```
#import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

```
# read dataset
dataframe = pd.read_csv("Jamboree_Admission.csv")
```

## Basic data cleaning and exploration

```
dataframe.head()
```

| | 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 |

```
dataframe.describe()
```

| | Serial No. | GRE Score | TOEFL Score | University Rating | SOP | LOR | CGPA |
|---|---|---|---|---|---|---|---|
| **count** | 500.000000 | 500.000000 | 500.000000 | 500.000000 | 500.000000 | 500.00000 | 500.000000 |
| **mean** | 250.500000 | 316.472000 | 107.192000 | 3.114000 | 3.374000 | 3.48400 | 8.576440 |
| **std** | 144.481833 | 11.295148 | 6.081868 | 1.143512 | 0.991004 | 0.92545 | 0.604813 |
| **min** | 1.000000 | 290.000000 | 92.000000 | 1.000000 | 1.000000 | 1.00000 | 6.800000 |
| **25%** | 125.750000 | 308.000000 | 103.000000 | 2.000000 | 2.500000 | 3.00000 | 8.127500 |
| **50%** | 250.500000 | 317.000000 | 107.000000 | 3.000000 | 3.500000 | 3.50000 | 8.560000 |
| **75%** | 375.250000 | 325.000000 | 112.000000 | 4.000000 | 4.000000 | 4.00000 | 9.040000 |

## EDA:

Range of Serial No. is 1 to 500. i.e. Unique Row Values.

Range of GRE Score is 290 to 340.

Range of TOEFL Score is 92 to 120.

Range of CGPA is 6.8 to 9.92.

Range of University Rating(Catagorical) is 1 to 5.

Range of SOP and LOR (Catagorical) is 1 to 5.

## The dataset has been thoroughly examined, revealing the absence of outliers. All data points fall within the expected range, ensuring the integrity and reliability of the dataset.

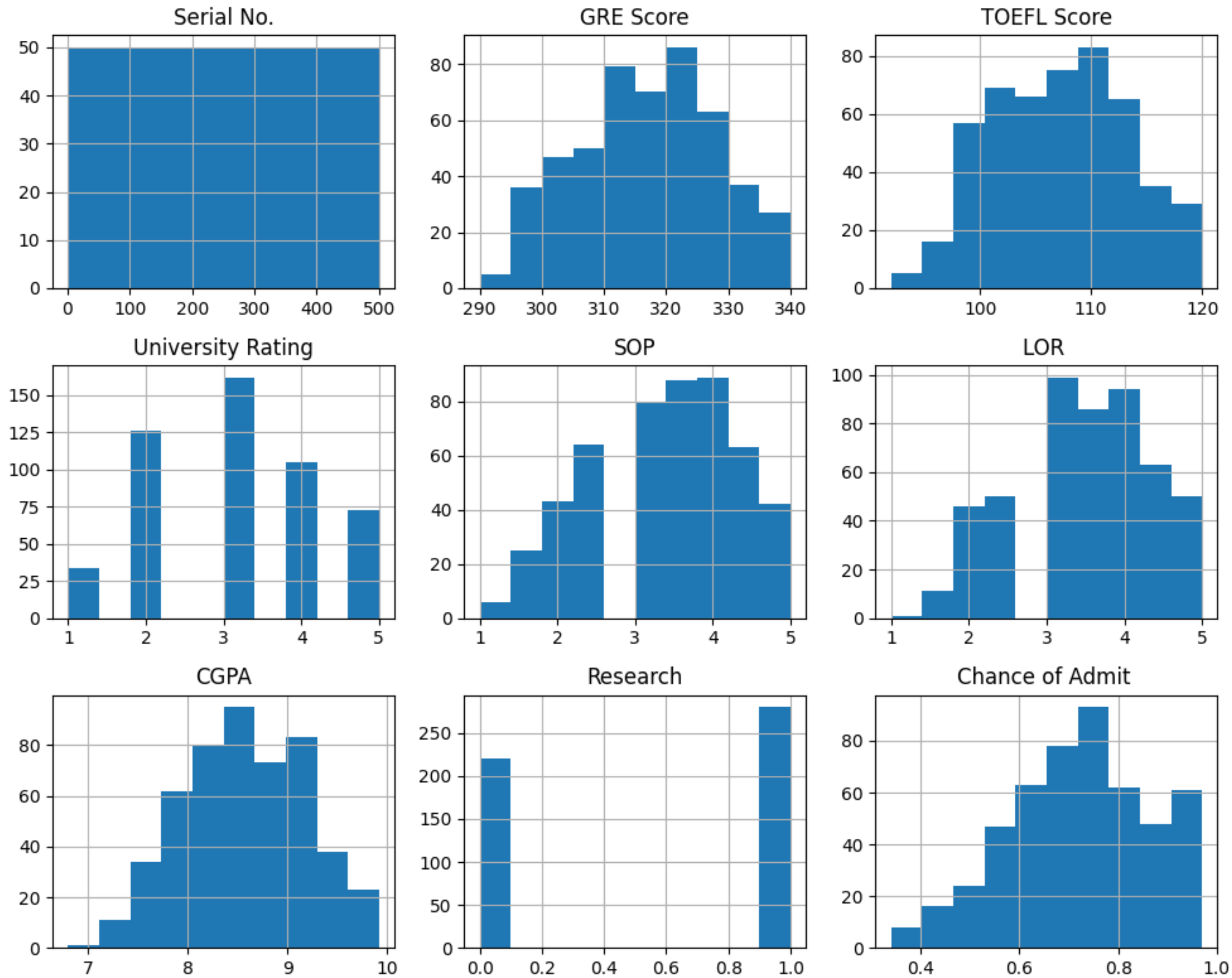
```
dataframe.info()
```

```
<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
```

```
# Checking NA values
dataframe.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
```

```
# Visualizing the distribution of numerical variables
dataframe.hist(figsize=(10, 8))
plt.tight_layout()
plt.show()
```



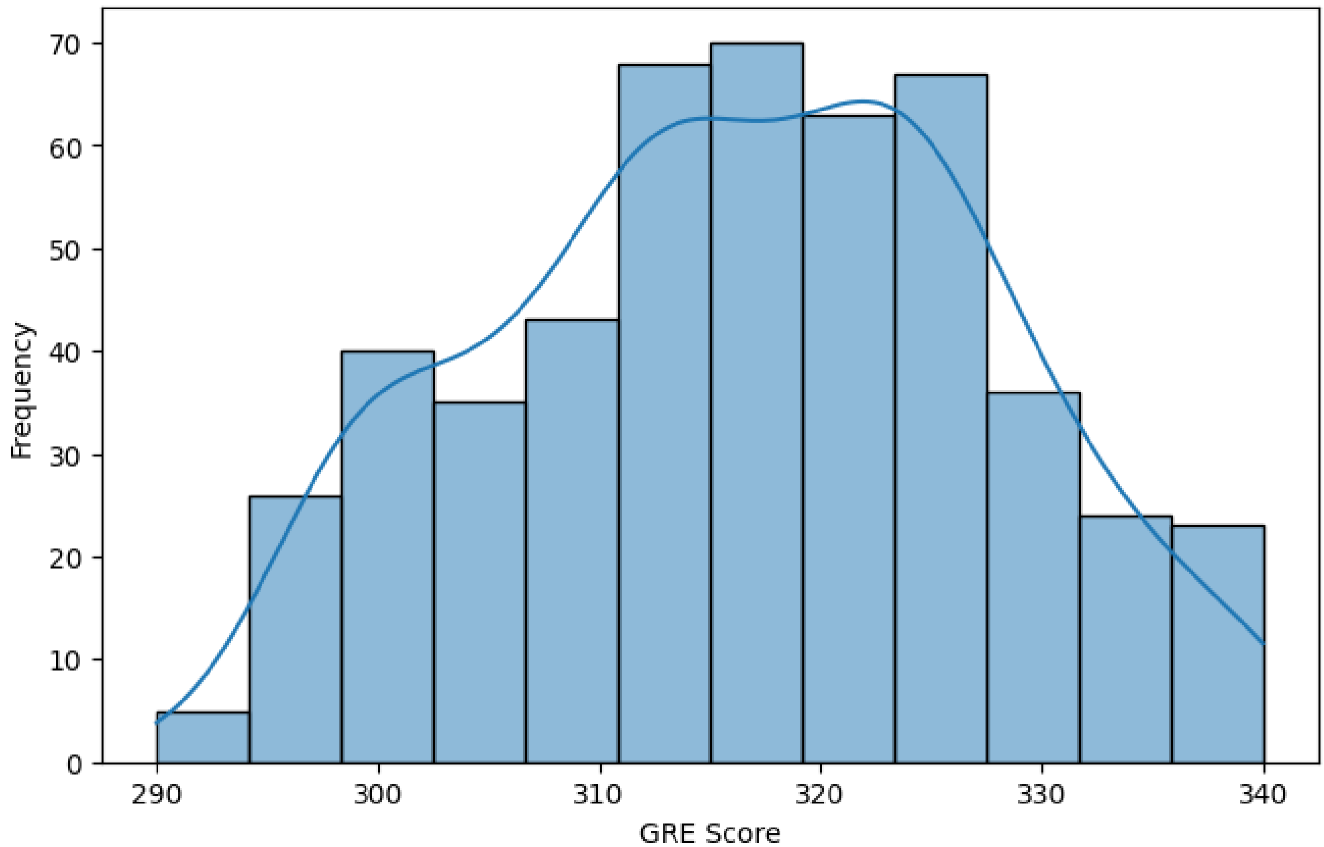

