

Jamboree Education!



```
import pandas as pd
import numpy as np

df=pd.read_csv("/content/Jamboree_Admission.csv")
```

Observations on shape of data, data types of all the attributes, conversion of categorical attributes to 'category' (If required), missing value detection, statistical summary.

```
df.head()
```

	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR
CGPA \						
0	1	337	118	4	4.5	4.5
9.65						
1	2	324	107	4	4.0	4.5
8.87						
2	3	316	104	3	3.0	3.5
8.00						
3	4	322	110	3	3.5	2.5
8.67						
4	5	314	103	2	2.0	3.0
8.21						

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

3	1	0.80
4	0	0.65

```
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
```

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

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

```
dtype: int64
```

```
df.shape
```

```
(500, 9)
```

Univariate Analysis (distribution plots of all the continuous variable(s) barplots/countplots of all the categorical variables)

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

```
import seaborn as sns
```

```
import matplotlib.pyplot as plt
```

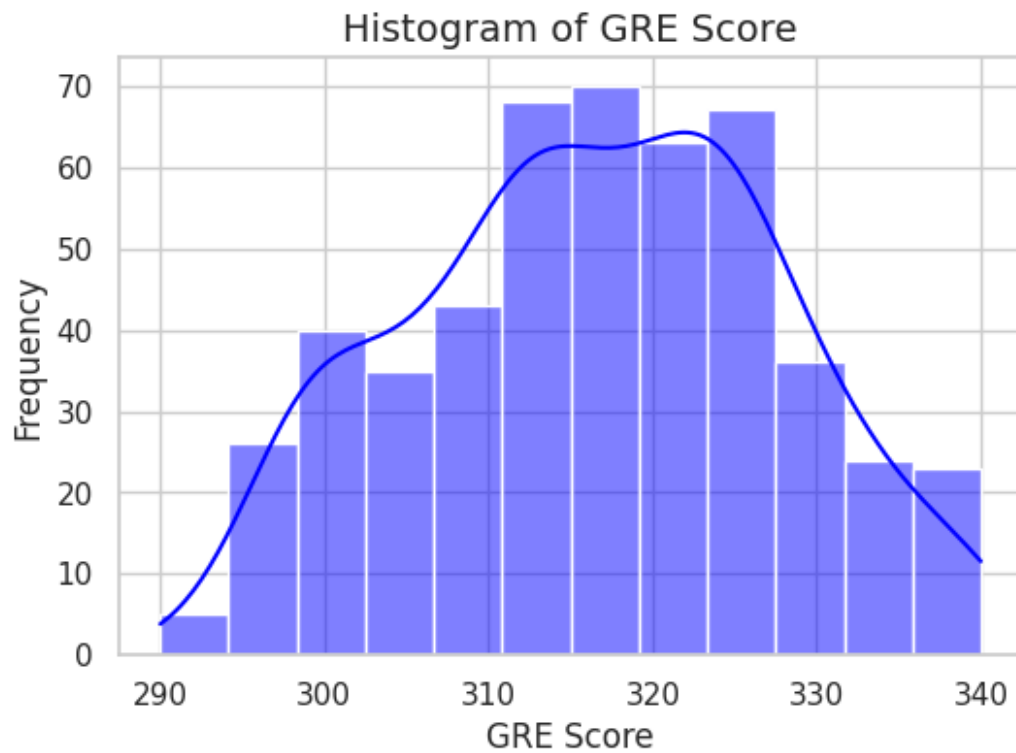
```
sns.set(style="whitegrid")
```

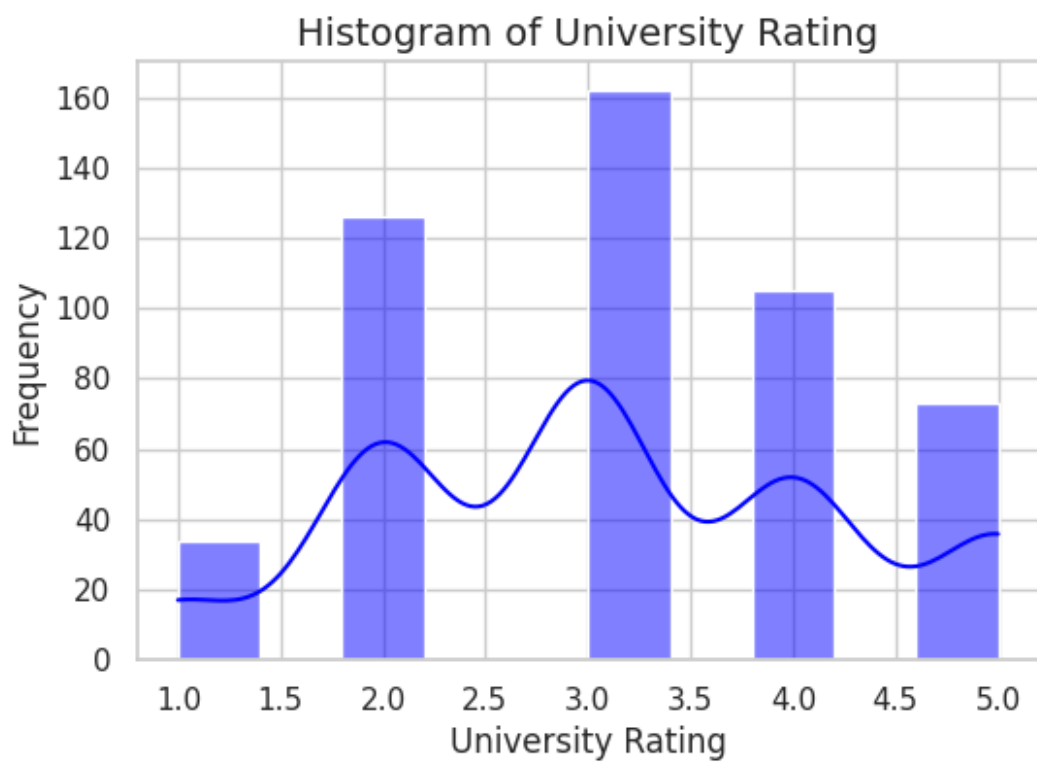
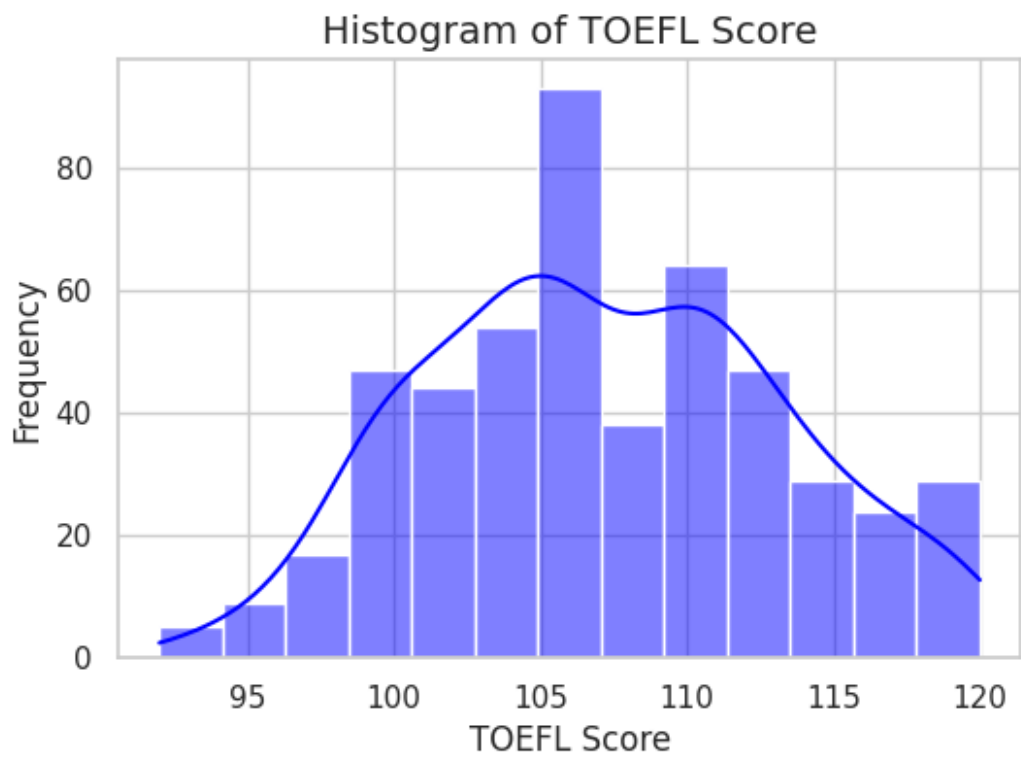
```
for column in df.columns:
```

