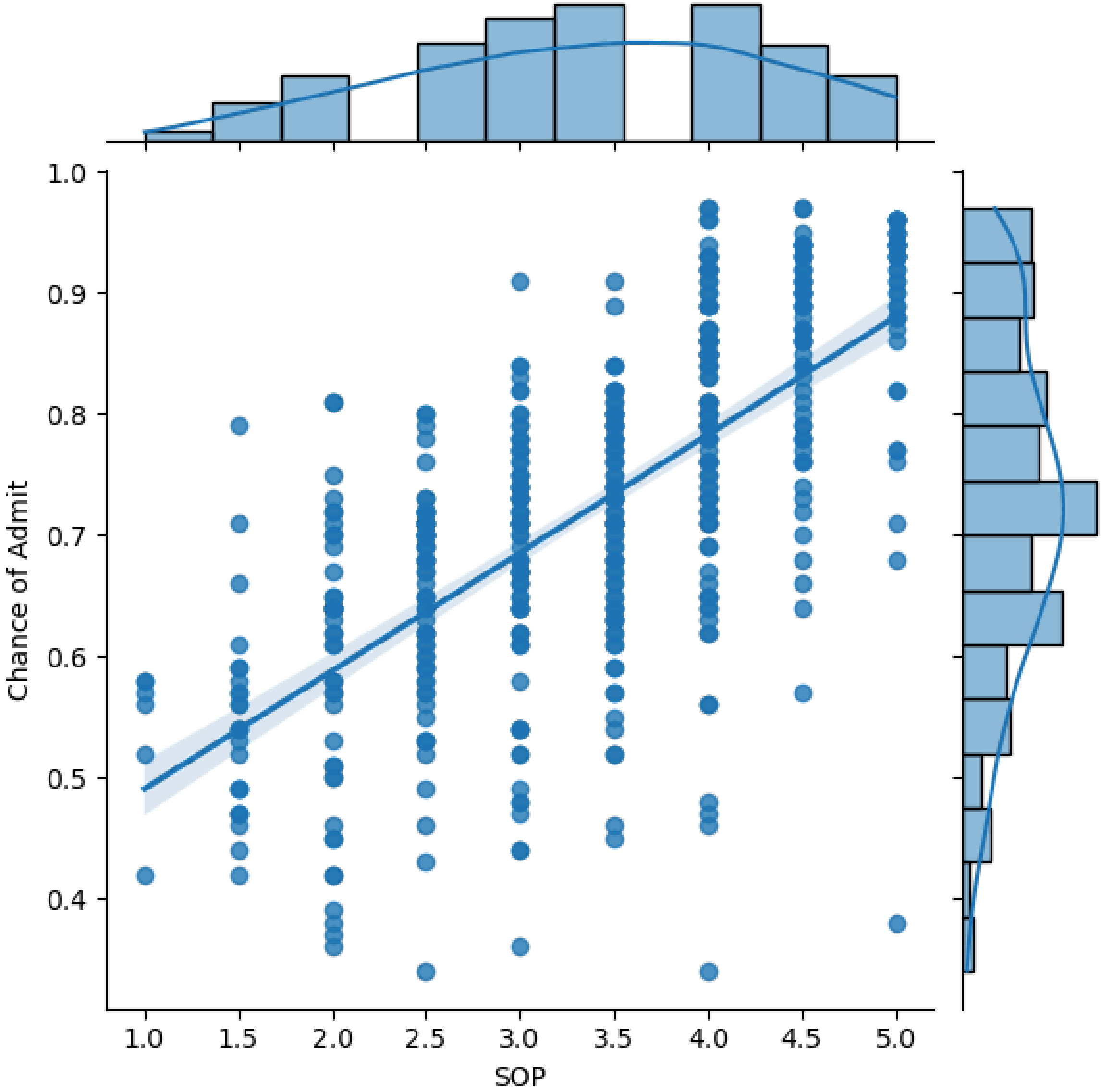

```
TOEFL Score
<Figure size 200x200 with 0 Axes>
```



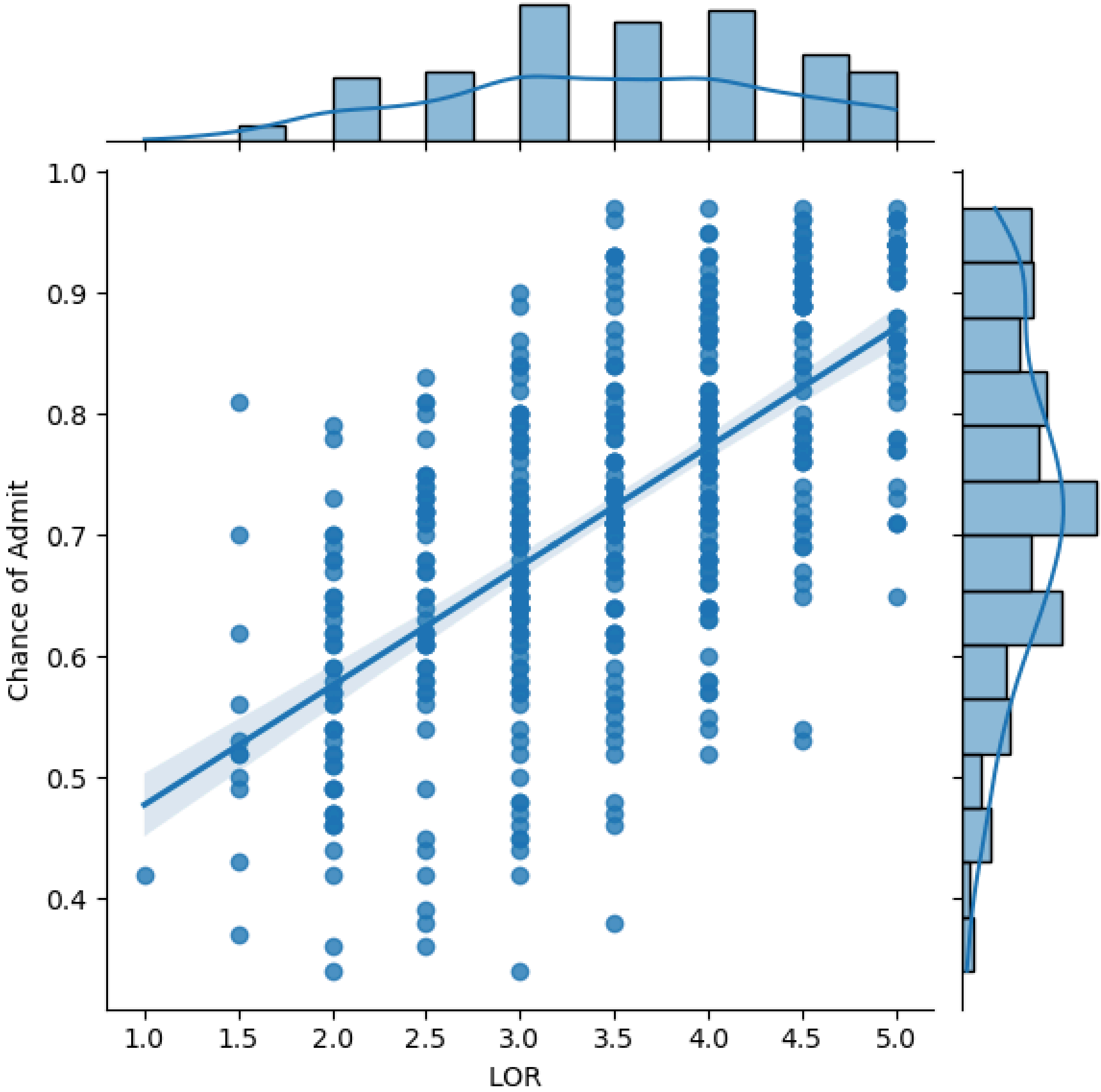

```
University Rating
<Figure size 200x200 with 0 Axes>
```



