Jamboree Education - Linear Regression

About Jamboree Eduction

- 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:

- Analyse the predictor variables to draw insights about the importance of various factors in prediction of chances of graduate admission and how they are related to each other.

Analysing basic metrics

In [1]:

```
#importing different libaries
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings("ignore")
import statsmodels.api as sm
from scipy import stats
```

In [2]:

```
#Loading of dataset
df = pd.read_csv("../scaler/Jamboree_Admission.csv")
df.head()
```

Out[2]:

	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

In [3]:
```
df.shape #to observe shape of data
```

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

- Dataset is of 500 rows and 9 attributes.

In [4]:
```
df.info() #to observe the data type
```

```
<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 [5]:
```
df.columns
```

Out[5]:
```
Index(['Serial No.', 'GRE Score', 'TOEFL Score', 'University Rating', 'SOP',
       'LOR ', 'CGPA', 'Research', 'Chance of Admit '],
      dtype='object')
```

In [6]:
```
df.isnull().sum() #missing or null values in data
```

Out[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
```

- There are no missing values in the data.

In [7]:
```python
df['Serial No.'].nunique()
```

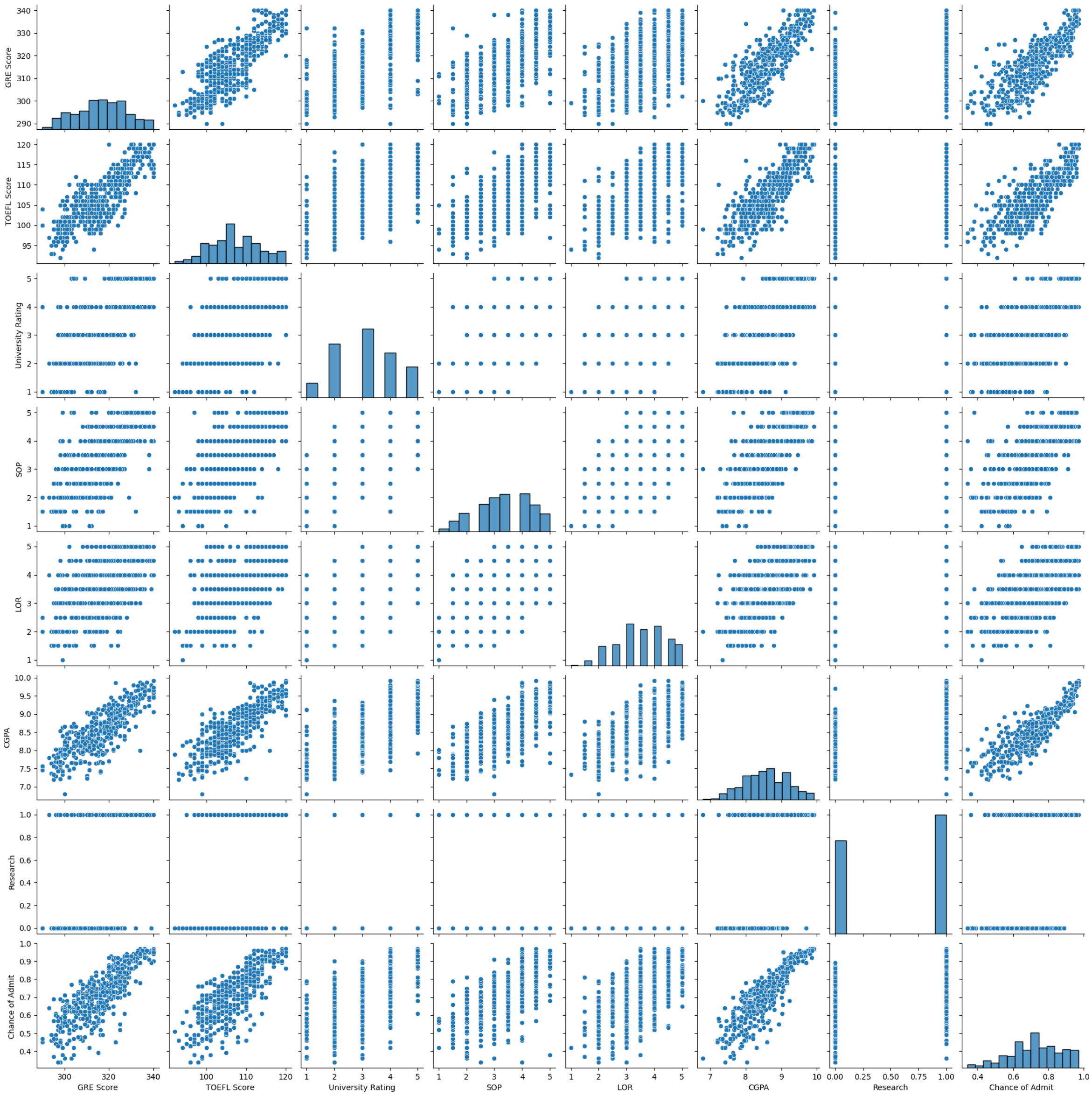
Out[7]: 500

In [8]:
```python
# Remove serial number as it is not a feature required for prediction
df.drop(columns=['Serial No.'], inplace=True)
```

In [9]:
```python
df.nunique()
```

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

In [10]:
```python
sns.pairplot(df)
plt.show()
```



- While university ranking, rating of SOP and LOR also have an impact on chances of admit, research is the only variable which doesn't have much of an impact
- We can see from the scatterplot that the values of university ranking, SOP, LOR and research are not continuous. We can convert these columns to categorical variables

In [11]:
```
df.rename(columns={'LOR ':'LOR', 'Chance of Admit ':'Chance of Admit'}, inplace=
```

In [12]:
```
df[['University Rating', 'SOP', 'LOR']] = df[['University Rating', 'SOP', 'LOR']
df['Research'] = df['Research'].astype('bool')
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    category
 3   SOP                500 non-null    category
 4   LOR                500 non-null    category
 5   CGPA               500 non-null    float64
 6   Research           500 non-null    bool
 7   Chance of Admit    500 non-null    float64
dtypes: bool(1), category(3), float64(2), int64(2)
memory usage: 18.6 KB
```

In [13]:
```
df.describe()
```

Out[13]:

	GRE Score	TOEFL Score	CGPA	Chance of Admit
count	500.000000	500.000000	500.000000	500.00000
mean	316.472000	107.192000	8.576440	0.72174
std	11.295148	6.081868	0.604813	0.14114
min	290.000000	92.000000	6.800000	0.34000
25%	308.000000	103.000000	8.127500	0.63000
50%	317.000000	107.000000	8.560000	0.72000
75%	325.000000	112.000000	9.040000	0.82000
max	340.000000	120.000000	9.920000	0.97000

- 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.
- Mean Research score is 0.56 while Median Research score is 1.0, this does not make sense since this is binary variable.

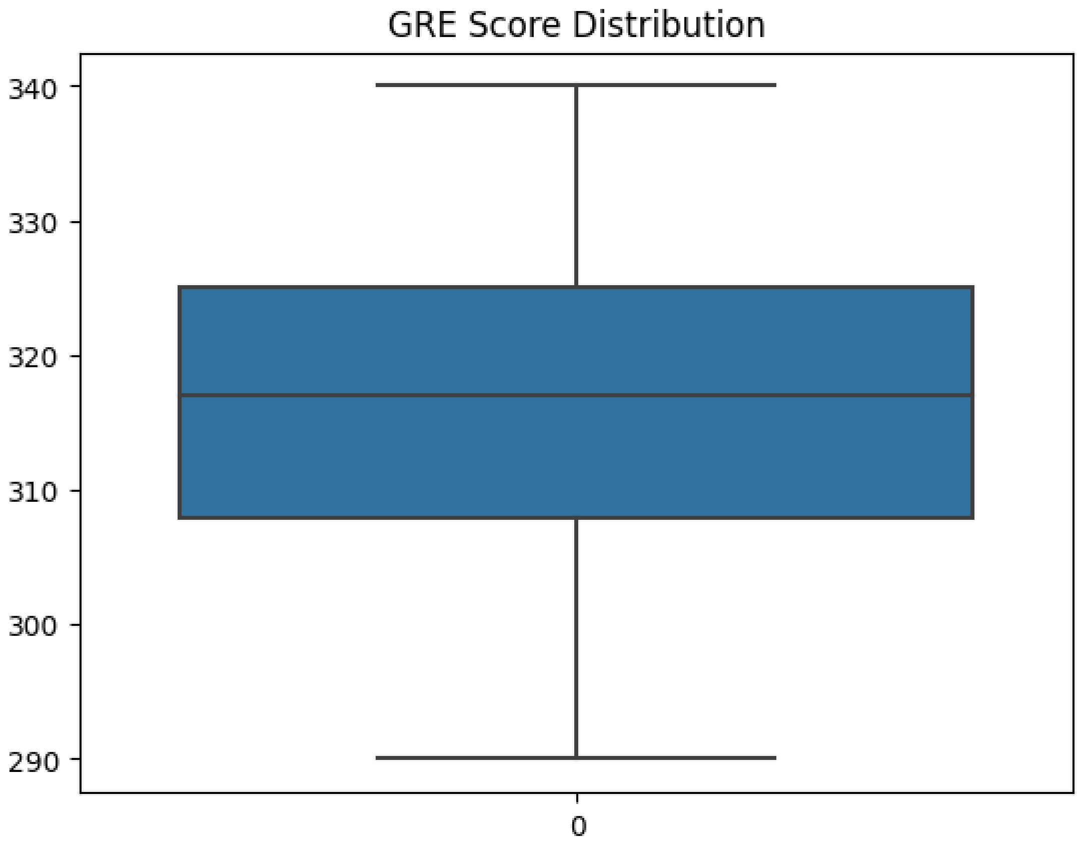
In [14]:
```
df.describe(include=['object','category'])
```

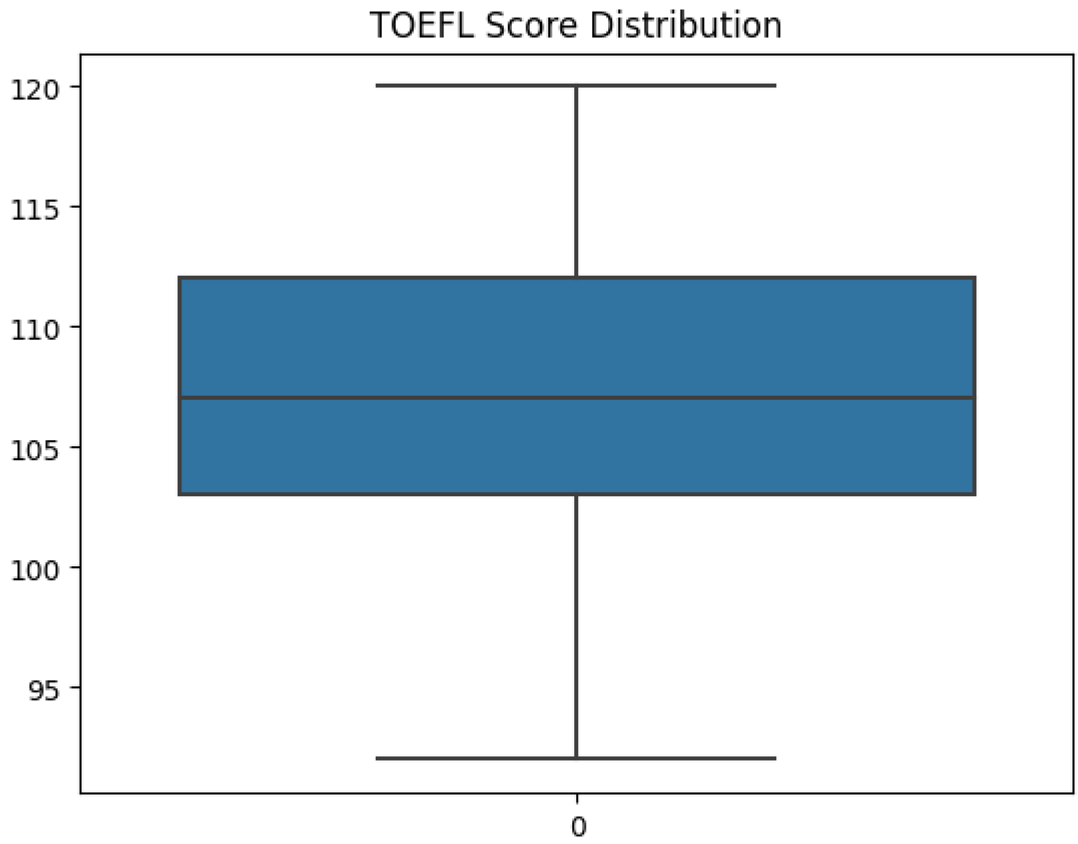
Out[14]:

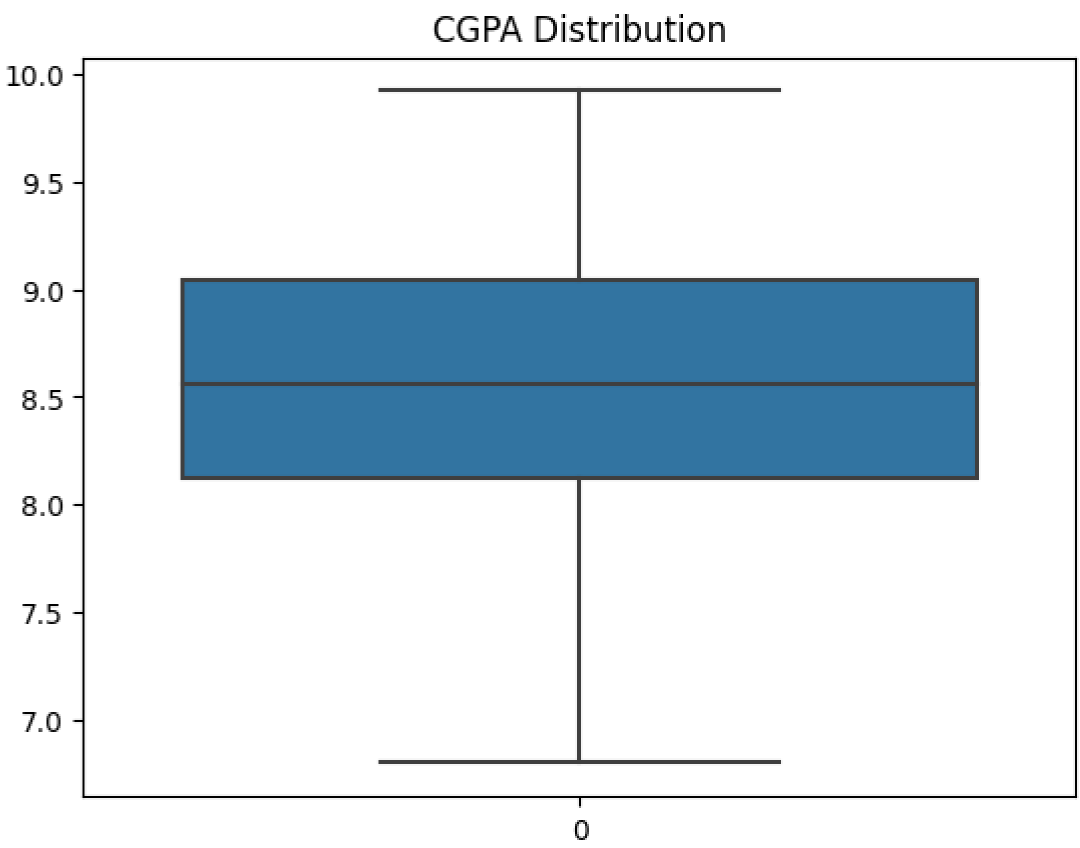
	University Rating	SOP	LOR
count	500	500.0	500.0
unique	5	9.0	9.0
top	3	4.0	3.0
freq	162	89.0	99.0

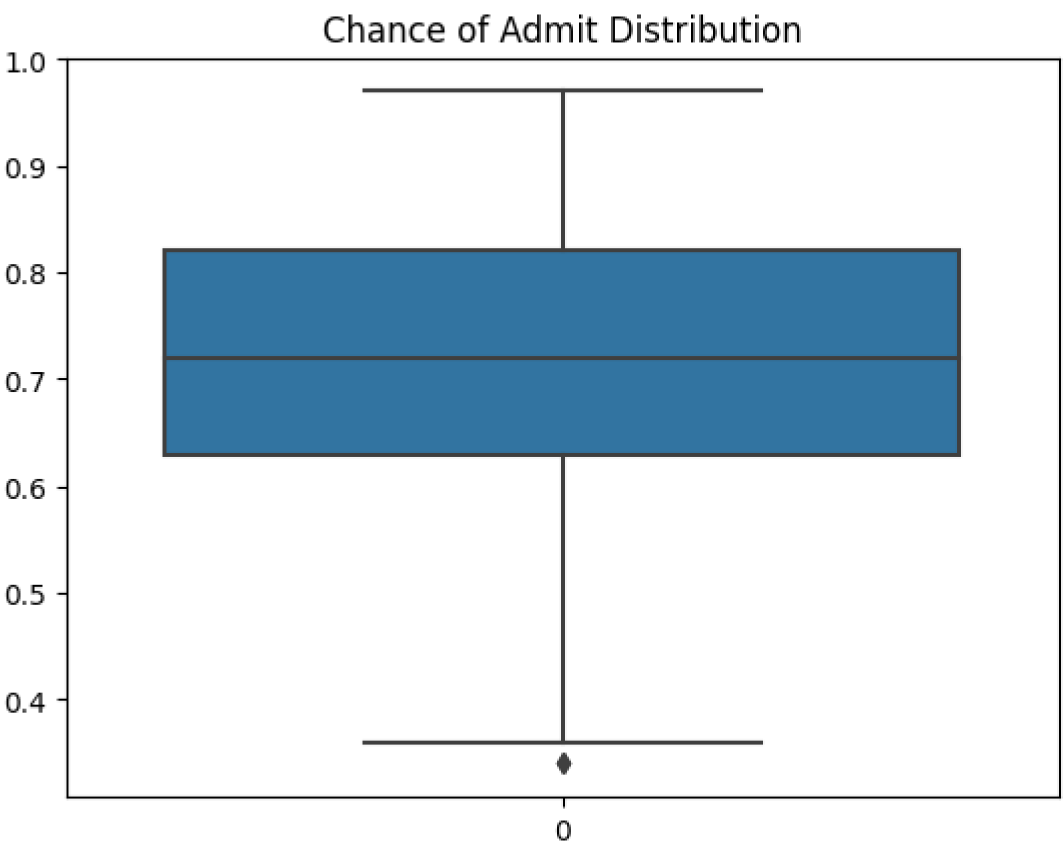
Univariate Analysis

In [15]:
```
# GRE Score,TOEFL Score,CGPA and Chance of Admit using boxplot
num_col = ['GRE Score', 'TOEFL Score', 'CGPA','Chance of Admit']
for col in num_col:
    sns.boxplot(df[col])
    plt.title(f'{col} Distribution')
    plt.show()
```


GRE Score Distribution
340
330
320
310
300
290
0


TOEFL Score Distribution
120
115
110
105
100
95
0



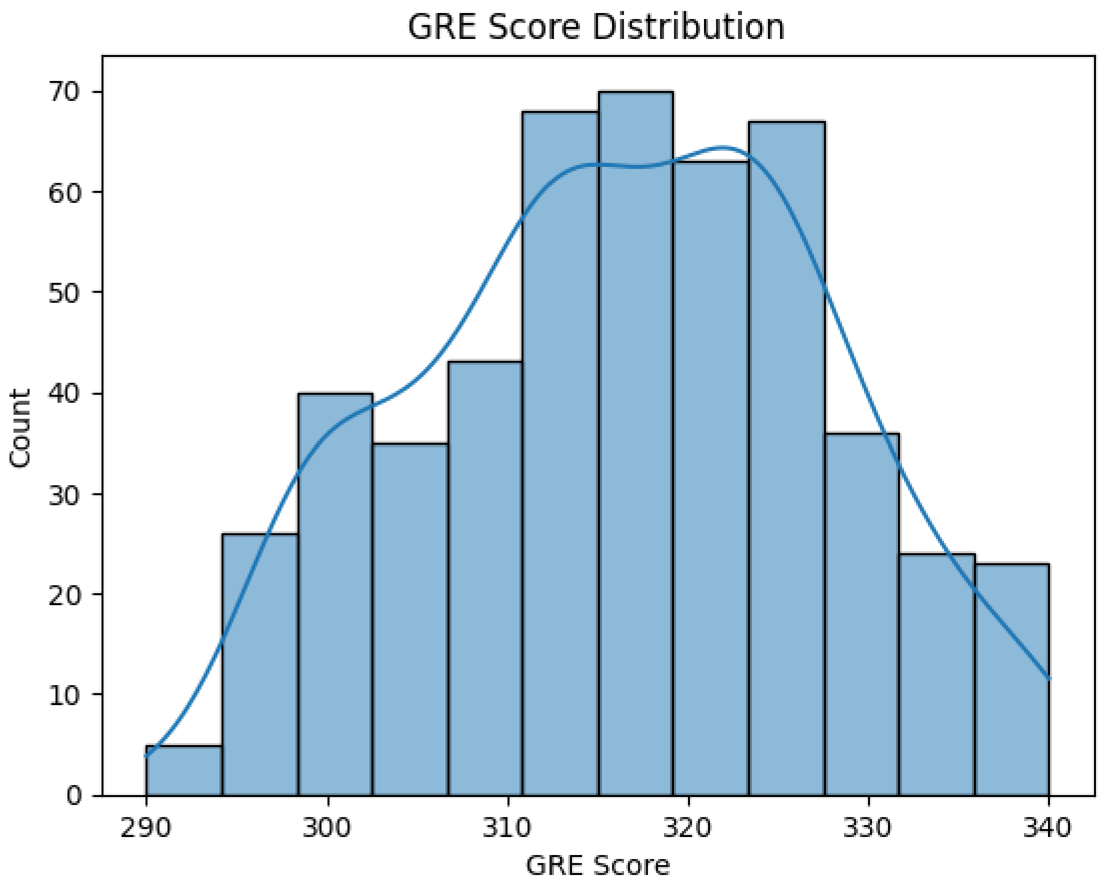


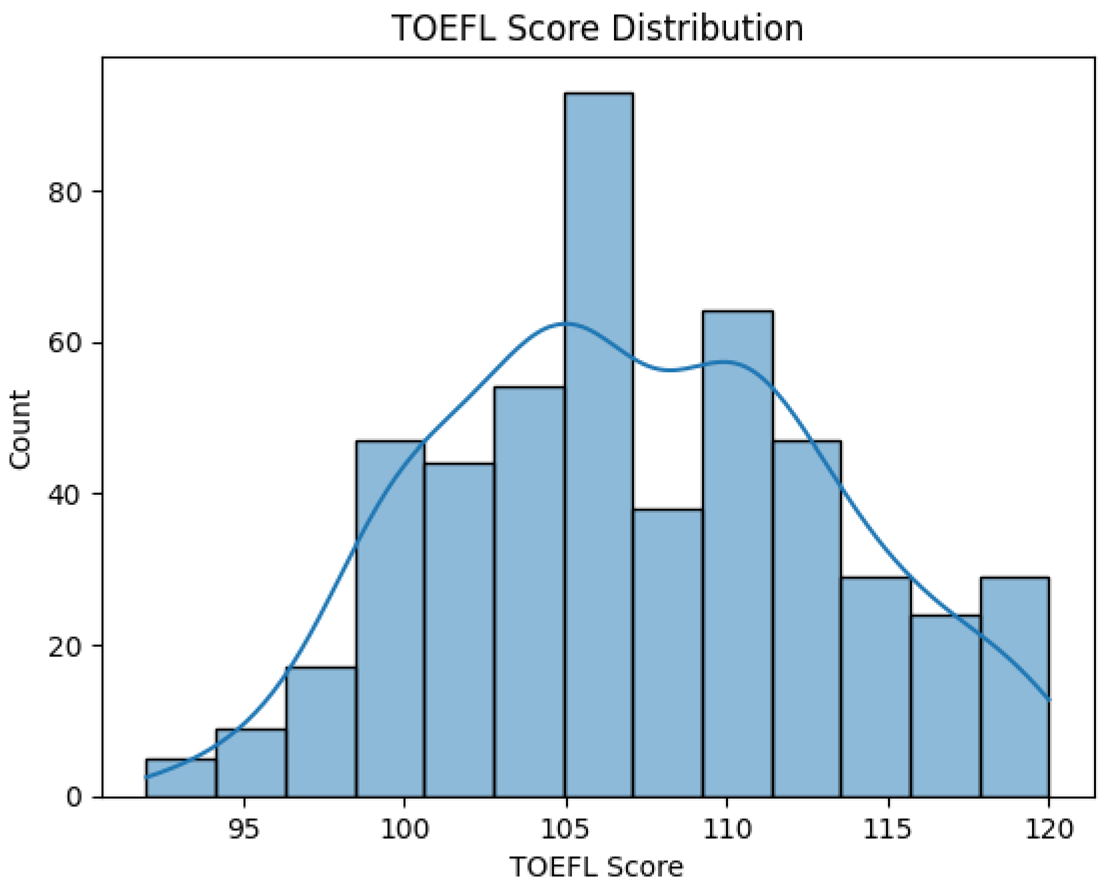
- Based on the above graph we donot have outliers for 'GRE Score', 'TOEFL Score' & 'CGPA'.

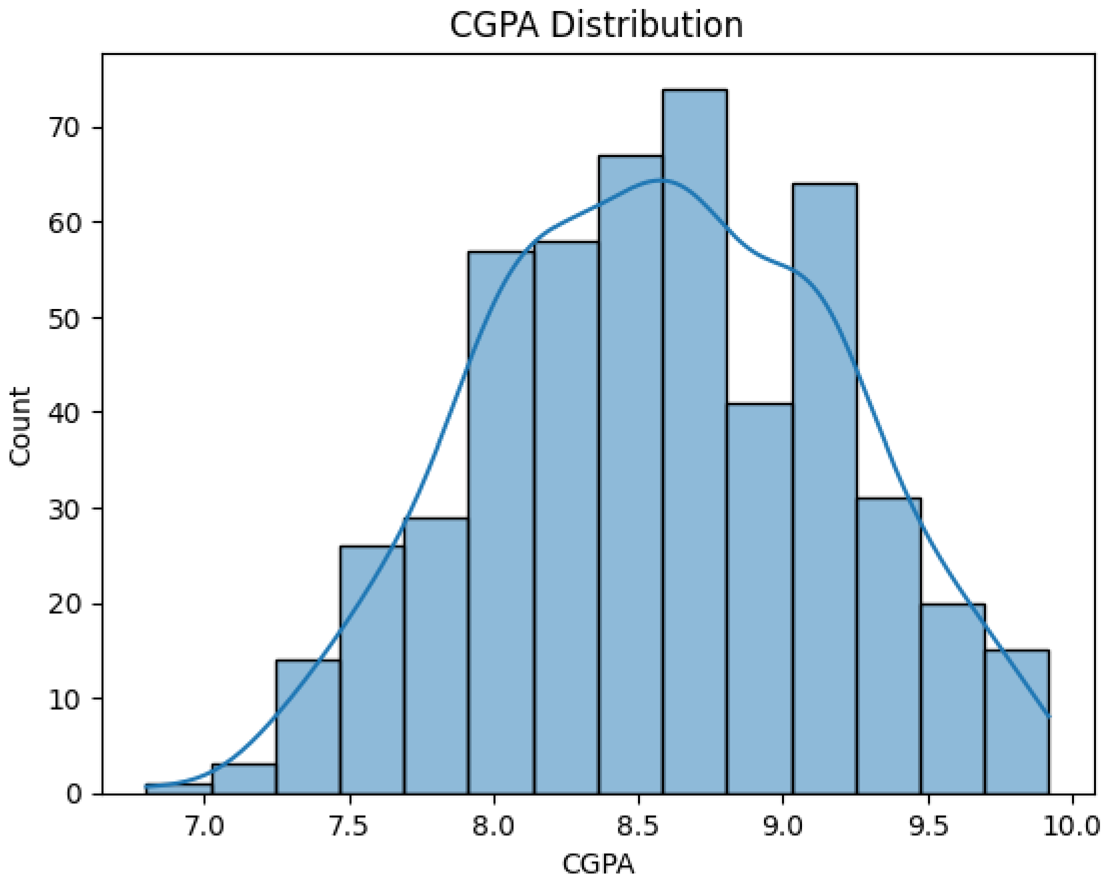
In [16]:

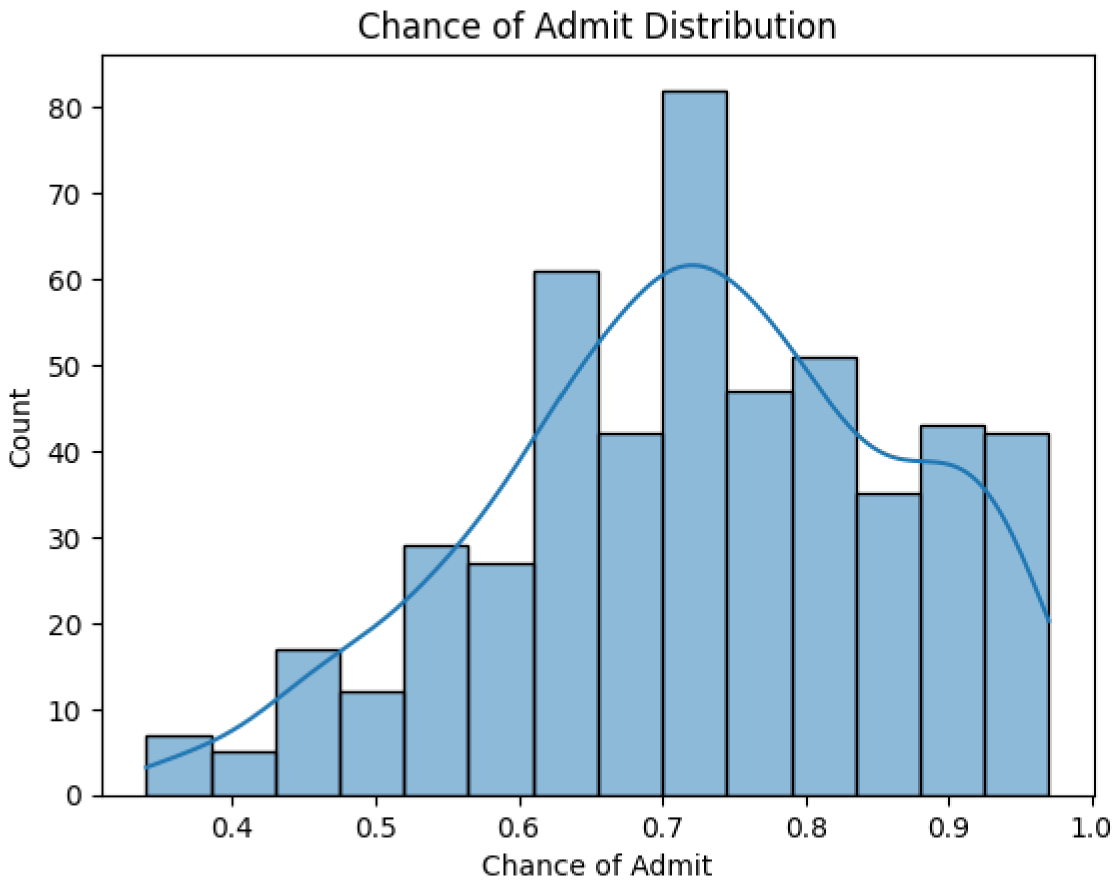
```
# GRE Score,TOEFL Score,CGPA and Chance of Admit using histplot
for col in num_col:
    sns.histplot(df[col],kde = True)
```

```
    plt.title(f'{col} Distribution')
    plt.show()
```





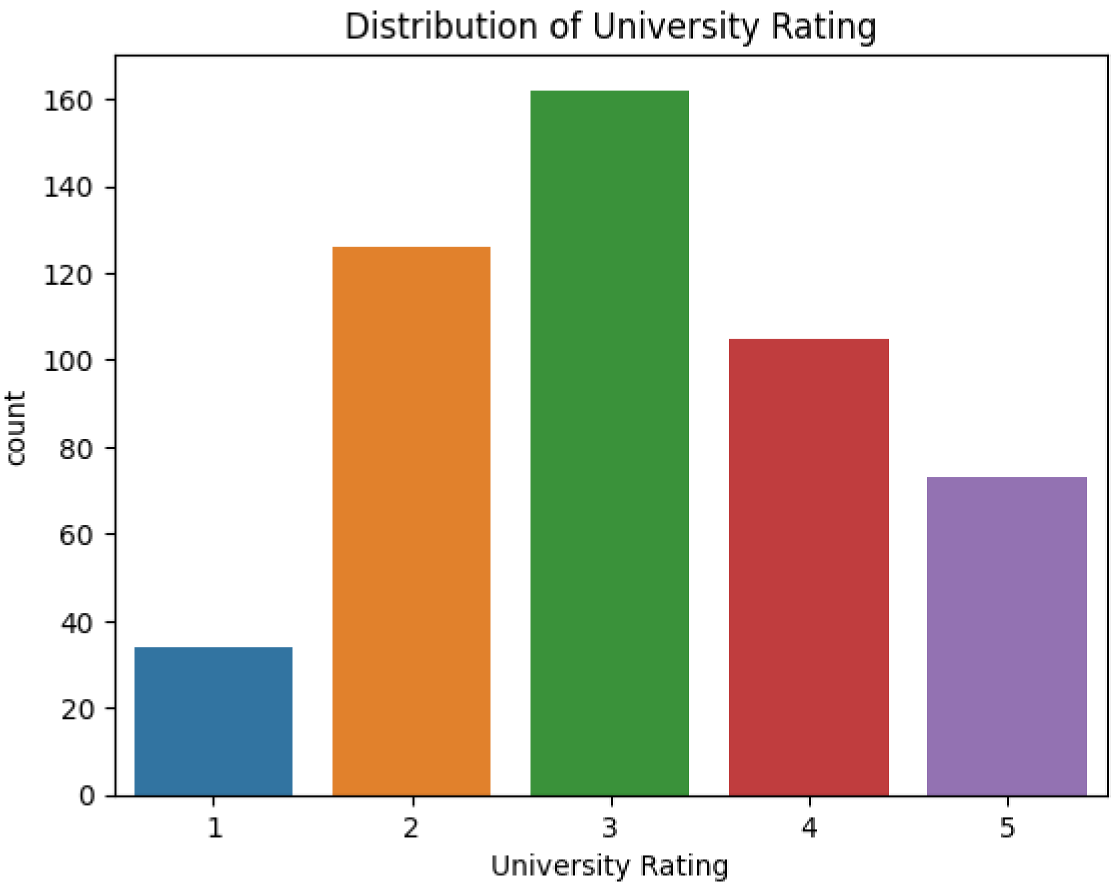




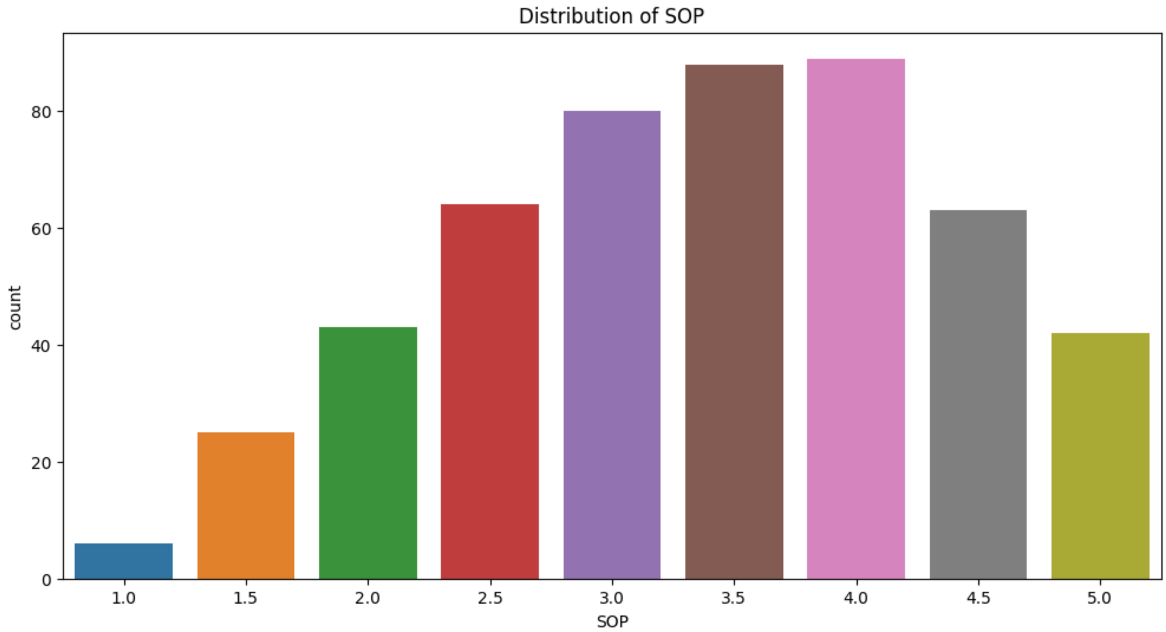
- GRE scores are between 290 and 340, with maximum students scoring in the range 310-330
- TOEFL scores are between 90 and 120, with maximum students scoring around 105

- CGPA ranges between 7 and 10, with maximum students scoring around 8.5
- Chance of Admit is a probability percentage between 0 and 1, with maximum students scoring around 70%-75%

In [17]:
```
sns.countplot(data=df,x='University Rating')
plt.title(f'Distribution of University Rating')
plt.show()
```



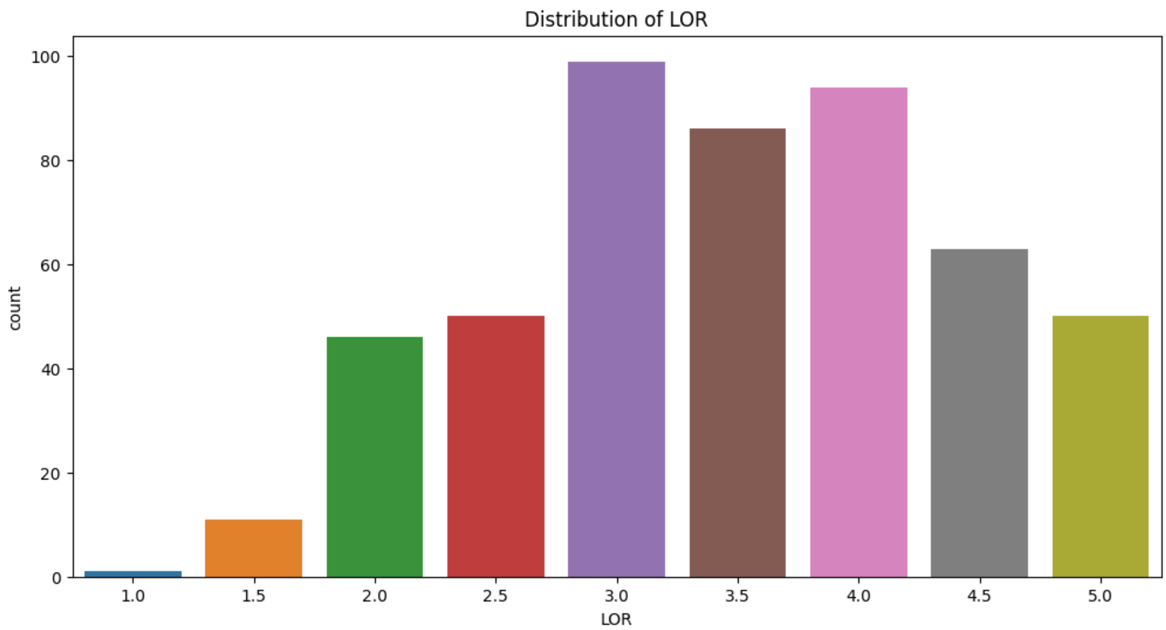
In [18]:
```
plt.figure(figsize=(12, 6))
sns.countplot(data=df,x='SOP')
plt.title(f'Distribution of SOP')
plt.show()
```



OBSERVATION:

- Most of the students have SOP between 3.5 - 4.

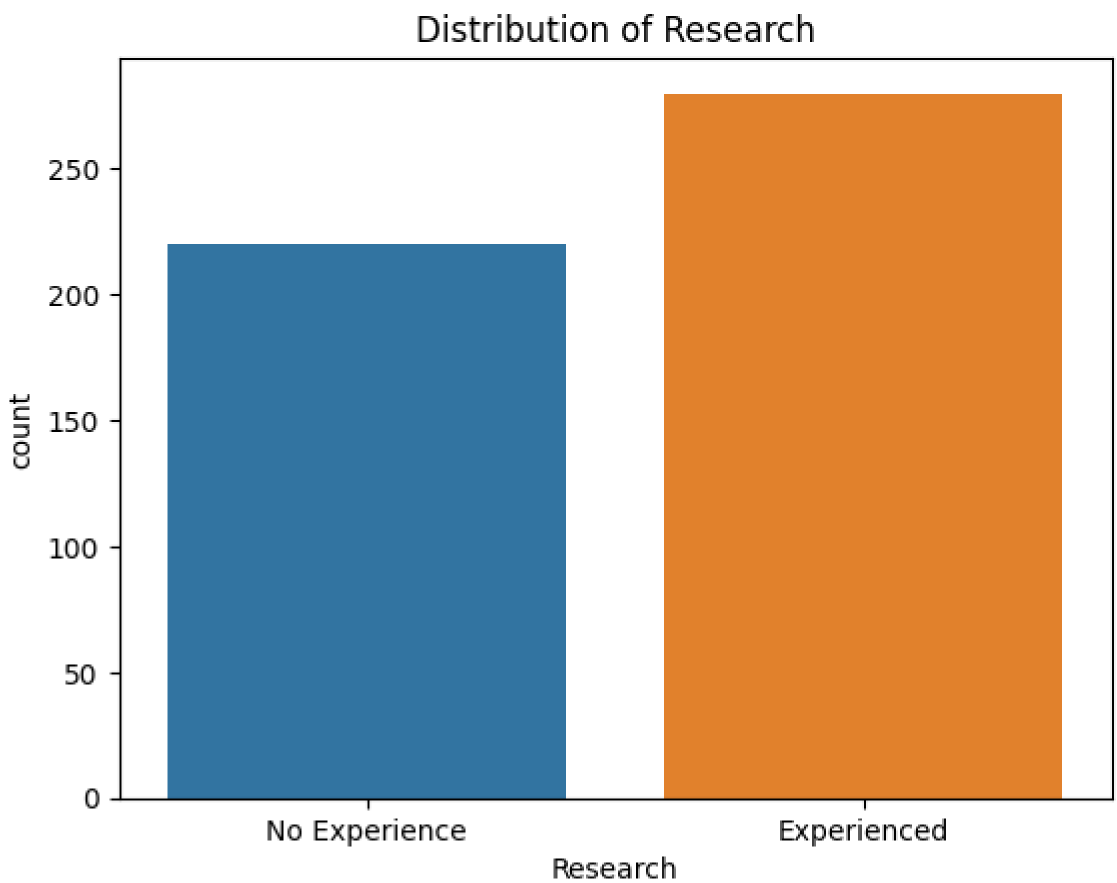
In [19]:
```
plt.figure(figsize=(12, 6))
sns.countplot(data=df,x='LOR')
plt.title(f'Distribution of LOR')
plt.show()
```



OBSERVATION:

- Most of the students have LOR between 3 - 4.

In [20]:
```
sns.countplot(data=df,x='Research')
plt.title(f'Distribution of Research')
plt.xticks([0, 1], ['No Experience', 'Experienced'])
plt.show()
```

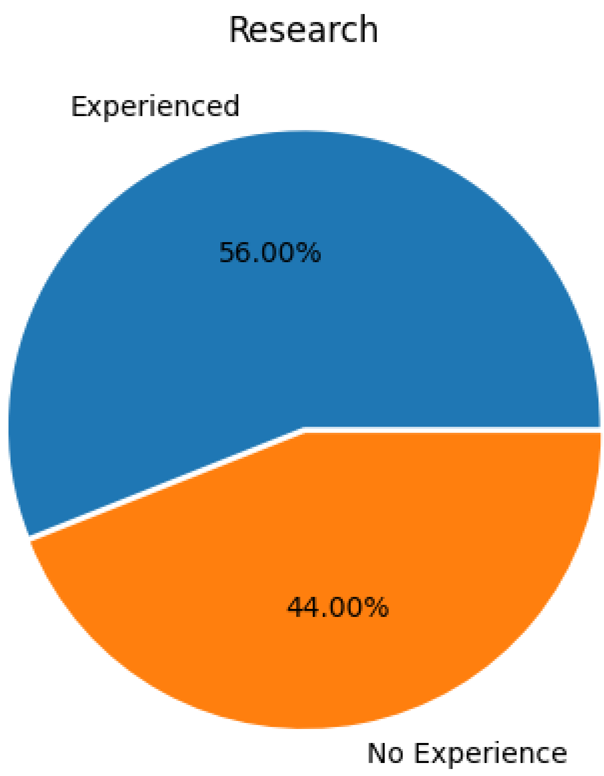


In [21]:
```
Research = df['Research'].value_counts(normalize=True).map(lambda calc: round(10
Research.columns = ['Research', 'Count']
Research
```

Out[21]:

	Research	Count
0	True	56.0
1	False	44.0

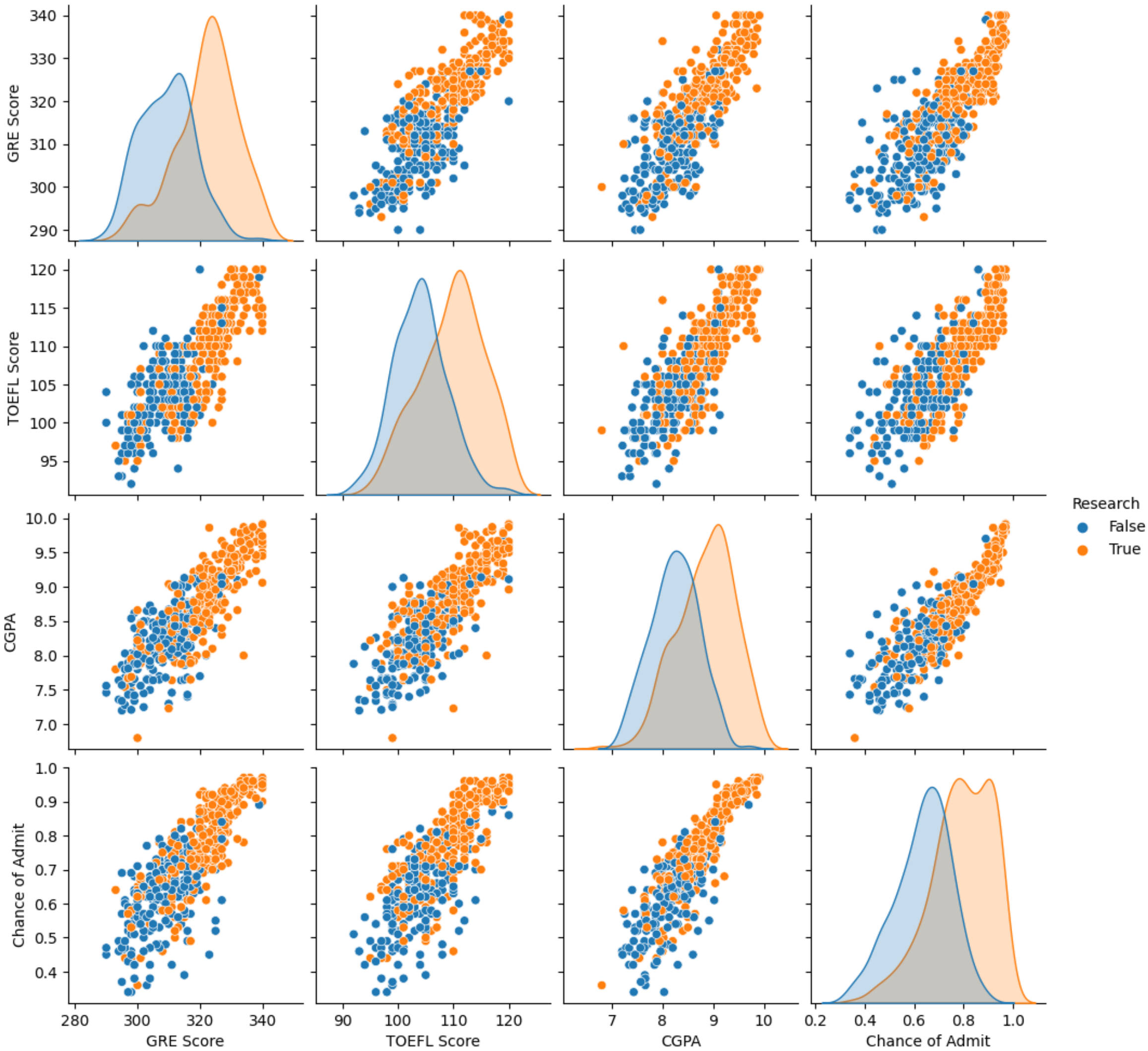
In [22]:
```
plt.pie(x = Research.Count, labels = ['Experienced', 'No Experience'], explode =
plt.title('Research')
plt.show()
```



OBSERVATION:

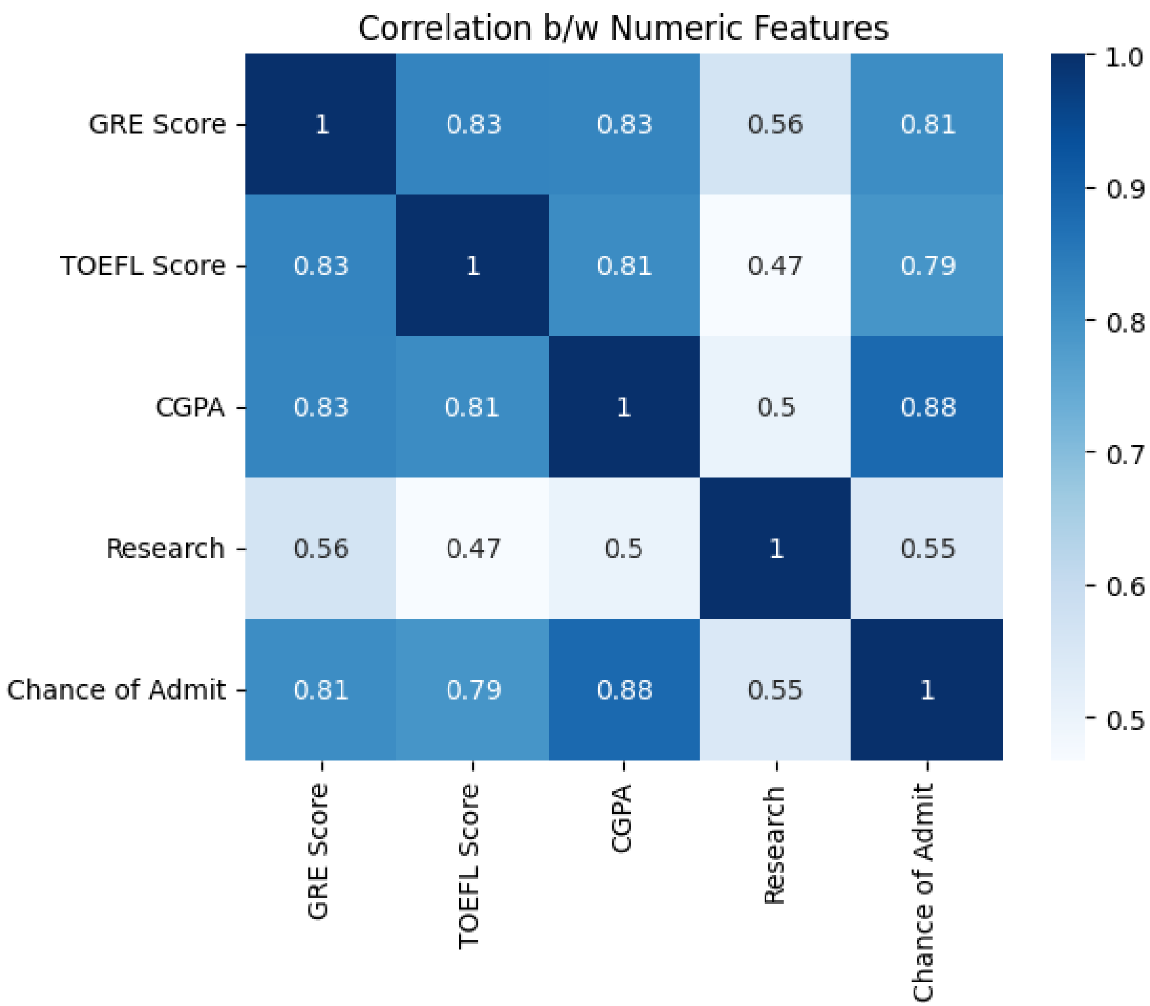
- 44% Of students had no experience in Research, while 56% of students do have experience in Research.

In [23]:
```
sns.pairplot(df,hue='Research')
plt.show()
```



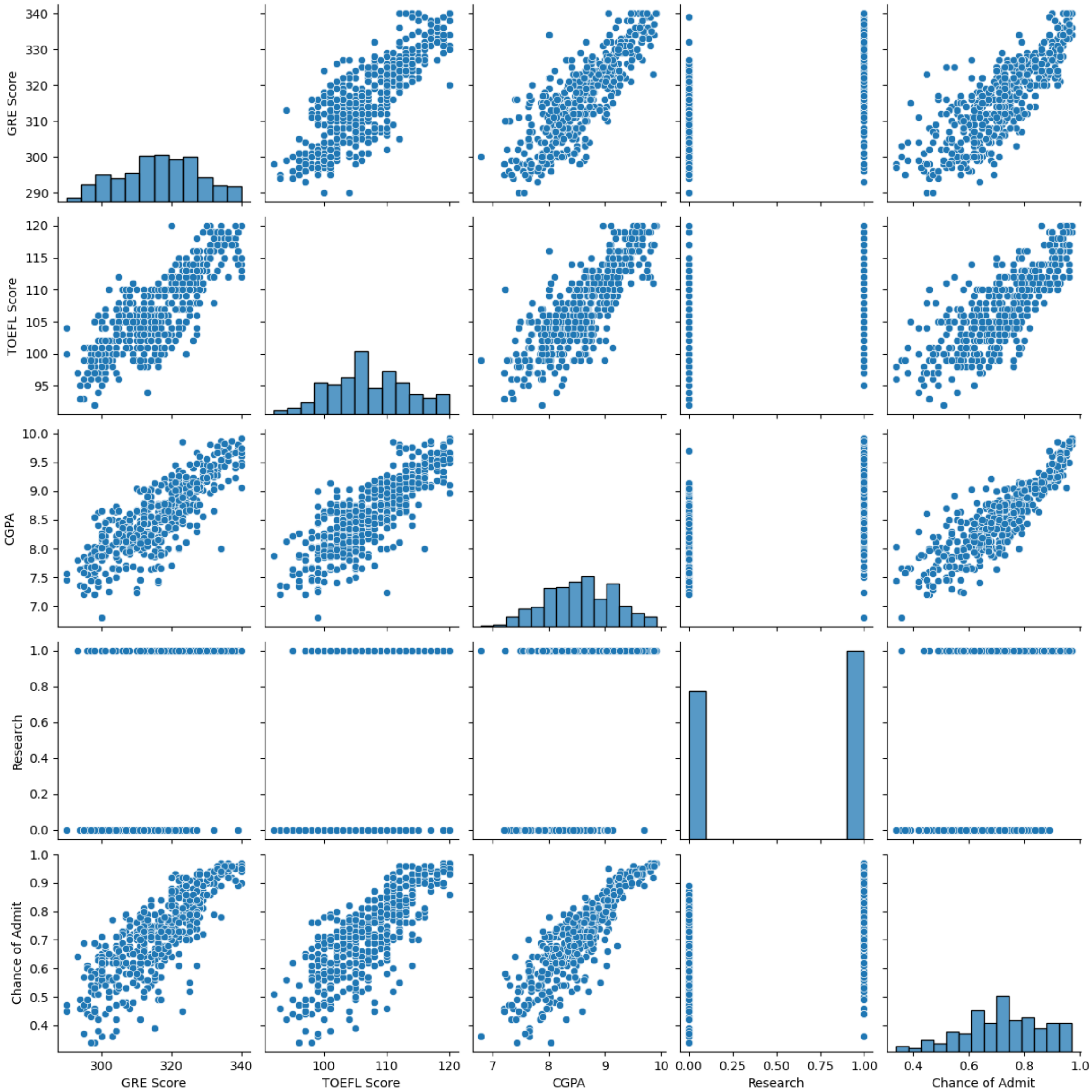
In [24]:

```
sns.heatmap(df.corr(), annot=True,cmap = "Blues")
plt.title('Correlation b/w Numeric Features')
plt.show()
```