```
dataframe.nunique()
```

```
Serial No.           500
GRE Score             49
TOEFL Score           29
University Rating      5
SOP                    9
LOR                    9
CGPA                 184
Research               2
Chance of Admit       61
dtype: int64
```

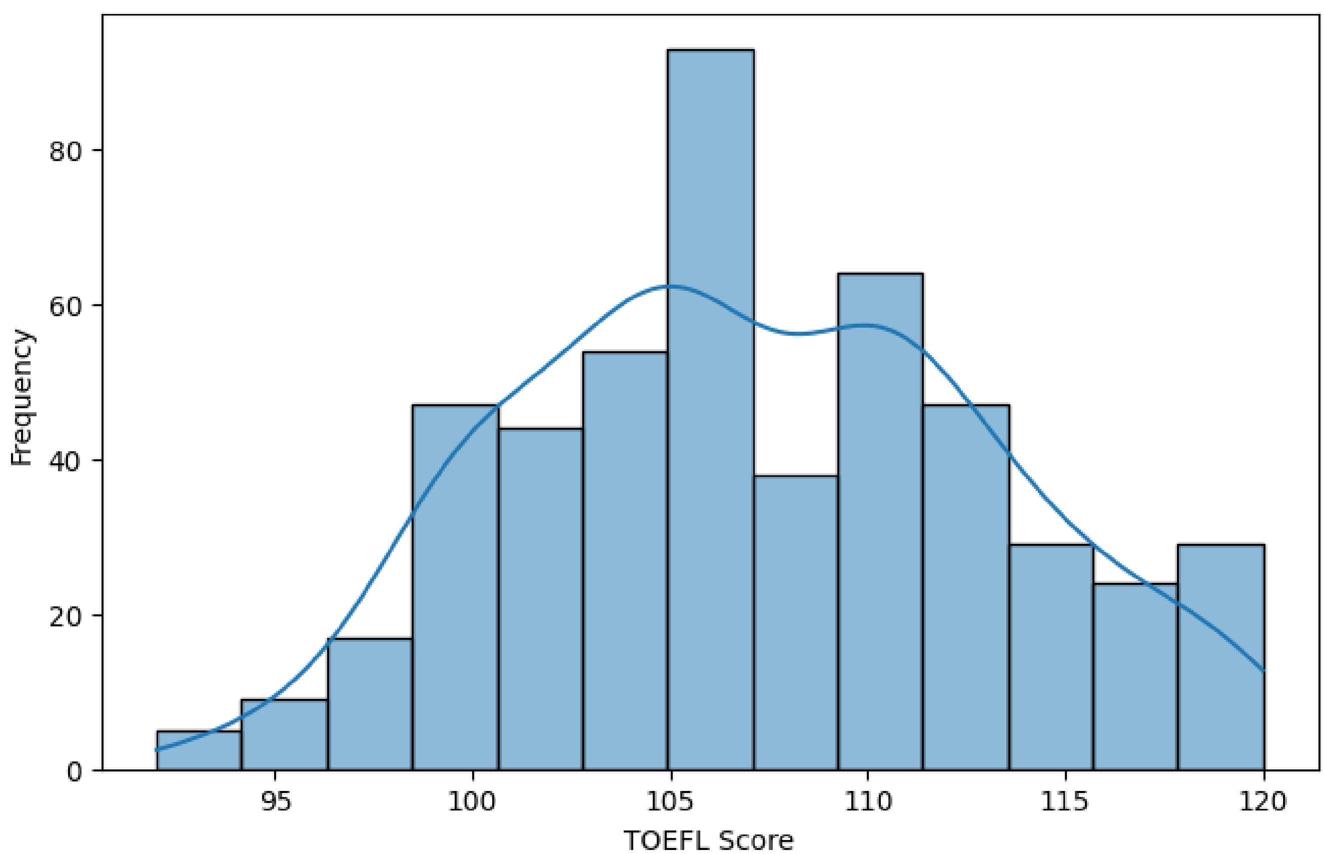
```
# Assuming 'dataframe' is your DataFrame
dataframe.drop(columns=['Serial No.'], inplace=True)
```

```
import seaborn as sns
# Univariate analysis for continuous variables (distribution plots)
continuous_vars = ['GRE Score', 'TOEFL Score', 'CGPA']
for var in continuous_vars:
    plt.figure(figsize=(8, 5))
    sns.histplot(dataframe[var], kde=True)
    plt.title(f'Distribution of {var}')
    plt.xlabel(var)
    plt.ylabel('Frequency')
    plt.show()