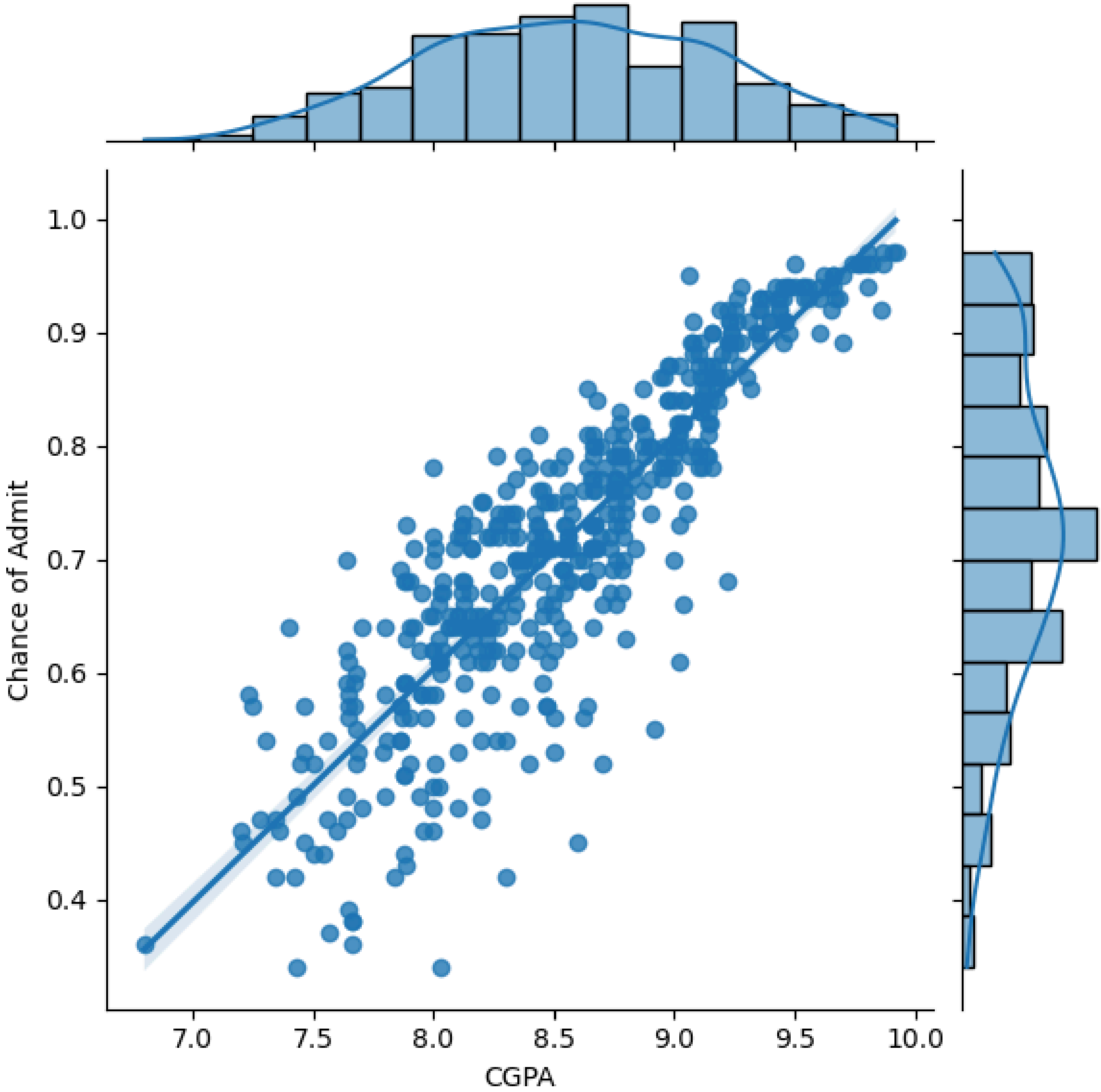

```
SOP
<Figure size 200x200 with 0 Axes>
```



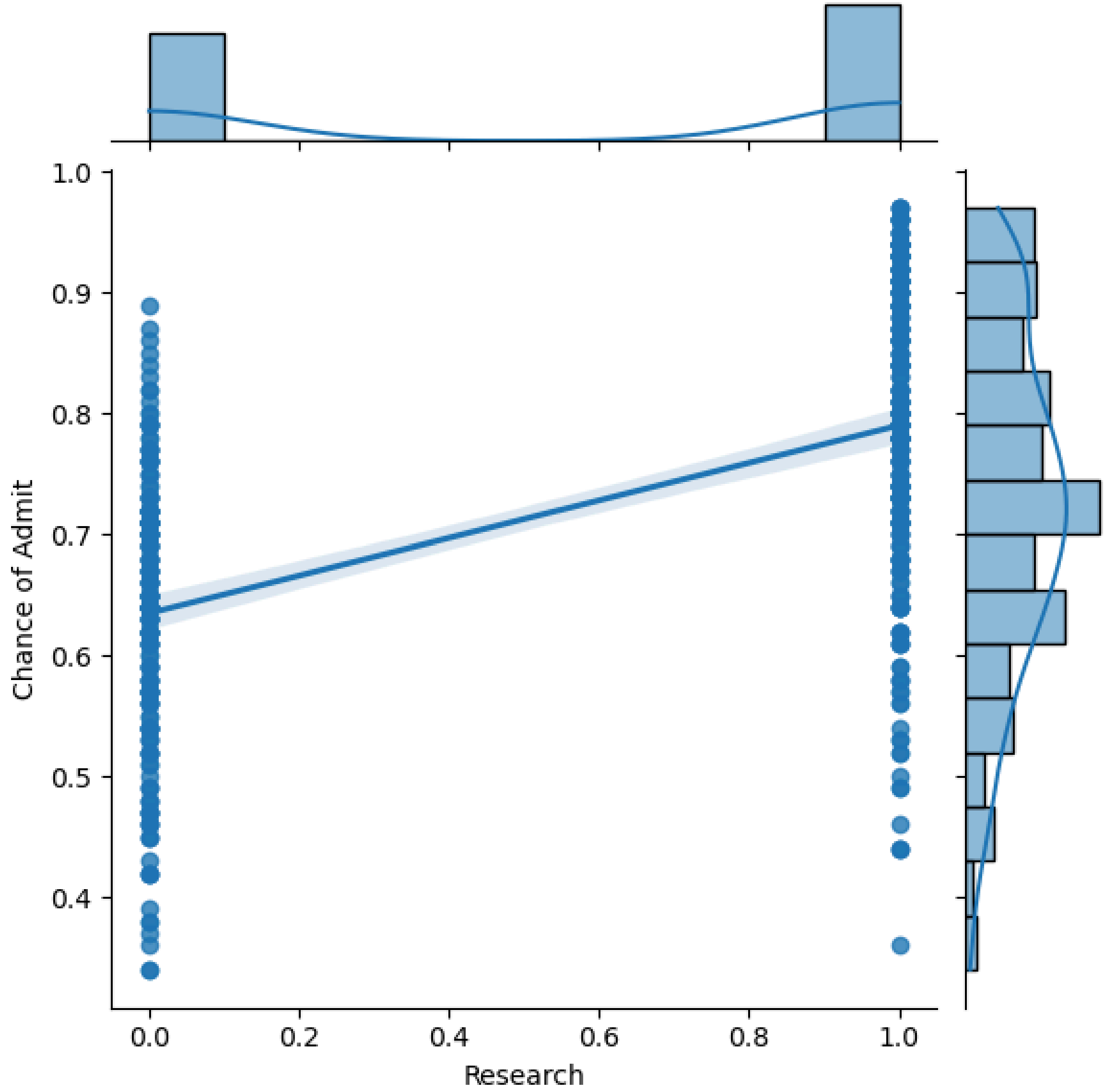

```
LOR
<Figure size 200x200 with 0 Axes>
```