- Confirming the inferences from pairplot, the correlation matrix also shows that exam scores (CGPA/GRE/TOEFL) have a strong positive correlation with chance of admit
- Infact, they are also highly correlated amongst themselves

In [25]:
```
sns.pairplot(df)
plt.show()
```



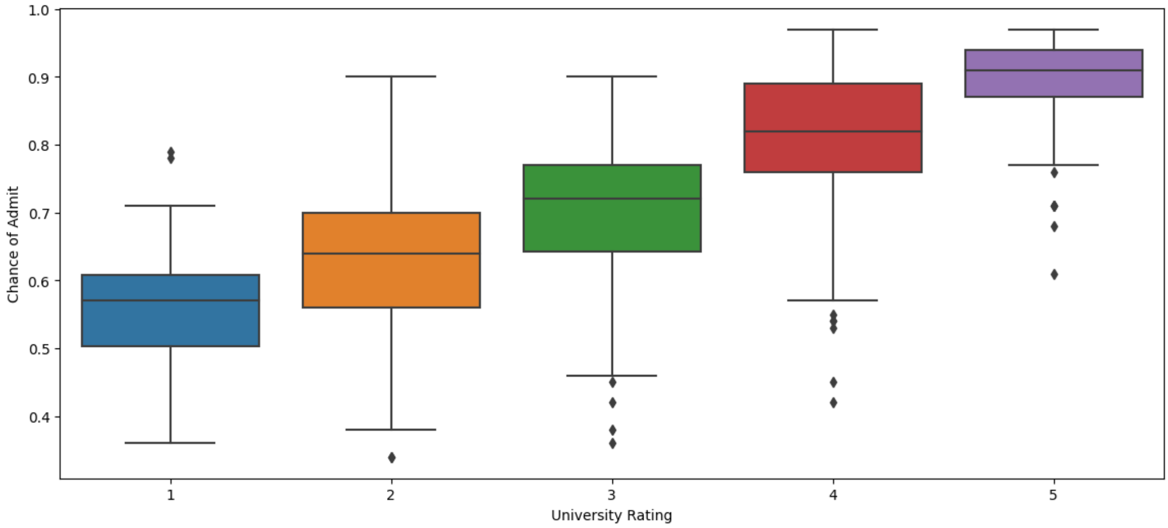
- GRE, TOEFL and CGPA have a high positive correlation with chance of admit
- research is the only variable which doesn't have much of an impact.

Bivariate Analysis

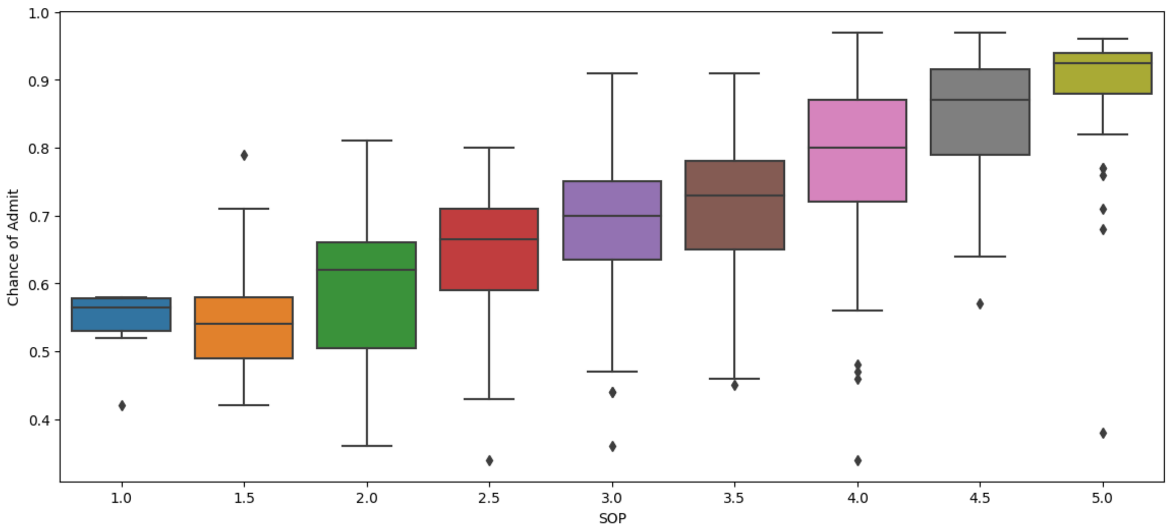
Categorical variables

1. 'Univarsity rating' vs 'Chance of Admit'
2. 'SOP' vs 'Chance of Admit'
3. 'LOR' vs 'Chance of Admit'
4. 'Research' vs 'Chance of Admit'

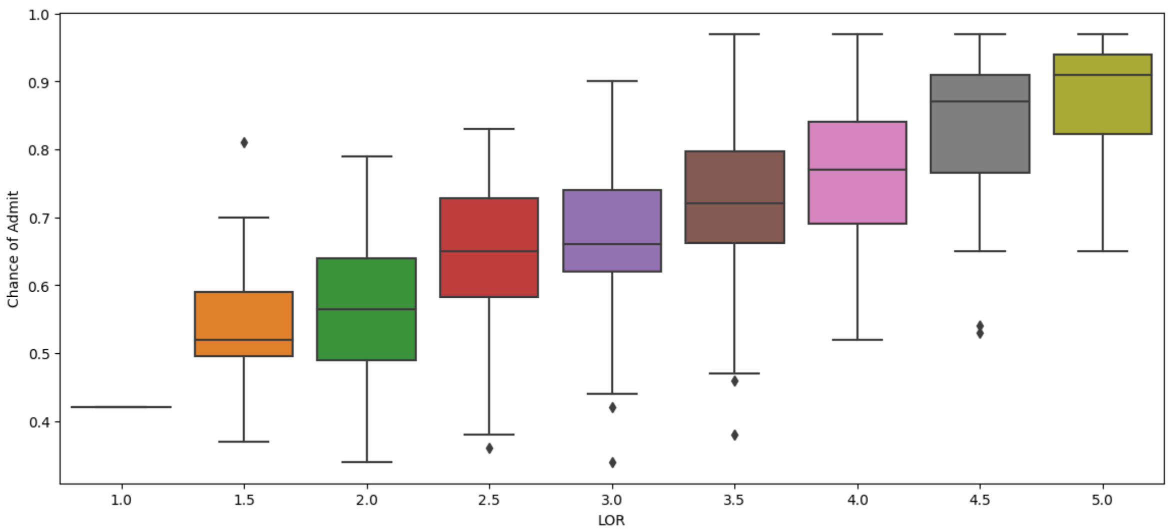
In [26]:
```
plt.figure(figsize=(14, 6))
sns.boxplot(x='University Rating', y='Chance of Admit', data=df)
plt.show()
```



In [27]:
```
plt.figure(figsize=(14, 6))
sns.boxplot(x='SOP', y='Chance of Admit', data=df)
plt.show()
```

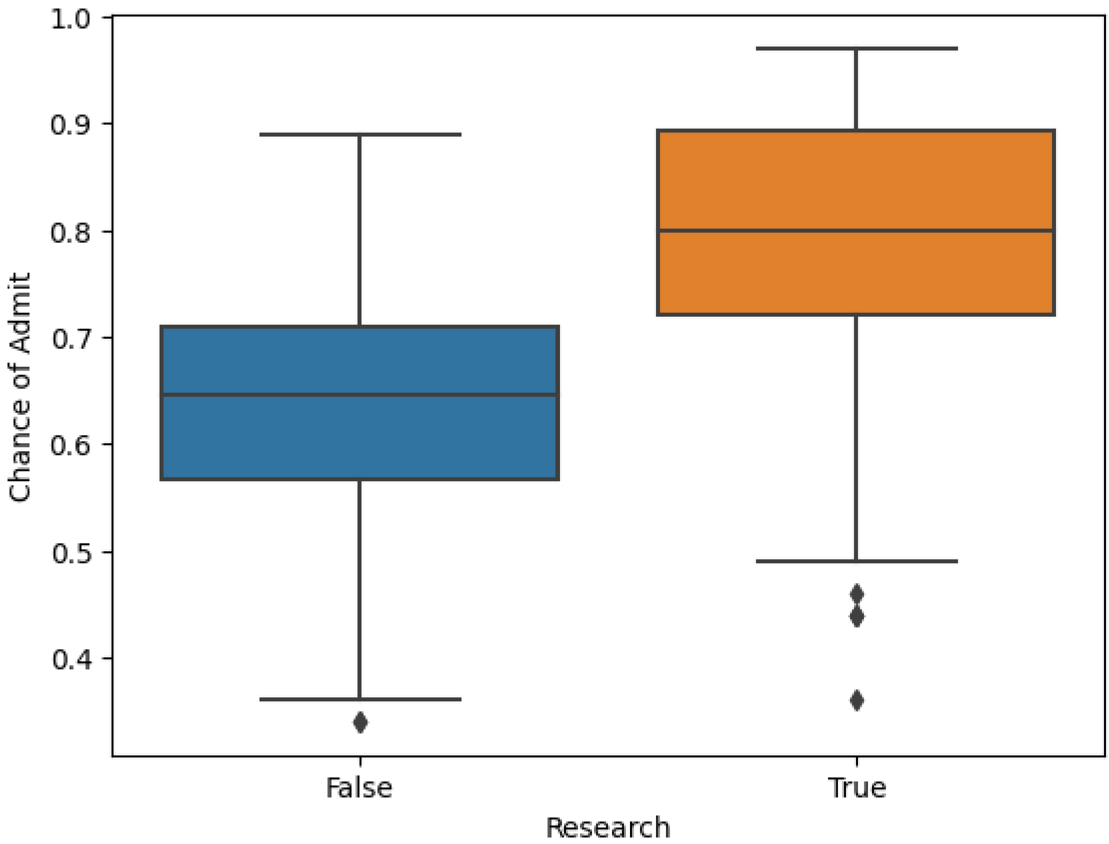


In [28]:
```
plt.figure(figsize=(14, 6))
sns.boxplot(x='LOR', y='Chance of Admit', data=df)
plt.show()
```



In [29]:
```
sns.boxplot(x='Research',y='Chance of Admit',data=df)
```

```python
plt.show()
```

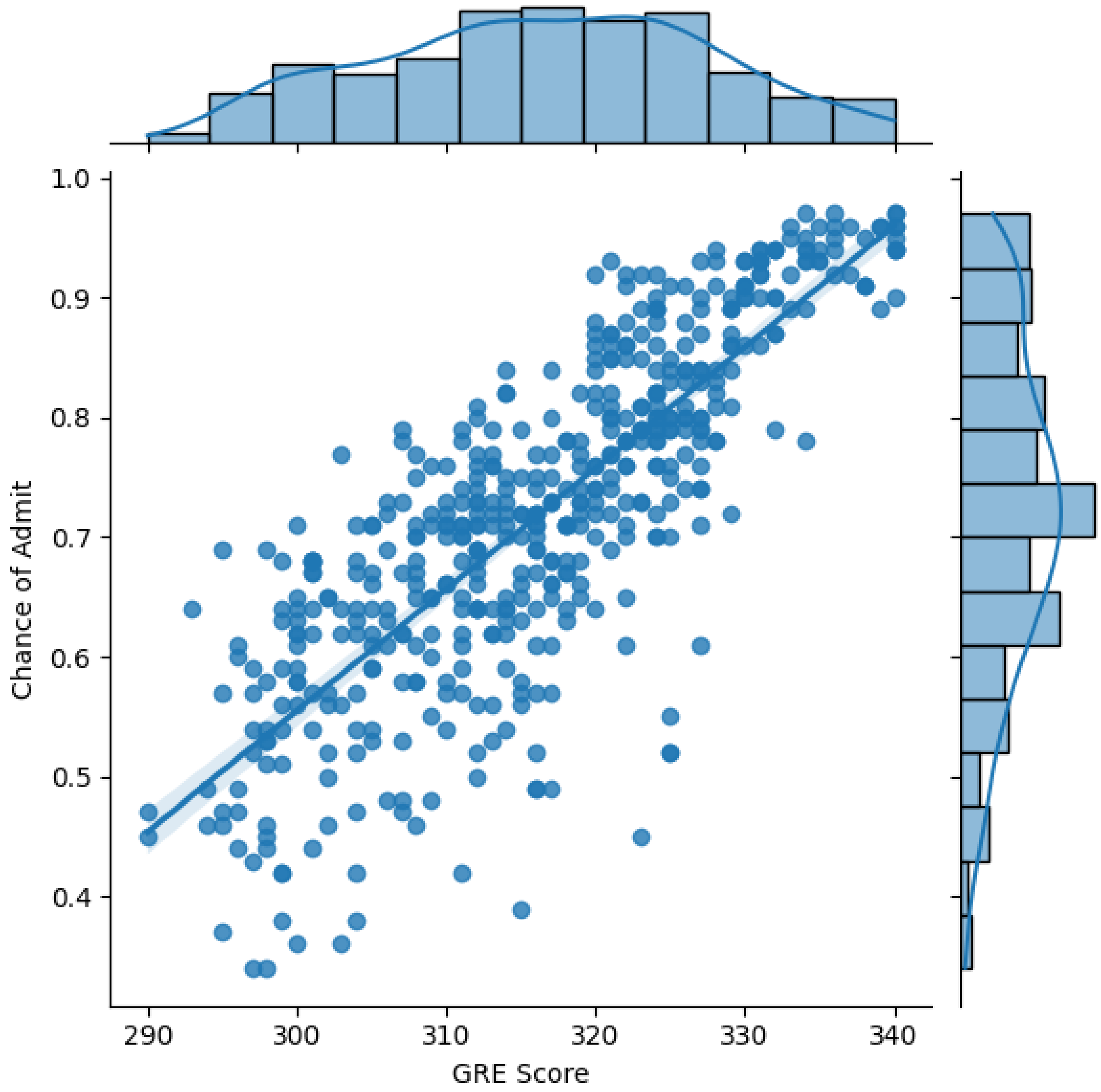


Numerical variables

1. 'GRE Score' vs 'Chance of Admit'
2. 'TOEFL Score' vs 'Chance of Admit'
3. 'CGPA' vs 'Chance of Admit'

In [30]:
```python
plt.figure(figsize=(14, 6))
sns.jointplot(x='GRE Score', y='Chance of Admit', data=df,kind = 'reg')
plt.show()
```

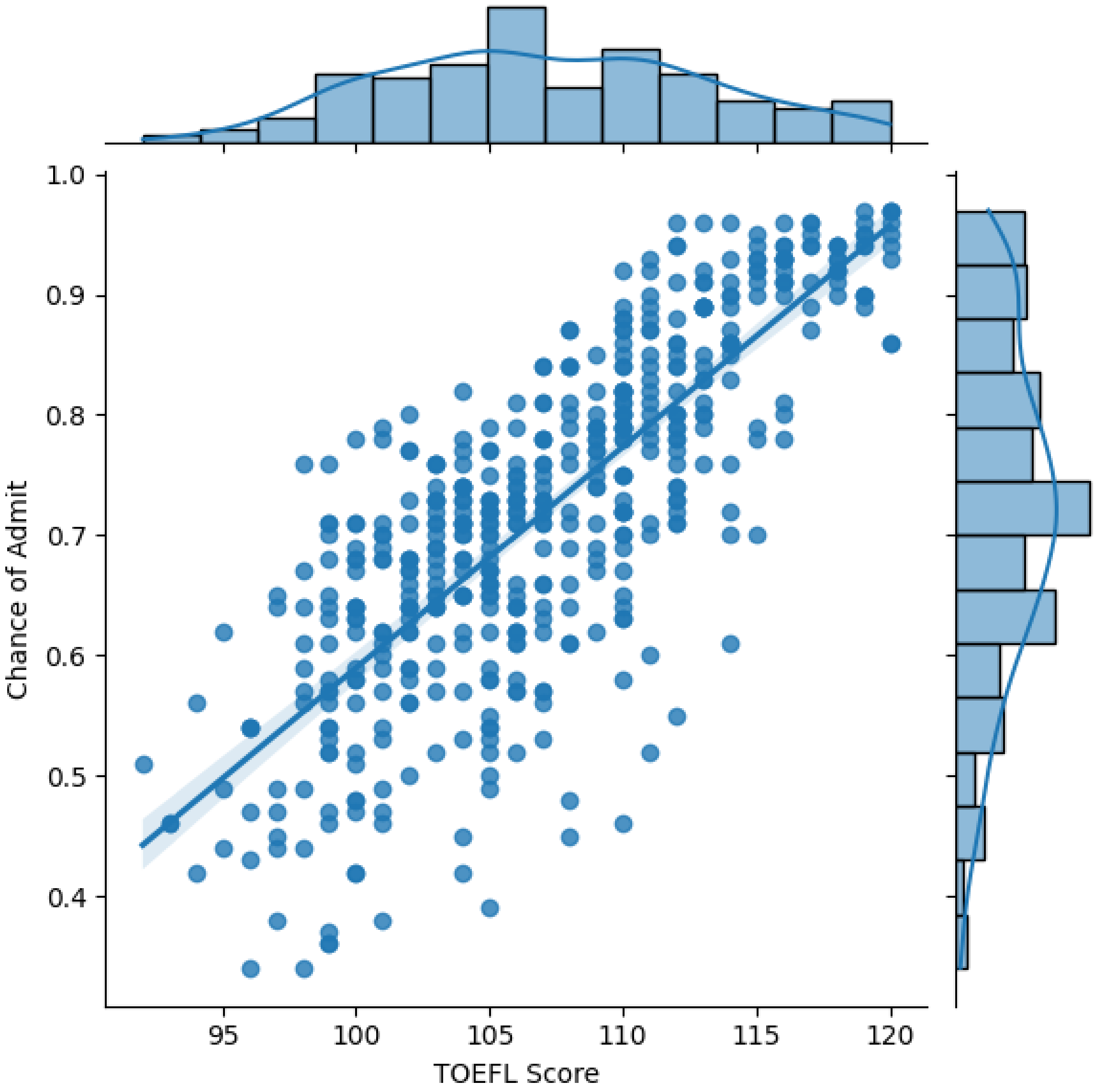
```
<Figure size 1400x600 with 0 Axes>
```



- Higher GRE scores are positively correlated with increased chance of admit, indicating a linear relationship between the two factors and variance is high.

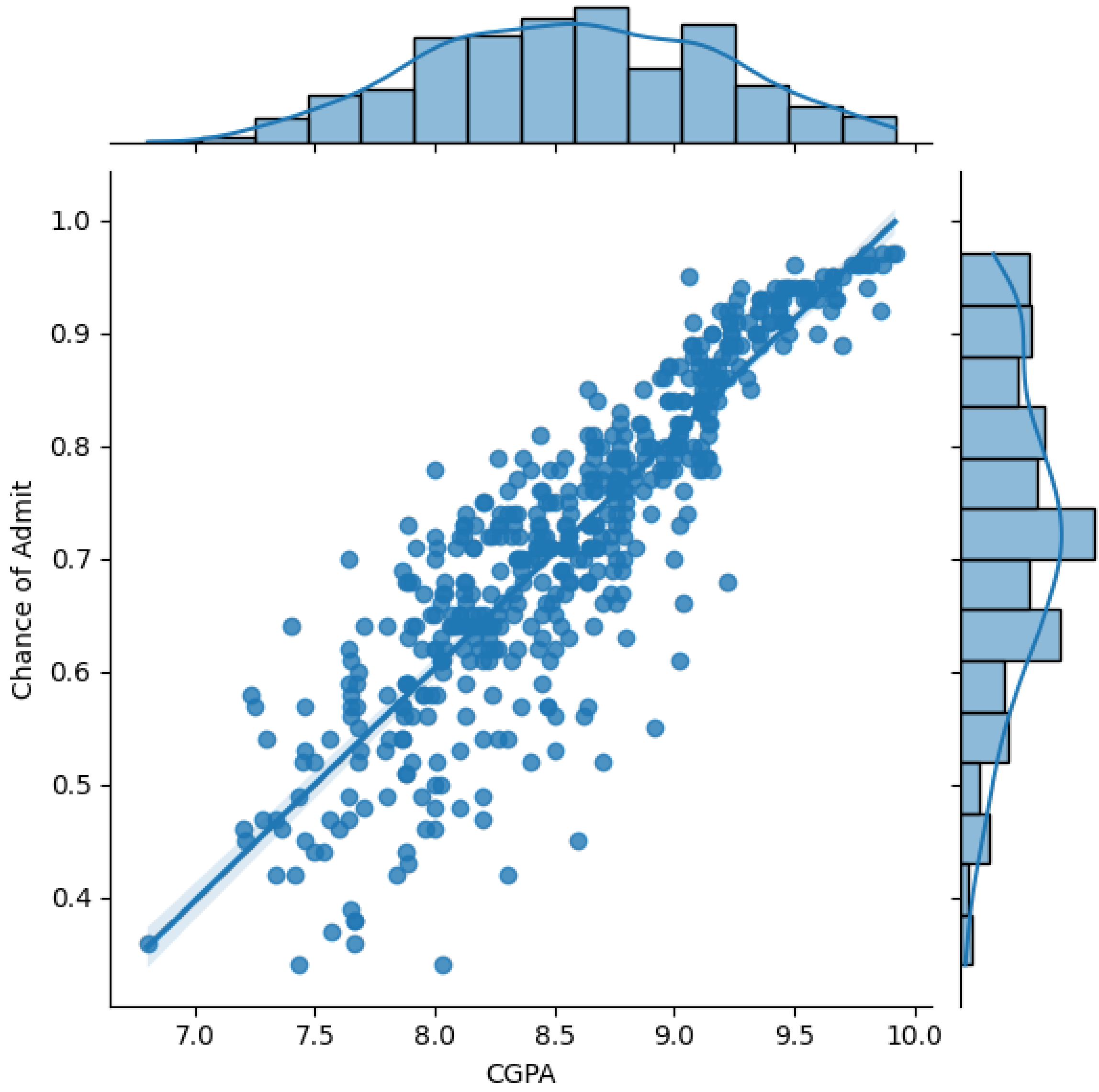
In [31]:
```
plt.figure(figsize=(14, 6))
sns.jointplot(x='TOEFL Score', y='Chance of Admit', data=df,kind = 'reg')
plt.show()
```

```
<Figure size 1400x600 with 0 Axes>
```



- The TOEFL Score increases, the Chance of Admit also increases as we can see, they have a linear relationship.
- Variance is low

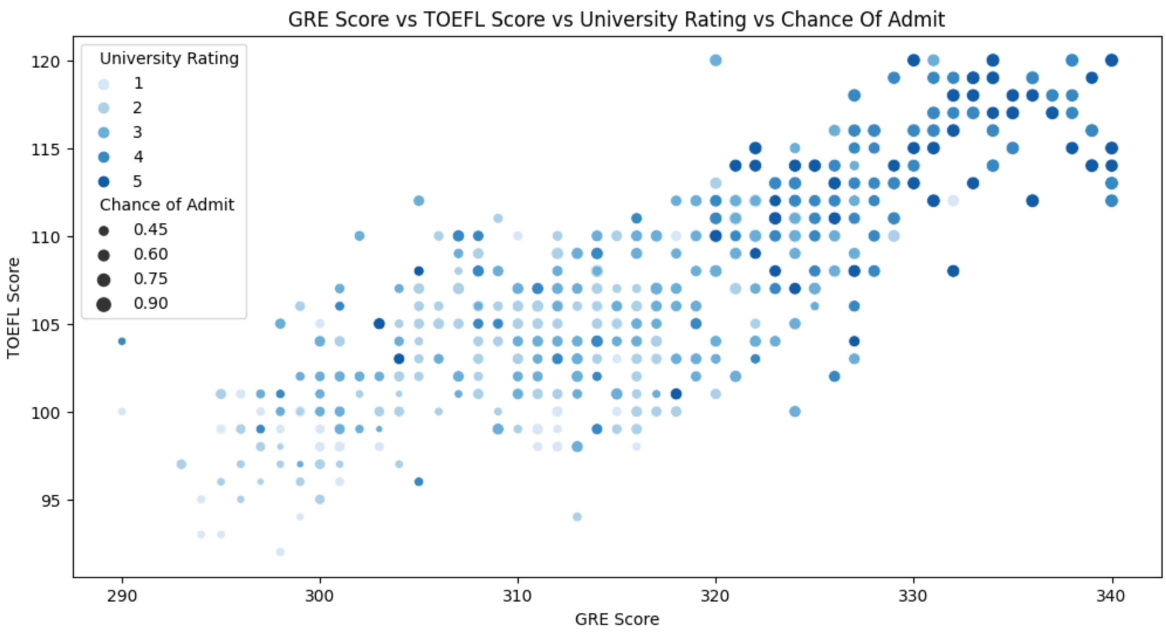
In [32]:
```
sns.jointplot(x='CGPA', y='Chance of Admit', data=df,kind = 'reg')
plt.show()
```



- The CGPA increases, the Chance of getting Admission also increases.