# Univariate analysis for categorical variables (bar plots/count plots)
categorical_vars = ['Research', 'University Rating','SOP', 'LOR ', 'Chance of Admit ']
for var in categorical_vars:
    plt.figure(figsize=(8, 5))
    sns.countplot(data=dataframe
              , x=var)
    plt.title(f'Count Plot of {var}')
    plt.xlabel(var)
    plt.ylabel('Count')
    plt.show()
```

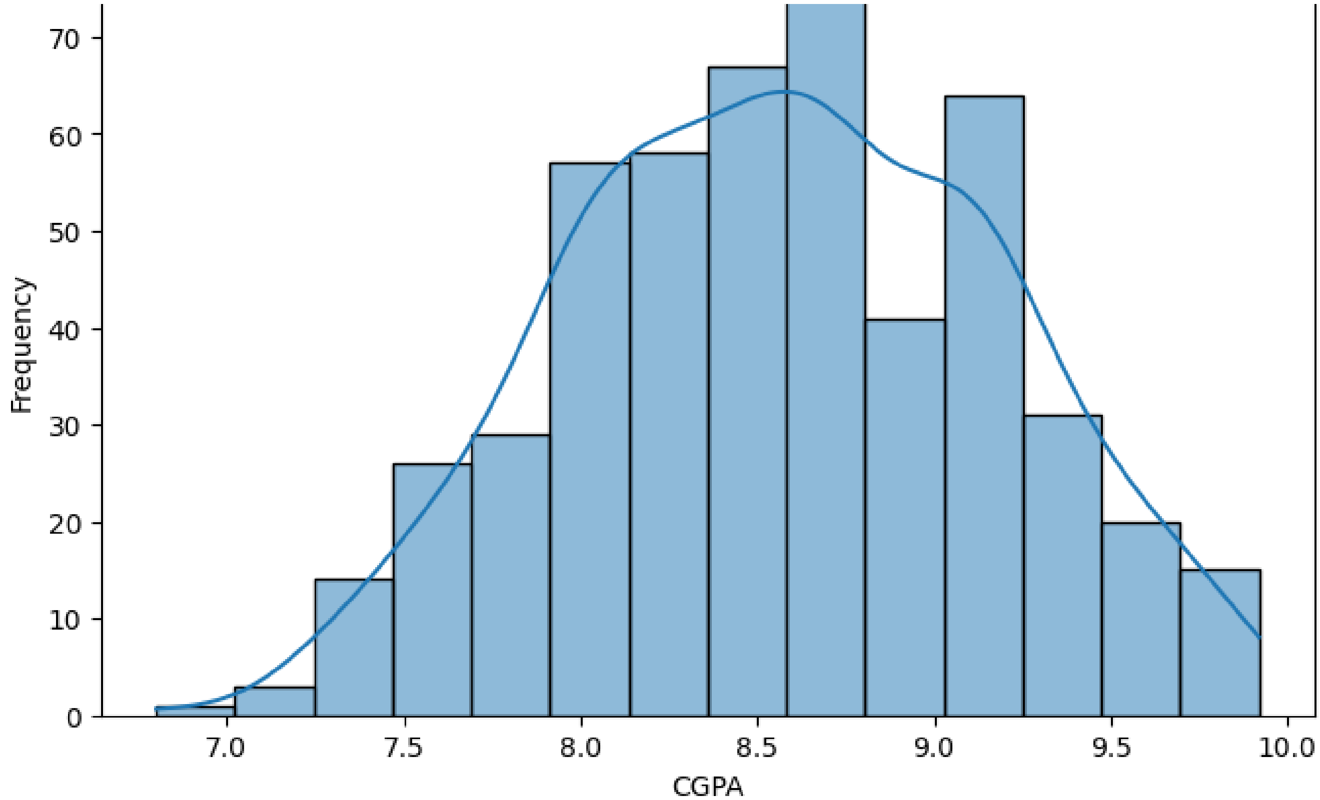
Distribution of GRE Score

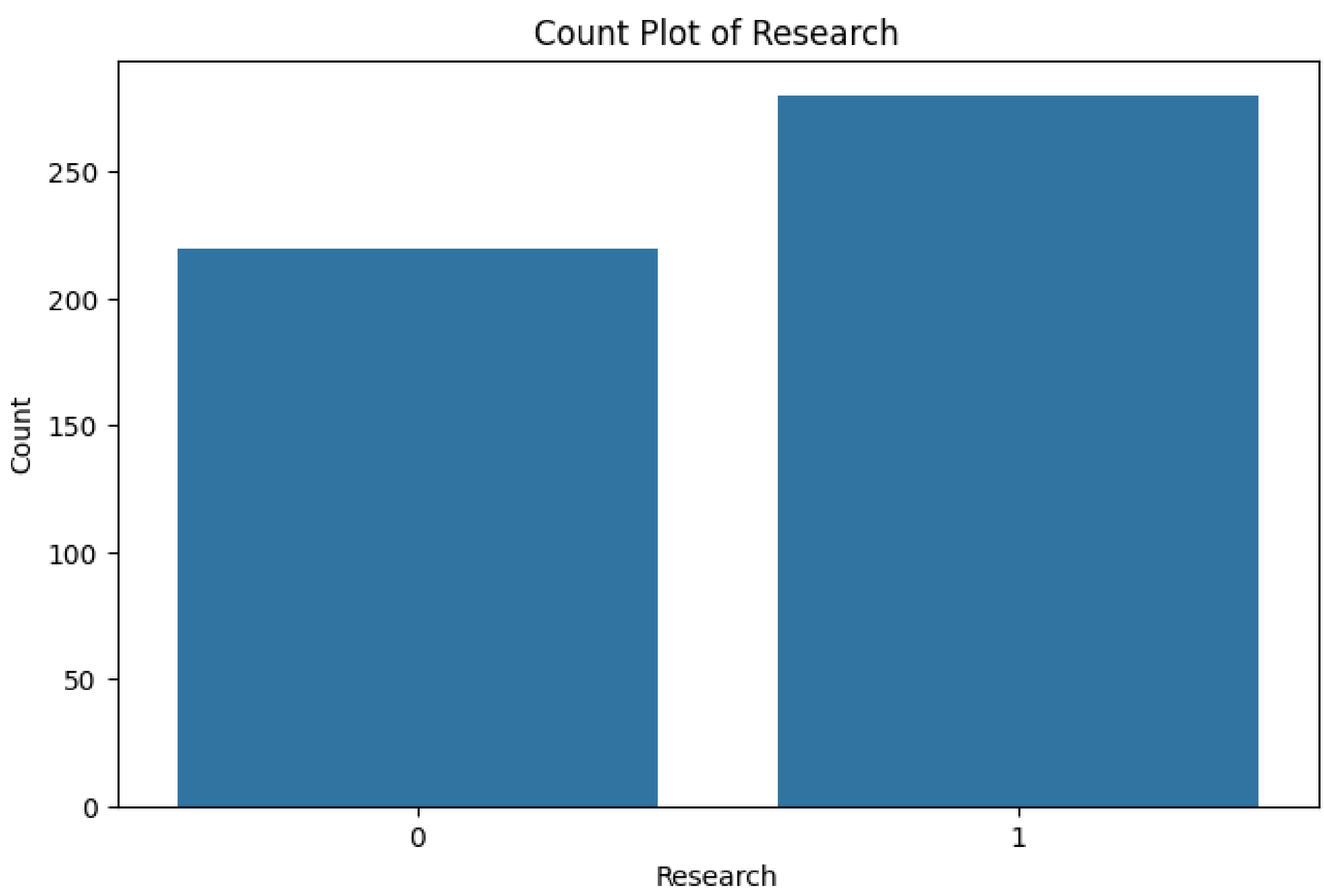


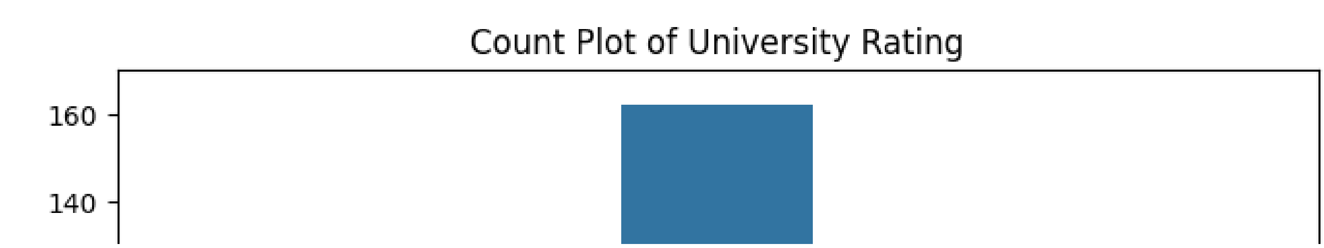

Distribution of TOEFL Score