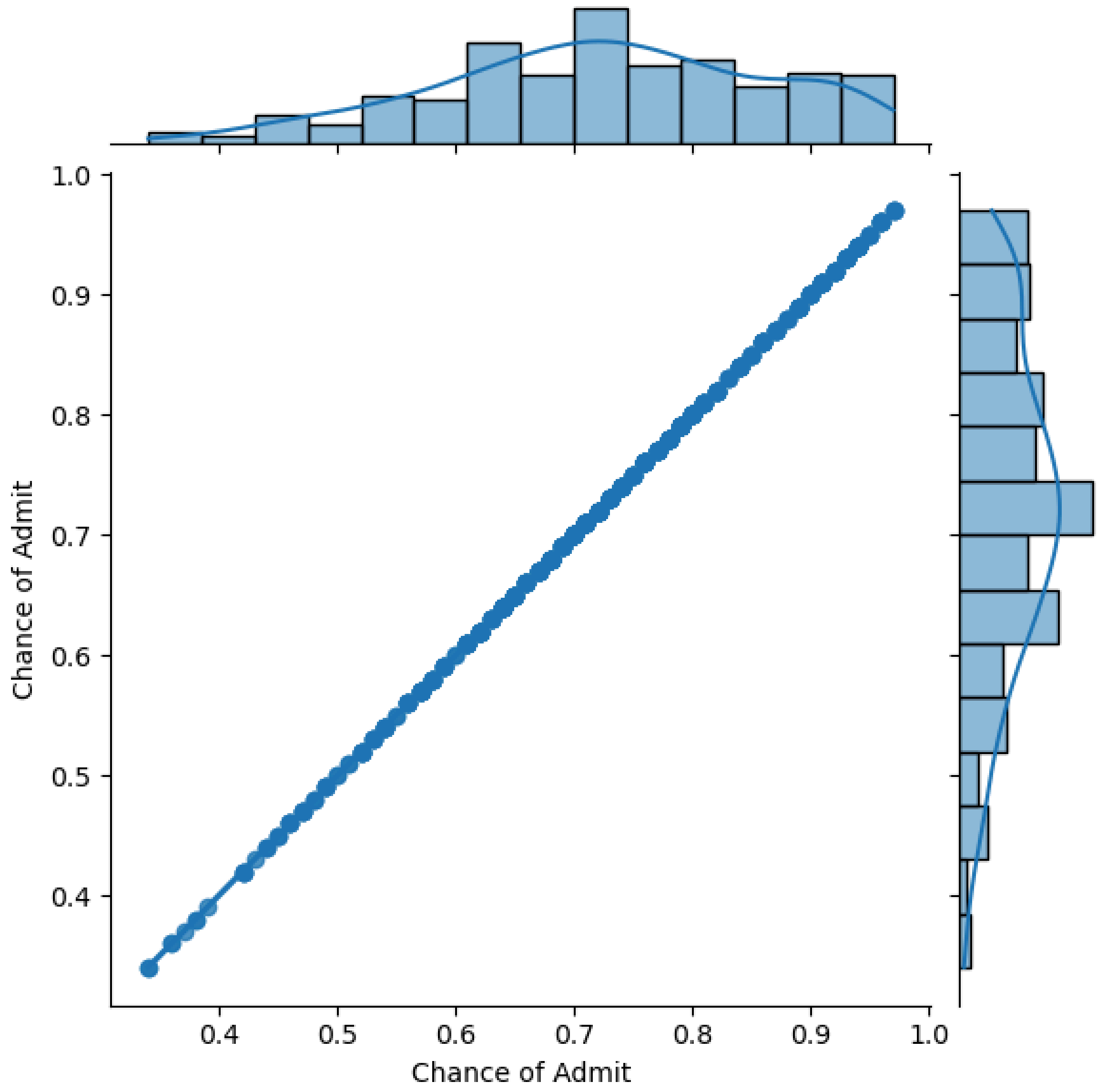
CGPA
<Figure size 200x200 with 0 Axes>



Research
<Figure size 200x200 with 0 Axes>




```
Chance of Admit
<Figure size 200x200 with 0 Axes>
```



In [572…

```
df.columns
```

Out[572]:

```
Index(['GRE Score', 'TOEFL Score', 'University Rating', 'SOP', 'LOR ', 'CGPA',
       'Research', 'Chance of Admit'],
      dtype='object')
```

Model Building

Predicting Graduate Admission Chances: A Linear Regression Approach

In [573…

```
from sklearn.preprocessing import StandardScaler

from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split

from statsmodels.stats.outliers_influence import variance_inflation_factor

from sklearn.metrics import r2_score,mean_squared_error,mean_absolute_error, adjusted_mutual_
from sklearn.feature_selection import f_regression
```

In [574…

```
X = df.drop(["Chance of Admit"],axis = 1)  # independent variables
y = df["Chance of Admit"].values.reshape(-1,1) # target / dependent variables
```

Standardising data

In [575…
```
standardizer = StandardScaler()
standardizer.fit(X)
x = standardizer.transform(X)  # standardising the data
```

test train spliting :

In [576…
```
X_train , X_test, y_train , y_test = train_test_split(x,y,
                                                     random_state = 1,
                                                      test_size = 0.2
                                                     )                         # test train s
```

In [577…
```
X_train.shape,X_test.shape  # after spliting, checking for the shape of test and  train data
```
Out[577]:
```
((400, 7), (100, 7))
```

In [578…
```
y_train.shape, y_test.shape
```
Out[578]:
```
((400, 1), (100, 1))
```

Training the model

In [579…
```
LinearRegression = LinearRegression()    # training LinearRegression model
LinearRegression.fit(X_train,y_train)
```
Out[579]:
```
▾ LinearRegression
LinearRegression()
```

In [580…
```
y_pred_train = LinearRegression.predict(X_train)    # training LinearRegression model

y_pred_test = LinearRegression.predict(X_test)
```

r2 score on train data:

In [581…
```
r2_score(y_train,y_pred_train )
```
Out[581]:
```
0.8215099192361265
```

r2 score on test data:

In [582…
```
r2_score(y_test,y_pred_test )
```
Out[582]:
```
0.8208741703103732
```

Model Co-efficients and Intercept with all the features (column names)

In [583…
```
ws = pd.DataFrame(LinearRegression.coef_.reshape(1,-1),columns=df.columns[:-1])
ws["Intercept"] = LinearRegression.intercept_
ws
```
Out[583]:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Intercept
0	0.020675	0.019284	0.007001	0.002975	0.013338	0.070514	0.009873	0.722881

In [584…

```
LinearRegression_Model_coefs = ws
LinearRegression_Model_coefs
```

Out[584]:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Intercept
0	0.020675	0.019284	0.007001	0.002975	0.013338	0.070514	0.009873	0.722881

In [585…

```
def AdjustedR2score(R2,n,d):
    return 1-(((1-R2)*(n-1))/(n-d-1))
```

In [586…

```
y_pred = LinearRegression.predict(X_test)

print("MSE:",mean_squared_error(y_test,y_pred)) # MSE
print("RMSE:",np.sqrt(mean_squared_error(y_test,y_pred))) #RMSE
print("MAE :",mean_absolute_error(y_test,y_pred) ) # MAE
print("r2_score:",r2_score(y_test,y_pred)) # r2score
print("Adjusted R2 score :", AdjustedR2score(r2_score(y_test,y_pred),len(X),X.shape[1]))  # a
```

```
MSE: 0.0034590988971363833
RMSE: 0.058814104576507695
MAE : 0.040200193804157944
r2_score: 0.8208741703103732
Adjusted R2 score : 0.8183256320830818
```

Assumptions of linear regression

1. Multicollinearity Check: The independent variables should not be highly correlated with each other
2. Residual Mean Close to Zero: The mean of the residuals should be close to zero, indicating that the model is unbiased
3. Linearity of Variables: The relationship between the independent and dependent variables should be approximately linear
4. Homoscedasticity Test: The variance of the residuals should be constant across all levels of the independent variables
5. Normality of Residuals: The residuals (errors) should be normally distributed around zero

1. Multicollinearity Check: Evaluating Variance Inflation Factor (VIF) scores

In [587…

```
def vif(newdf):
    # VIF dataframe
    vif_data = pd.DataFrame()
    vif_data["feature"] = newdf.columns

    # calculating VIF for each feature
    vif_data["VIF"] = [variance_inflation_factor(newdf.values, i)
                          for i in range(len(newdf.columns))]
    return vif_data
```

In [588…

```
res = vif(df.iloc[:,:-1])
res
```

Out[588]:

	feature	VIF
0	GRE Score	1308.061089
1	TOEFL Score	1215.951898
2	University Rating	20.933361
3	SOP	35.265006
4	LOR	30.911476
5	CGPA	950.817985
6	Research	2.869493

In [589…

```
# drop GRE Score and again calculate the VIF
res = vif(df.iloc[:, 1:-1])
res
```

Out[589]:

	feature	VIF
0	TOEFL Score	639.741892
1	University Rating	19.884298
2	SOP	33.733613
3	LOR	30.631503
4	CGPA	728.778312
5	Research	2.863301

In [590…

```
# drop TOEFL Score and again calculate the VIF
res = vif(df.iloc[:,2:-1])
res
```

Out[590]:

	feature	VIF
0	University Rating	19.777410
1	SOP	33.625178
2	LOR	30.356252
3	CGPA	25.101796
4	Research	2.842227

In [591…

```
# Now dropping the SOP and again calculate VIF
res = vif(df.iloc[:,2:-1].drop(columns=['SOP']))
res
```

Out[591]:

	feature	VIF
0	University Rating	15.140770
1	LOR	26.918495
2	CGPA	22.369655
3	Research	2.819171

In [592…

```
# dropping the LOR
newdf = df.iloc[:,2:-1].drop(columns=['SOP'])
newdf = newdf.drop(columns=['LOR '], axis=1)
res = vif(newdf)
res
```

Out[592]:

	feature	VIF
0	University Rating	12.498400
1	CGPA	11.040746
2	Research	2.783179

In [593…

```
# finally dropping the University Rating
newdf = newdf.drop(columns=['University Rating'])
res = vif(newdf)
res
```

Out[593]:

	feature	VIF
0	CGPA	2.455008
1	Research	2.455008

Observation:

- Multicollinearity is present in the data
- There are two features left - CGPA and Research are the only two variables which are important in making the prediction for Chance of Admit

2. Residual Mean Close to Zero

In [594…

```
residuals1 = y_test - y_pred_test
residuals1 = residuals1.reshape((-1,))
print('Mean of Residuals: ', residuals1.mean())
```