MultiVariate Analysis

In [33]:
```
plt.figure(figsize=(12, 6))
sns.scatterplot(x='GRE Score',y='TOEFL Score',hue='University Rating',size='Chan
plt.title('GRE Score vs TOEFL Score vs University Rating vs Chance Of Admit')
plt.show()
```



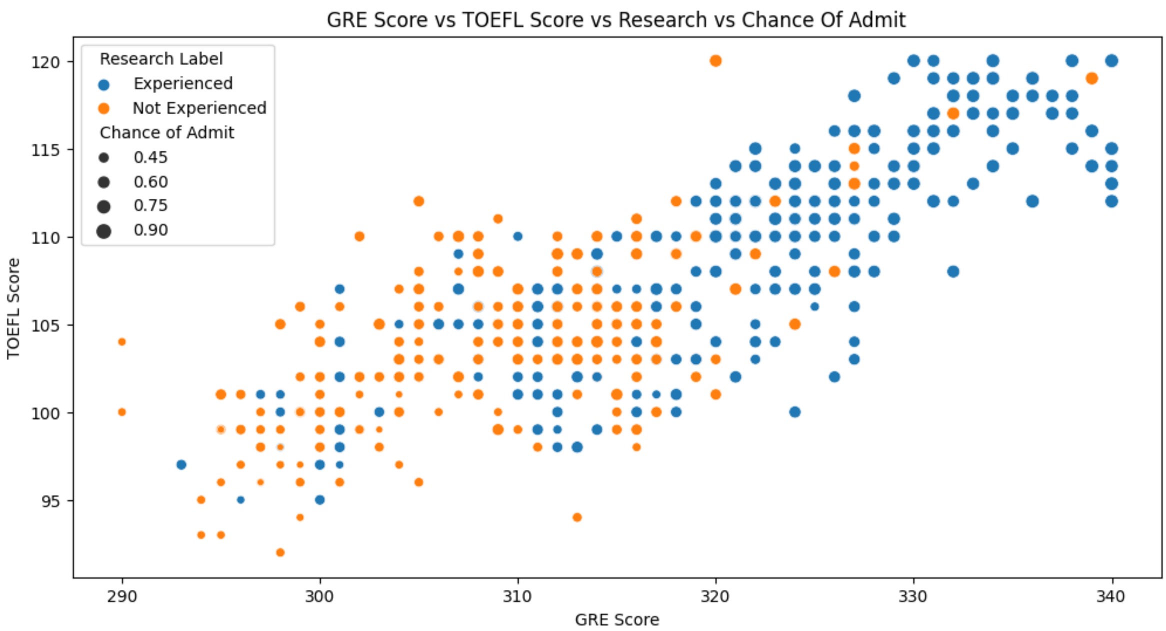
In [34]:
```
plt.figure(figsize=(12, 6))

research_labels = {True: 'Experienced', False: 'Not Experienced'}
df['Research Label'] = df['Research'].replace(research_labels)

sns.scatterplot(x='GRE Score', y='TOEFL Score', hue='Research Label', size='Chan

plt.xlabel('GRE Score')
plt.ylabel('TOEFL Score')
plt.title('GRE Score vs TOEFL Score vs Research vs Chance Of Admit')

plt.show()
```



Linear Regression

In [35]:
```
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler

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, adj
from sklearn.feature_selection import f_regression
```

In [36]:
```
num_col.remove('Chance of Admit')
```

In [37]:
```
# Separate predictor and target variables
cat_cols = ['University Rating', 'SOP', 'LOR','Research']
x = df[num_col + cat_cols]
y = df[['Chance of Admit']]
```

In [38]:
```
x.head()
```

Out[38]:

	GRE Score	TOEFL Score	CGPA	University Rating	SOP	LOR	Research
0	337	118	9.65	4	4.5	4.5	True
1	324	107	8.87	4	4.0	4.5	True
2	316	104	8.00	3	3.0	3.5	True
3	322	110	8.67	3	3.5	2.5	True
4	314	103	8.21	2	2.0	3.0	False

In [39]:
```
y.head()
```

Out[39]:

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

In [40]:
```
# Split the data into training and test data
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2,random_s
print(f'Shape of x_train: {x_train.shape}')
print(f'Shape of x_test: {x_test.shape}')
```

```
Shape of x_train: (400, 7)
Shape of x_test: (100, 7)
```

In [41]:
```
print(f'Shape of y_train: {y_train.shape}')
print(f'Shape of y_test: {y_test.shape}')
```

```
Shape of y_train: (400, 1)
Shape of y_test: (100, 1)
```

In [42]:
```
#Initialising object of class MinMaxScaler() for Standardisation
scaler_x = MinMaxScaler()
```

In [43]:
```
x_cat_encoded = pd.concat([x_train, x_test])
x_cat_encoded.head(10)
```

Out[43]:

	GRE Score	TOEFL Score	CGPA	University Rating	SOP	LOR	Research
249	321	111	8.83	3	3.5	4.0	True
433	316	111	8.54	4	4.0	5.0	False
19	303	102	8.50	3	3.5	3.0	False
322	314	107	8.27	2	2.5	4.0	False
332	308	106	8.21	3	3.5	2.5	True
56	316	102	7.40	3	2.0	3.0	False
301	319	108	8.76	2	2.5	3.0	False
229	324	111	9.01	4	3.0	3.0	True
331	311	105	8.12	2	3.0	2.0	True
132	309	105	8.56	5	3.5	3.5	False

In [44]:
```
#Fitting scaler_x to the training data
scaler_x.fit(x_cat_encoded)
```

Out[44]:
```
▾ MinMaxScaler
MinMaxScaler()
```

In [45]:
```
all_cols = x_train.columns
#Transforming numeric columns of x_train and x_test
x_train[all_cols]=scaler_x.transform(x_train[all_cols])
x_test[all_cols]=scaler_x.transform(x_test[all_cols])
```

In [46]:
```
x_test.head()
```

Out[46]:

	GRE Score	TOEFL Score	CGPA	University Rating	SOP	LOR	Research
361	0.88	0.857143	0.878205	0.75	0.750	0.625	1.0
73	0.48	0.571429	0.717949	0.75	0.875	0.750	1.0
374	0.50	0.464286	0.272436	0.25	0.250	0.375	0.0
155	0.44	0.607143	0.605769	0.50	0.500	0.500	0.0
104	0.72	0.714286	0.721154	0.50	0.625	0.500	1.0

In [47]:
```
#Initialising object of Class LinearRegression()
lr_Test = LinearRegression()    # training LinearRegression model
lr_Test.fit(x_train,y_train)
```

Out[47]:
```
▾ LinearRegression
LinearRegression()
```

In [48]:
```
#r2 score on train data
r2_score(y_train,lr_Test.predict(x_train))
```
Out[48]: 0.8210671369321554

In [49]:
```
#r2 score on test data
r2_score(y_test,lr_Test.predict(x_test))
```
Out[49]: 0.8188432567829629

In [50]:
```
def AdjustedR2score(R2,n,d):
    return 1-(((1-R2)*(n-1))/(n-d-1))
```
In [51]:
```
y_pred = lr_Test.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.sh
```
```
MSE: 0.0037046553987884106
RMSE: 0.060865880415783113
MAE : 0.04272265427705366
r2_score: 0.8188432567829629
Adjusted R2 score : 0.816265823444509
```

- The similarity in training and test data loss scores indicates an absence of model overfitting.

1. A Mean Absolute Error at 0.04 points to an average deviation of 4% between actual and predicted chance of admit values.
2. A Root Mean Square Error registered at 0.06 indicates an average root squared deviation of 6% between predicted and actual values.
3. The R2 Score of 0.82 signifies the model's capacity to encompass 82% of the data's variability.
4. Adjusted R2, an extension of R2, portrays how the alteration in feature count impacts predictive accuracy.

Multicolillinearity check using VIF score

In [52]:
```
scaler = StandardScaler()
X_tr_scaled = scaler.fit_transform(x_train)
vif = pd.DataFrame()
X_t = pd.DataFrame(X_tr_scaled, columns=x_train.columns)
vif['Features'] = X_t.columns
vif['VIF'] = [variance_inflation_factor(X_t.values, i) for i in range(X_t.shape[
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[52]:

	Features	VIF
2	CGPA	4.65
0	GRE Score	4.49
1	TOEFL Score	3.66
4	SOP	2.79
3	University Rating	2.57
5	LOR	1.98
6	Research	1.52

- With all VIF scores below 5, there's little indication of pronounced multicollinearity issues.

Residual analysis

In [53]:
```
y_predicted = lr_Test.predict(x_test)
y_predicted.shape
```

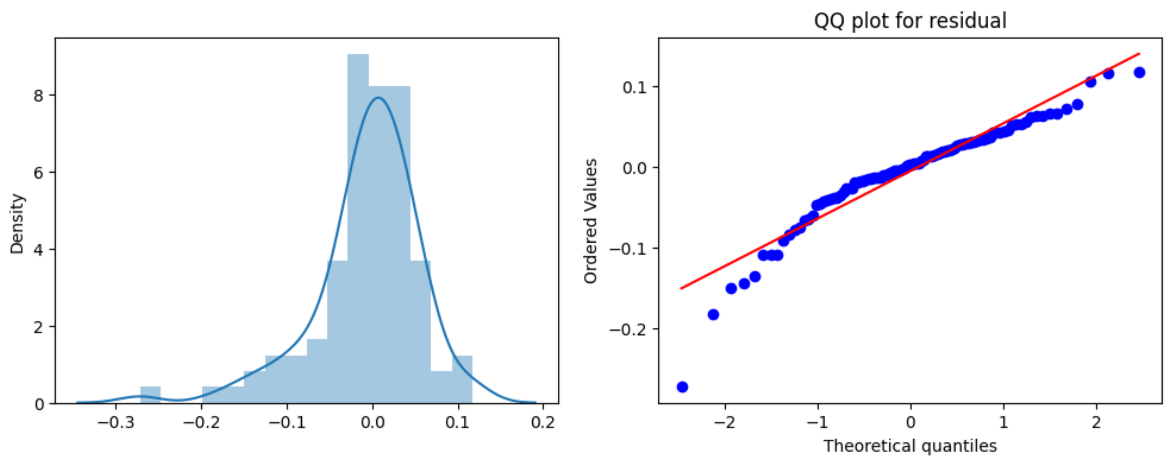
Out[53]: (100, 1)

In [54]:
```
#Mean of Residuals
residuals = y_test.values - y_predicted
print('Mean of Residuals: ', residuals.mean())
```

```
Mean of Residuals:  -0.005453623717661331
```

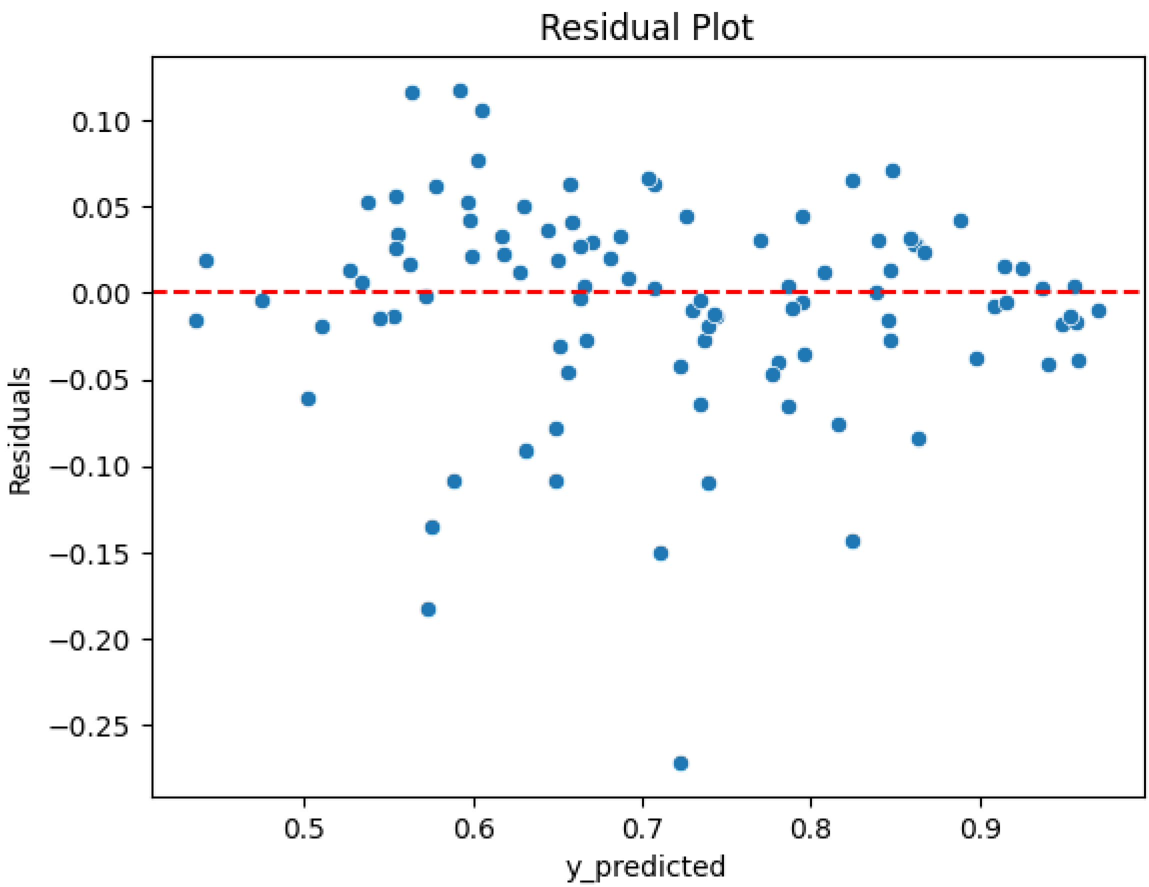
- Since the mean of residuals is very close to 0, we can say that the model is unbiased

In [55]:
```
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()
```



Test of homoscedasticity

In [56]:
```
# Test of homoscedasticity and plotting y_predicted and residuals
sns.scatterplot(x = y_predicted.reshape((-1,)), y=residuals.reshape((-1,)))
plt.title('Residual Plot')
plt.xlabel('y_predicted')
plt.ylabel('Residuals')
plt.axhline(y=0, color='r', linestyle='--')
plt.show();
```



- Since the residual plot shows no clear pattern or trend in residuals, we can conclude that linearity of variables exists.

In [57]:
```
# Scatterplot of residuals with each independent variable to check for Homosceda
plt.figure(figsize=(12,6))
i=1
for col in x_test.columns[:-1]:
  ax = plt.subplot(2,3,i)
  sns.scatterplot(x=x_test[col].values.reshape((-1,)), y=residuals.reshape((-1,)
  plt.title(f'Residual Plot with {col}')
  plt.xlabel(col)
  plt.ylabel('Residual')
  i+=1

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

- Since we do not see any significant change in the spread of residuals with respect to change in independent variables, we can conclude that homoscedasticity is met.

Model Regularisation

In [58]:
```
from sklearn.linear_model import Ridge  # L2 regualrization
from sklearn.linear_model import Lasso  # L1 regualrization
from sklearn.linear_model import ElasticNet
```

Ridge and Lasso regression are both regularization techniques used to prevent overfitting in linear regression models. They work by adding a penalty term to the cost function, which helps to control the complexity of the model by shrinking the coefficient values.

Ridge Regression(L2 regularization)

In [59]:
```
#Initialising instance of Ridge classes
model_ridge = Ridge()
# Fitting the models to training data
model_ridge.fit(x_train, y_train)
```

Out[59]:
```
▾ Ridge
Ridge()
```

In [60]:
```
# Predicting values for train and test data
y_train_ridge = model_ridge.predict(x_train)
y_test_ridge = model_ridge.predict(x_test)
```

In [61]:
```
y_pred = model_ridge.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.sh
```

```
MSE: 0.0037591425219283543
RMSE: 0.06131184650561712
MAE : 0.04335003429327535
r2_score: 0.8161788497834546
Adjusted R2 score : 0.813563508215333
```

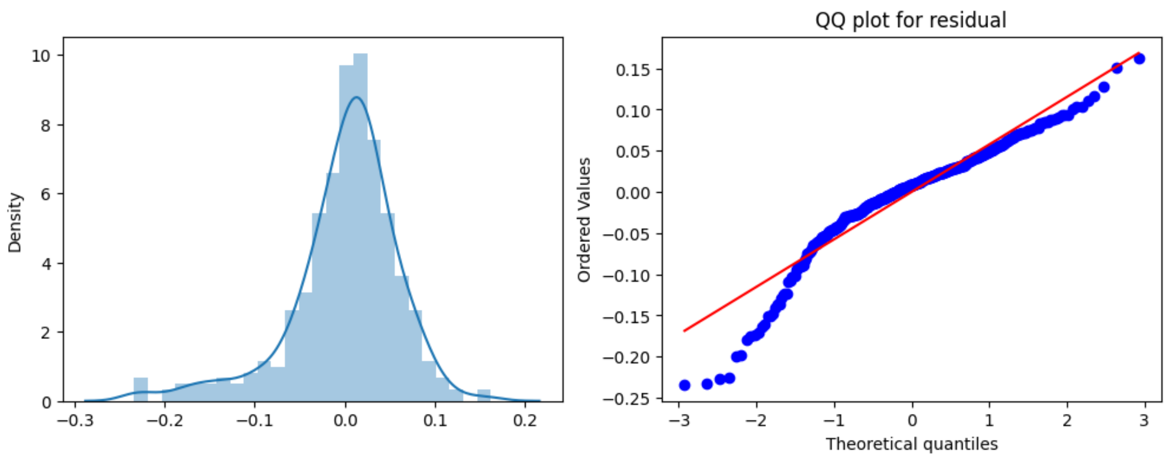
In [62]:
```
y_predicted = model_ridge.predict(x_train)
y_predicted.shape
```

Out[62]: (400, 1)

In [63]:
```
#Mean of Residuals
residuals = y_train.values - y_predicted
print('Mean of Residuals: ', residuals.mean())
```

```
Mean of Residuals:  8.743006318923108e-17
```

In [64]:
```
residuals = y_train.values - 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()
```



Lasso Regression(L1 regularization)

In [65]:
```
#Initialising instance of Lasso classes
model_lasso = Lasso()
# Fitting the models to training data
model_lasso.fit(x_train, y_train)
```

Out[65]:
```
▾ Lasso
Lasso()
```

In [66]:
```
# Predicting values for train and test data
y_train_lasso = model_lasso.predict(x_train)
y_test_lasso = model_lasso.predict(x_test)
```

In [67]:
```
y_pred = model_lasso.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.sh
```

```
MSE: 0.020598230624999995
RMSE: 0.1435208369018241
MAE : 0.116268
r2_score: -0.007248441320293l2
Adjusted R2 score : -0.021579211826882716
```

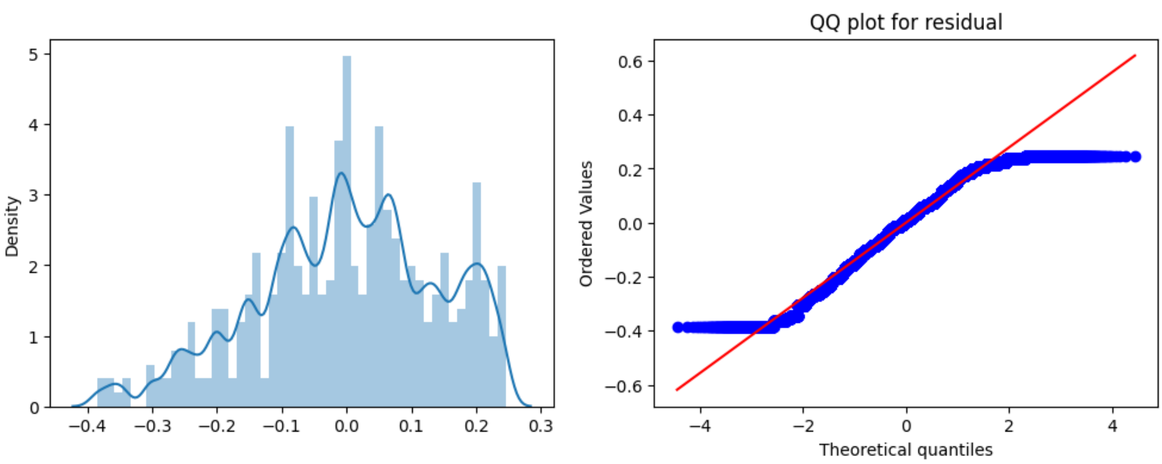
In [68]:
```
y_predicted = model_lasso.predict(x_train)
y_predicted.shape
```

Out[68]: (400,)

In [69]:
```
#Mean of Residuals
residuals = y_train.values - y_predicted
print('Mean of Residuals: ', residuals.mean())
```

```
Mean of Residuals:  1.014299755297543e-16
```

In [70]:
```
residuals = y_train.values - 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()
```



L1 and L2 regularisation(ElasticNet)

In [71]:
```
#Initialising instance of ElasticNet classes
model_ElasticNet = ElasticNet()
# Fitting the models to training data
model_ElasticNet.fit(x_train , y_train)
```

Out[71]:
```
▾ ElasticNet
ElasticNet()
```

In [72]:
```
# Predicting values for train and test data
y_train_ElasticNet = model_ElasticNet.predict(x_train)
y_test_ElasticNet = model_ElasticNet.predict(x_test)
```

In [73]:
```
y_pred = model_ElasticNet.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.sh
```

```
MSE: 0.020598230624999995
RMSE: 0.1435208369018241
MAE : 0.116268
r2_score: -0.00724844132029312
Adjusted R2 score : -0.021579211826882716
```

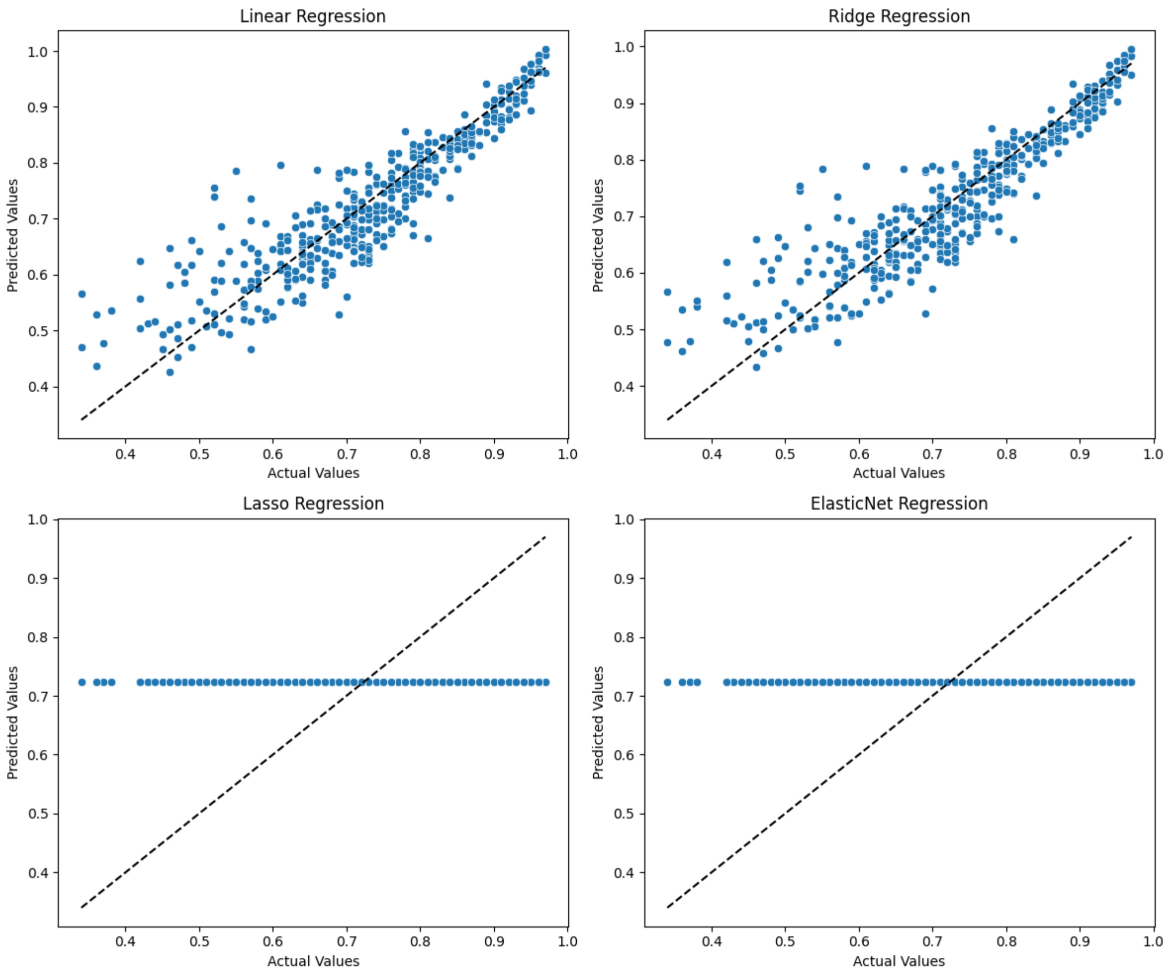
Identifying Best Model

In [74]:
```
# Actual v/s Predicted values for training data
y_pred_train = lr_Test.predict(x_train)

actual_values = y_train.values.reshape((-1,))
predicted_values = [y_pred_train.reshape((-1,)), y_train_ridge.reshape((-1,)), y
model = ['Linear Regression', 'Ridge Regression', 'Lasso Regression','ElasticNet

plt.figure(figsize=(12,10))
i=1
for preds in predicted_values:
  ax = plt.subplot(2,2,i)
  sns.scatterplot(x=actual_values, y=preds)
  plt.plot([min(actual_values),max(actual_values)], [min(actual_values),max(actu
  plt.xlabel('Actual Values')
  plt.ylabel('Predicted Values')
  plt.title(model[i-1])
  i+=1

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



- While Linear Regression and Ridge regression have similar scores, Lasso regression and ElasticNet Regression has not performed well on both training and test data.

In [75]:
```
y_pred = model_ElasticNet.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))) #RMS
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


y_pred = lr_Test.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))
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),le


y_pred = model_ridge.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))) #RMS
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
```

```
y_pred = model_lasso.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))) #RMS
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
```

In [76]:

```
A = pd.DataFrame([LinearRegression_model_metrics,LassoModel_model_metrics,RidgeM
A
```

Out[76]:

	MSE	RMSE	MAE	R2_SCORE	ADJUSTED_R2
Linear Regression Model	0.003705	0.060866	0.042723	0.818843	0.816266
Lasso Regression Model	0.020598	0.143521	0.116268	-0.007248	-0.021579
Ridge Regression Model	0.003759	0.061312	0.043350	0.816179	0.813564
ElasticNet Regression Model	0.020598	0.143521	0.116268	-0.007248	-0.021579

Observations:

- The chance of admit distribution skews left for the target variable.
- Exam scores (CGPA/GRE/TOEFL) exhibit a robust positive correlation with the chance of admit, and these variables showcase significant mutual correlation.
- Categorical variables like university ranking, research, SOP/LOR quality display an upward trend concerning chances of admit.
- fist column was observed as unique row identifier which was dropped and was not required for model building.
- No null values were present in data.
- No Significant amount of outliers were found in data.
- Chance of admission(target variable) and GRE score(an independent feature) are nearly normally distributed.
- Independent Variables (Input data): GRE Score, TOEFL Score, University Rating, SOP, LOR, CGPA, Research
- Target/Dependent Variable : Chance of Admission (the value we want to predict)
- from 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.
- chances of admit is a probability measure , which is within 0 to 1 which is good (no outliers or misleading 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.

- From boxplots (distribution of chance of admission (probability of getting admission) as per GRE score) : with higher GRE score , there is high probability of getting an admission .
- Both Linear Regression and Ridge Regression models, the optimal choices, capture up to 82% variance in the chance of admit. Yet, achieving superior outcomes becomes challenging due to high predictor variable collinearity.
- Aside from multicollinearity, predictor variables fulfil Linear Regression prerequisites: residuals' mean approximates zero, variable linearity, residual normality, and established homoscedasticity.

Actionable Insights & Recommendations:

- Considering the strong correlation among exam scores, augmenting the model with additional independent features is advisable for enhanced predictive accuracy.
- Awareness of CGPA and Research Capabilities : Seminars can be organised to increase the awareness regarding CGPA and Research Capabilities to enhance the chance of admission.
- education institute can not just help student to improve their CGPA score but also assist them writing good LOR and SOP thus helping them admit to better university.
- The education institute can not just help student to improve their GRE Score but can also assist them writing good LOR and SOP thus helping them admit to a better University.
- University rating can be a good predictor, but it definitely has some outliers.
- The other predictors can be SOP and LOR, but they will have less weights and we have to handle the outliers.