Problem Statement

- 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.
- We'll use different ML techniques to find out how different factors impact a person's probablity of getting into IVY League College.
- We'll use a linear regression model to see what are the chances of a student to get admission based on his/her scores on different criterias.

In [540]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import make_pipeline
from sklearn.linear_model import LinearRegression,Ridge,Lasso
from sklearn.metrics import r2_score,mean_absolute_error,mean_squared_error
import statsmodels.api as sm
from sklearn.preprocessing import PolynomialFeatures
```

In [488]:

```
df = pd.read_csv('Jamboree_Admission.csv')
```

In [489]:

```
df
```

Out[489]:

	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

In [490]:

```
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 [491]:

```
df.shape
```

Out[491]:

```
(500, 9)
```

In [492]:

```
df.describe(include='all')
```

Out[492]:

	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Re
count	500.000000	500.000000	500.000000	500.000000	500.000000	500.00000	500.000000	500.(
mean	250.500000	316.472000	107.192000	3.114000	3.374000	3.48400	8.576440	0.!
std	144.481833	11.295148	6.081868	1.143512	0.991004	0.92545	0.604813	0.·
min	1.000000	290.000000	92.000000	1.000000	1.000000	1.00000	6.800000	0.(
25%	125.750000	308.000000	103.000000	2.000000	2.500000	3.00000	8.127500	0.(
50%	250.500000	317.000000	107.000000	3.000000	3.500000	3.50000	8.560000	1.(
75%	375.250000	325.000000	112.000000	4.000000	4.000000	4.00000	9.040000	1.(
max	500.000000	340.000000	120.000000	5.000000	5.000000	5.00000	9.920000	1.(

In [493]:

```
df.rename(columns = {'LOR ':'LOR','Chance of Admit ':'Chance of Admit'},inplace=True
```

In [494]:

```
df.drop('Serial No.',axis=1,inplace=True)
```

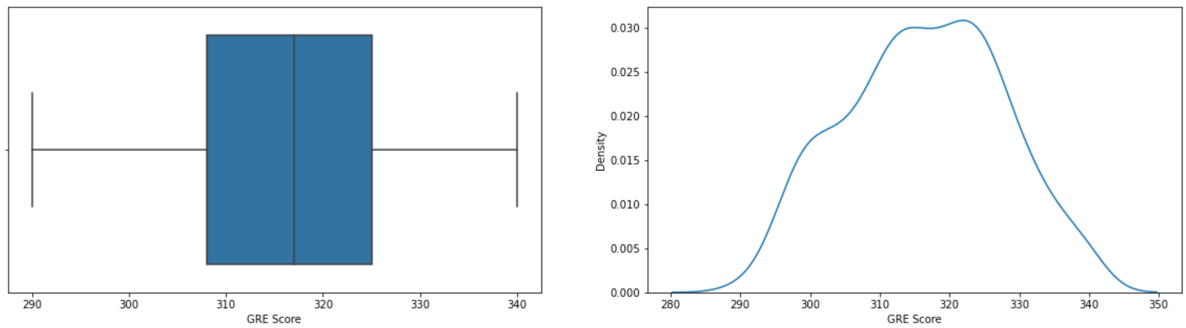
Univariate Analysis

In [495]:

```
def plot_univariate(column):
    fig, ax =plt.subplots(1,2,figsize=(20,5))
    sns.boxplot(x=df[column],ax=ax[0])
    sns.kdeplot(x=df[column],ax=ax[1])
    plt.show()
```

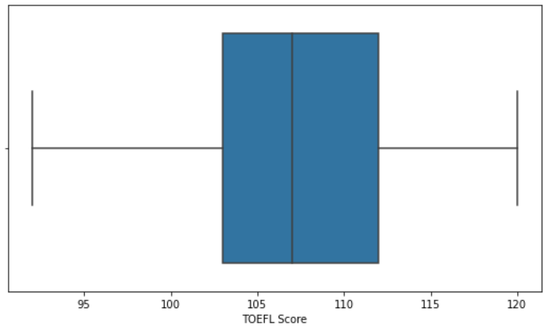
In [496]:

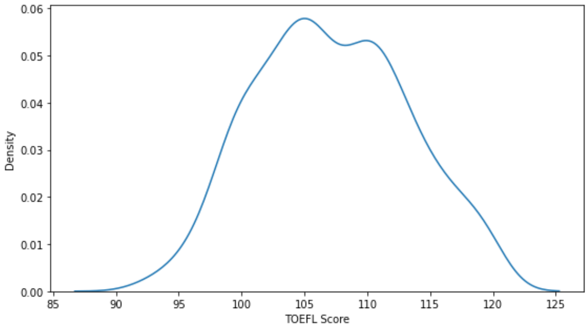
```
plot_univariate('GRE Score')
```



In [497]:

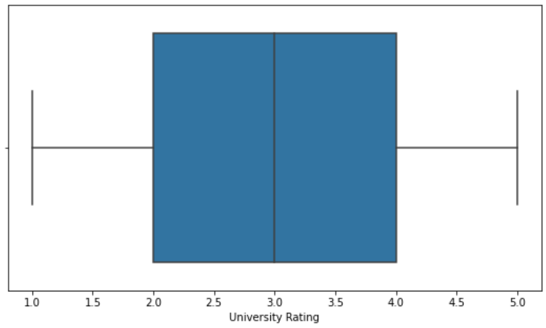
```
plot_univariate('TOEFL Score')
```

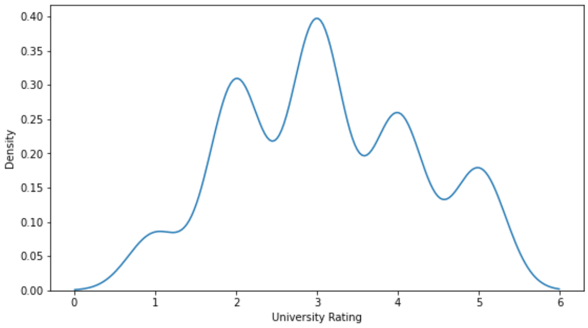




In [498]:

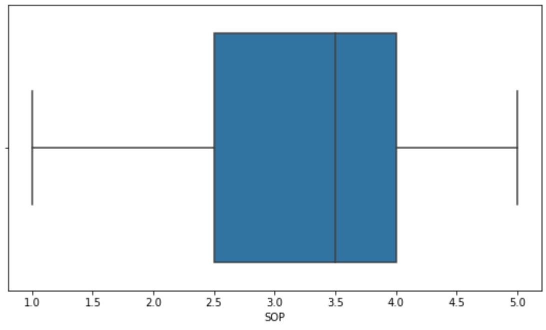
```
plot_univariate('University Rating')
```

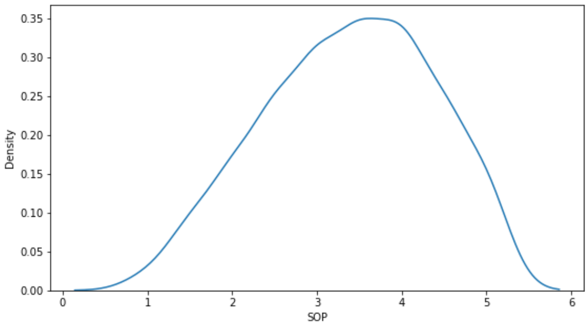




In [499]:

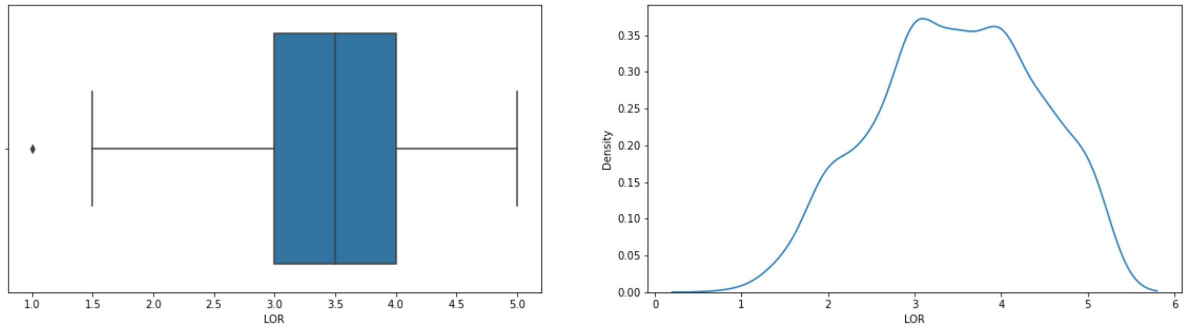
```
plot_univariate('SOP')
```





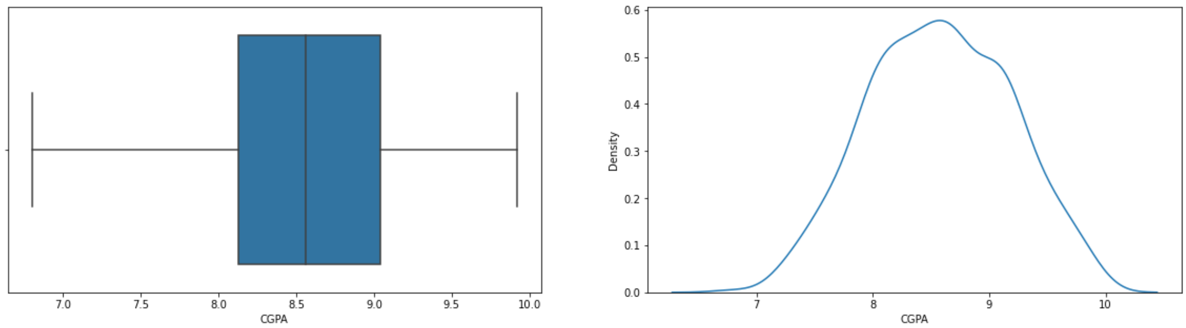
In [500]:

```
plot_univariate('LOR')
```



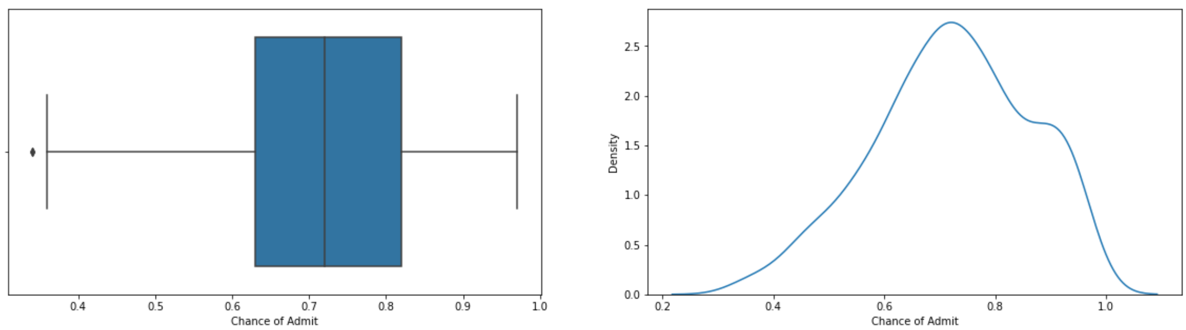
In [501]:

```
plot_univariate('CGPA')
```



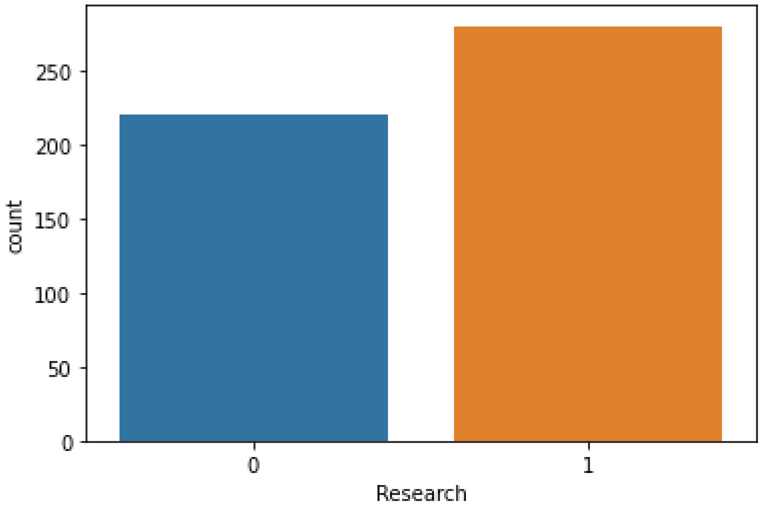
In [502]:

```
plot_univariate('Chance of Admit')
```



In [503]:

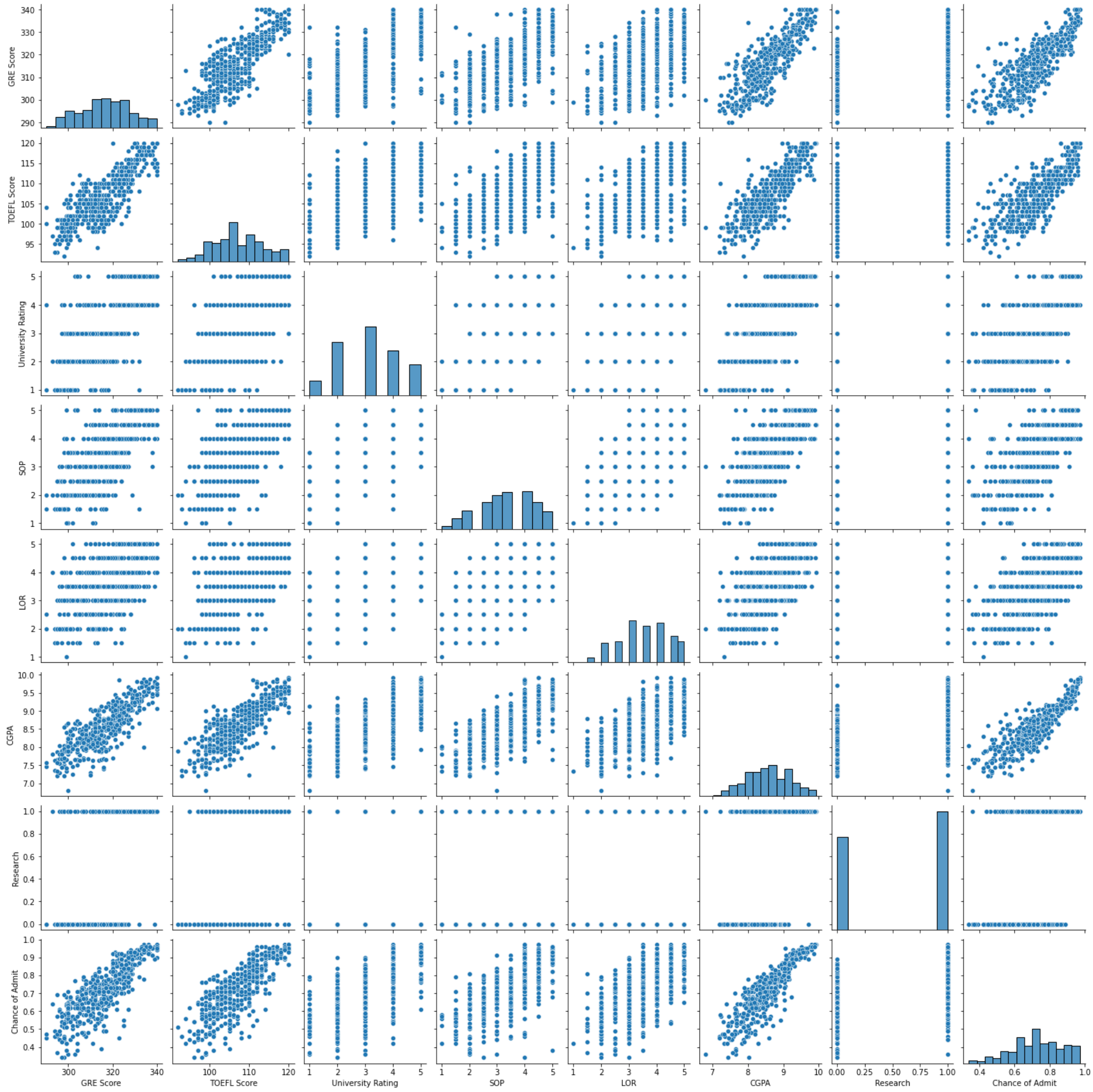
```
sns.countplot(x = df['Research'])
plt.show()
```



Bivariate Analysis

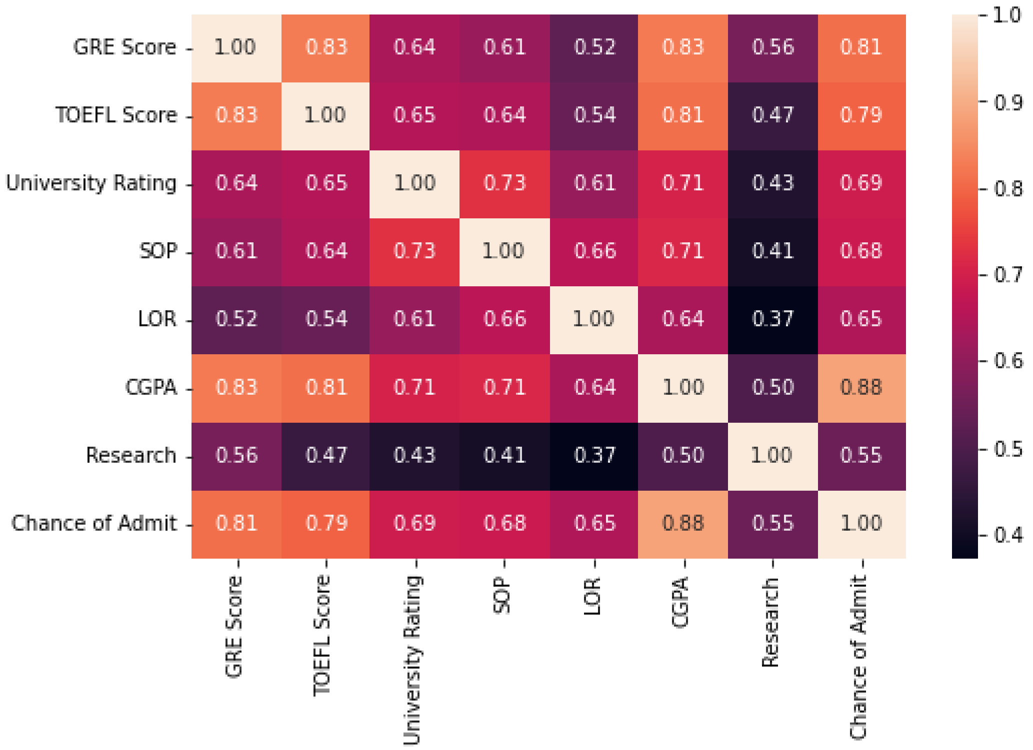
In [504]:

```
sns.pairplot(df)
plt.show()
```



In [505]:

```
fig, ax = plt.subplots(figsize=(8, 5))
sns.heatmap(df.corr(), annot=True, fmt='.2f', ax=ax)
plt.show()
```



Insights based on EDA: From the above univariate and bivariate Analysis we can infer the following.
- There are no missing values and outliers in the dataset.
- GRE Score, TOEFL Score and CGPA score are highly positively correlated to chance of Admit.
- GRE Score and TOEFL Score are highly correlated.
- CGPA, TOEFL and GRE Score are highly intercorrelated.
- There is not much impact of Research on chance of Admit.
- LOR and SOP can have an impact on Chance of Admit but they don't play very crucial role.

- There are no outliers in the dataset since all the values have an upper limit and a lower limit like GRE Score, TOEFL Score,LOR, SOP, University Rating etc.

In [506]:

```
df.duplicated().sum()
```

Out[506]:

```
0
```

In [507]:

```
df.isnull().sum()
```

Out[507]:

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

Model Building

In [566]:

```
y = df['Chance of Admit']
X = df.drop(['Chance of Admit'],axis=1)
```

In [567]:

```
X
```

Out[567]:

	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
...	...	...	...	...	...	...	...
495	332	108	5	4.5	4.0	9.02	1
496	337	117	5	5.0	5.0	9.87	1
497	330	120	5	4.5	5.0	9.56	1
498	312	103	4	4.0	5.0	8.43	0
499	327	113	4	4.5	4.5	9.04	0

500 rows × 7 columns

In [568]:

```
y
```

Out[568]:

```
0      0.92
1      0.76
2      0.72
3      0.80
4      0.65
       ...
495    0.87
496    0.96
497    0.93
498    0.73
499    0.84
Name: Chance of Admit, Length: 500, dtype: float64
```

Type *Markdown* and LaTeX: α^2

In [569]:

```
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.2,random_state=1)
```

In [570]:

```
print("shape of X train is: {}".format(X_train.shape))
print("shape of X test is: {}".format(X_test.shape))
print("shape of y train is: {}".format(y_train.shape))
print("shape of y_test is: {}".format(y_test.shape))
```

```
shape of X train is: (400, 7)
shape of X test is: (100, 7)
shape of y train is: (400,)
shape of y_test is: (100,)
```

In [571]:

```
scaler = StandardScaler()
model = LinearRegression()

scaled = scaler.fit(X_train)
X_train_scaled_df = scaled.transform(X_train)
X_test_scaled_df = scaled.transform(X_test)
```

Training a Linear Regression Model

In [574]:

```
model.fit(X_train_scaled_df,y_train)

y_train_pred = model.predict(X_train_scaled_df)
y_test_pred = model.predict(X_test_scaled_df)

print("Test data r2_score: {}".format(r2_score(y_test,y_test_pred)))
print("Train data r2 score {}".format(r2_score(y_train,y_train_pred)))
```

```
Test data r2_score: 0.8208741703103731
Train data r2 score 0.8215099192361265
```

Coefficients of Trained Model

In [575]:

```
feature_names = X_train.columns

coefs = pd.DataFrame(
    model.coef_,
    columns=["Coefficients"],
    index=feature_names,
)

coefs
```

Out[575]:

	Coefficients
GRE Score	0.020910
TOEFL Score	0.019658
University Rating	0.007011
SOP	0.003049
LOR	0.013528
CGPA	0.070693
Research	0.009890

Training a Ridge Model

In [578]:

```
ridge_model = Ridge(alpha=5)
ridge_model.fit(X_train_scaled_df,y_train)
y_train_pred_ridge = ridge_model.predict(X_train_scaled_df)
y_test_pred_ridge = ridge_model.predict(X_test_scaled_df)

print("Test data r2_score: {}".format(r2_score(y_test,y_test_pred_ridge)))
print("Train data r2 score {}".format(r2_score(y_train,y_train_pred_ridge)))
```

```
Test data r2_score: 0.8202931046792501
Train data r2 score 0.8214073027417684
```

Training a Lasso Model

In [579]:

```
lasso_model = Lasso(alpha=5)
lasso_model.fit(X_train_scaled_df,y_train)
y_train_pred_lasso = ridge_model.predict(X_train_scaled_df)
y_test_pred_lasso = ridge_model.predict(X_test_scaled_df)

print("Test data r2_score: {}".format(r2_score(y_test,y_test_pred_lasso)))
print("Train data r2 score {}".format(r2_score(y_train,y_train_pred_lasso)))
```

```
Test data r2_score: 0.8202931046792501
Train data r2 score 0.8214073027417684
```

Testing Linear Regression Assumptions

checking Multicollinearity

In [581]:

```
def check_vif(X):
    vif_data = pd.DataFrame()
    vif_data["feature"] = X.columns

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

In [582]:

```
check_vif(X)
```

```
             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 [583]:

```
new_X = X.drop(['TOEFL Score','University Rating','SOP','LOR','CGPA'],axis=1)
```

In [584]:

```
new_X
```

Out[584]:

	GRE Score	Research
0	337	1
1	324	1
2	316	1
3	322	1
4	314	0
...	...	...
495	332	1
496	337	1
497	330	1
498	312	0
499	327	0

500 rows × 2 columns

In [585]:

```
check_vif(new_X)
```

```
     feature       VIF
0  GRE Score  2.377465
1   Research  2.377465
```

Mean of Residuals

In [587]:

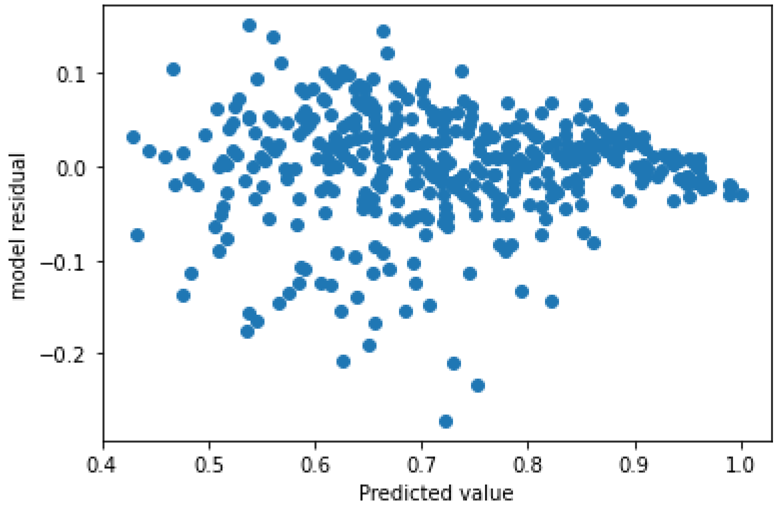
```
###Mean of residuals
y_pred = model.predict(X_train_scaled_df)
residual = np.mean(y_train - y_pred)
print(residual)
```

```
-4.3576253716537396e-17
```

Linearity Check

In [588]:

```
y_pred = model.predict(X_train_scaled_df)
residual = y_train-y_pred
plt.scatter(y_pred,residual)
plt.xlabel("Predicted value")
plt.ylabel("model residual")
plt.show()
```

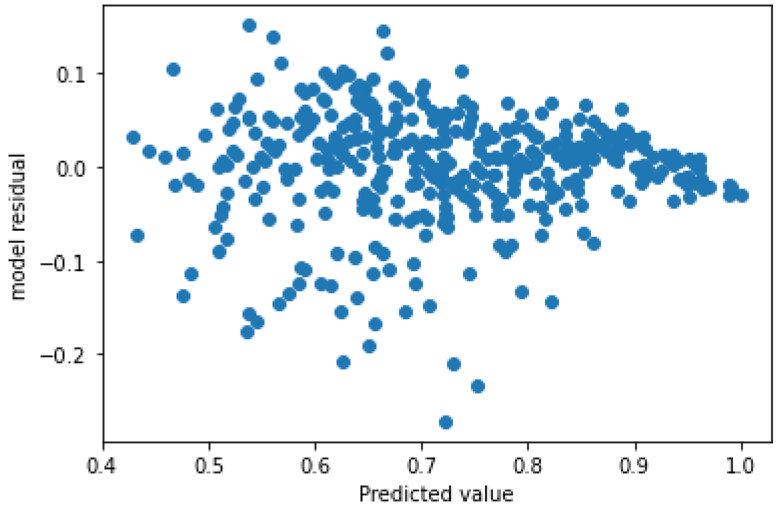


The plot doesn't show any pattern

check for Homoscedasticity

In [591]:

```
y_pred = model.predict(X_train_scaled_df)
residual = y_train-y_pred
plt.scatter(y_pred,residual)
plt.xlabel("Predicted value")
plt.ylabel("model residual")
plt.show()
```



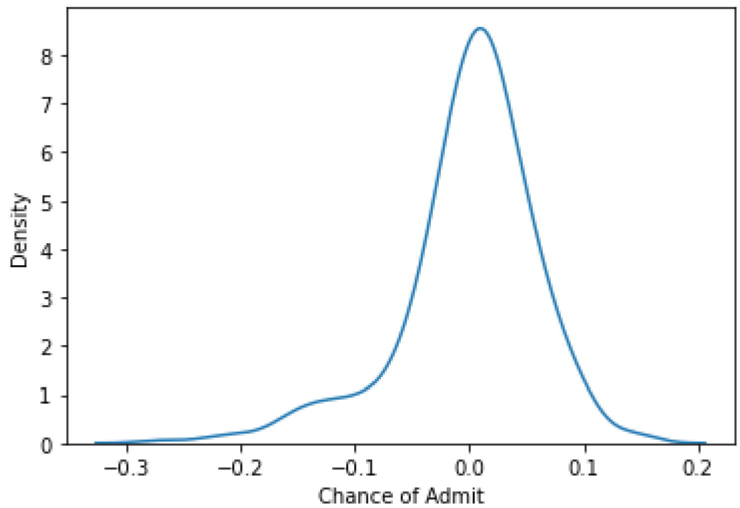

```
<div class="alert alert-block alert-info">
<b>There is a funnel shape being formed in the data. Thus it does not follow
Homoscedasticity</br>
    </div>
```