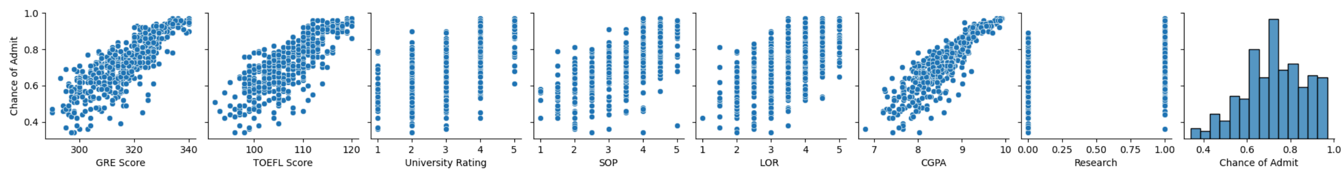
```
Mean of Residuals:  -0.005706590389232245
```

Observation: Since the mean of residuals is very close to 0, we can say that the model is unbiased

3. Linearity of Variables

In [595…

```
sns.pairplot(df,y_vars = ["Chance of Admit"])
plt.show()
```



Observation: GRE score, TOEFL score and CGPA have very high correlation with Change of admission

4. Test of homoscedasticity

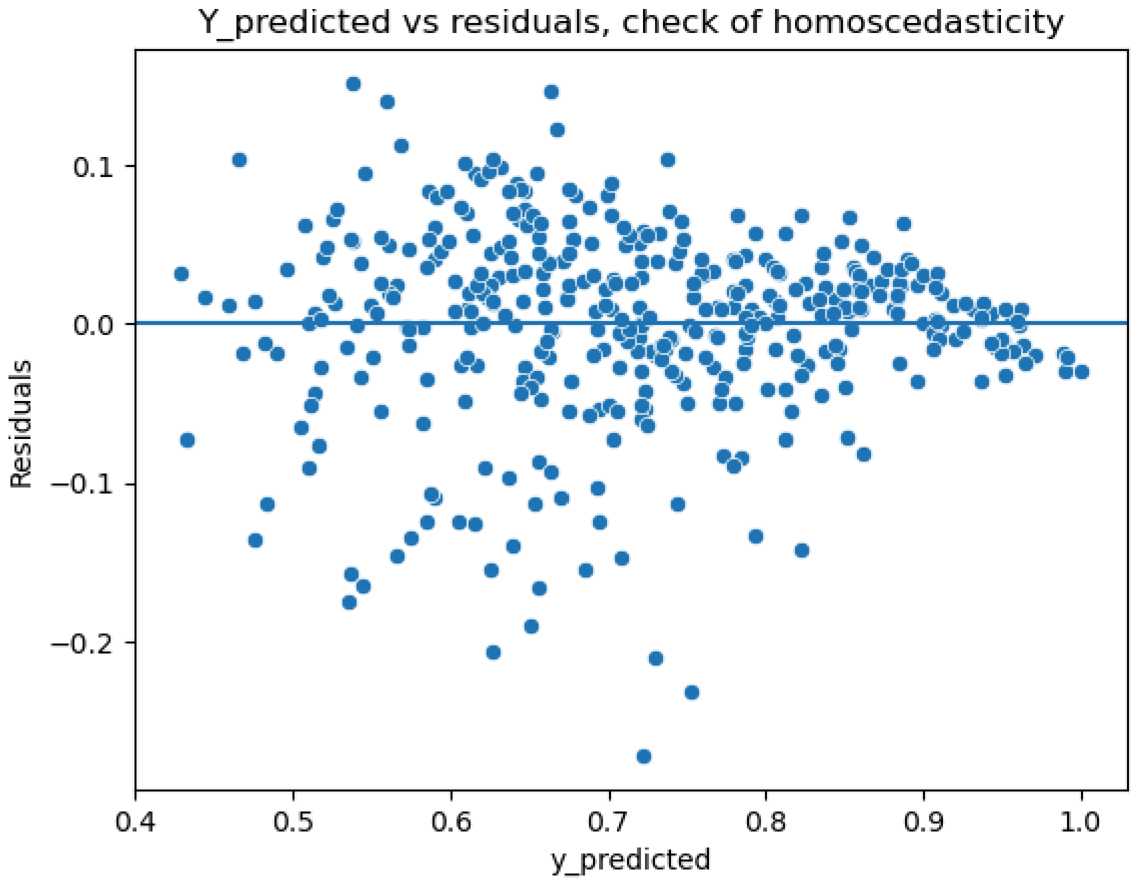
In [596…

```
y_predicted = LinearRegression.predict(X_train)
y_predicted.shape
residuals = (y_train - y_predicted)
```

In [597…

```
# Test of homoscedasticity
sns.scatterplot(x=y_predicted.reshape(-1,), y=residuals.reshape(-1,))
```

```
plt.xlabel('y_predicted')
plt.ylabel('Residuals')
plt.axhline(y=0)
plt.title("Y_predicted vs residuals, check of homoscedasticity")
plt.show()
```

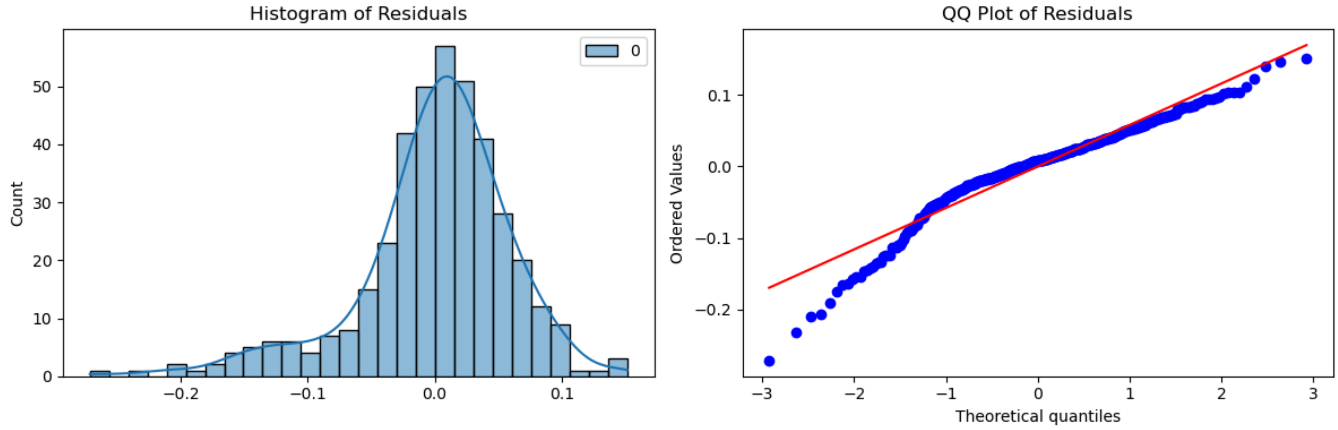


Observation: Since we do not see any significant change in the spread of residuals (the plot is not creating a cone type shape), We can coclude that homoscedasticity is met

5. Normality of Residuals

In [598…

```
residuals = (y_train - y_predicted)

# Create a figure and two subplots
fig, axes = plt.subplots(1, 2, figsize=(12, 4))

# Plot histogram of residuals
sns.histplot(residuals, kde=True, ax=axes[0])
axes[0].set_title('Histogram of Residuals')

# Plot QQ plot of residuals
stats.probplot(residuals.reshape(-1,), plot=axes[1])
axes[1].set_title('QQ Plot of Residuals')

plt.tight_layout()
plt.show()
```



Observation:

- The histogram shows that there is a negative skew in the distribution of residuals but it is close to a normal distribution
- The QQ plot shows that residuals are slightly deviating from the straight diagonal.

Model Regularisation

In [599…

```
from sklearn.linear_model import Ridge  # L2 regualrization
from sklearn.linear_model import Lasso  # L1 regualrization
from sklearn.linear_model import ElasticNet
```

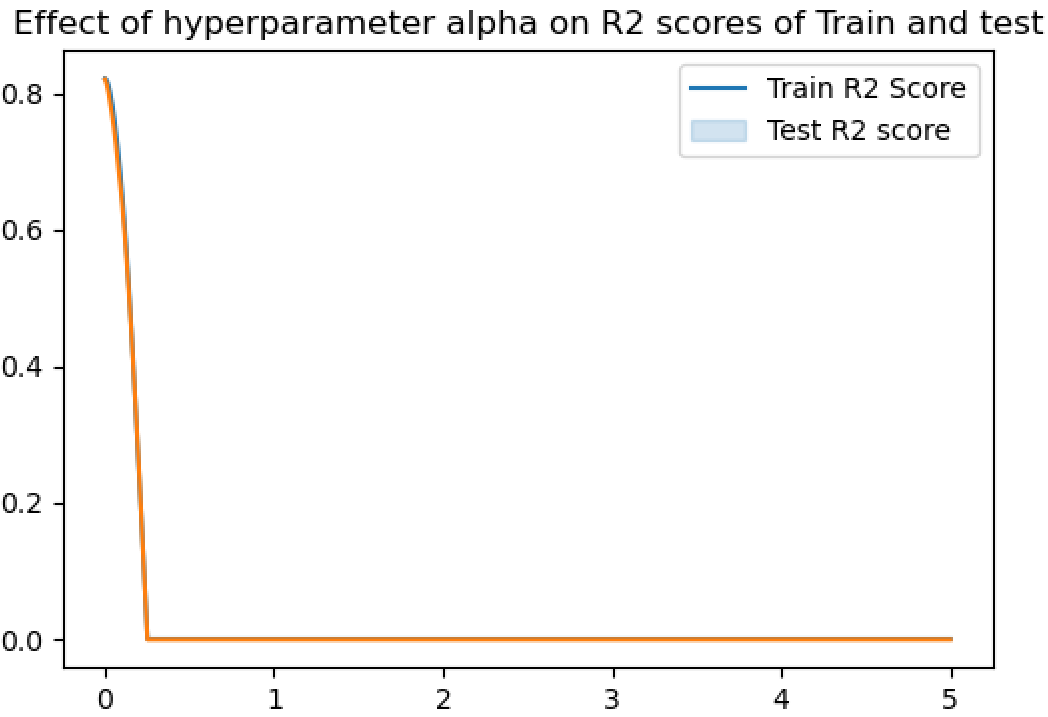
L2 Regularization (Ridge Regularization)