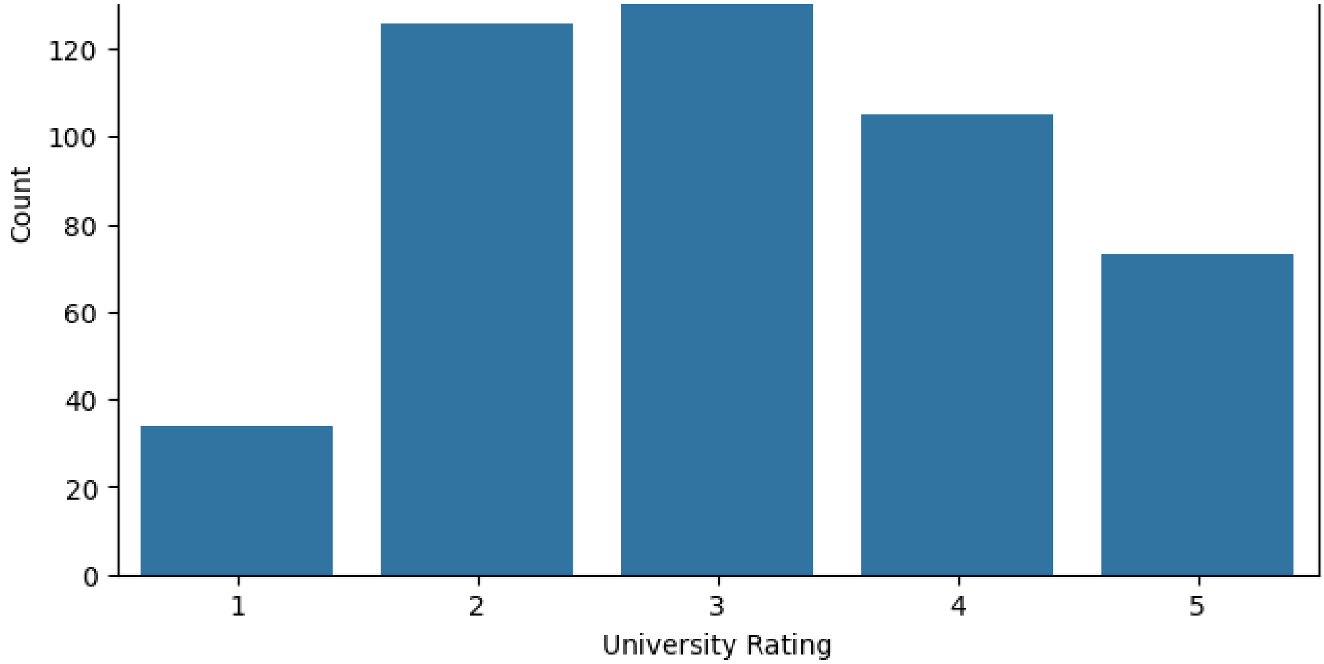


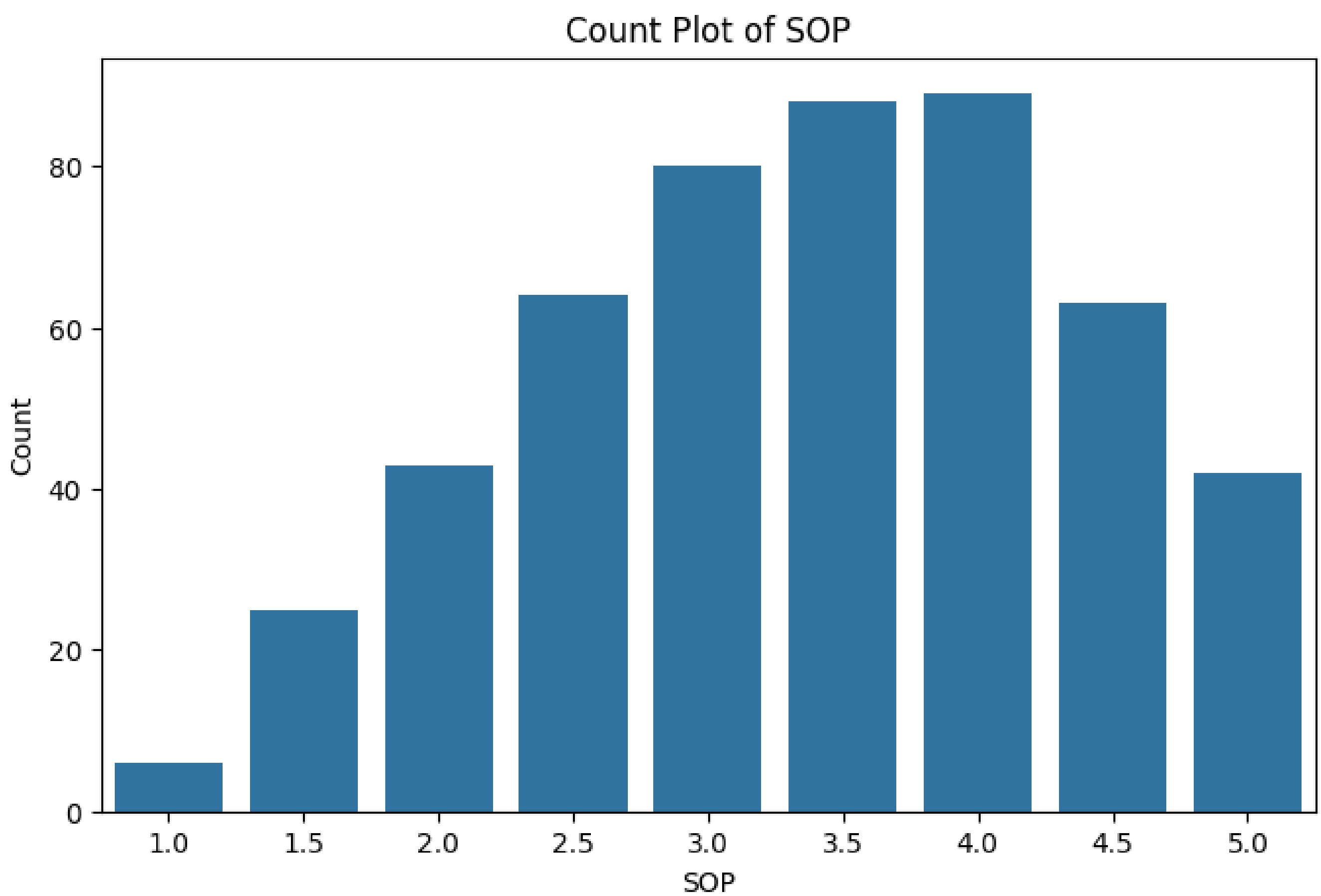

Distribution of CGPA

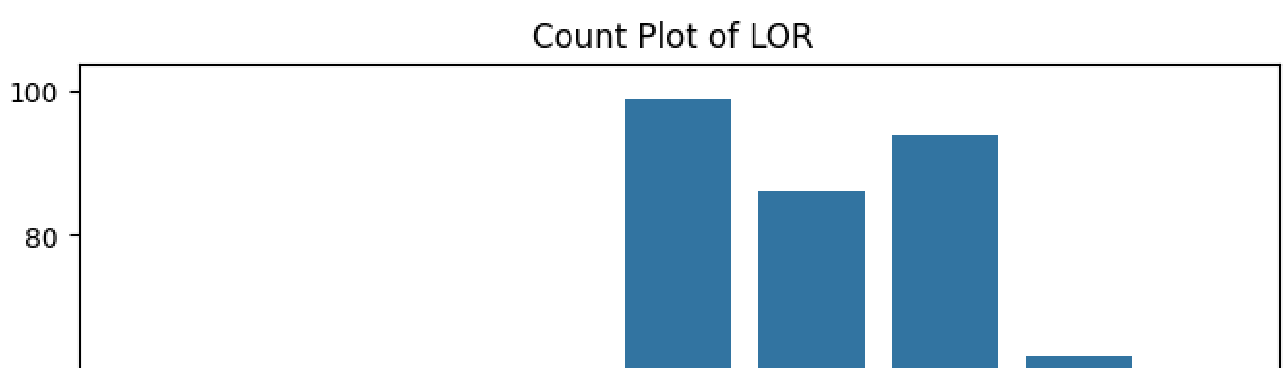

Frequency
70
60
50
40
30
20
10
0
7.0
7.5
8.0
8.5
9.0
9.5
10.0
CGPA

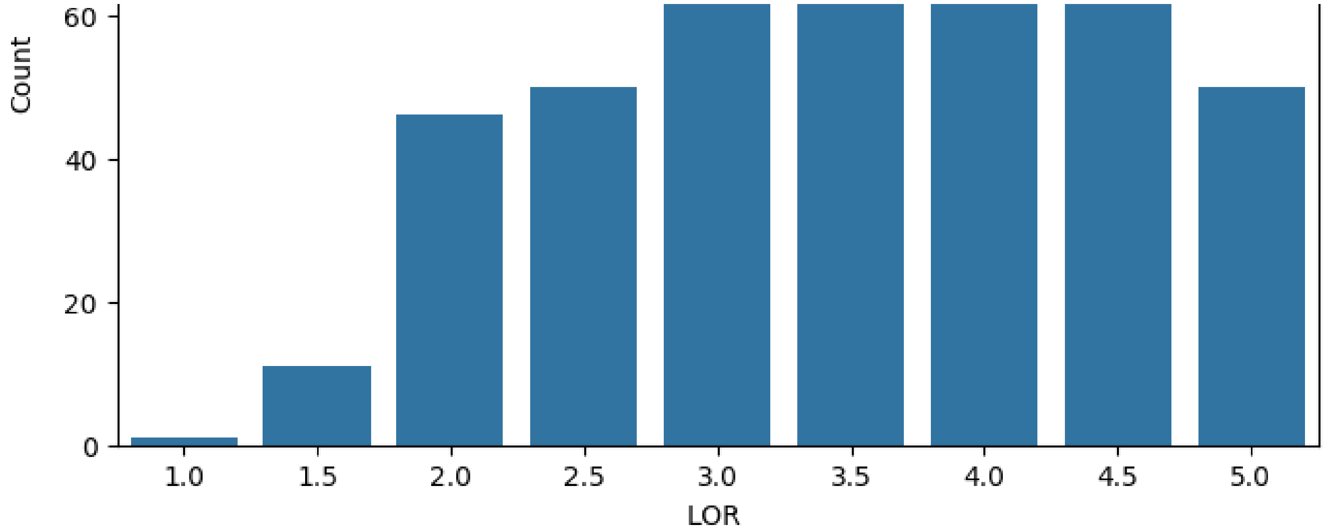

Count Plot of Research
Count
250
200
150
100
50
0
0
1
Research

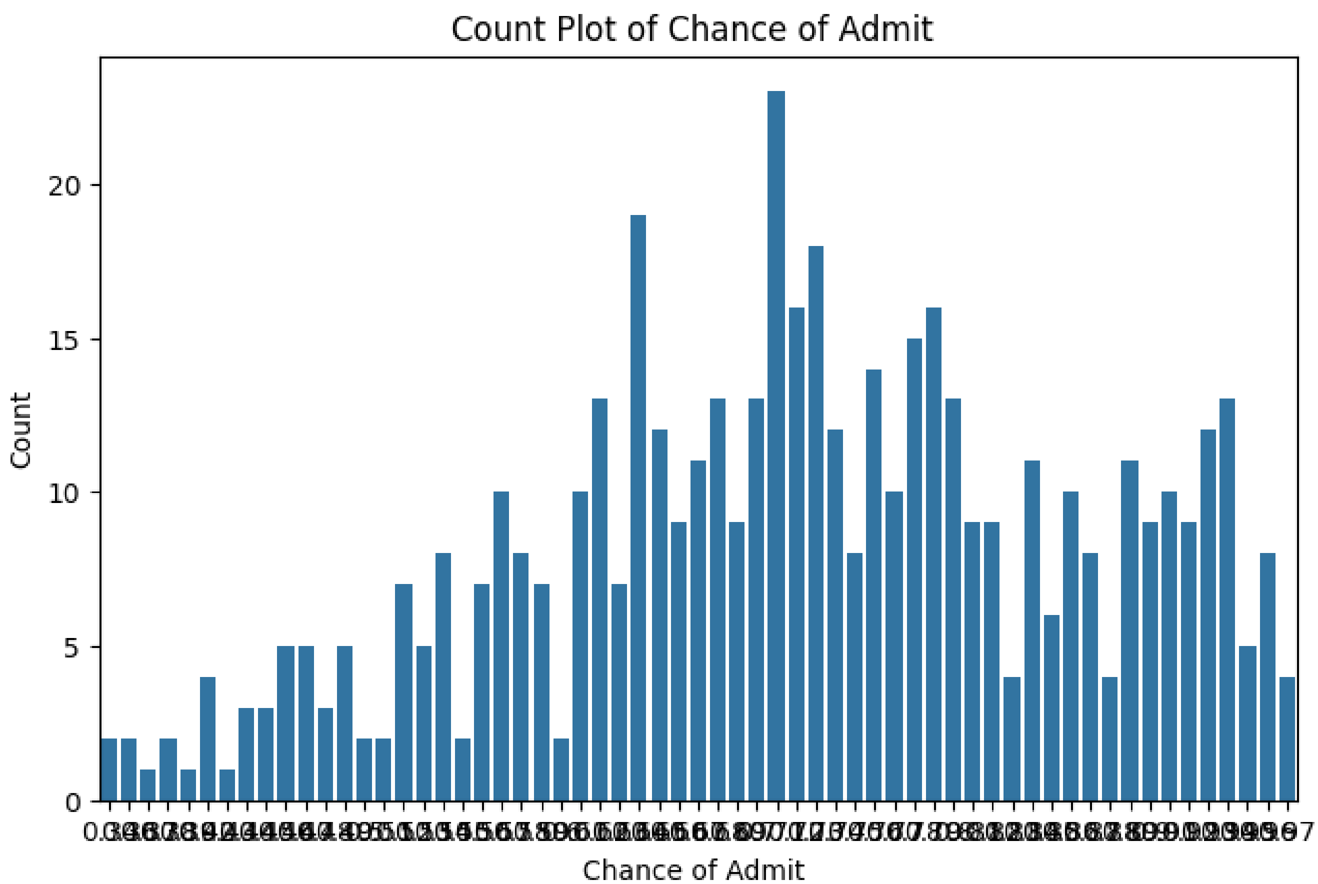

Count Plot of University Rating
160
140


Count
0
20
40
60
80
100
120
1
2
3
4
5
University Rating


Count Plot of SOP
Count
0
20
40
60
80
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
SOP


Count Plot of LOR
80
100

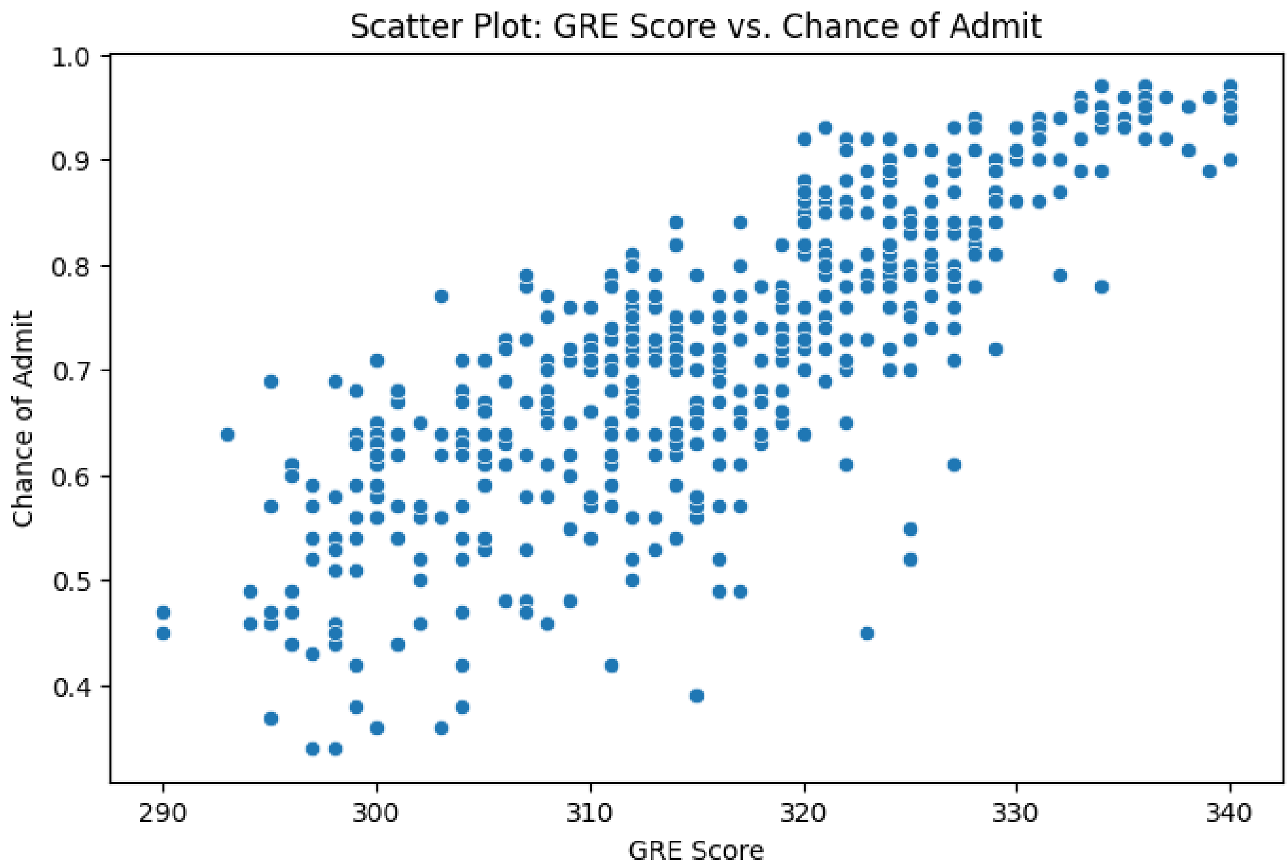


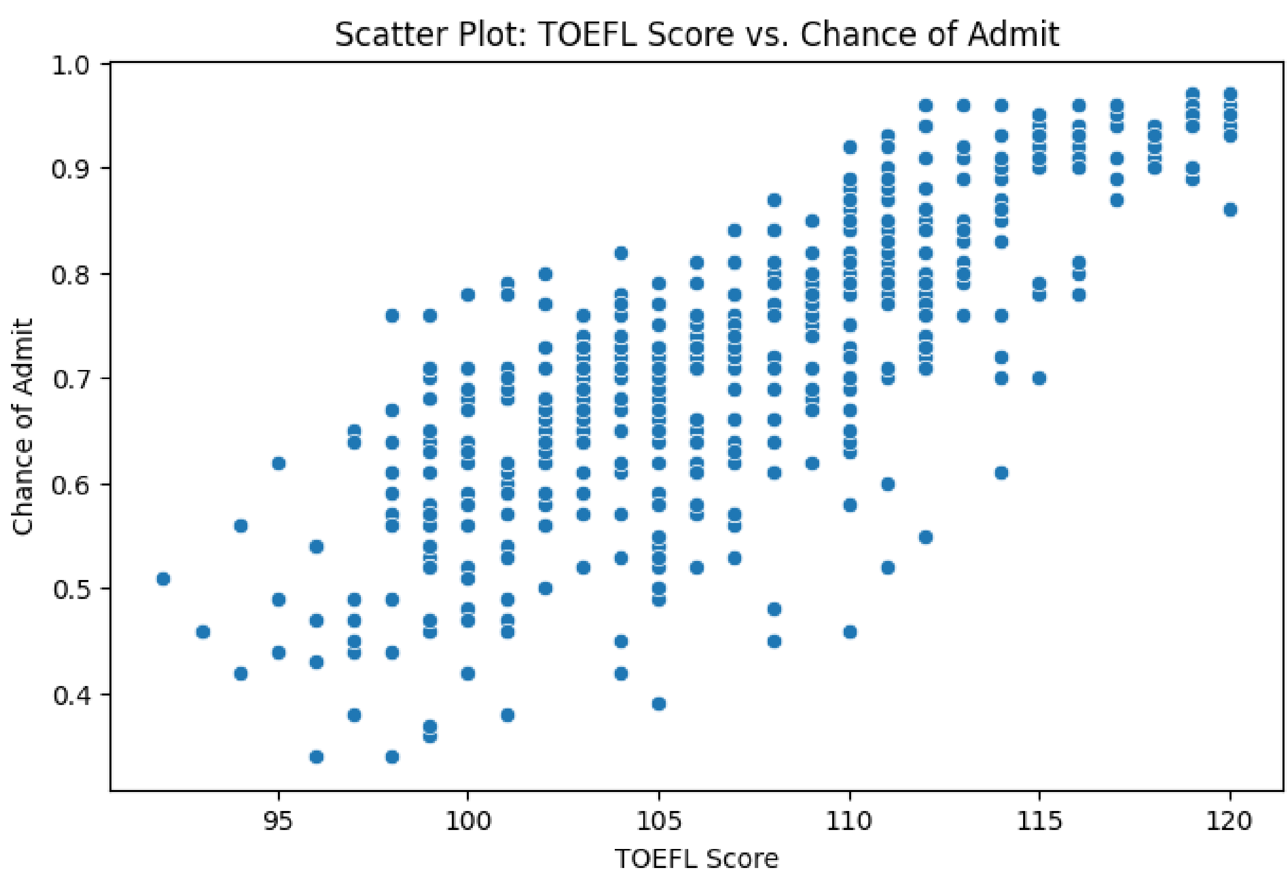



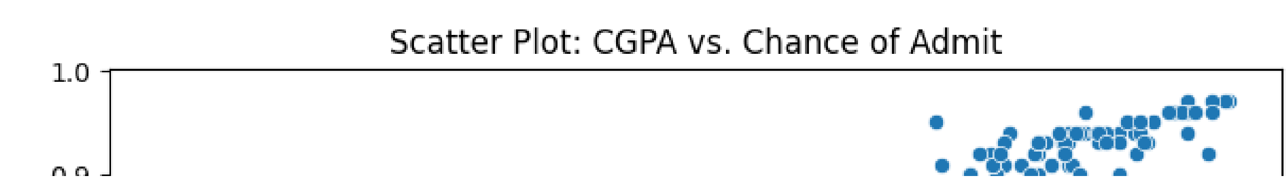

## EDA

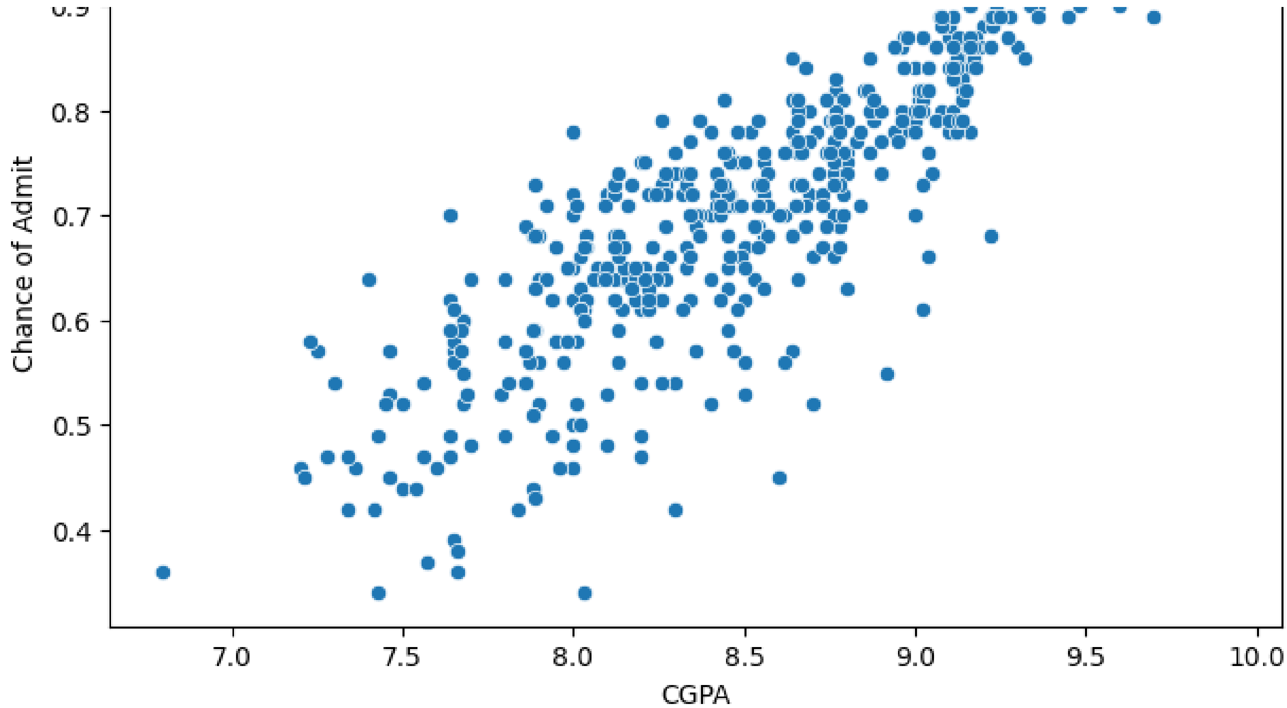
The attributes GRE Scores, TOEFL Scores, University Rating, CGPA, SOP, and LOR exhibit a normal distribution pattern, indicating that the majority of observations cluster around the mean, with symmetric tails on either side. This distributional characteristic suggests a balanced distribution of values across the dataset, aligning with typical expectations for these attributes.

```
#Bivariate Analysis '
for var in continuous_vars+categorical_vars[:-1]:
    if var=='Reaseach':
      continue
    plt.figure(figsize=(8, 5))
    sns.scatterplot(data=dataframe, x=var, y='Chance of Admit ')
    plt.title(f'Scatter Plot: {var} vs. Chance of Admit')
    plt.xlabel(var)
    plt.ylabel('Chance of Admit')
    plt.show()
```

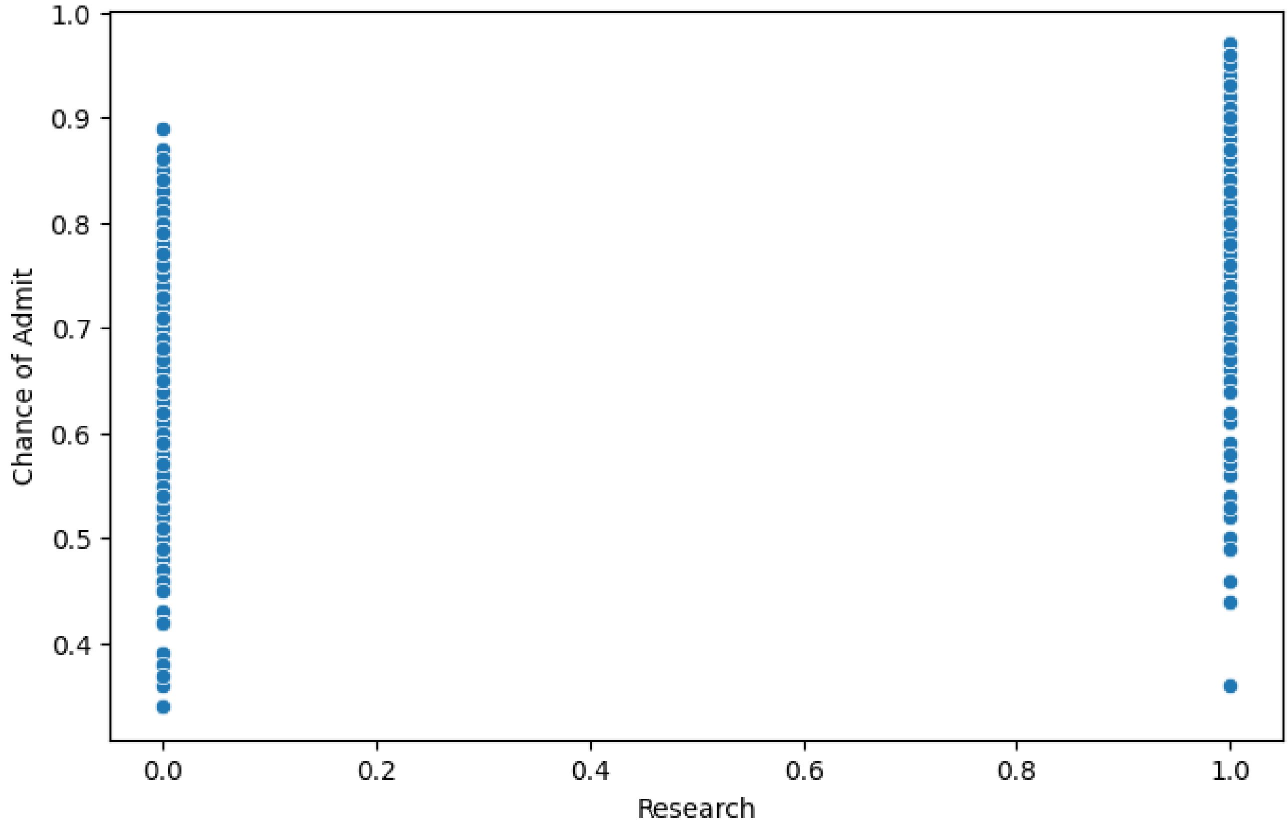

Scatter Plot: GRE Score vs. Chance of Admit
Chance of Admit
GRE Score
0.4
0.5
0.6
0.7
0.8
0.9
1.0
290
300
310
320
330
340


Scatter Plot: TOEFL Score vs. Chance of Admit
Chance of Admit
TOEFL Score
0.4
0.5
0.6
0.7
0.8
0.9
1.0
95
100
105
110
115
120

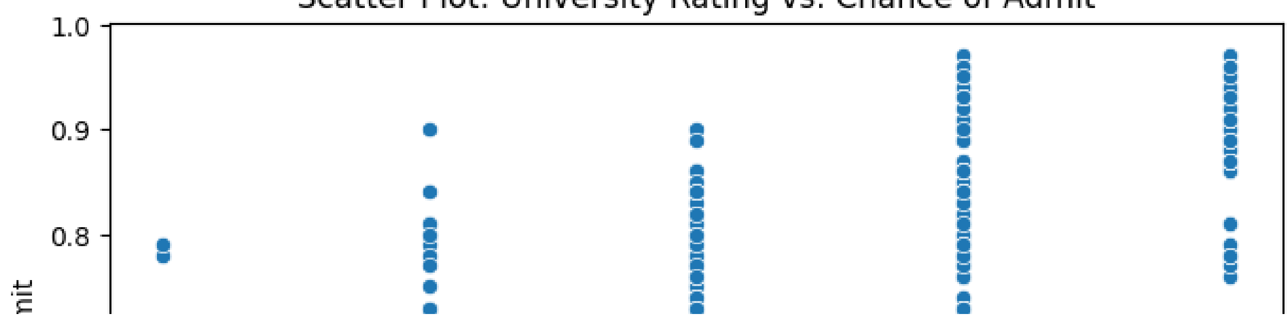

Scatter Plot: CGPA vs. Chance of Admit
1.0

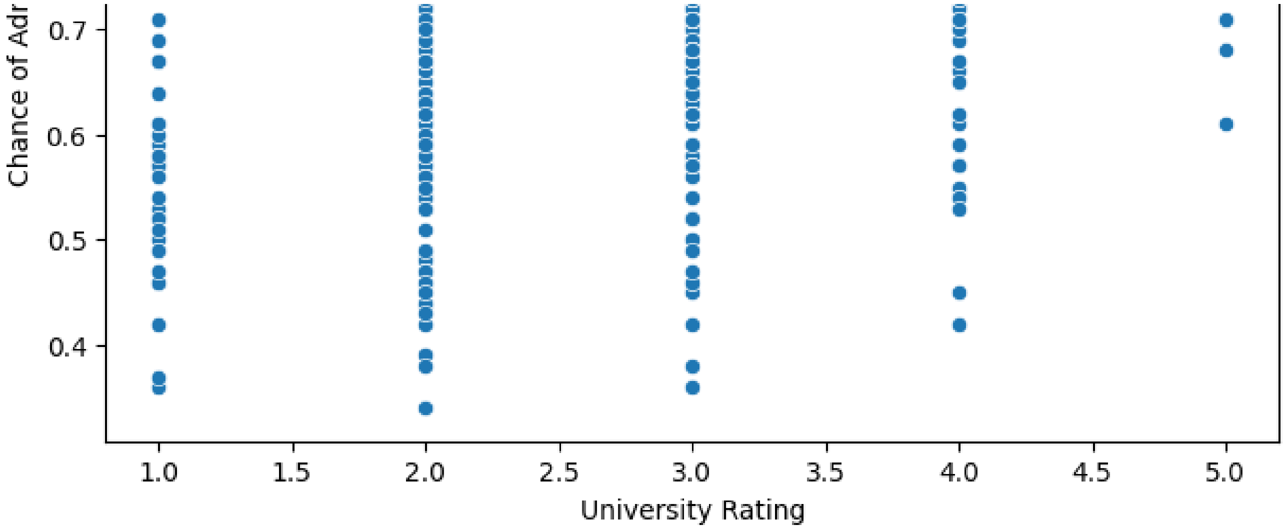


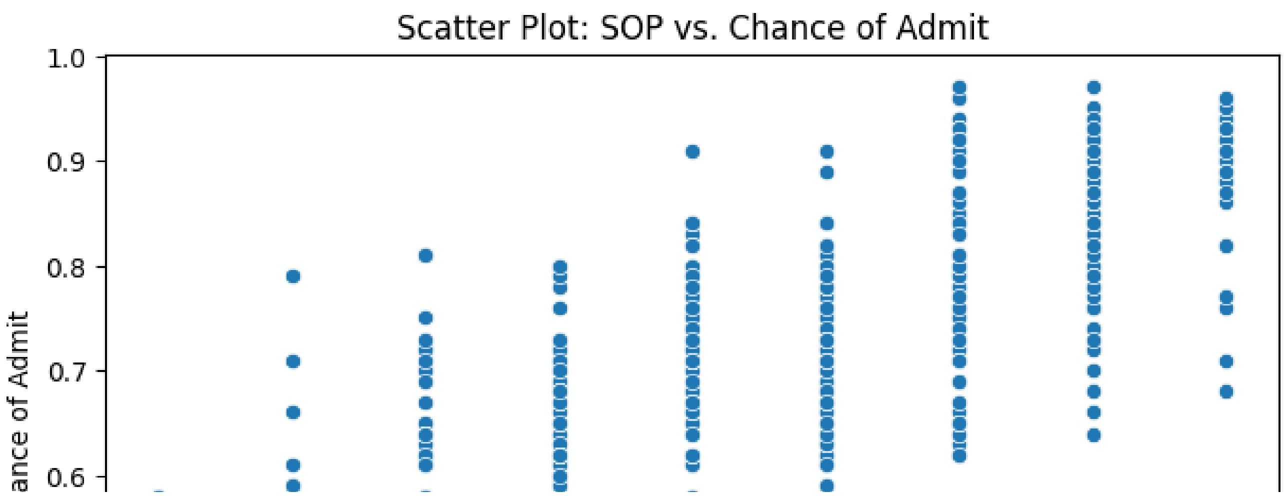

Scatter Plot: Research vs. Chance of Admit




Scatter Plot: University Rating vs. Chance of Admit






- As the GRE score increases, there seems to be a positive trend in the 'Chance of Admit'. Higher GRE scores are associated with higher chances of admission.
- Similar to the GRE score, higher TOEFL scores appear to correlate with higher chances of admission. There is a positive relationship between TOEFL scores and the 'Chance of Admit'.
- There is a noticeable positive relationship between CGPA and the 'Chance of Admit'. Higher CGPA scores correspond to higher chances of admission.
- The scatter plot suggests that there may be a positive relationship between the Statement of Purpose (SOP) score and the 'Chance of Admit'. Students with stronger SOP scores tend to have higher chances of admission.
- Similarly, there appears to be a positive correlation between the Letter of Recommendation (LOR) score and the 'Chance of Admit'. Higher LOR scores are associated with higher chances of admission.
- It is seen that students with research experience are more likely to be admitted compared to those without research experience.

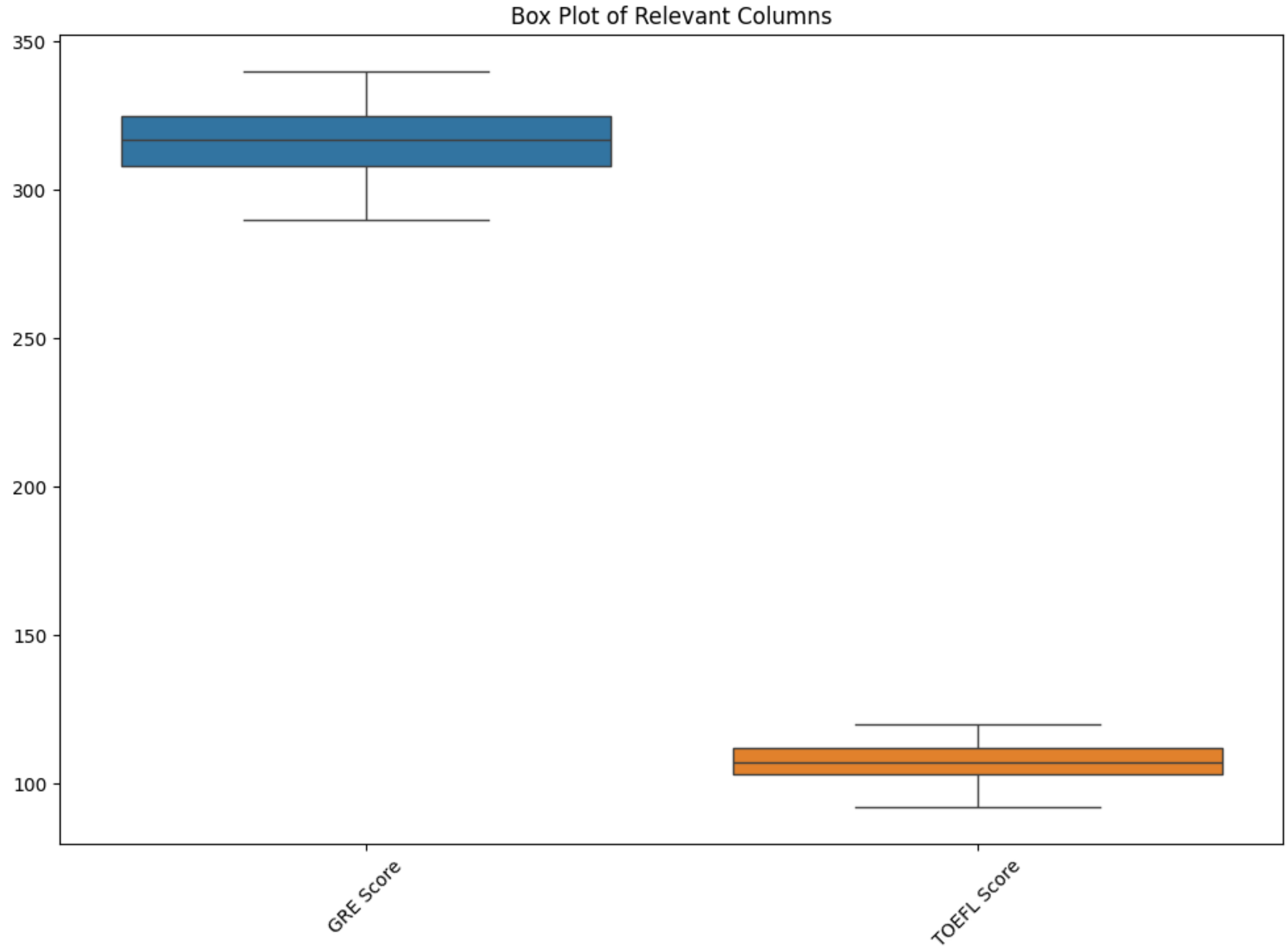
# Data Preprocessing

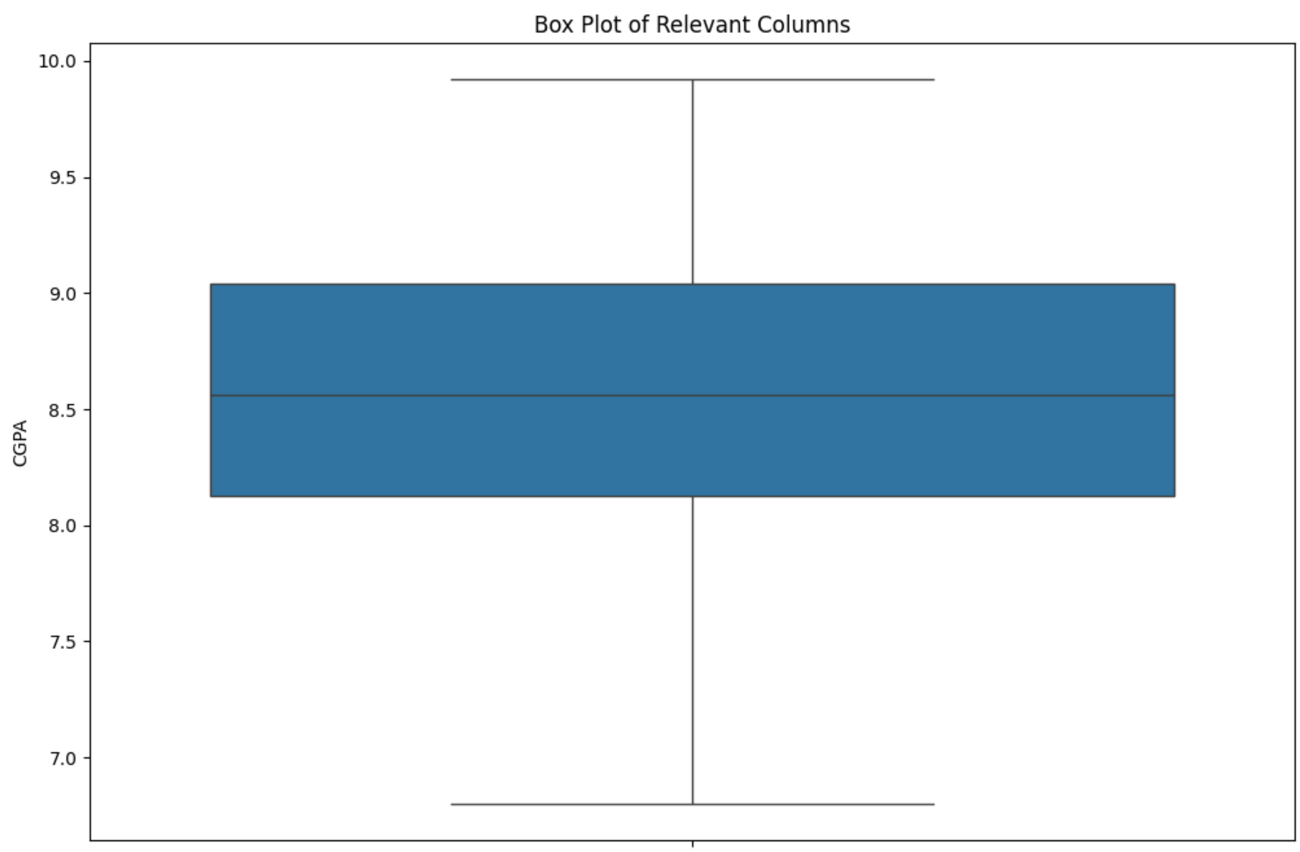
```
#Duplicate value check
duplicate_rows = dataframe[dataframe.duplicated()]
dataframe.drop_duplicates(inplace=True)
```

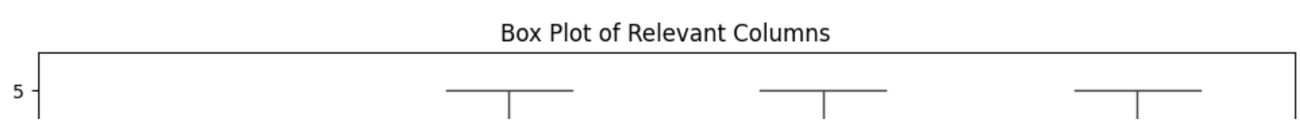
```
#Missing value treatment
dataframe.isnull().sum()
```

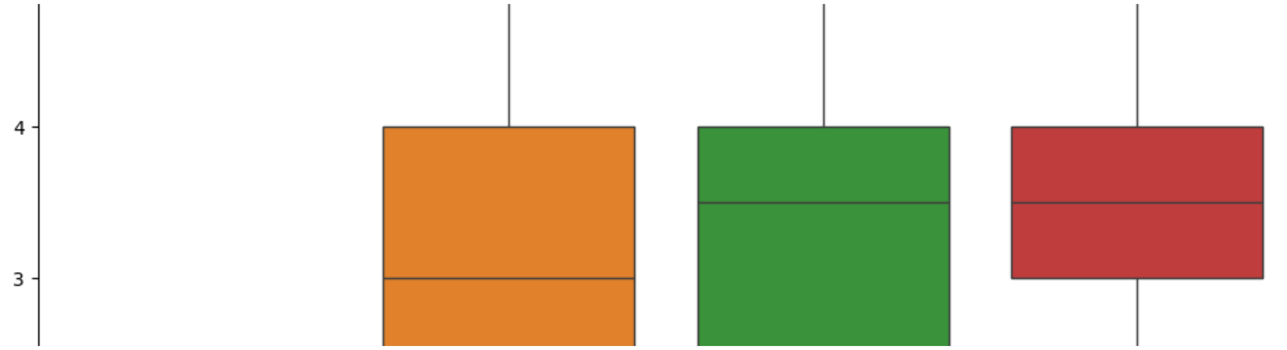
```
GRE Score            0
TOEFL Score          0
University Rating    0
SOP                  0
LOR                  0
CGPA                 0
Research             0
Chance of Admit      0
dtype: int64
```

```
# Visualizing distribution of data points using box plots
plt.figure(figsize=(12, 8))
sns.boxplot(data=dataframe[['GRE Score', 'TOEFL Score']])
plt.title('Box Plot of Relevant Columns')
plt.xticks(rotation=45)
plt.show()

# Visualizing distribution of data points using box plots
plt.figure(figsize=(12, 8))
sns.boxplot(data=dataframe['CGPA'])
plt.title('Box Plot of Relevant Columns')
plt.xticks(rotation=45)
plt.show()

# Visualizing distribution of data points using box plots
plt.figure(figsize=(12, 8))
sns.boxplot(data=dataframe[categorical_vars[:-1]])
plt.title('Box Plot of Relevant Columns')
plt.xticks(rotation=45)
plt.show()
```


Box Plot of Relevant Columns
350
300
250
200
150
100
GRE Score
TOEFL Score


Box Plot of Relevant Columns
10.0
9.5
9.0
8.5
8.0
7.5
7.0
CGPA


Box Plot of Relevant Columns
5




```
#Outlier treatment
for var in continuous_vars+categorical_vars:
    Q1 = dataframe[var].quantile(0.25)
    Q3 = dataframe[var].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    dataframe[var] = dataframe[var].clip(lower=lower_bound, upper=upper_bound)
```

```
# Feacture Engineering
dataframe['strength'] = dataframe['SOP'] + dataframe['LOR ']
dataframe.drop(columns=['SOP','LOR '],inplace=True)
dataframe['strength']
```

```
0       9.0
1       8.5
2       6.5
3       6.0
4       5.0
       ...
495     8.5
496    10.0
497     9.5
498     9.0
499     9.0
Name: strength, Length: 500, dtype: float64
```

```
dataframe
```

| | GRE Score | TOEFL Score | University Rating | CGPA | Research | Chance of Admit | strength |
|---|---|---|---|---|---|---|---|
| **0** | 337 | 118 | 4 | 9.65 | 1 | 0.92 | 9.0 |
| **1** | 324 | 107 | 4 | 8.87 | 1 | 0.76 | 8.5 |
| **2** | 316 | 104 | 3 | 8.00 | 1 | 0.72 | 6.5 |
| **3** | 322 | 110 | 3 | 8.67 | 1 | 0.80 | 6.0 |
| **4** | 314 | 103 | 2 | 8.21 | 0 | 0.65 | 5.0 |
| **...** | ... | ... | ... | ... | ... | ... | ... |
| **495** | 332 | 108 | 5 | 9.02 | 1 | 0.87 | 8.5 |
| **496** | 337 | 117 | 5 | 9.87 | 1 | 0.96 | 10.0 |
| **497** | 330 | 120 | 5 | 9.56 | 1 | 0.93 | 9.5 |
| **498** | 312 | 103 | 4 | 8.43 | 0 | 0.73 | 9.0 |
| **499** | 327 | 113 | 4 | 9.04 | 0 | 0.84 | 9.0 |

500 rows × 7 columns

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder


# Split data into features (X) and target variable (y)
X = dataframe.drop(columns=['Chance of Admit '])
y = dataframe['Chance of Admit ']
columns = X.columns
# Normalize numerical features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state
```

```
X_train
```

```
array([[ 0.40128156,  0.62675052, -0.09979274,  0.41965703,  0.88640526,
         0.36760129],
       [-0.0418297 ,  0.62675052,  0.77558214, -0.06031039, -1.12815215,
         1.22782272],
       [-1.193919  , -0.8545401 , -0.09979274, -0.12651279, -1.12815215,
        -0.20587966],
       ...,
       [-1.28254125, -1.34830364, -1.85054249, -2.19533785, -1.12815215,
        -1.63958204],
       [-0.66218548, -0.36077656, -0.97516761, -1.48366203, -1.12815215,
        -0.20587966],
```

```
       [-0.21907421, -0.19618871, -0.97516761, -0.5402778 , -1.12815215,
         0.36760129]])
```

## Model building

```
from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.metrics import mean_squared_error, r2_score
# Build Linear Regression model
linear_reg = LinearRegression()
linear_reg.fit(X_train, y_train)

# Predictions train data
y_train_pred = linear_reg.predict(X_train)
```

```
coefficients = linear_reg.coef_
coefficients
```

```
array([0.02724941, 0.0171936 , 0.00170568, 0.06804298, 0.01188039,
       0.01769839])
```

```
# Display model coefficients with column names
coefficients = linear_reg.coef_
coefficients_df = pd.DataFrame({'Feature': columns, 'Coefficient': coefficients})
print("\nLinear Regression Coefficients:")
print(coefficients_df)
```

```
Linear Regression Coefficients:
             Feature  Coefficient
0          GRE Score     0.027249
1        TOEFL Score     0.017194
2  University Rating     0.001706
3               CGPA     0.068043
4           Research     0.011880
5           strength     0.017698
```

```
# Model statistics
train_rmse = np.sqrt(mean_squared_error(y_train, y_train_pred))
train_r2 = r2_score(y_train, y_train_pred)
train_rmse,train_r2
```

```
(0.05960406654108408, 0.8195686865143701)
```

### Root mean square error and r2 are good for train dataset.

```
# Lasso Regression
lasso_reg = Lasso(alpha=1)  # The alpha parameter for regularization strength
lasso_reg.fit(X_train, y_train)
lasso_train_rmse = np.sqrt(mean_squared_error(y_train, lasso_reg.predict(X_train)))
lasso_train_r2 = r2_score(y_train, lasso_reg.predict(X_train))

print("Losso Regression Model Statistics:")
print("Train RMSE:", lasso_train_rmse)
print("Train R^2 Score:", lasso_train_r2)
```

```
Losso Regression Model Statistics:
Train RMSE: 0.1403201161630078
Train R^2 Score: 0.0
```

```
# Ridge Regression
ridge_reg = Ridge(alpha=0.5)  # You can adjust the alpha parameter for regularization streng
ridge_reg.fit(X_train, y_train)
ridge_train_rmse = np.sqrt(mean_squared_error(y_train, ridge_reg.predict(X_train)))
ridge_train_r2 = r2_score(y_train, ridge_reg.predict(X_train))

print("Ridge Regression Model Statistics:")
print("Train RMSE:", ridge_train_rmse)
print("Train R^2 Score:", ridge_train_r2)
```

```
Ridge Regression Model Statistics:
Train RMSE: 0.05960422545786763
Train R^2 Score: 0.8195677243786006
```

# Testing the assumptions of the linear regression model

```
#Multicollinearity check by VIF score
from statsmodels.stats.outliers_influence import variance_inflation_factor
def calculate_vif(X):
    vif_data = pd.DataFrame()
    vif_data["Feature"] = columns
    vif_data["VIF"] = [variance_inflation_factor(X.values, i) for i in range(len(X.columns))
    return vif_data

# Convert trainingDataFrame if they are numpy arrays
X_train_df = pd.DataFrame(X_train)
vif_scores_train = calculate_vif(X_train_df)
print("VIF Scores for Training Data:")
print(vif_scores_train)
```

```
VIF Scores for Training Data:
             Feature       VIF
0          GRE Score  4.488243
1        TOEFL Score  3.637750
```

```
2  University Rating  2.528933
3               CGPA  4.653647
4           Research  1.517161
5           strength  2.719518
```

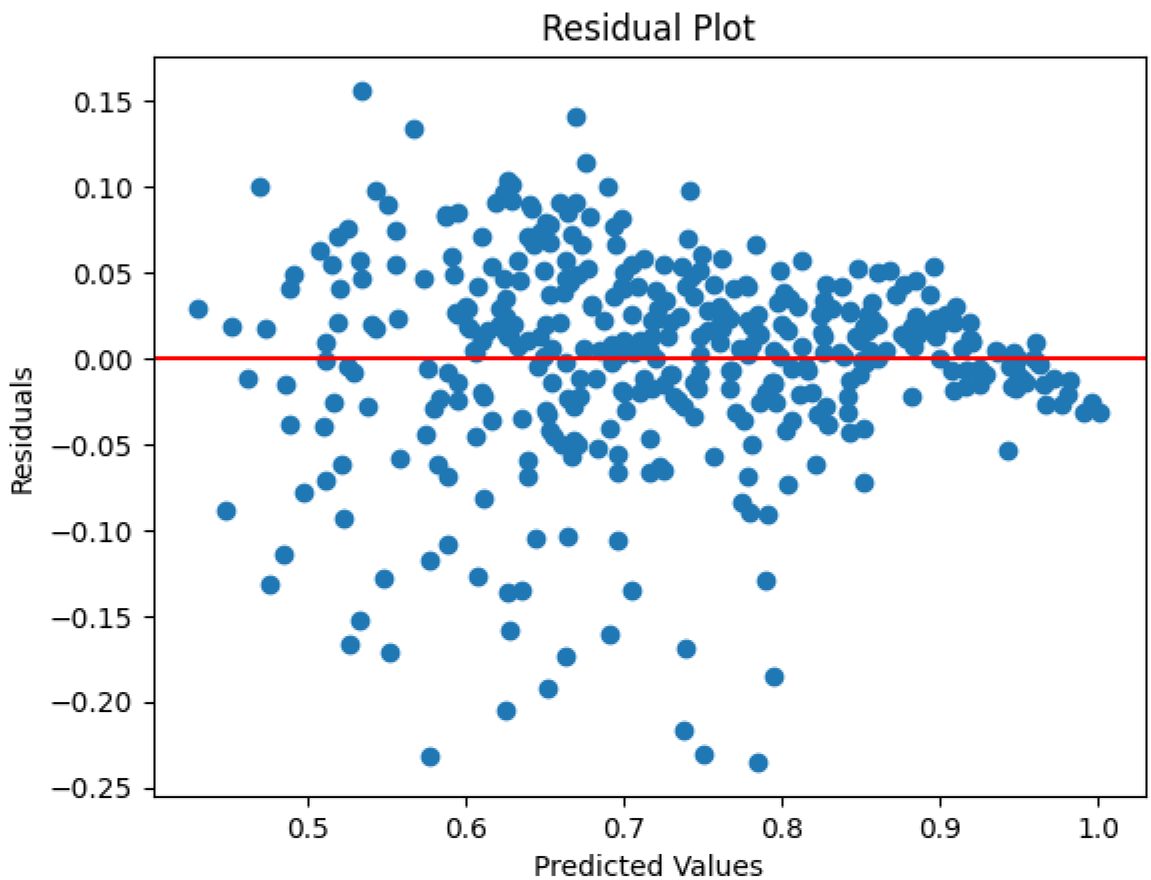
There is some degree of multicollinearity present in the dataset, with several variables exhibiting moderate levels of multicollinearity, none of the VIF scores exceed the commonly accepted threshold of 5, suggesting that multicollinearity may not be a significant issue in this model.

```
# Calculate residuals
residuals = y_train - y_train_pred

# Calculate mean of residuals
mean_residuals = np.mean(residuals)

print("Mean of Residuals:", mean_residuals)
```

```
Mean of Residuals: -5.620504062164855e-17
```

The mean of residuals is close to zero, indicating that the model's predictions are not having multicollinearity and unbiased on average.

```
# Create residual plot
plt.scatter(y_train_pred, residuals)
plt.axhline(y=0, color='r')
plt.xlabel('Predicted Values')
plt.ylabel('Residuals')
plt.title('Residual Plot')
plt.show()
```



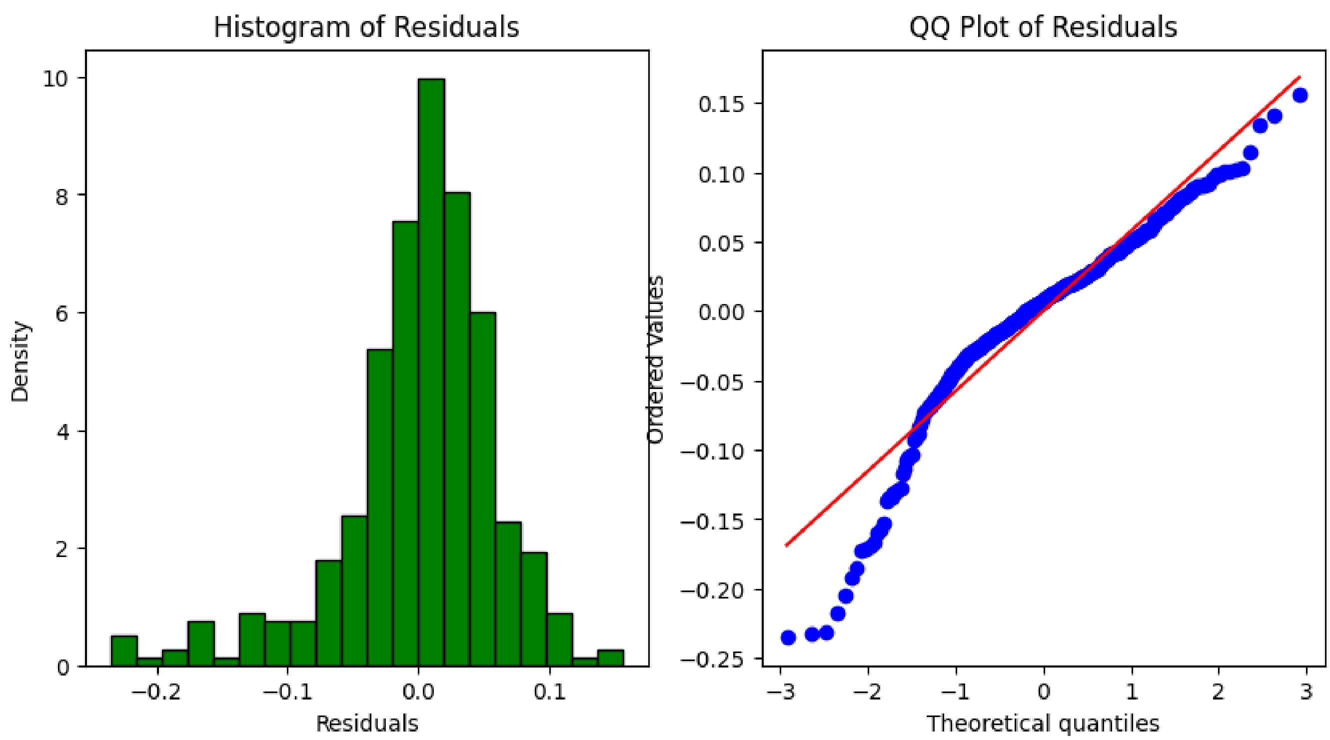

The absence of any discernible pattern in the residual plot suggests that multicollinearity among the predictor variables is not a significant concern.

```
from statsmodels.stats.diagnostic import het_goldfeldquandt

# Perform Goldfeld-Quandt test
gq_test = het_goldfeldquandt(residuals, X_train)
print("Goldfeld-Quandt Test p-value:", gq_test[1])
```

```
Goldfeld-Quandt Test p-value: 0.6848802285877097
```

p-value is more than 0.05.So, there is insufficient evidence to conclude that heteroscedasticity is present in the residuals

```
import scipy.stats as stats
# Plot histogram/density plot of residuals
plt.figure(figsize=(10, 5))
plt.subplot(1, 2, 1)
plt.hist(residuals, bins=20, density=True, color='g', edgecolor='black')
plt.title('Histogram of Residuals')
plt.xlabel('Residuals')
plt.ylabel('Density')

# Plot QQ plot of residuals
plt.subplot(1, 2, 2)
stats.probplot(residuals, dist="norm", plot=plt)
plt.title('QQ Plot of Residuals')
plt.show()

# Assess normality
normality_result = stats.normaltest(residuals)
print("Normality Test p-value:", normality_result.pvalue)
```




```
Normality Test p-value: 3.9414129522879716e-20
```

## Residuals may visually appear to be in almost a normal distribution.

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

# Calculate Mean Absolute Error (MAE)
mae = mean_absolute_error(y_train, y_train_pred)

# Calculate Root Mean Squared Error (RMSE)
rmse = np.sqrt(mean_squared_error(y_train, y_train_pred))

# Calculate R-squared (R2)
r2 = r2_score(y_train, y_train_pred)

# Calculate Adjusted R-squared (Adj R2)
n = len(y_train)
p = X.shape[1]
adj_r2 = 1 - ((1 - r2) * (n - 1) / (n - p - 1))

print("Mean Absolute Error (MAE):", mae)
print("Root Mean Squared Error (RMSE):", rmse)
print("R-squared (R2):", r2)
print("Adjusted R-squared (Adj R2):", adj_r2)
```

```
Mean Absolute Error (MAE): 0.042542909235852445
Root Mean Squared Error (RMSE): 0.05960406654108408
R-squared (R2): 0.8195686865143701
Adjusted R-squared (Adj R2): 0.8168140099726048
```

The MAE and RMSE values are relatively low, suggesting that the model's predictions are close to the actual values. The R-squared and Adjusted R-squared values are relatively high, indicating that a large proportion of the variance in the target variable is explained by the model.

```
# Train the linear regression model
model = LinearRegression()
model.fit(X_train, y_train)

# Make predictions on test data
y_test_pred = model.predict(X_test)
```

```
# Calculate Mean Absolute Error (MAE)
mae = mean_absolute_error(y_test, y_test_pred)

# Calculate Root Mean Squared Error (RMSE)
rmse = np.sqrt(mean_squared_error(y_test, y_test_pred))
```