Normality of residuals

In [594]:

```

sns.kdeplot(residual)
plt.show()
```

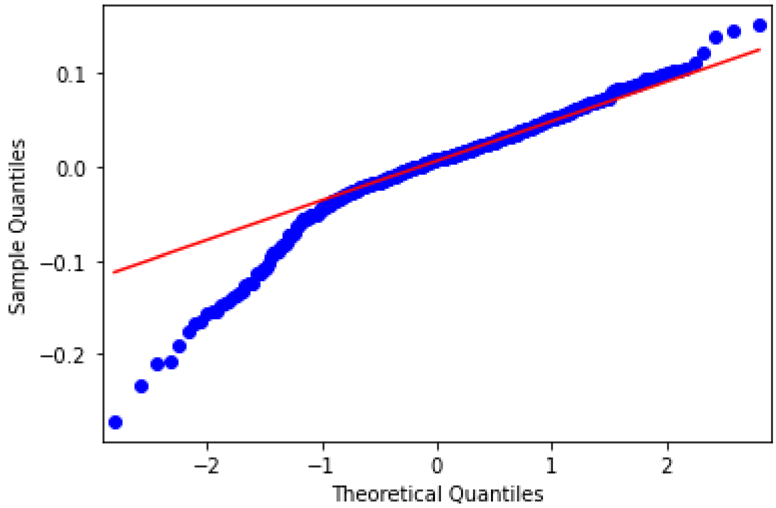


The data follows a normal distribution with some outliers on the left side which causes a left tail. This can be observed in the qqplot below.

In [595]:

```
sm.qqplot(residual,line='q')
plt.show()
```

```
/opt/anaconda3/lib/python3.9/site-packages/statsmodels/graphics/gofplo
ts.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)
```



Performance Evaluation

Performance Evaluation for Linear Model without Regularization

In [536]:

```
## Performance evaluation for Linear Model without Regularization
print("Performance Evaluation for Linear Regression Model")
print("R2 Score Evaluation")
print("Test data r2_score: {}".format(r2_score(y_test,y_test_pred)))
print("Train data r2 score {}".format(r2_score(y_train,y_train_pred)))
print("--------------------------------------------------------------------")
print("Mean Absolute Error Evaluation")
print("Test data mean absolute error: {}".format(mean_absolute_error(y_test,y_test_p
print("Train data mean absolute error {}".format(mean_absolute_error(y_train,y_trair
print("--------------------------------------------------------------------")
print("Root Mean Squared Error Evaluation")
print("Test data RMSE: {}".format(mean_squared_error(y_test,y_test_pred,squared=Fals
print("Train data RMSE {}".format(mean_squared_error(y_train,y_train_pred,squared=Fa

print("--------------------------------------------------------------------")
print("Adjust R2 Score Evaluation")
test_r2 = r2_score(y_test,y_test_pred)
train_r2 = r2_score(y_train,y_train_pred)
adjusted_r2_test = 1-(1-test_r2)*(X_test_scaled_df.shape[0]-1)/(X_test_scaled_df.sha
adjusted_r2_train = 1-(1-train_r2)*(X_train_scaled_df.shape[0]-1)/(X_train_scaled_df
print("Test data Adjusted R2: {}".format(adjusted_r2_test))
print("Train data Adjusted R2 {}".format(adjusted_r2_train))
```

```
Performance Evaluation for Linear Regression Model
R2 Score Evaluation
Test data r2_score: 0.8208741703103731
Train data r2 score 0.8215099192361265
--------------------------------------------------------------------
Mean Absolute Error Evaluation
Test data mean absolute error: 0.040200193804157944
Train data mean absolute error 0.04294488315548092
--------------------------------------------------------------------
Root Mean Squared Error Evaluation
Test data RMSE: 0.0588141045765077
Train data RMSE 0.05977752557506849
--------------------------------------------------------------------
Adjust R2 Score Evaluation
Test data Adjusted R2: 0.807245031094858
Train data Adjusted R2 0.818322596365343
```

Performance Evaluation for Ridge Regression Model

In [598]:

```
print("Performance Evaluation for Ridge Regularization Model")
print("R2 Score Evaluation")
print("Test data r2_score: {}".format(r2_score(y_test,y_test_pred_ridge)))
print("Train data r2 score {}".format(r2_score(y_train,y_train_pred_ridge)))
print("--------------------------------------------------------------------")
print("Mean Absolute Error Evaluation")
print("Test data mean absolute error: {}".format(mean_absolute_error(y_test,y_test_p
print("Train data mean absolute error {}".format(mean_absolute_error(y_train,y_trair
print("--------------------------------------------------------------------")
print("Root Mean Squared Error Evaluation")
print("Test data RMSE: {}".format(mean_squared_error(y_test,y_test_pred_ridge,square
print("Train data RMSE {}".format(mean_squared_error(y_train,y_train_pred_ridge,squa

print("--------------------------------------------------------------------")
print("Adjust R2 Score Evaluation")
test_r2 = r2_score(y_test,y_test_pred_ridge)
train_r2 = r2_score(y_train,y_train_pred_ridge)
adjusted_r2_test = 1-(1-test_r2)*(X_test_scaled_df.shape[0]-1)/(X_test_scaled_df.sha
adjusted_r2_train = 1-(1-train_r2)*(X_train_scaled_df.shape[0]-1)/(X_train_scaled_df
print("Test data Adjusted R2: {}".format(adjusted_r2_test))
print("Train data Adjusted R2 {}".format(adjusted_r2_train))
```

```
Performance Evaluation for Ridge Regularization Model
R2 Score Evaluation
Test data r2_score: 0.8202931046792501
Train data r2 score 0.8214073027417684
--------------------------------------------------------------------
Mean Absolute Error Evaluation
Test data mean absolute error: 0.04033521414652057
Train data mean absolute error 0.042903999862959674
--------------------------------------------------------------------
Root Mean Squared Error Evaluation
Test data RMSE: 0.058909420770696774
Train data RMSE 0.05979470658223978
--------------------------------------------------------------------
Adjust R2 Score Evaluation
Test data Adjusted R2: 0.8066197539483235
Train data Adjusted R2 0.8182181474335857
```

Performance Evaluation for Lasso Regression Model

In [600]:

```
## Performance evaluation for Lasso Model
print("Performance Evaluation for Lasso Regression Model")
print("R2 Score Evaluation")
print("Test data r2_score: {}".format(r2_score(y_test,y_test_pred_lasso)))
print("Train data r2 score {}".format(r2_score(y_train,y_train_pred_lasso)))
print("--------------------------------------------------------------------")
print("Mean Absolute Error Evaluation")
print("Test data mean absolute error: {}".format(mean_absolute_error(y_test,y_test_p
print("Train data mean absolute error {}".format(mean_absolute_error(y_train,y_trair
print("--------------------------------------------------------------------")
print("Root Mean Squared Error Evaluation")
print("Test data RMSE: {}".format(mean_squared_error(y_test,y_test_pred_lasso,square
print("Train data RMSE {}".format(mean_squared_error(y_train,y_train_pred_lasso,squa

print("--------------------------------------------------------------------")
print("Adjust R2 Score Evaluation")
test_r2 = r2_score(y_test,y_test_pred_lasso)
train_r2 = r2_score(y_train,y_train_pred_lasso)
adjusted_r2_test = 1-(1-test_r2)*(X_test_scaled_df.shape[0]-1)/(X_test_scaled_df.sha
adjusted_r2_train = 1-(1-train_r2)*(X_train_scaled_df.shape[0]-1)/(X_train_scaled_df
print("Test data Adjusted R2: {}".format(adjusted_r2_test))
print("Train data Adjusted R2 {}".format(adjusted_r2_train))
```

```
Performance Evaluation for Lasso Regression Model
R2 Score Evaluation
Test data r2_score: 0.8202931046792501
Train data r2 score 0.8214073027417684
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Mean Absolute Error Evaluation
Test data mean absolute error: 0.04033521414652057
Train data mean absolute error 0.042903999862959674
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Root Mean Squared Error Evaluation
Test data RMSE: 0.058909420770696774
Train data RMSE 0.05979470658223978
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Adjust R2 Score Evaluation
Test data Adjusted R2: 0.8066197539483235
Train data Adjusted R2 0.8182181474335857
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Insights and Recommendations

Significance of predictor variables:
- CGPA and GRE Score play the most important role in chance of Admit whereas University Rating and Research plays the least important role.
Additional Data sources and model improvement
- To improve the model, more data is required to train the model
. - More data can be collected from different Ivy Colleges to improve the model.
- Improved model will help in streamlining the process of applying the for different universities.
- This will reduce the load of scrutiny on Ivy Colleges, since students will beforehand know what are their chances of getting admitted to a particular university and they'll apply to those Universities where they have high chance of Admittance.
- This will help universities admit students based on their capabilities and also reduce human error. Also it will improve the interpretability for why a particular student got admitted and other got rejected.

In [ ]:

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