In [600…

```
## Hyperparameter Tuning : for appropriate lambda value :

train_R2_score = []
test_R2_score = []
lambdas = []
train_test_difference_Of_R2 =  []
lambda_ = 0
while lambda_ <= 5:
    lambdas.append(lambda_)
    RidgeModel = Ridge(lambda_)
    RidgeModel.fit(X_train,y_train)
    trainR2 = RidgeModel.score(X_train,y_train)
    testR2 = RidgeModel.score(X_test,y_test)
    train_R2_score.append(trainR2)
    test_R2_score.append(testR2)

    lambda_ += 0.01
```

In [640…

```
plt.figure(figsize=(6, 4))
sns.lineplot(x=lambdas, y=train_R2_score)
sns.lineplot(x=lambdas, y=test_R2_score)
plt.legend(['Train R2 Score', 'Test R2 score'])
plt.title("Effect of hyperparameter alpha on R2 scores of Train and test")

plt.show()
```



In [602…

```
RidgeModel = Ridge(alpha = 0.1)
RidgeModel.fit(X_train,y_train)
trainR2 = RidgeModel.score(X_train,y_train)
testR2 = RidgeModel.score(X_test,y_test)
```

In [603…

```
trainR2,testR2
```

Out[603]:

```
(0.8215098726041209, 0.8208639536156421)
```

In [604…

```
RidgeModel.coef_
```

Out[604]:

```
array([[0.02069489, 0.01929637, 0.00700953, 0.00298992, 0.01334235,
        0.07044884, 0.00987467]])
```

In [605…

```
RidgeModel_coefs = pd.DataFrame(RidgeModel.coef_.reshape(1,-1),columns=df.columns[:-1])
RidgeModel_coefs["Intercept"] = RidgeModel.intercept_
RidgeModel_coefs
```

Out[605]:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Intercept
0	0.020695	0.019296	0.00701	0.00299	0.013342	0.070449	0.009875	0.722882

In [606…

```
LinearRegression_Model_coefs
```

Out[606]:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Intercept
0	0.020675	0.019284	0.007001	0.002975	0.013338	0.070514	0.009873	0.722881

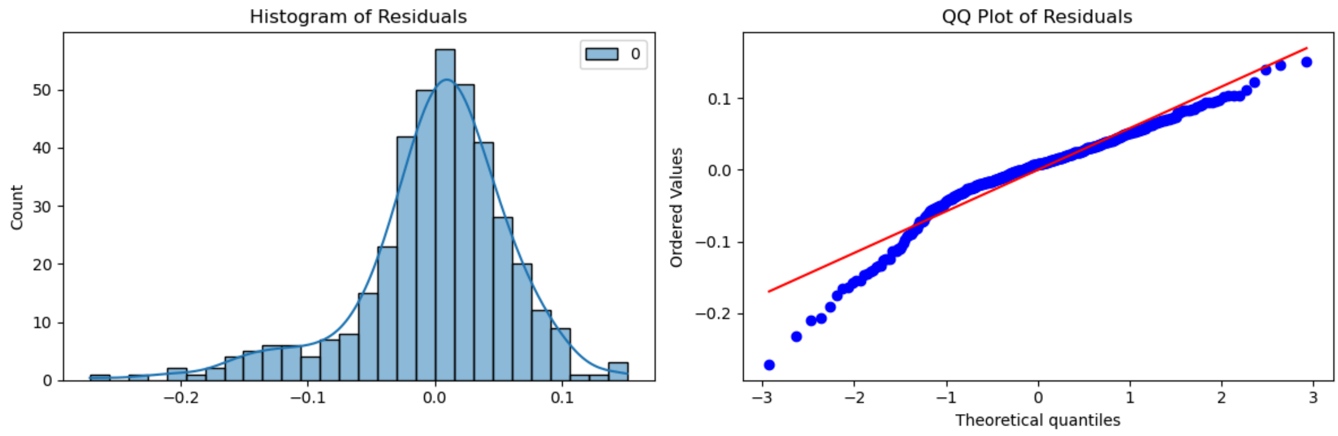
In [607…

```
y_pred = RidgeModel.predict(X_test)

print("MSE:",mean_squared_error(y_test,y_pred)) # MSE
print("RMSE:",np.sqrt(mean_squared_error(y_test,y_pred))) #RMSE
print("MAE :",mean_absolute_error(y_test,y_pred) ) # MAE
print("r2_score:",r2_score(y_test,y_pred)) # r2score
print("Adjusted R2 score :", AdjustedR2score(r2_score(y_test,y_pred),len(X),X.shape[1]))  # a
```

```
MSE: 0.003459296191728334
RMSE: 0.05881578182535988
MAE : 0.04020305511705696
r2_score: 0.8208639536156421
Adjusted R2 score : 0.8183152700288728
```

In [608…

```
residuals = (y_train - y_predicted)

# Create a figure and two subplots
fig, axes = plt.subplots(1, 2, figsize=(12, 4))

# Plot histogram of residuals using displot
sns.histplot(residuals, kde=True, ax=axes[0])
axes[0].set_title('Histogram of Residuals')

# Plot QQ plot of residuals
stats.probplot(residuals.reshape(-1,), plot=axes[1])
axes[1].set_title('QQ Plot of Residuals')

plt.tight_layout()
plt.show()
```



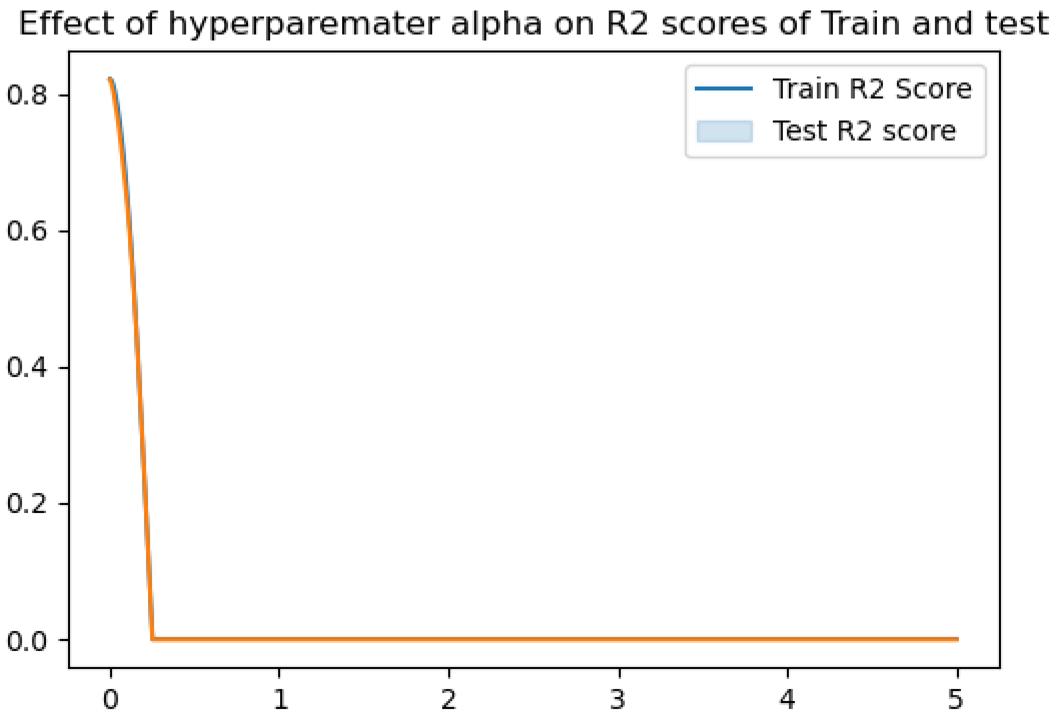
L1 regularization: Lasso

In [609…

```
train_R2_score = []
test_R2_score = []
lambdas = np.arange(0.001, 5, 0.001)

for lambda_ in lambdas:
    LassoModel = Lasso(alpha=lambda_)
    LassoModel.fit(X_train, y_train)
    trainR2 = LassoModel.score(X_train, y_train)
    testR2 = LassoModel.score(X_test, y_test)
    train_R2_score.append(trainR2)
    test_R2_score.append(testR2)
```