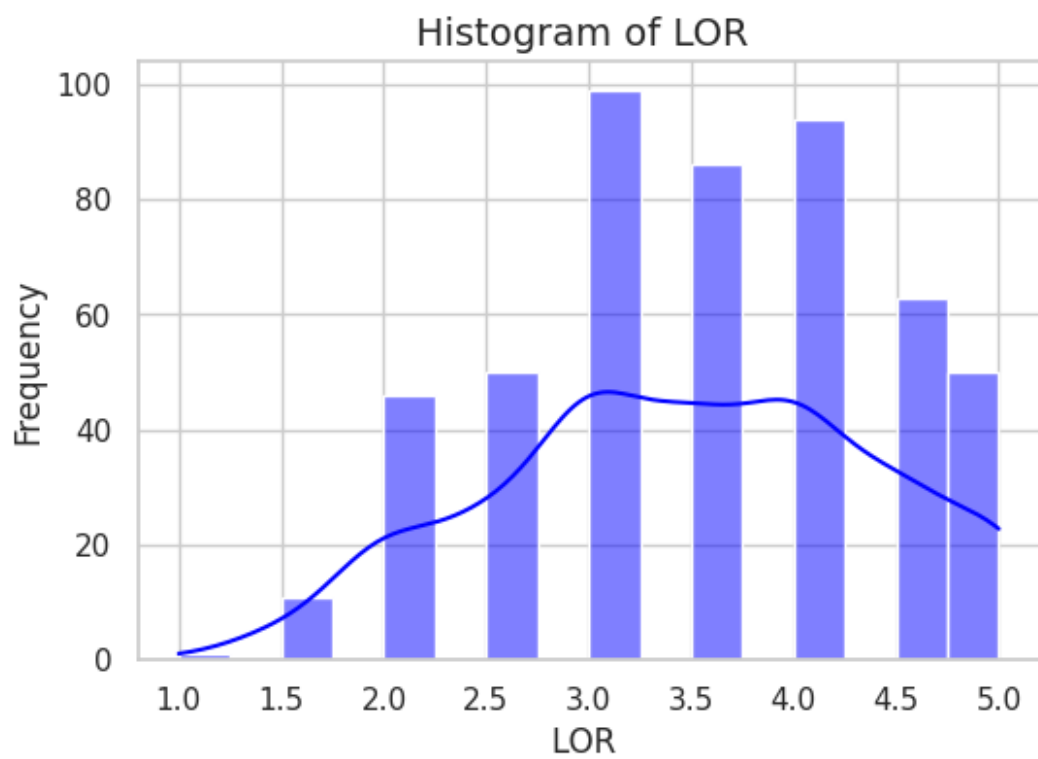
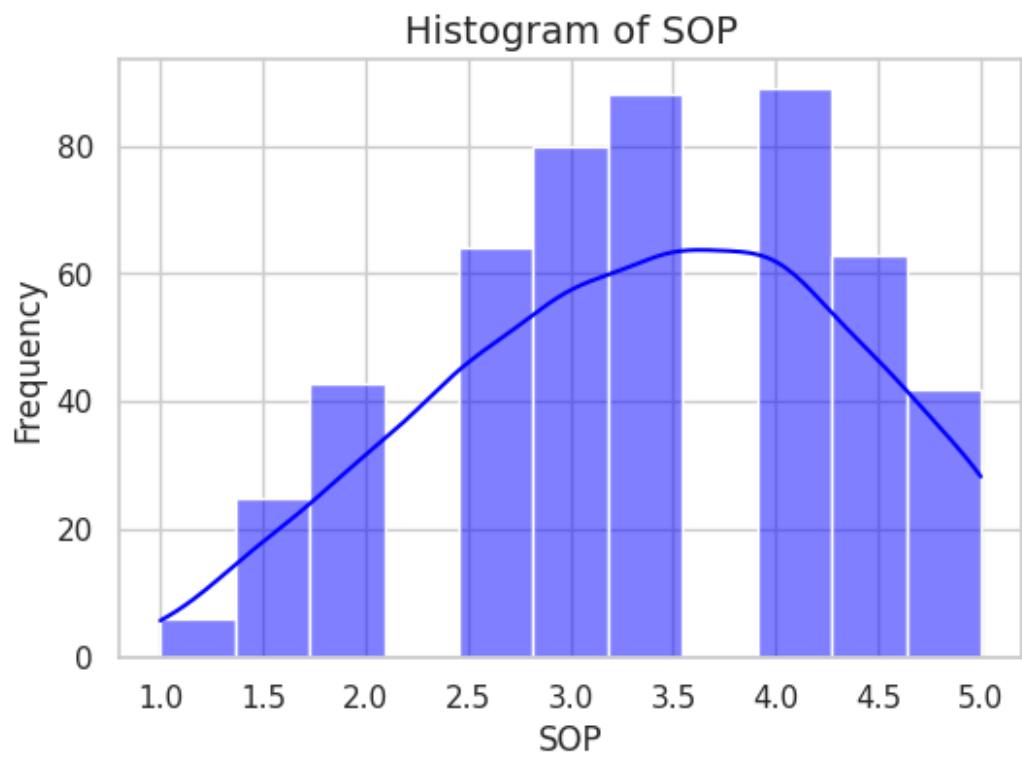
```
    plt.figure(figsize=(6, 4))
```

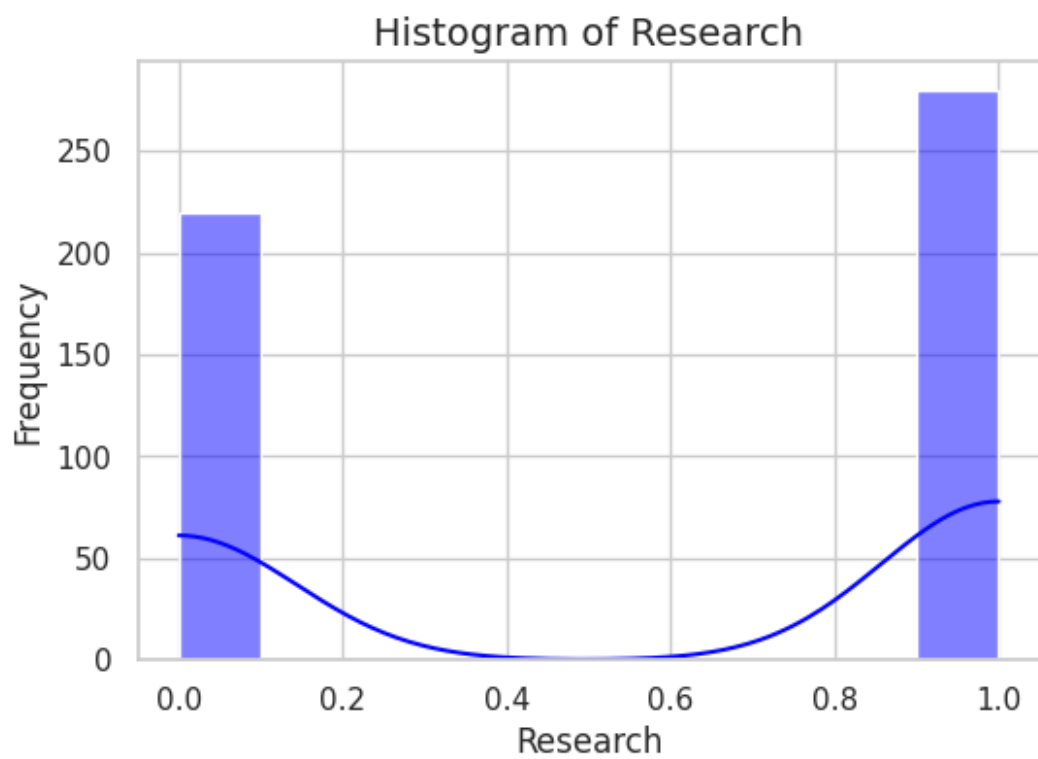
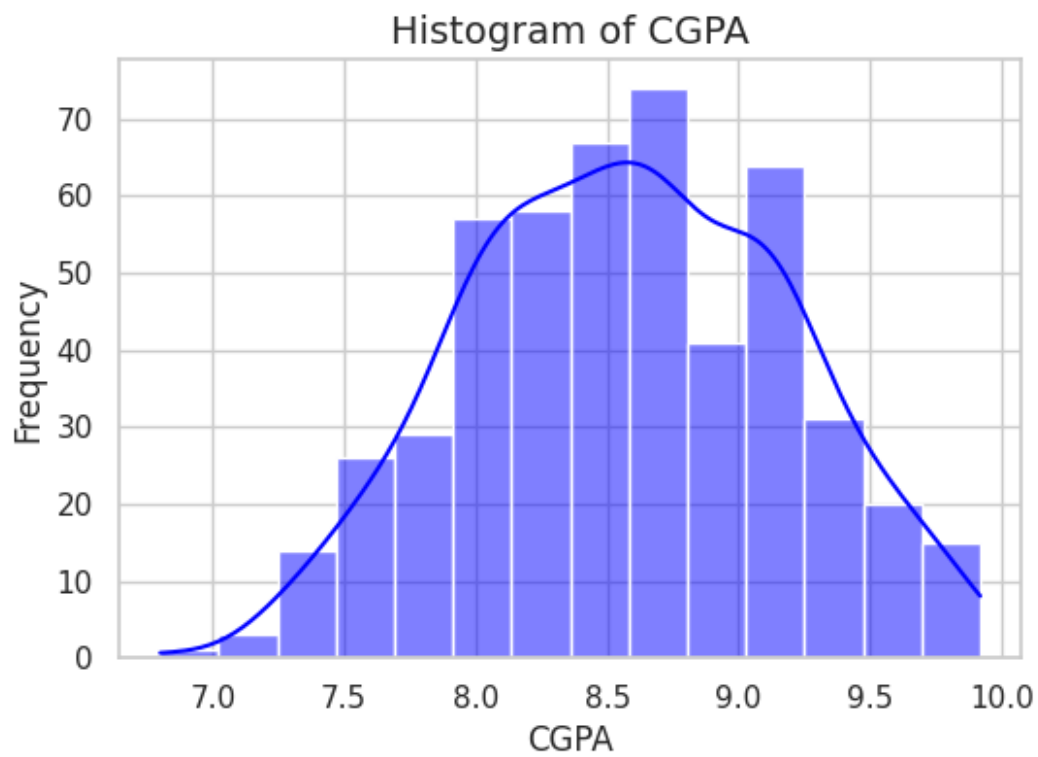
```
    sns.histplot(df[column], kde=True, color='blue')
```

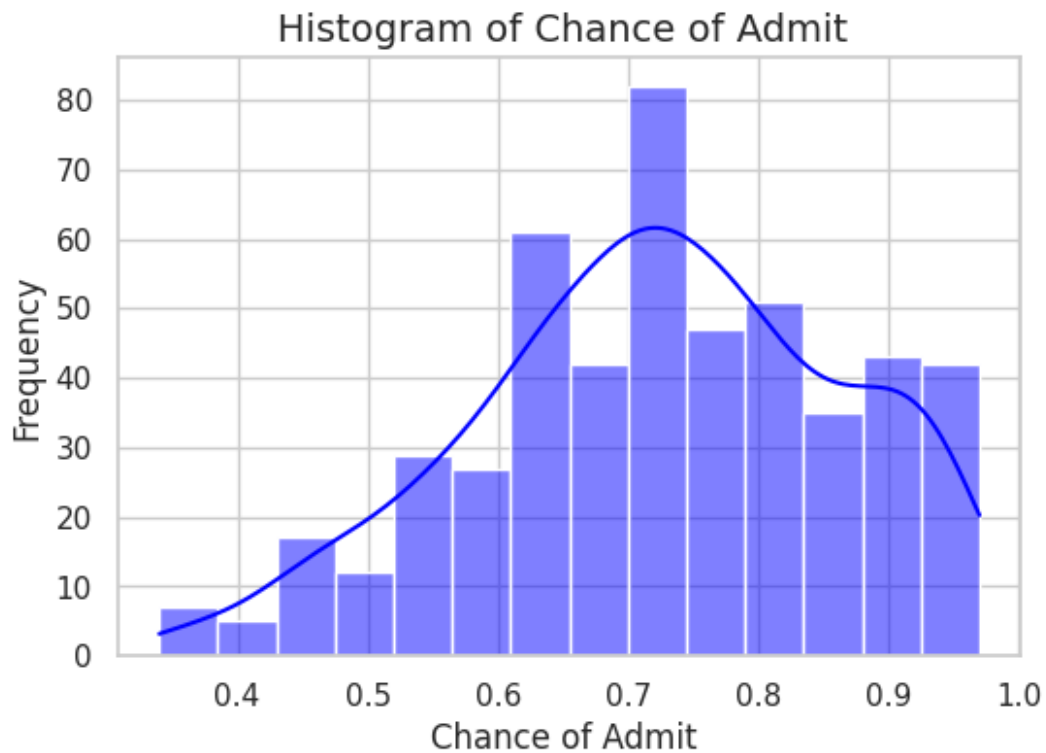
```
plt.title(f'Histogram of {column}', fontsize=14)
plt.xlabel(column, fontsize=12)
plt.ylabel('Frequency', fontsize=12)
plt.show()
```



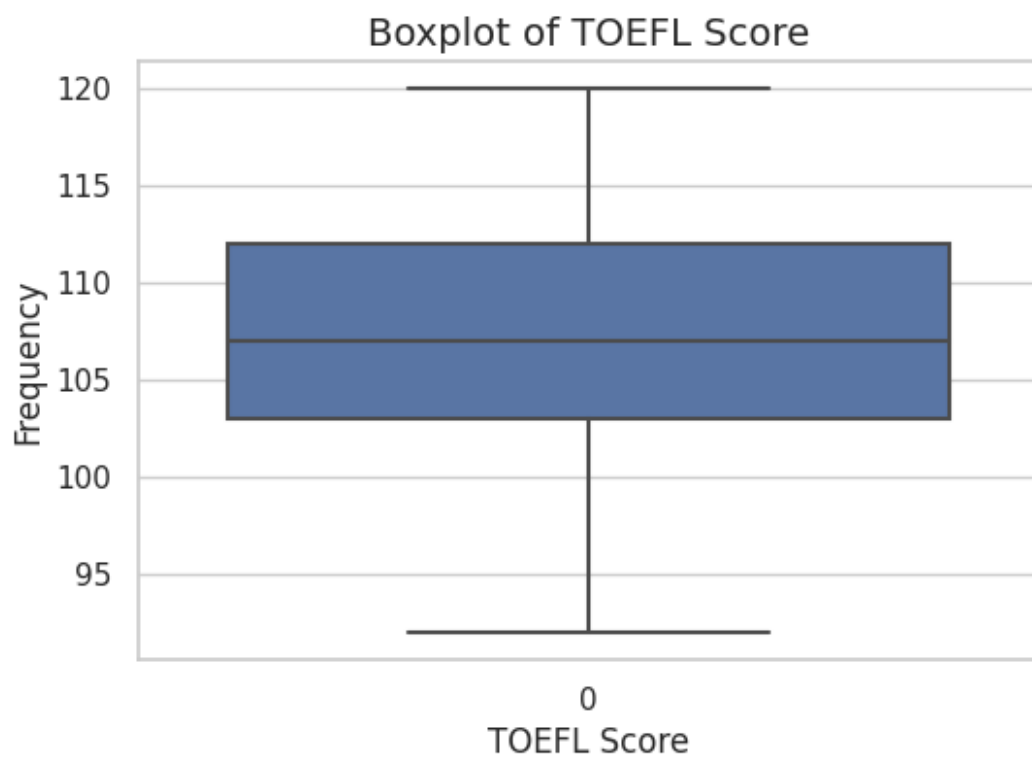
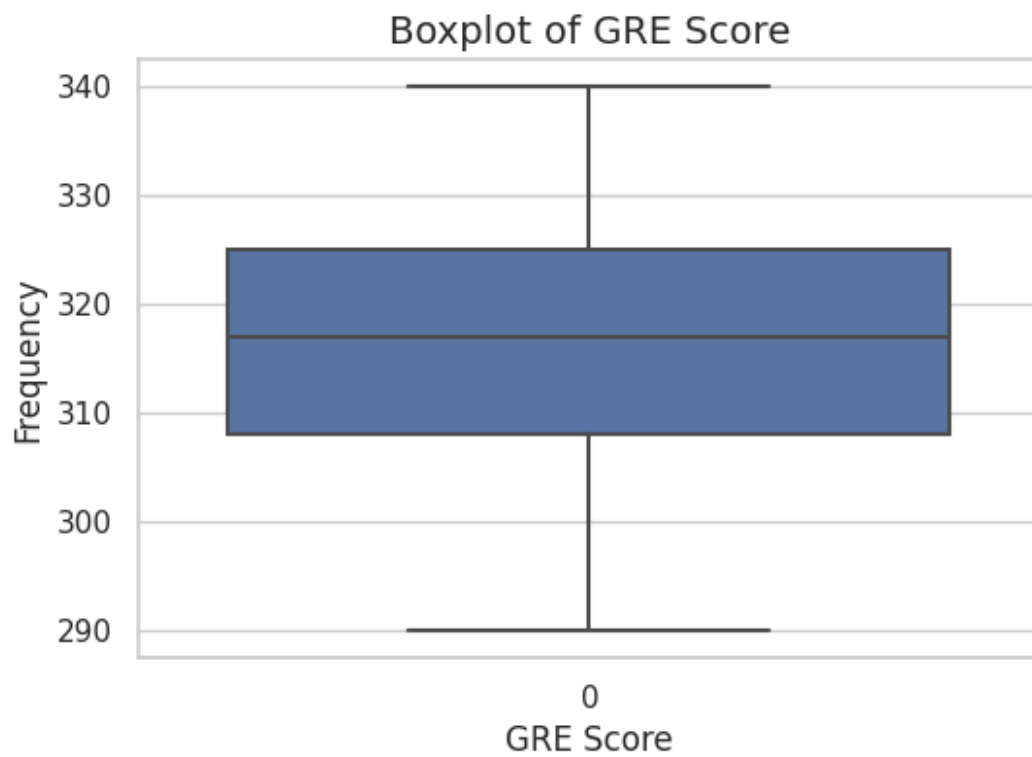


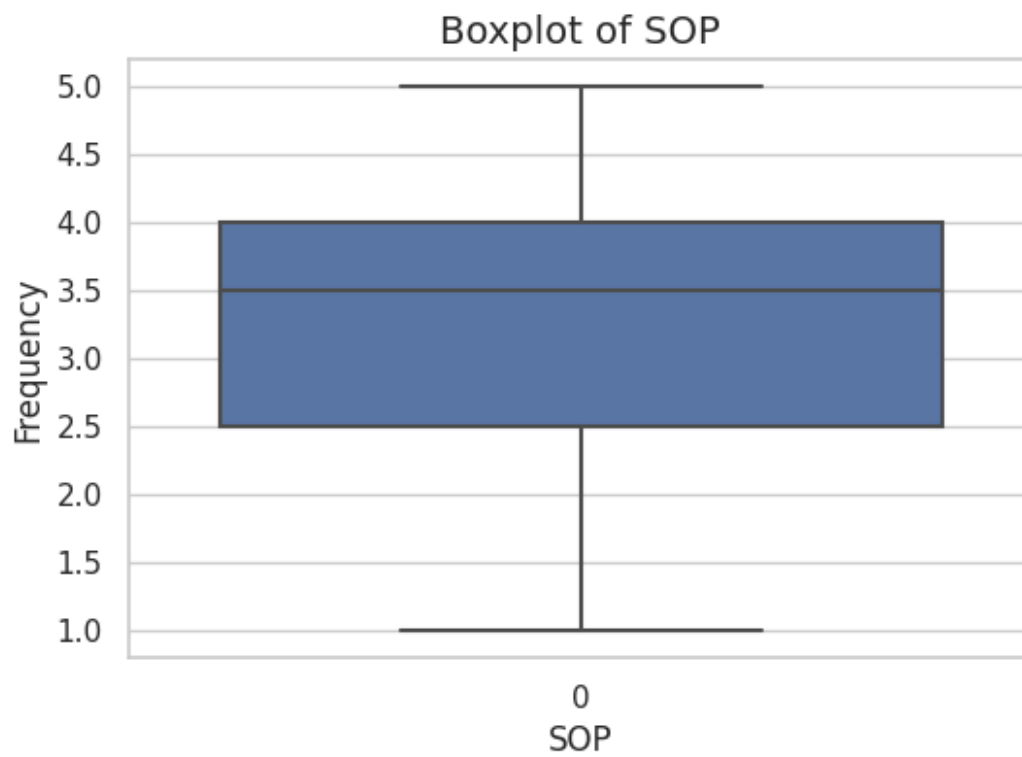
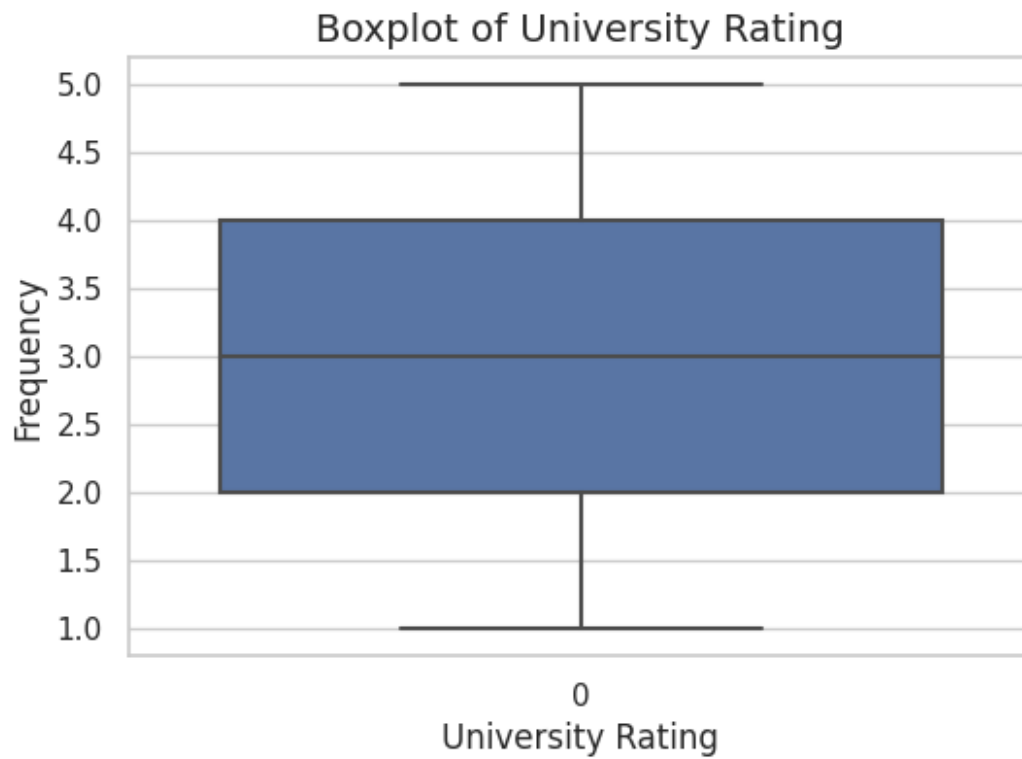


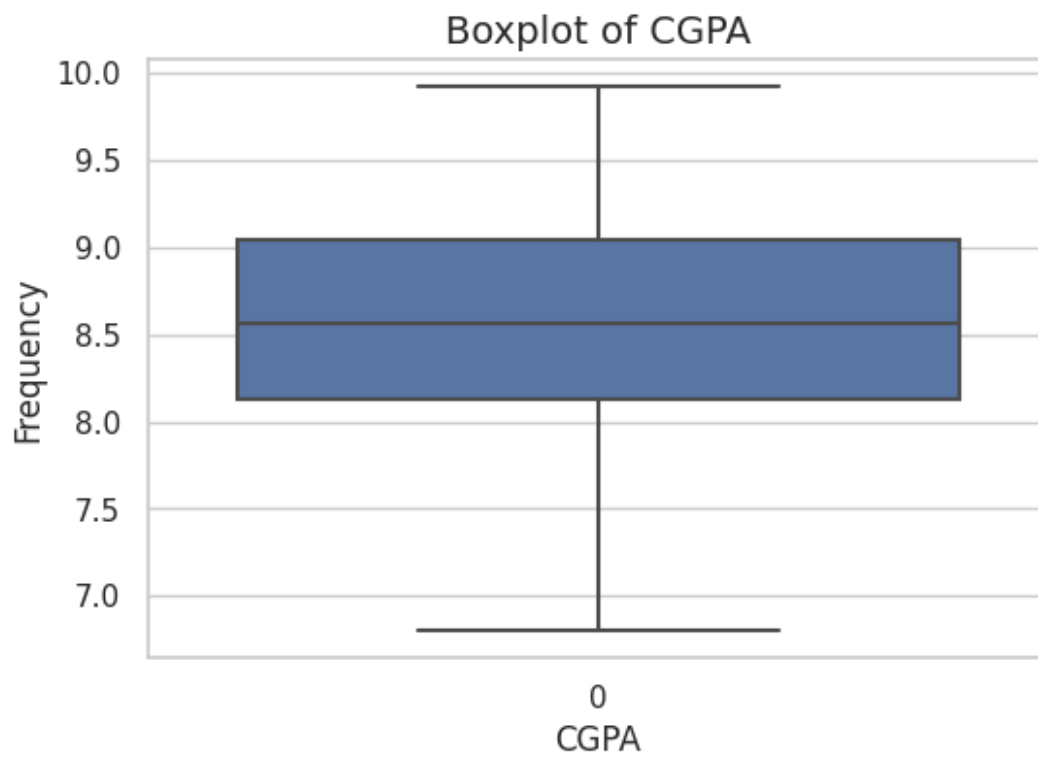
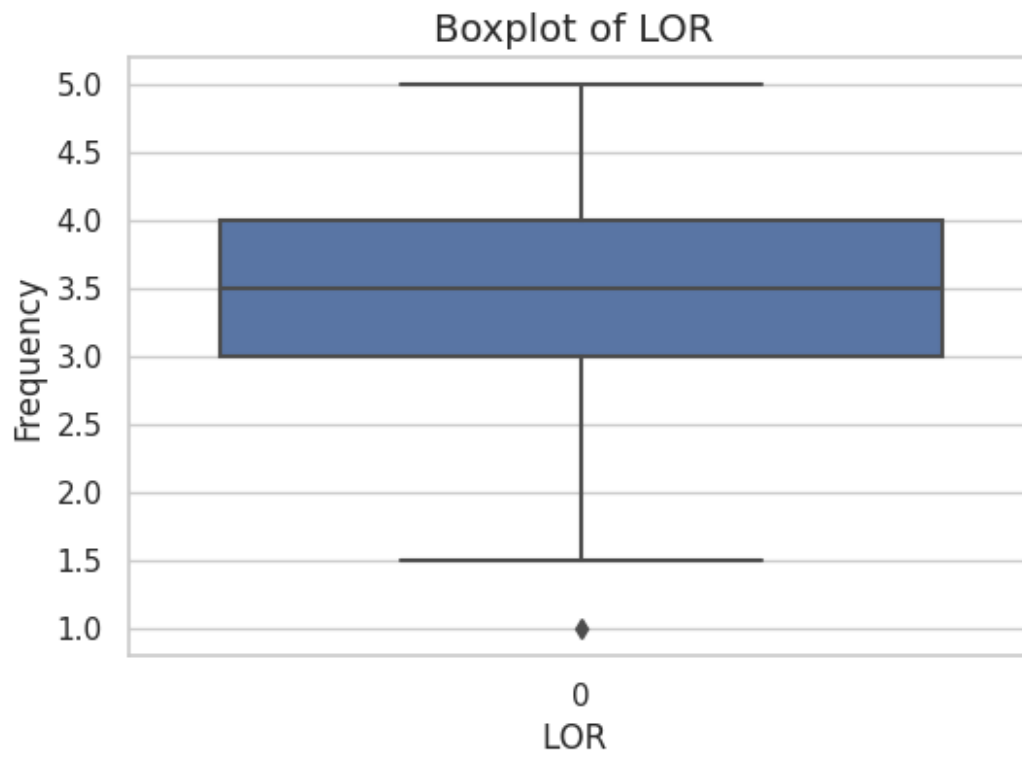


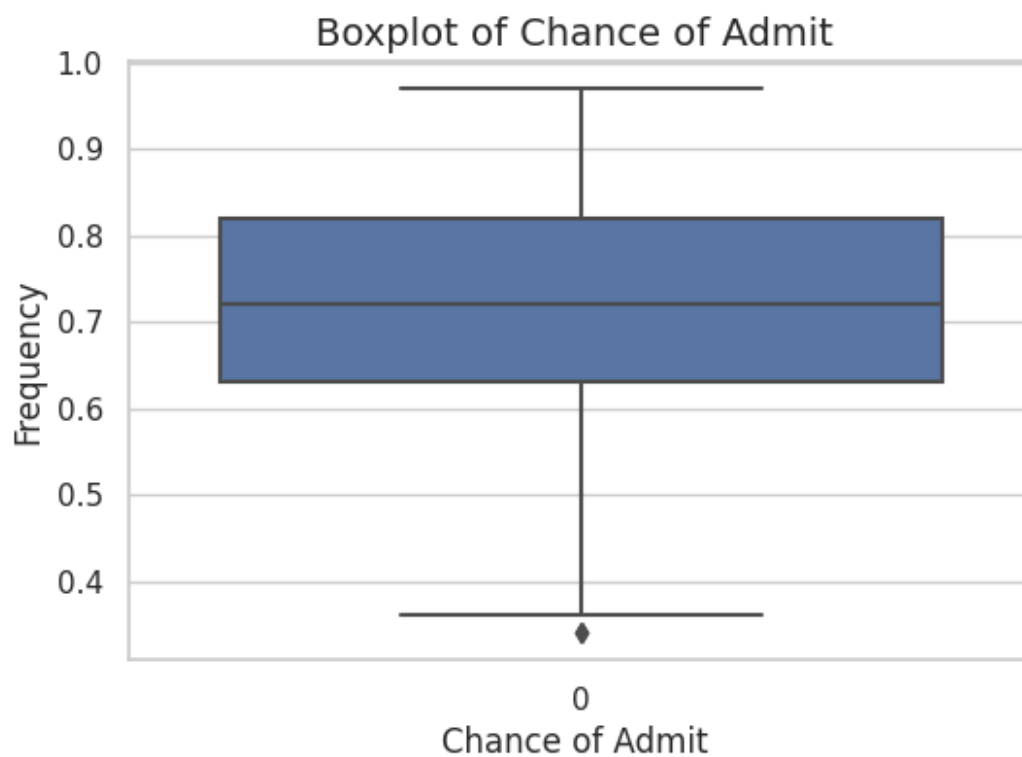
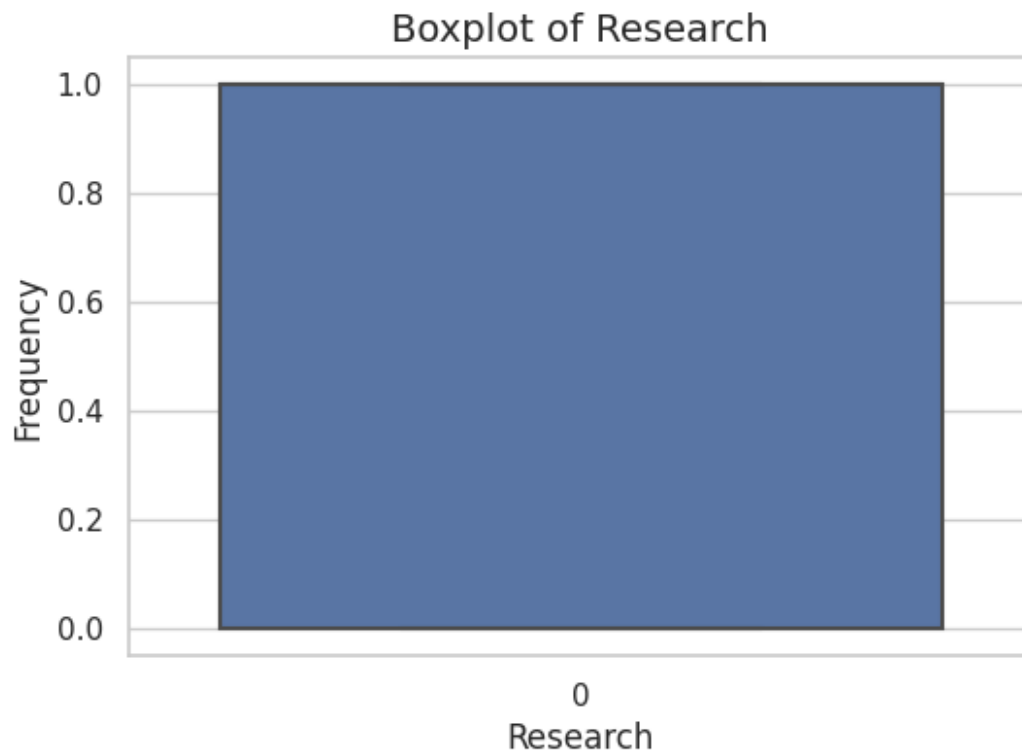


```
for column in df.columns:  
    plt.figure(figsize=(6, 4))  
    sns.boxplot(df[column])  
    plt.title(f'Boxplot of {column}', fontsize=14)  
    plt.xlabel(column, fontsize=12)  
    plt.ylabel('Frequency', fontsize=12)  
    plt.show()
```









outliers found in LOR and ADMIT columns

Bivariate Analysis (Relationships between important variables)

1. Data Preprocessing (10 Points)

- Duplicate value check
- Missing value treatment
- Outlier treatment
- Feature engineering
- Data preparation for modeling

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

sc= ['GRE Score', 'TOEFL Score', 'University Rating', 'SOP', 'LOR ',
     'CGPA']
X= df.drop(columns='Chance of Admit ')
Y= df["Chance of Admit "]

from sklearn.preprocessing import MinMaxScaler
scaler= MinMaxScaler()
X[sc]= scaler.fit_transform(X[sc])

from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(X, Y,
                                                    test_size=0.2, random_state=2)
```

Model building :

- Build the Linear Regression model and comment on the model statistics
- Display model coefficients with column names

```
import statsmodels.api as sm
X_sm= sm.add_constant(X_train)
model= sm.OLS(Y_train, X_sm)
result= model.fit()
print(result.summary())
```

OLS Regression Results

```
=====
=====
Dep. Variable:          Chance of Admit      R-squared:
0.829
```

```

Model:                                OLS    Adj. R-squared:
0.826
Method:                               Least Squares    F-statistic:
272.1
Date:                                Sun, 07 Jan 2024    Prob (F-statistic):
3.33e-146
Time:                                04:01:35    Log-Likelihood:
573.41
No. Observations:                     400    AIC:
-1131.
Df Residuals:                         392    BIC:
-1099.
Df Model:                             7

```

Covariance Type: nonrobust

```

=====
=====
                                coef    std err          t      P>|t|
[0.025    0.975]
-----
const                0.3450    0.010    34.259    0.000
0.325    0.365
GRE Score            0.1067    0.027     3.893    0.000
0.053    0.161
TOEFL Score          0.0826    0.027     3.024    0.003
0.029    0.136
University Rating    0.0194    0.016     1.185    0.237    -
0.013    0.052
SOP                  0.0084    0.020     0.428    0.669    -
0.030    0.047
LOR                  0.0744    0.018     4.131    0.000
0.039    0.110
CGPA                 0.3537    0.033    10.633    0.000
0.288    0.419
Research             0.0247    0.007     3.476    0.001
0.011    0.039
=====
=====
Omnibus:                94.166    Durbin-Watson:
1.943
Prob(Omnibus):          0.000    Jarque-Bera (JB):
231.309
Skew:                   -1.158    Prob(JB):
5.92e-51
Kurtosis:               5.918    Cond. No.
23.4
=====
=====

```

=====

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Testing the assumptions of linear regression model (50 Points)

- Multicollinearity check by VIF score (variables are dropped one-by-one till none has $VIF > 5$) (10 Points)
- Mean of residuals is nearly zero (10 Points)
- Linearity of variables (no pattern in residual plot) (10 Points)
- Test for Homoscedasticity (10 Points)
- Normality of residuals (almost bell-shaped curve in residuals distribution, points in QQ plot are almost all on the line) (10 Points)

```
from statsmodels.stats.outliers_influence import
variance_inflation_factor

vif=pd.DataFrame()
vif["features"]= X_sm.columns
vif['VIF_score'] = [variance_inflation_factor(X_sm, i) for i in
range(X_sm.shape[1])]
vif["VIF_score"]= round(vif["VIF_score"], 2)
vif.sort_values(by='VIF_score', ascending=False)
```

	features	VIF_score
0	const	11.94
6	CGPA	4.77
1	GRE Score	4.24
2	TOEFL Score	4.06
4	SOP	2.71
3	University Rating	2.59
5	LOR	1.98
7	Research	1.47

Mean of residuals is nearly zero

On Test data

```
X_test_sm= sm.add_constant(X_test)
Y_test_pred= result.predict(X_test_sm)
error_test= Y_test-Y_test_pred

error_test.mean()
```

```
-0.006100917484112264
```

On train data(Mean of residuals)

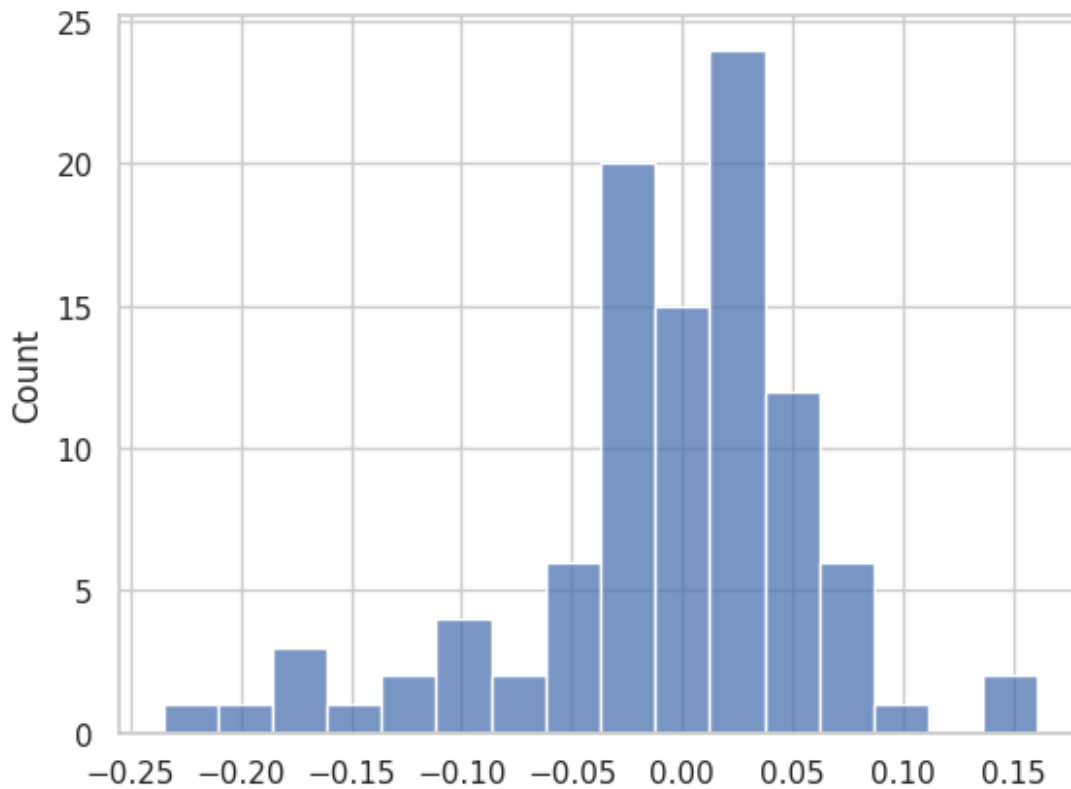
```
Y_train_pred= result.predict(X_sm)  
error_train= Y_train-Y_train_pred  
error_train.mean()
```

```
-1.6597834218146091e-16
```

Linearity of variables (no pattern in residual plot)

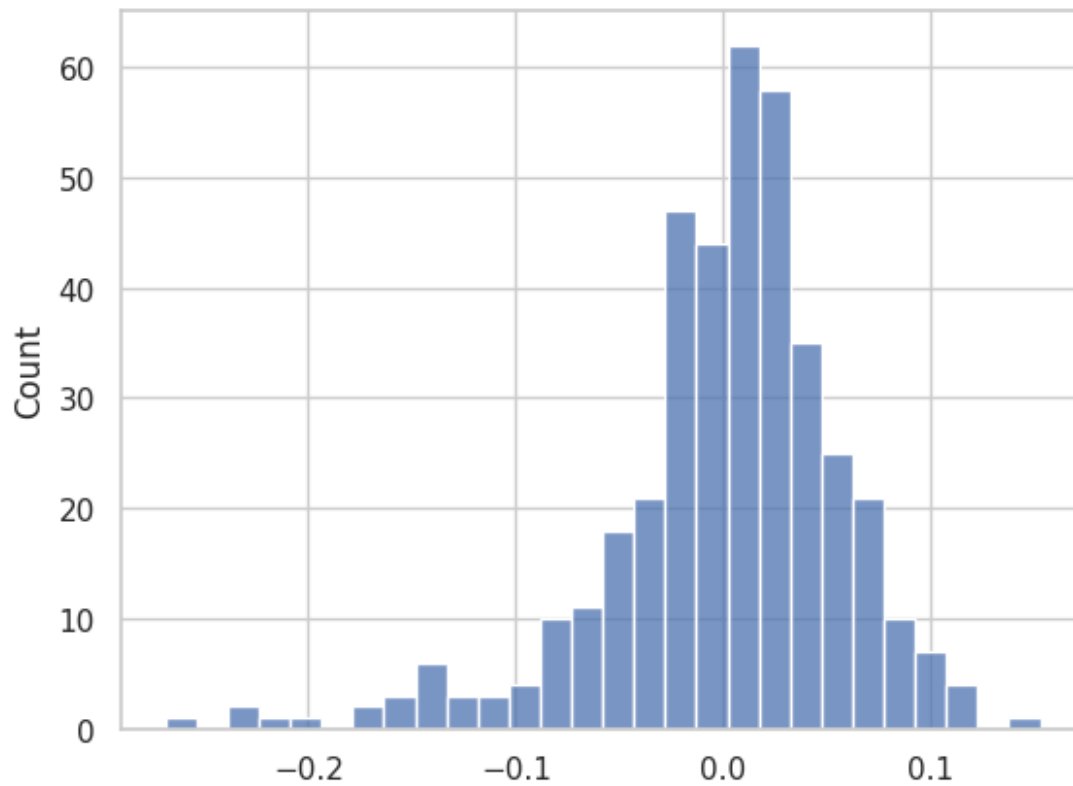
```
sns.histplot(error_test)
```

```
<Axes: ylabel='Count'>
```



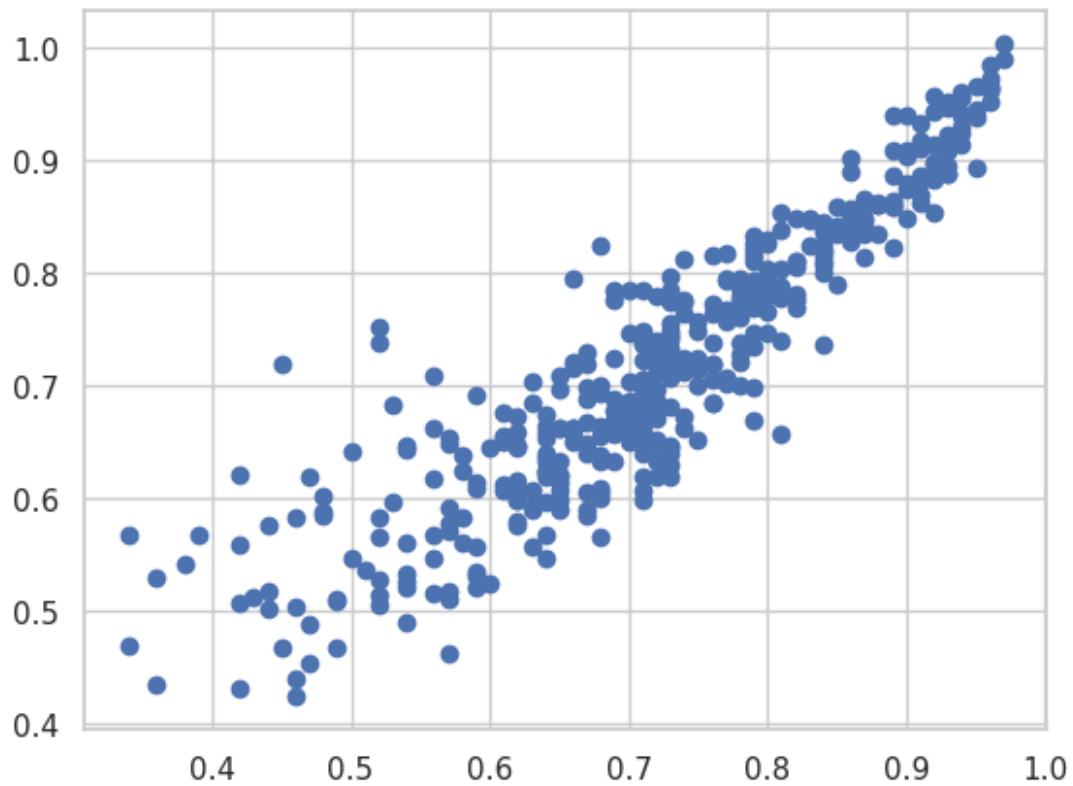
```
sns.histplot(error_train)
```

```
<Axes: ylabel='Count'>
```

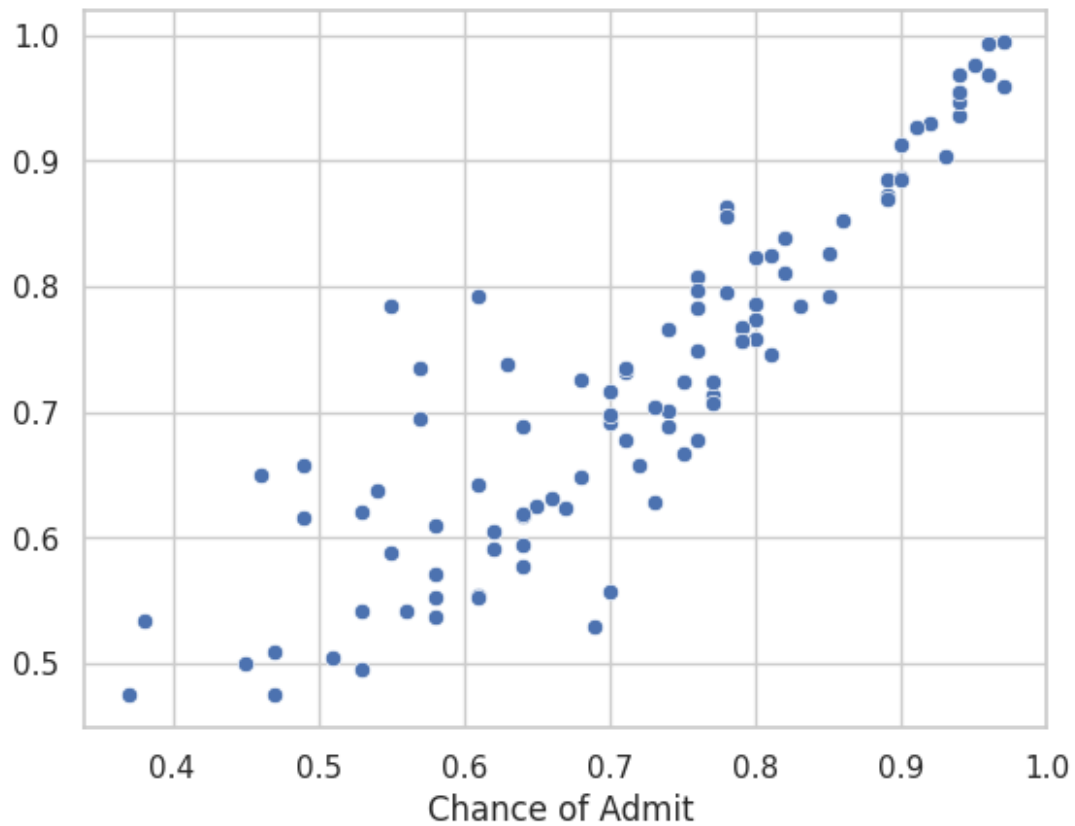


```
plt.scatter(Y_train, Y_train_pred)
```

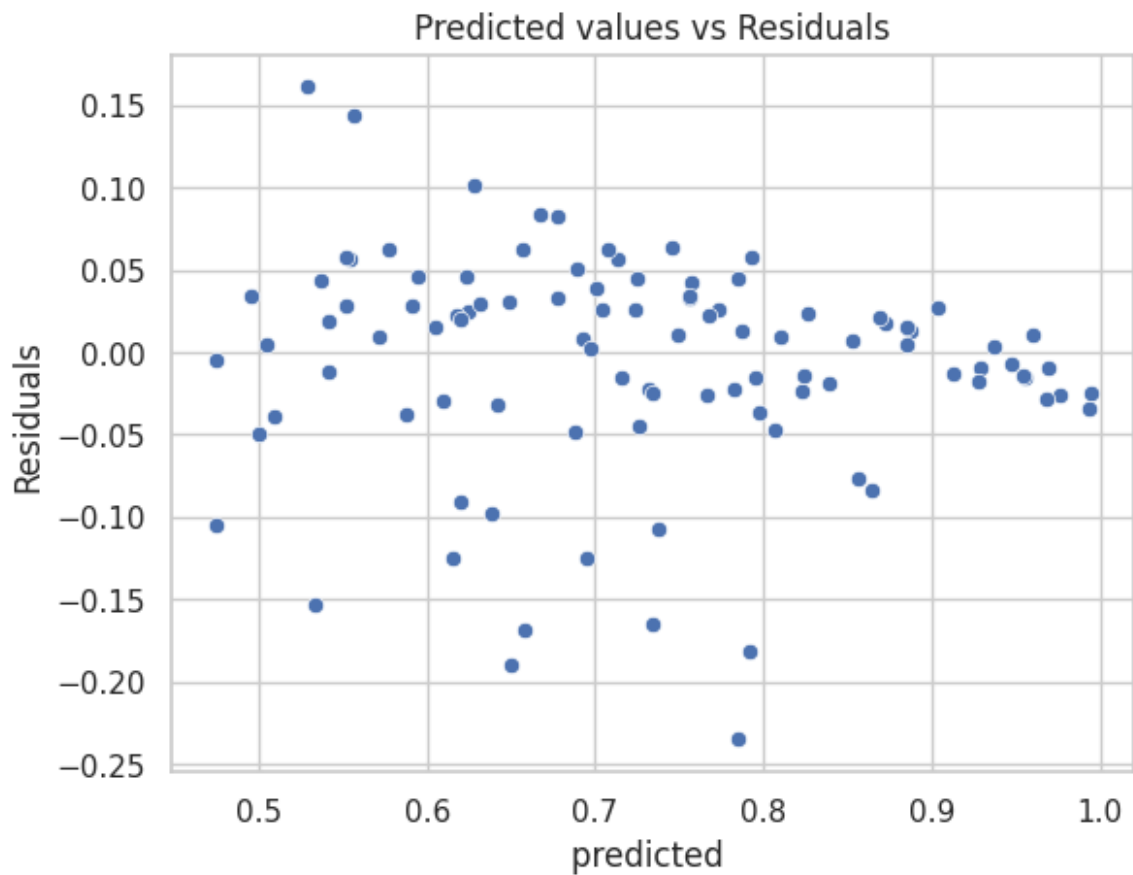
```
<matplotlib.collections.PathCollection at 0x7b86dbc57b80>
```

```
sns.scatterplot(x=Y_test, y=Y_test_pred)  
<Axes: xlabel='Chance of Admit '>
```

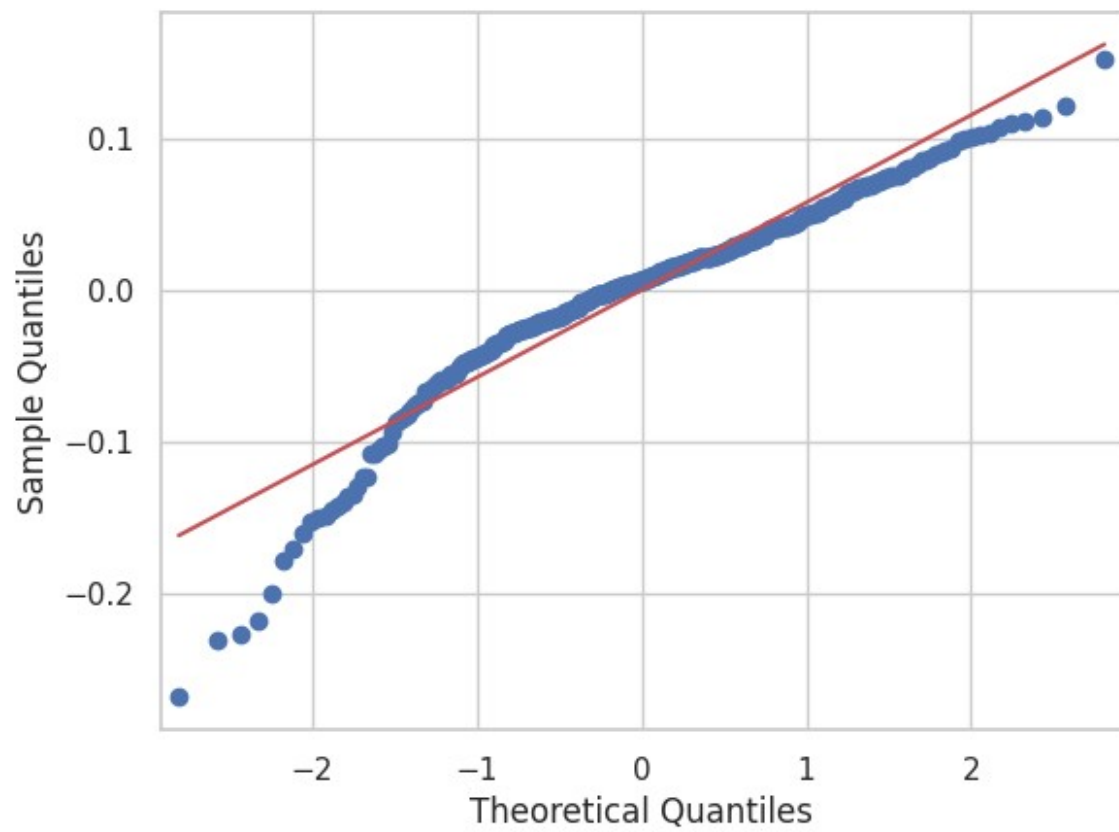


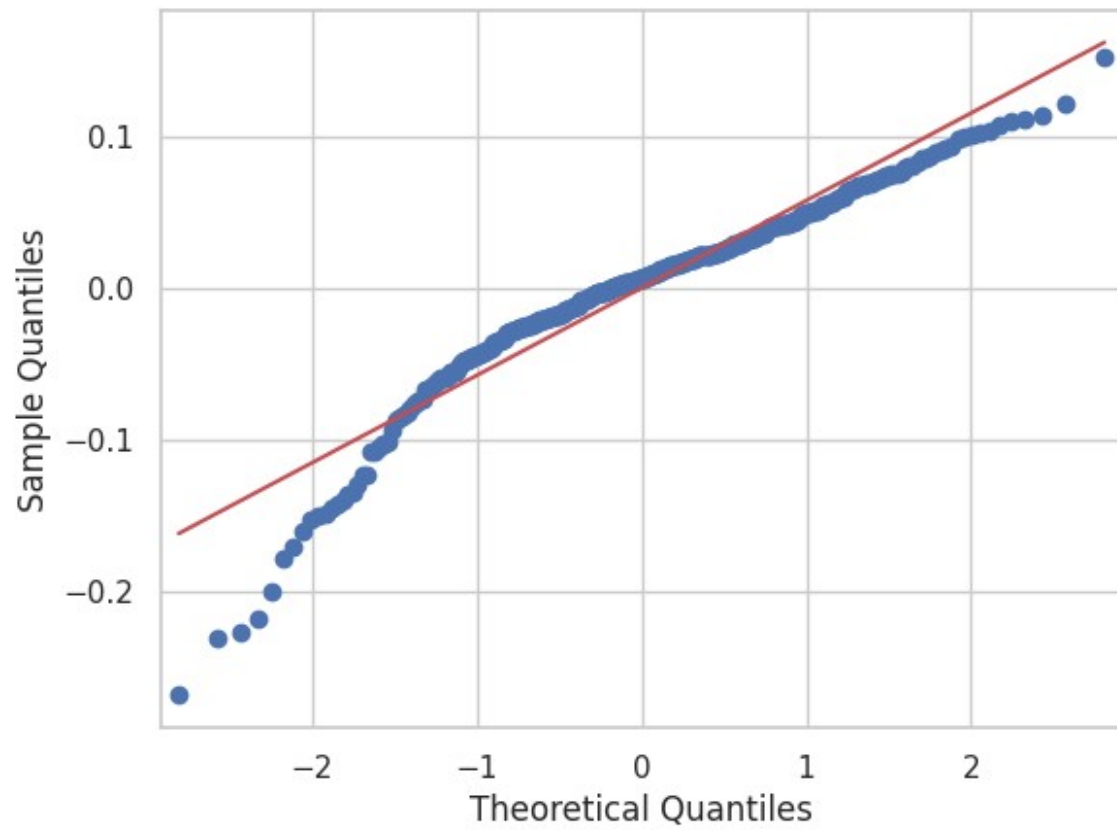
```
sns.scatterplot(x= Y_test_pred,y=error_test)
plt.xlabel("predicted ")
plt.ylabel("Residuals")
plt.title("Predicted values vs Residuals")
Text(0.5, 1.0, 'Predicted values vs Residuals')
```



Q-Q plot (residuals on train data)

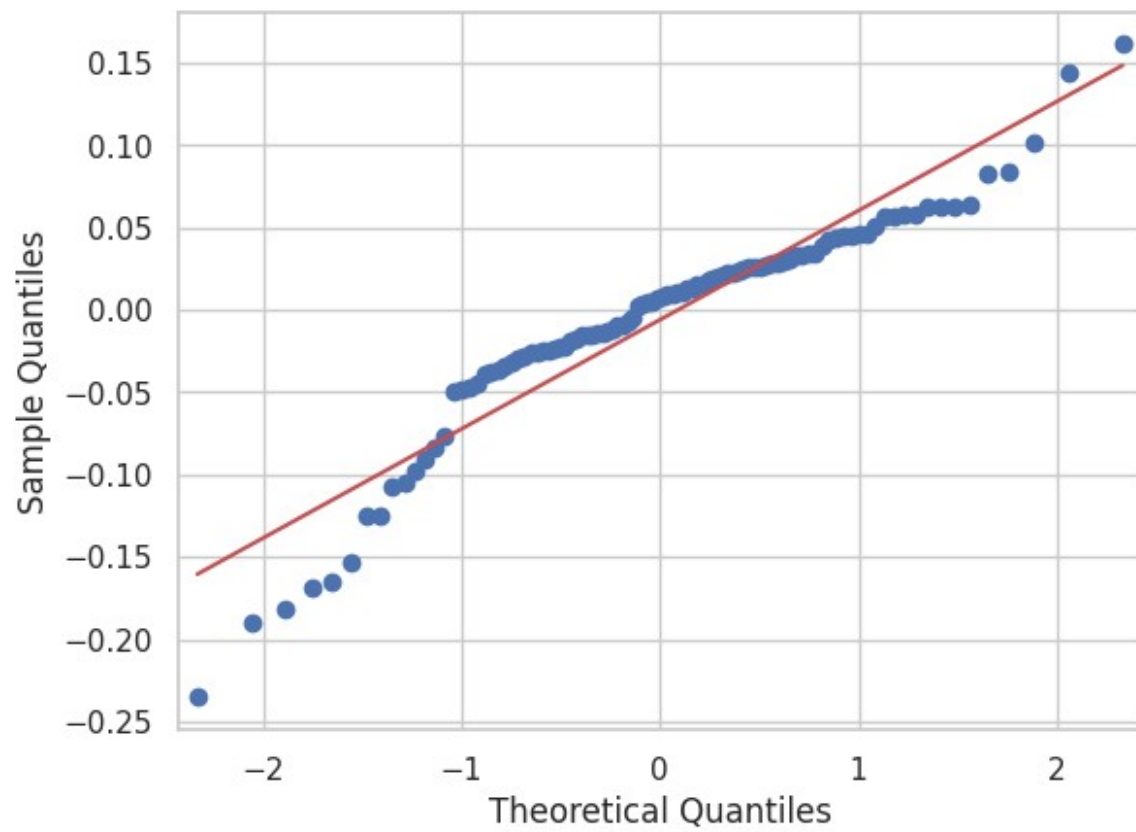
```
from statsmodels.graphics.gofplots import qqplot
qqplot( error_train, line='s')
```

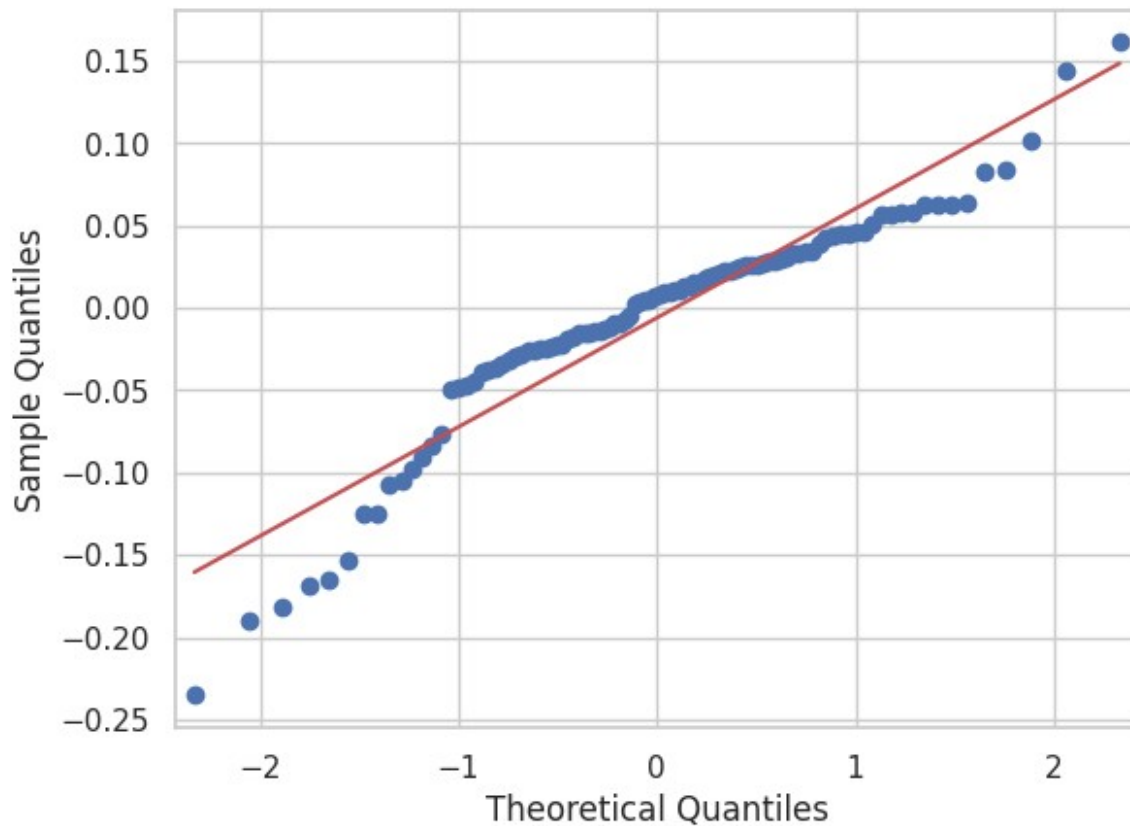




Q-Q plot (residuals on test data)

```
qqplot(error_test, line='s')
```





Test for Homoscedasticity

- Null Hypothesis: Heteroscedasticity is not present.
- Alternate Hypothesis: Heteroscedasticity is present.

```
from statsmodels.compat import lzip
import statsmodels.stats.api as sms

name = ['F statistic', 'p-value']
test = sms.het_goldfeldquandt(Y_train, X_sm)
lzip(name, test)

[('F statistic', 1.0772994279987238), ('p-value',
0.30323276479815664)]
```

Model performance evaluation

- Metrics checked - MAE, RMSE, R2, Adj R2

```
from sklearn.metrics import r2_score, mean_squared_error,
mean_absolute_error
```

For Test data

```
print("r2 score: ", r2_score(Y_test,Y_test_pred))
print("mean squared error: ", mean_squared_error(Y_test,Y_test_pred))
print("mean absolute error: ",
mean_absolute_error(Y_test,Y_test_pred))
```

```
r2 score:  0.7927524897595928
mean squared error:  0.004429285498957571
mean absolute error:  0.04730057428620608
```

Train data

```
print(result.summary())
```

OLS Regression Results

```
=====
=====
Dep. Variable:          Chance of Admit    R-squared:
0.829
Model:                                OLS    Adj. R-squared:
0.826
Method:                    Least Squares    F-statistic:
272.1
Date:                      Sun, 07 Jan 2024    Prob (F-statistic):
3.33e-146
Time:                      04:48:29    Log-Likelihood:
573.41
No. Observations:          400    AIC:
-1131.
Df Residuals:              392    BIC:
-1099.
Df Model:                  7
```

```
Covariance Type:          nonrobust
```

```
=====
=====
[0.025      0.975]
-----
-----
const                0.3450    0.010    34.259    0.000
0.325      0.365
GRE Score            0.1067    0.027     3.893    0.000
0.053      0.161
TOEFL Score          0.0826    0.027     3.024    0.003
```


0.029	0.136					
University Rating		0.0194	0.016	1.185	0.237	-
0.013	0.052					
SOP		0.0084	0.020	0.428	0.669	-
0.030	0.047					
LOR		0.0744	0.018	4.131	0.000	
0.039	0.110					
CGPA		0.3537	0.033	10.633	0.000	
0.288	0.419					
Research		0.0247	0.007	3.476	0.001	
0.011	0.039					

=====

=====

Omnibus:	94.166	Durbin-Watson:
1.943		
Prob(Omnibus):	0.000	Jarque-Bera (JB):
231.309		
Skew:	-1.158	Prob(JB):
5.92e-51		
Kurtosis:	5.918	Cond. No.
23.4		

=====

=====

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Based on significance level we can drop SOP and University rating

```
X_sm_SOP_Urating= X_sm.drop(columns=["SOP", "University Rating"])
modell= sm.OLS(Y_train, X_sm_SOP_Urating)
result1=modell.fit()
print(result1.summary())
```

OLS Regression Results

=====

=====

Dep. Variable:	Chance of Admit	R-squared:
0.828		
Model:	OLS	Adj. R-squared:
0.826		
Method:	Least Squares	F-statistic:
380.3		
Date:	Sun, 07 Jan 2024	Prob (F-statistic):
2.65e-148		
Time:	04:58:07	Log-Likelihood:
572.28		

No. Observations: 400 AIC:
-1133.
Df Residuals: 394 BIC:
-1109.
Df Model: 5

Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025
0.975]					

const	0.3425	0.010	34.923	0.000	0.323
0.362					
GRE Score	0.1086	0.027	3.970	0.000	0.055
0.162					
TOEFL Score	0.0887	0.027	3.298	0.001	0.036
0.142					
LOR	0.0836	0.017	5.050	0.000	0.051
0.116					
CGPA	0.3667	0.032	11.465	0.000	0.304
0.430					
Research	0.0254	0.007	3.573	0.000	0.011
0.039					
=====					
=====					
Omnibus:	90.913		Durbin-Watson:		
1.941					
Prob(Omnibus):	0.000		Jarque-Bera (JB):		
218.765					
Skew:	-1.127		Prob(JB):		
3.13e-48					
Kurtosis:	5.837		Cond. No.		
20.6					
=====					
=====					

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Metric values after dropping SOP and University rating

```
Y_pred_new= result1.predict(X_sm_SOP_Urating)
print("r2 score: ", r2_score(Y_train,Y_pred_new))
print("mean squared error: ", mean_squared_error(Y_train,Y_pred_new))
```

```
print("mean absolute error: ",  
mean_absolute_error(Y_train,Y_pred_new))  
  
r2 score: 0.8283544154206002  
mean squared error: 0.003348330647824238  
mean absolute error: 0.04166067850716051
```

Recommendations

- Important features to increase chances of admit are a good CGPA, GRE, TOEFL score respectively
- The model predicts with an accuracy of 82%
- University rating and SOP are insignificant features