In [641…

```
plt.figure(figsize = (6,4))

sns.lineplot(x=lambdas, y=train_R2_score)
sns.lineplot(x=lambdas, y=test_R2_score)
plt.legend(['Train R2 Score','Test R2 score'])
plt.title("Effect of hyperparemater alpha on R2 scores of Train and test")


plt.show()
```



In [611…
```
LassoModel = Lasso(alpha=0.001)
LassoModel.fit(X_train , y_train)
trainR2 = LassoModel.score(X_train,y_train)
testR2 = LassoModel.score(X_test,y_test)
```

In [612…
```
trainR2,testR2
```

Out[612]:
```
(0.82142983289567, 0.8198472607571161)
```

In [613…
```
Lasso_Model_coefs = pd.DataFrame(LassoModel.coef_.reshape(1,-1),columns=df.columns[:-1])
Lasso_Model_coefs["Intercept"] = LassoModel.intercept_
Lasso_Model_coefs
```

Out[613]:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Intercept
0	0.020616	0.019069	0.006782	0.002808	0.012903	0.070605	0.009278	0.722863

In [614…
```
RidgeModel_coefs
```

Out[614]:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Intercept
0	0.020695	0.019296	0.00701	0.00299	0.013342	0.070449	0.009875	0.722882

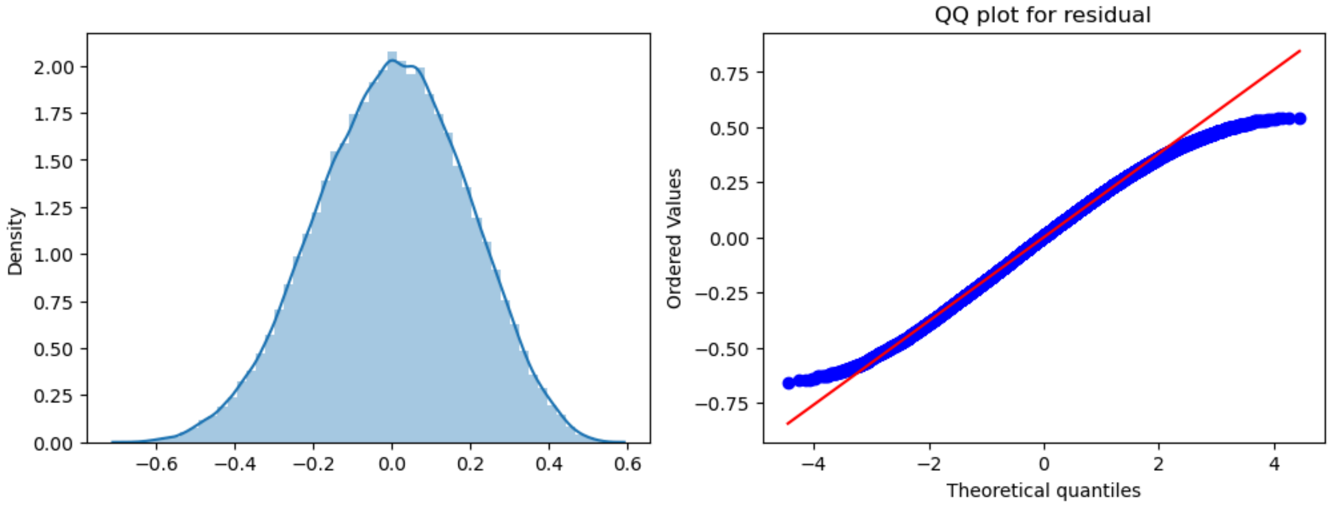
In [615…
```
LinearRegression_Model_coefs
```

Out[615]:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Intercept
0	0.020675	0.019284	0.007001	0.002975	0.013338	0.070514	0.009873	0.722881

In [616…
```
y_predicted = LassoModel.predict(X_train)

residuals = (y_train - y_predicted)
plt.figure(figsize=(12,4))
plt.subplot(1,2,1)
sns.distplot(residuals)
plt.subplot(1,2,2)
stats.probplot(residuals.reshape(-1,), plot = plt)
plt.title('QQ plot for residual')
plt.show()
```

```
C:\Users\hp\AppData\Local\Temp\ipykernel_18660\2857349529.py:6: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(residuals)
```



In [617…

```
y_pred = LassoModel.predict(X_test)

print("MSE:",mean_squared_error(y_test,y_pred)) # MSE
print("RMSE:",np.sqrt(mean_squared_error(y_test,y_pred))) #RMSE
print("MAE :",mean_absolute_error(y_test,y_pred) ) # MAE
print("r2_score:",r2_score(y_test,y_pred)) # r2score
print("Adjusted R2 score :", AdjustedR2score(r2_score(y_test,y_pred),len(X),X.shape[1]))  # a
```

```
MSE: 0.0034789295475193297
RMSE: 0.058982451182697807
MAE : 0.04022896061335951
r2_score: 0.8198472607571161
Adjusted R2 score : 0.8172841120280507
```

ElasticNet

L1 and L2 regularisation : Elastic net linear regression uses the penalties from both the lasso and ridge techniques to regularize regression models.

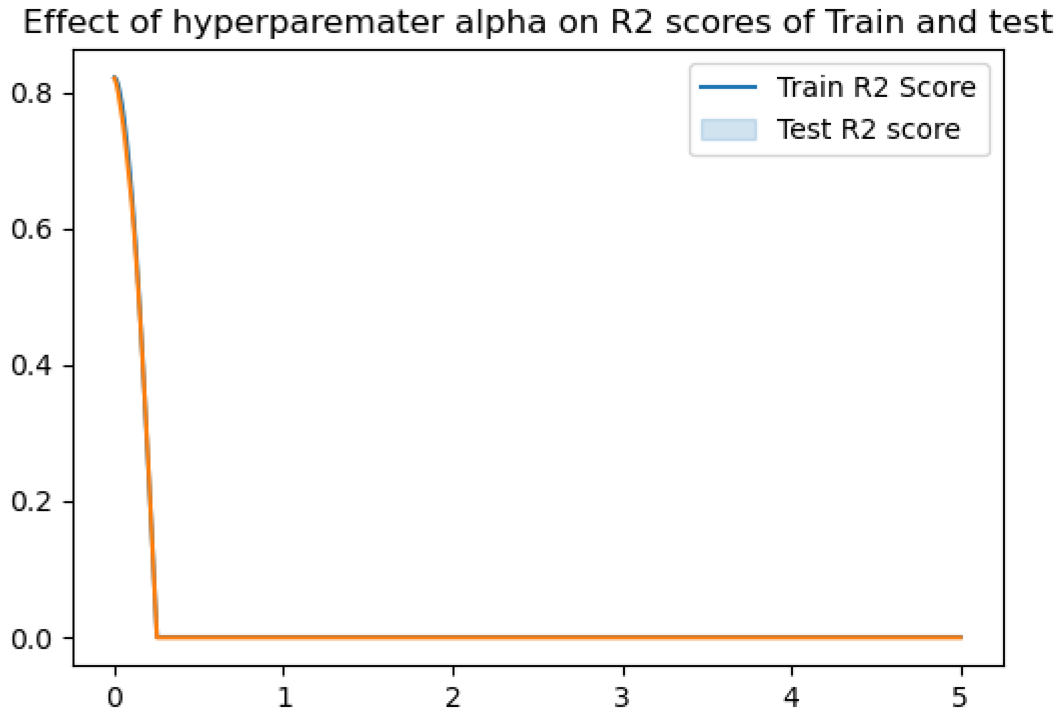
In [618…

```
from sklearn.linear_model import ElasticNet
import numpy as np

train_R2_score = []
test_R2_score = []
lambdas = np.arange(0.001, 5, 0.001)

for lambda_ in lambdas:
    ElasticNet_model = ElasticNet(alpha=lambda_)
    ElasticNet_model.fit(X_train, y_train)
    trainR2 = ElasticNet_model.score(X_train, y_train)
    testR2 = ElasticNet_model.score(X_test, y_test)
    train_R2_score.append(trainR2)
    test_R2_score.append(testR2)
```

In [642…

```
plt.figure(figsize = (6,4))

sns.lineplot(x=lambdas, y=train_R2_score)
sns.lineplot(x=lambdas, y=test_R2_score)
```

```
plt.legend(['Train R2 Score','Test R2 score'])
plt.title("Effect of hyperparemater alpha on R2 scores of Train and test")


plt.show()
```



In [620…

```
ElasticNet_model = ElasticNet(alpha=0.001)
ElasticNet_model.fit(X_train , y_train)
trainR2 = ElasticNet_model.score(X_train,y_train)
testR2 = ElasticNet_model.score(X_test,y_test)
```

In [621…

```
trainR2,testR2
```

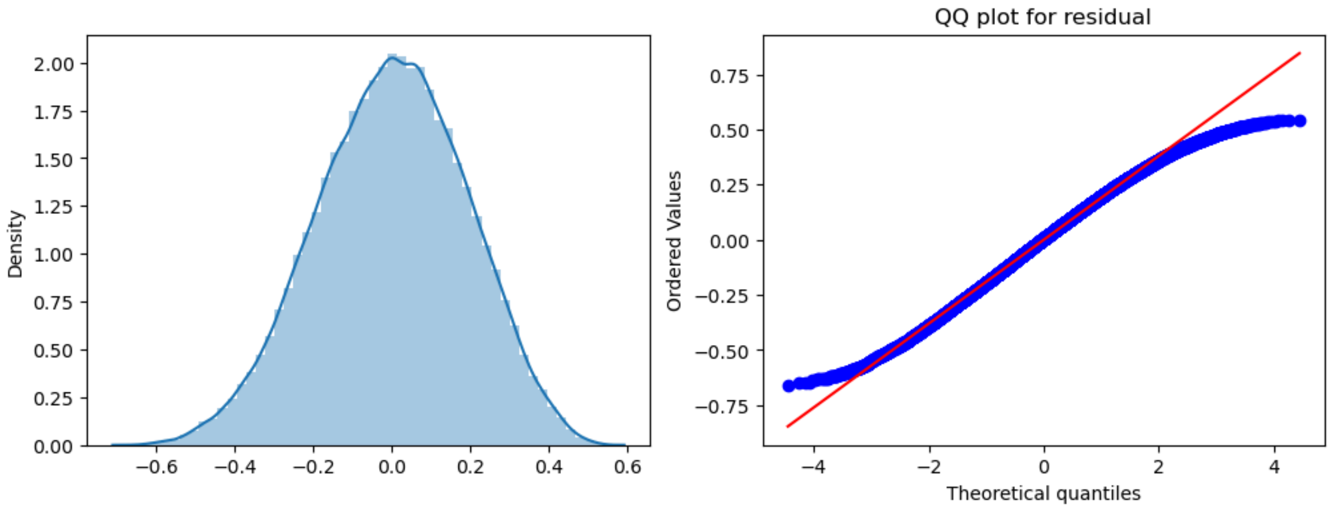
Out[621]:

```
(0.8214893364453533, 0.8203602261096284)
```

In [622…

```
y_predicted = ElasticNet_model.predict(X_train)

residuals = (y_train - y_predicted)
plt.figure(figsize=(12,4))
plt.subplot(1,2,1)
sns.distplot(residuals)
plt.subplot(1,2,2)
stats.probplot(residuals.reshape(-1,), plot = plt)
plt.title('QQ plot for residual')
plt.show()
```

```
C:\Users\hp\AppData\Local\Temp\ipykernel_18660\791257488.py:6: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(residuals)
```



In [623…

```
y_pred = ElasticNet_model.predict(X_test)

print("MSE:",mean_squared_error(y_test,y_pred)) # MSE
print("RMSE:",np.sqrt(mean_squared_error(y_test,y_pred))) #RMSE
print("MAE :",mean_absolute_error(y_test,y_pred) ) # MAE
print("r2_score:",r2_score(y_test,y_pred)) # r2score
print("Adjusted R2 score :", AdjustedR2score(r2_score(y_test,y_pred),len(X),X.shape[1]))  # a
```

```
MSE: 0.003469023673596966
RMSE: 0.058898418260569324
MAE : 0.04021407699792928
r2_score: 0.8203602261096284
Adjusted R2 score : 0.8178043756680987
```

In [624…

```
ElasticNet_model_coefs = pd.DataFrame(ElasticNet_model.coef_.reshape(1,-1),columns=df.columns
ElasticNet_model_coefs["Intercept"] = ElasticNet_model.intercept_
ElasticNet_model_coefs
```

Out[624]:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Intercept
0	0.020679	0.019199	0.006908	0.00292	0.013128	0.070437	0.009581	0.722873

In [625…

```
RidgeModel_coefs
```

Out[625]:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Intercept
0	0.020695	0.019296	0.00701	0.00299	0.013342	0.070449	0.009875	0.722882

In [626…

```
Lasso_Model_coefs
```

Out[626]:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Intercept
0	0.020616	0.019069	0.006782	0.002808	0.012903	0.070605	0.009278	0.722863

In [627…

```
LinearRegression_Model_coefs
```

Out[627]:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Intercept
0	0.020675	0.019284	0.007001	0.002975	0.013338	0.070514	0.009873	0.722881

In [628…

```
y_pred = ElasticNet_model.predict(X_test)
ElasticNet_model_metrics = []
ElasticNet_model_metrics.append(mean_squared_error(y_test,y_pred)) # MSE
ElasticNet_model_metrics.append(np.sqrt(mean_squared_error(y_test,y_pred))) #RMSE
ElasticNet_model_metrics.append(mean_absolute_error(y_test,y_pred) ) # MAE
ElasticNet_model_metrics.append(r2_score(y_test,y_pred)) # r2score
ElasticNet_model_metrics.append(AdjustedR2score(r2_score(y_test,y_pred),len(X),X.shape[1]))
```

In [629…
```
y_pred = LinearRegression.predict(X_test)
LinearRegression_model_metrics = []
LinearRegression_model_metrics.append(mean_squared_error(y_test,y_pred)) # MSE
LinearRegression_model_metrics.append(np.sqrt(mean_squared_error(y_test,y_pred))) #RMSE
LinearRegression_model_metrics.append(mean_absolute_error(y_test,y_pred) ) # MAE
LinearRegression_model_metrics.append(r2_score(y_test,y_pred)) # r2score
LinearRegression_model_metrics.append(AdjustedR2score(r2_score(y_test,y_pred),len(X),X.shape[
```

In [630…
```
y_pred = RidgeModel.predict(X_test)
RidgeModel_model_metrics = []
RidgeModel_model_metrics.append(mean_squared_error(y_test,y_pred)) # MSE
RidgeModel_model_metrics.append(np.sqrt(mean_squared_error(y_test,y_pred))) #RMSE
RidgeModel_model_metrics.append(mean_absolute_error(y_test,y_pred) ) # MAE
RidgeModel_model_metrics.append(r2_score(y_test,y_pred)) # r2score
RidgeModel_model_metrics.append(AdjustedR2score(r2_score(y_test,y_pred),len(X),X.shape[1]))
```

In [631…
```
y_pred = LassoModel.predict(X_test)
LassoModel_model_metrics = []
LassoModel_model_metrics.append(mean_squared_error(y_test,y_pred)) # MSE
LassoModel_model_metrics.append(np.sqrt(mean_squared_error(y_test,y_pred))) #RMSE
LassoModel_model_metrics.append(mean_absolute_error(y_test,y_pred) ) # MAE
LassoModel_model_metrics.append(r2_score(y_test,y_pred)) # r2score
LassoModel_model_metrics.append(AdjustedR2score(r2_score(y_test,y_pred),len(X),X.shape[1]))
```

In [632…
```
ElasticNet_model_metrics
```

Out[632]:
```
[0.003469023673596966,
 0.058898418260569324,
 0.04021407699792928,
 0.8203602261096284,
 0.8178043756680987]
```

In [633…
```
A = pd.DataFrame([LinearRegression_model_metrics,LassoModel_model_metrics,RidgeModel_model_me
                  ElasticNet_model_metrics],columns=["MSE","RMSE","MAE","R2_SCORE","ADJUSTED_
                 index = ["Linear Regression Model","Lasso Regression Model","Ridge Regressio
                          "ElasticNet Regression Model"])
A
```

Out[633]:

	MSE	RMSE	MAE	R2_SCORE	ADJUSTED_R2
Linear Regression Model	0.003459	0.058814	0.040200	0.820874	0.818326
Lasso Regression Model	0.003479	0.058982	0.040229	0.819847	0.817284
Ridge Regression Model	0.003459	0.058816	0.040203	0.820864	0.818315
ElasticNet Regression Model	0.003469	0.058898	0.040214	0.820360	0.817804

In [634…
```
B = pd.DataFrame(LinearRegression_Model_coefs.append(Lasso_Model_coefs).append(RidgeModel_coe
B.index = ["Linear Regression Model","Lasso Regression Model","Ridge Regression Model","Elast
```

```
C:\Users\hp\AppData\Local\Temp\ipykernel_18660\1174321538.py:1: FutureWarning: The frame.appe
nd method is deprecated and will be removed from pandas in a future version. Use pandas.conca
t instead.
  B = pd.DataFrame(LinearRegression_Model_coefs.append(Lasso_Model_coefs).append(RidgeModel_c
oefs).append(ElasticNet_model_coefs))
C:\Users\hp\AppData\Local\Temp\ipykernel_18660\1174321538.py:1: FutureWarning: The frame.appe
nd method is deprecated and will be removed from pandas in a future version. Use pandas.conca
t instead.
  B = pd.DataFrame(LinearRegression_Model_coefs.append(Lasso_Model_coefs).append(RidgeModel_c
oefs).append(ElasticNet_model_coefs))
```

In [635…
```
REPORT = B.reset_index().merge(A.reset_index())
```

In [636…
```
REPORT = REPORT.set_index("index")
REPORT
```

Out[636]:

index	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Intercept	MSE	RMS
Linear Regression Model	0.020675	0.019284	0.007001	0.002975	0.013338	0.070514	0.009873	0.722881	0.003459	0.05881
Lasso Regression Model	0.020616	0.019069	0.006782	0.002808	0.012903	0.070605	0.009278	0.722863	0.003479	0.05898
Ridge Regression Model	0.020695	0.019296	0.007010	0.002990	0.013342	0.070449	0.009875	0.722882	0.003459	0.05881
ElasticNet Regression Model	0.020679	0.019199	0.006908	0.002920	0.013128	0.070437	0.009581	0.722873	0.003469	0.05889

Insights

- Independent Variables (Input data): GRE Score, TOEFL Score, University Rating, SOP, LOR, CGPA, Research
- Target/Dependent Variable : Chance of Admit
- The distribution of target variable (chances of admit) is left-skewed
- Exam scores (CGPA/GRE/TOEFL) have a strong positive correlation with chance of admit. These variables are also highly correlated amongst themselves
- The categorical variables such as university ranking, research, quality of SOP and LOR also show an upward trend for chances of admit
- Chance of admission(target variable) and GRE score(an independent feature) are nearly normally distrubted.
- From boxplots (distribution of chance of admition (probability of getting admition) as per GRE score) : with higher GRE score,there is high probability of getting an admition .
- Students having high toefl score , has higher probability of getting admition .
- from count plots, we can observe , statement of purpose SOP strength is positively correlated with Chance of Admission .
- we can also similar pattern in Letter of Recommendation Stength and University rating , have positive correlation with Chaces of Admission .
- Student having research has higher chances of Admission , but also we can observe some outliers within that caregory.

In [637…

```
REPORT
```

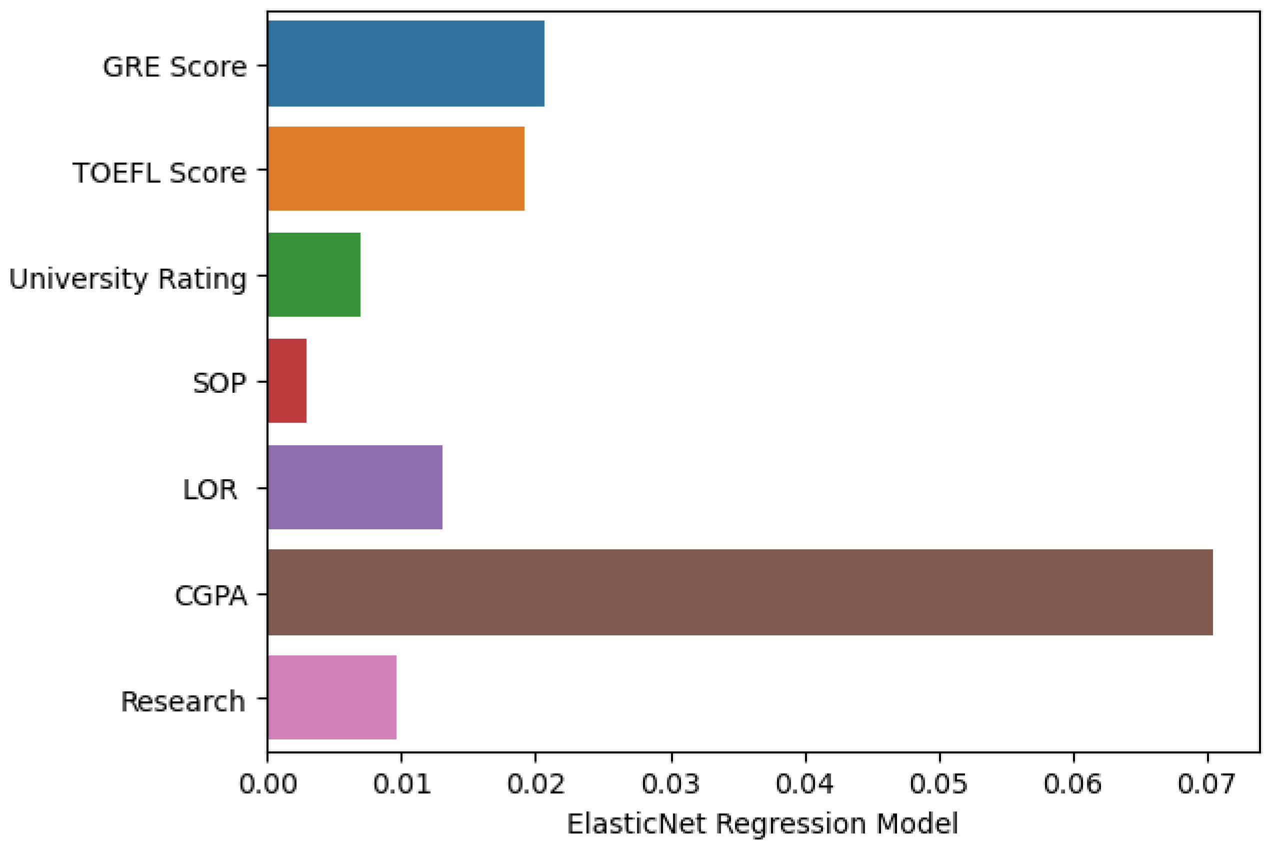
Out[637]:

index	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Intercept	MSE	RMS
Linear Regression Model	0.020675	0.019284	0.007001	0.002975	0.013338	0.070514	0.009873	0.722881	0.003459	0.05881
Lasso Regression Model	0.020616	0.019069	0.006782	0.002808	0.012903	0.070605	0.009278	0.722863	0.003479	0.05898
Ridge Regression Model	0.020695	0.019296	0.007010	0.002990	0.013342	0.070449	0.009875	0.722882	0.003459	0.05881
ElasticNet Regression Model	0.020679	0.019199	0.006908	0.002920	0.013128	0.070437	0.009581	0.722873	0.003469	0.05889

In [638…

```
sns.barplot(y  = REPORT.loc["ElasticNet Regression Model"][0:7].index,
            x = REPORT.loc["ElasticNet Regression Model"][0:7])
```

Out[638]: <Axes: xlabel='ElasticNet Regression Model'>



Insights from Regression Analysis

- From the regression analysis conducted (as indicated by the bar chart and REPORT file), it is evident that CGPA emerges as the most crucial feature for predicting admission chances. Additionally, significant importance is attributed to GRE and TOEFL scores.
- Regarding the predictor variables, they predominantly meet the conditions requisite for Linear Regression, although multicollinearity is apparent in the data. Notably, CGPA and Research stand out as the sole pivotal variables in predicting the Chance of Admit. While the mean of residuals

approximates zero and conditions such as linearity of variables, normality of residuals, and homoscedasticity are satisfied, not all residuals exhibit perfect normal distribution. Upon observing the residual plot, some degree of heteroscedasticity becomes apparent.
- Furthermore, both regularized models, Ridge and Lasso, yield outcomes akin to the Linear Regression Model. Similarly, ElasticNet (L1+L2) also presents closely aligned results, along with other metrics across all models.

Actionable Insights and Recommendations

- Educational institutions can support students not only in enhancing their CGPA scores but also in crafting compelling Letters of Recommendation (LOR) and Statements of Purpose (SOP), thereby improving their chances of admission to prestigious universities.
- Increasing awareness about CGPA and research capabilities through seminars can enhance the likelihood of admission.
- It is imperative to conduct surveys for awareness and marketing campaigns as students cannot alter their current attributes. This helps create a favorable impression on students at the undergraduate level, bolstering the company's reputation and aiding students in preparing for future endeavors.
- Implementing a dashboard for students upon logging into the website fosters healthy competition and facilitates the creation of progress reports. *Given the high correlation among exam scores, incorporating additional independent variables is advisable for improved prediction accuracy. These variables could include work experience, internships, performance in mock interviews, involvement in extracurricular activities, or diversity factors.

Possible Model Improvement Areas

- Incorporate new features such as the GRE_TOEFL_CGPA_Ratio, calculated as the ratio of GRE score, TOEFL score, and CGPA, to capture additional information.
- Explore the implementation of a non-linear model to potentially capture more complex relationships and improve predictive performance.

End of Project *

In [ ]: