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

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.metrics import r2_score

from statsmodels.stats.outliers_influence import variance_inflation_factor
from scipy import stats
```

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

1. Define Problem Statement and perform Exploratory Data Analysis

1.1 Definition of problem:

1. Do identify the patterns in the data by using univariate, Bivariate and Muktivariate analysis
2. To Predict the chances of graduate admission based on the given features.

1.2 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.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
```

There are no missing values in the dataset.

```
df.describe()
```

	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Cl of /
count	500.000000	500.000000	500.000000	500.000000	500.000000	500.00000	500.000000	500.000000	500.(
mean	250.500000	316.472000	107.192000	3.114000	3.374000	3.48400	8.576440	0.560000	0.7
std	144.481833	11.295148	6.081868	1.143512	0.991004	0.92545	0.604813	0.496884	0.1
min	1.000000	290.000000	92.000000	1.000000	1.000000	1.00000	6.800000	0.000000	0.3
25%	125.750000	308.000000	103.000000	2.000000	2.500000	3.00000	8.127500	0.000000	0.(
50%	250.500000	317.000000	107.000000	3.000000	3.500000	3.50000	8.560000	1.000000	0.7
75%	375.250000	325.000000	112.000000	4.000000	4.000000	4.00000	9.040000	1.000000	0.8
max	500.000000	340.000000	120.000000	5.000000	5.000000	5.00000	9.920000	1.000000	0.9

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

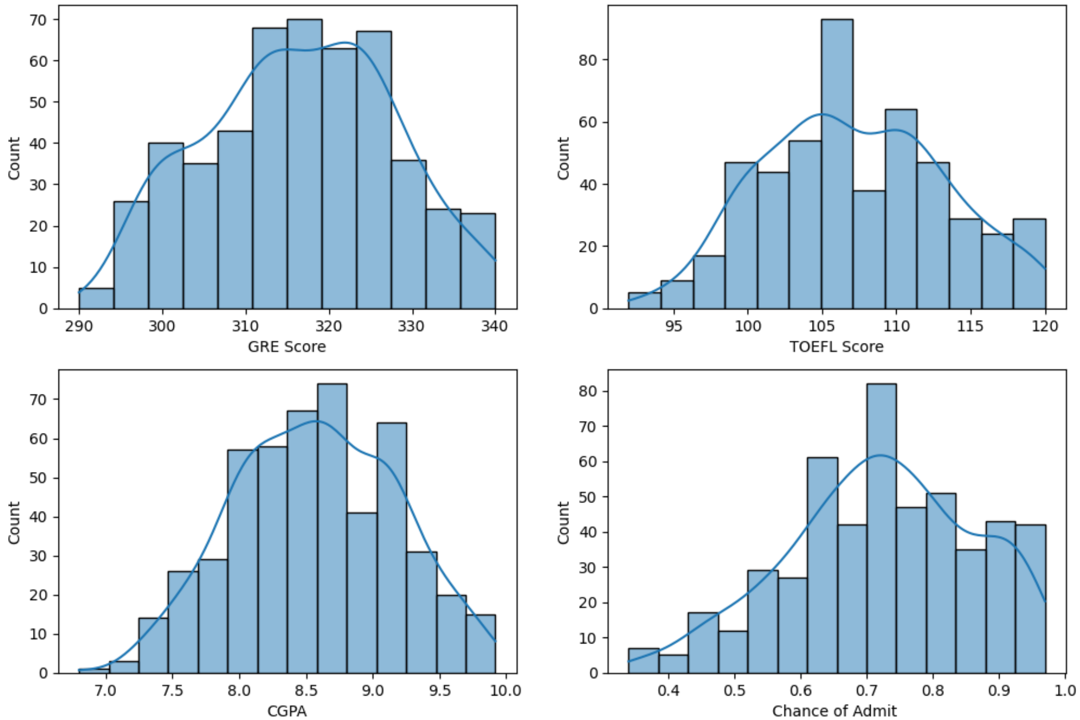
```
Serial No.           0
GRE Score            0
TOEFL Score          0
University Rating    0
SOP                  0
LOR                  0
CGPA                 0
Research             0
Chance of Admit      0
dtype: int64
```

```
# segregating the columns based categorical and numerical data
cat_cols = ['University Rating', 'SOP', 'LOR ', 'Research']
num_cols = ['GRE Score', 'TOEFL Score', 'CGPA']
target = 'Chance of Admit '
```

1.3 Univariate Analysis

```
# Distribution of each numerical variables(Kde plots)
rows, cols = 2, 2
fig, axs = plt.subplots(rows,cols, figsize=(12, 8))
index = 0
for row in range(rows):
    for col in range(cols):
```

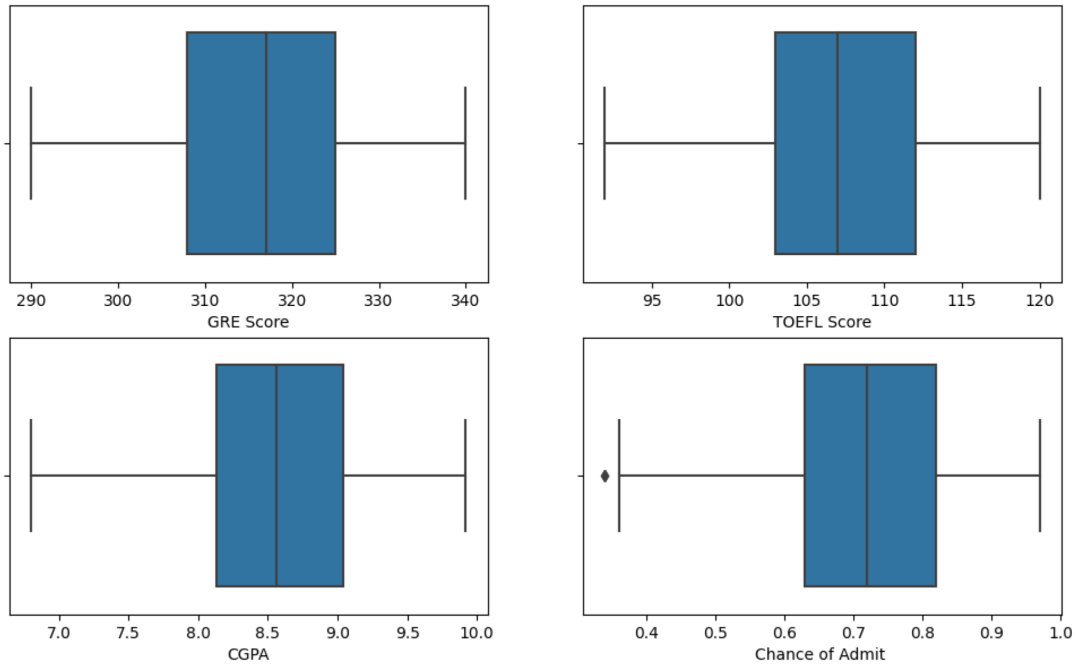
```
            sns.histplot(df[num_cols[index]], kde=True, ax=axs[row,col])
            index += 1
        break

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



Every numerical feature plot follows almost Gaussian distribution

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

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

```
    index += 1

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



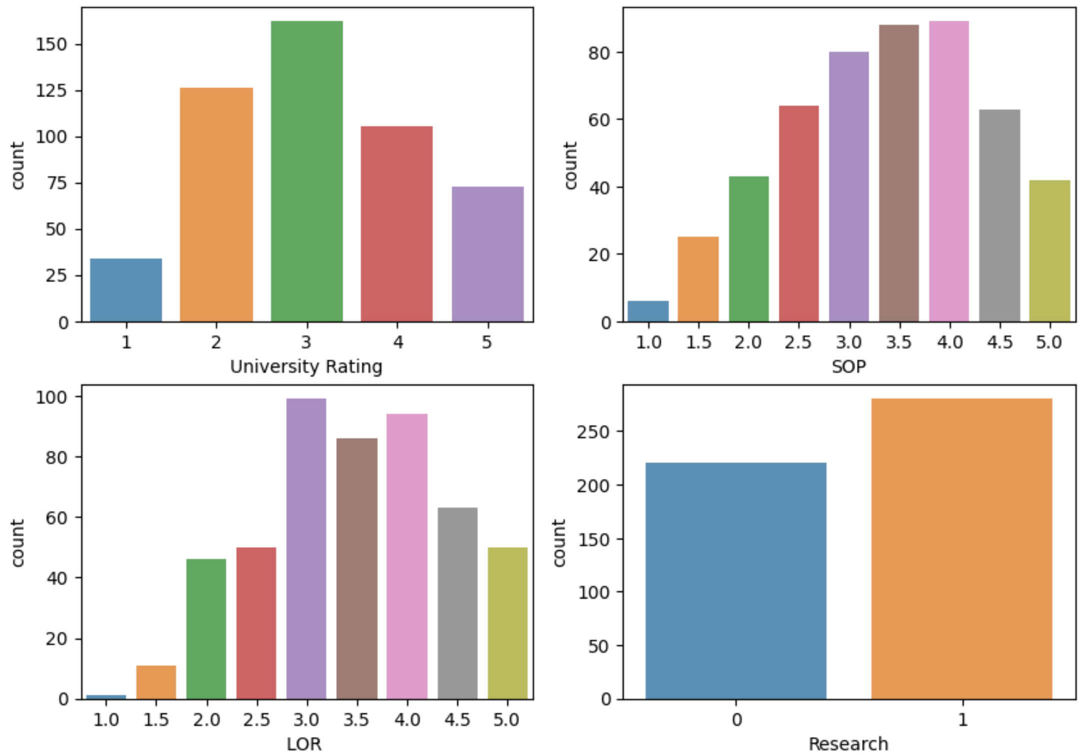
There are no outliers present in the dataset.

```
# check unique values in categorical variables
for col in cat_cols:
    print("Column:  {:18}   Unique values: {}".format(col, df[col].nunique()))
```

```
     Column:  University Rating    Unique values: 5
     Column:  SOP                  Unique values: 9
     Column:  LOR                  Unique values: 9
     Column:  Research             Unique values: 2
```

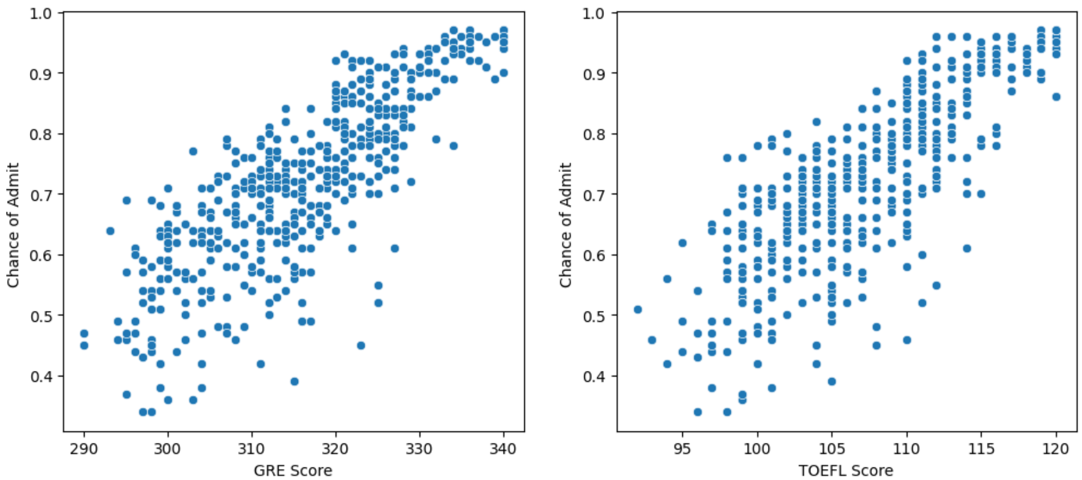
```
# countplots for categorical variables
cols, rows = 2, 2
fig, axs = plt.subplots(rows, cols, figsize=(10, 7))
```

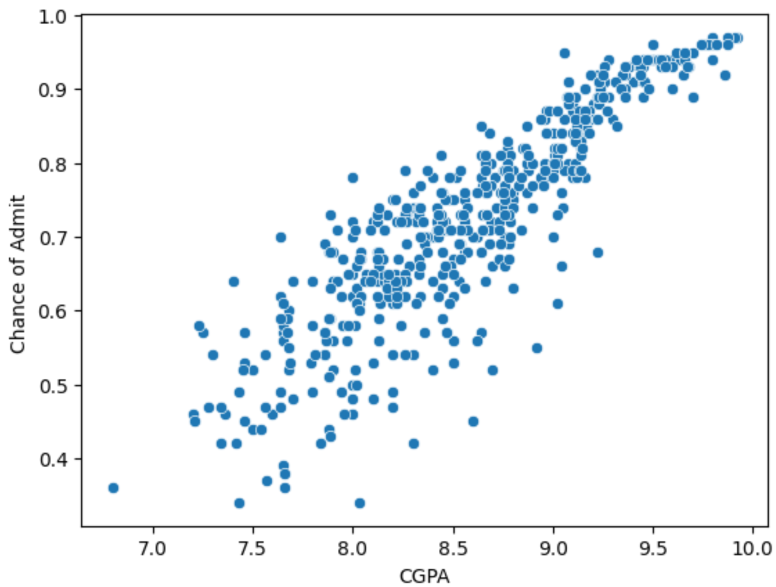
```
index = 0
for row in range(rows):
    for col in range(cols):
        sns.countplot(x=cat_cols[index], data=df, ax=axs[row, col], alpha=0.8)
        index += 1

plt.show()
```



1.4 Bivariate Analysis

```
# check relation bw continuous variables & target variable
fig, axs = plt.subplots(1, 2, figsize=(12,5))

sns.scatterplot(x=num_cols[0], y=target, data=df, ax=axs[0])
sns.scatterplot(x=num_cols[1], y=target, data=df, ax=axs[1])
plt.show()
sns.scatterplot(x=num_cols[2], y=target, data=df)
plt.show()
```

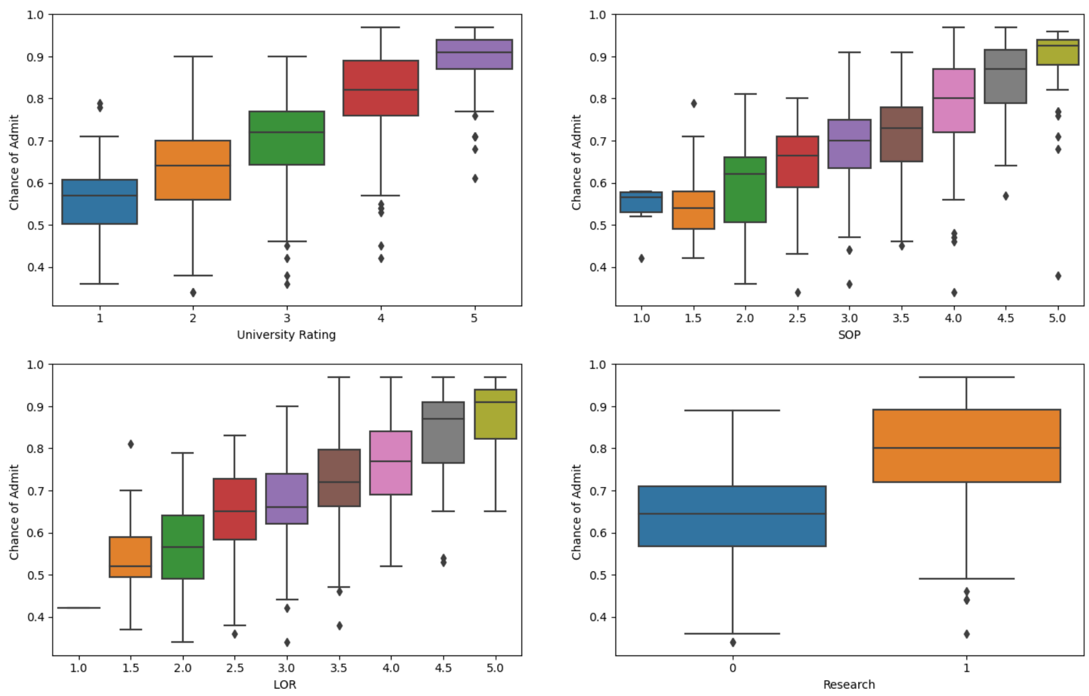




Seems like there is a linear correlation between the continuous variables and the target variable

```
rows, cols = 2,2
fig, axs = plt.subplots(rows, cols, figsize=(16,10))

index = 0
for row in range(rows):
    for col in range(cols):
```

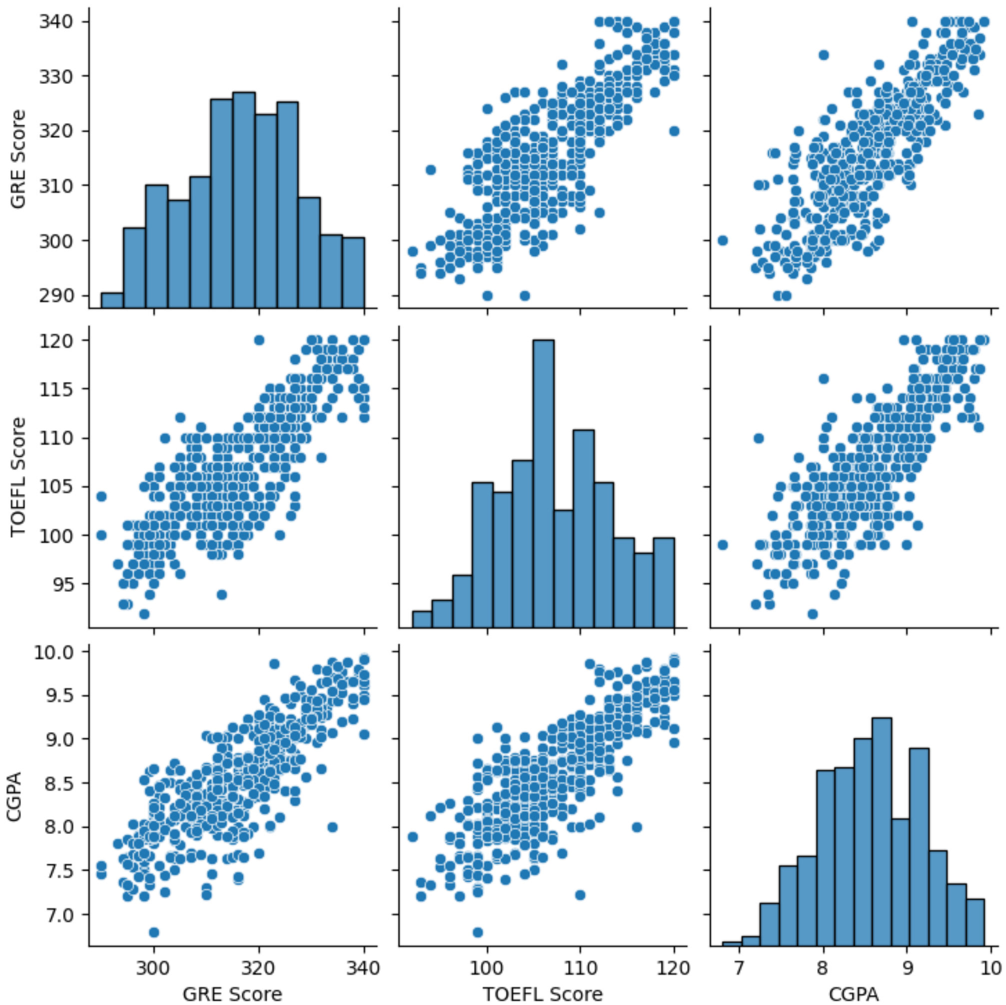
```
    sns.boxplot(x=cat_cols[index], y=target, data=df, ax=axs[row,col])
    index += 1
```



1. As you can see from the graphs, as tge rating increases the Chance of Admit also increases.
2. Students who have the research experience have more chances of Admin as compared to other students who don't have the research experience.

Multivariate Analysis

```
sns.pairplot(df[num_cols])
plt.show()
```

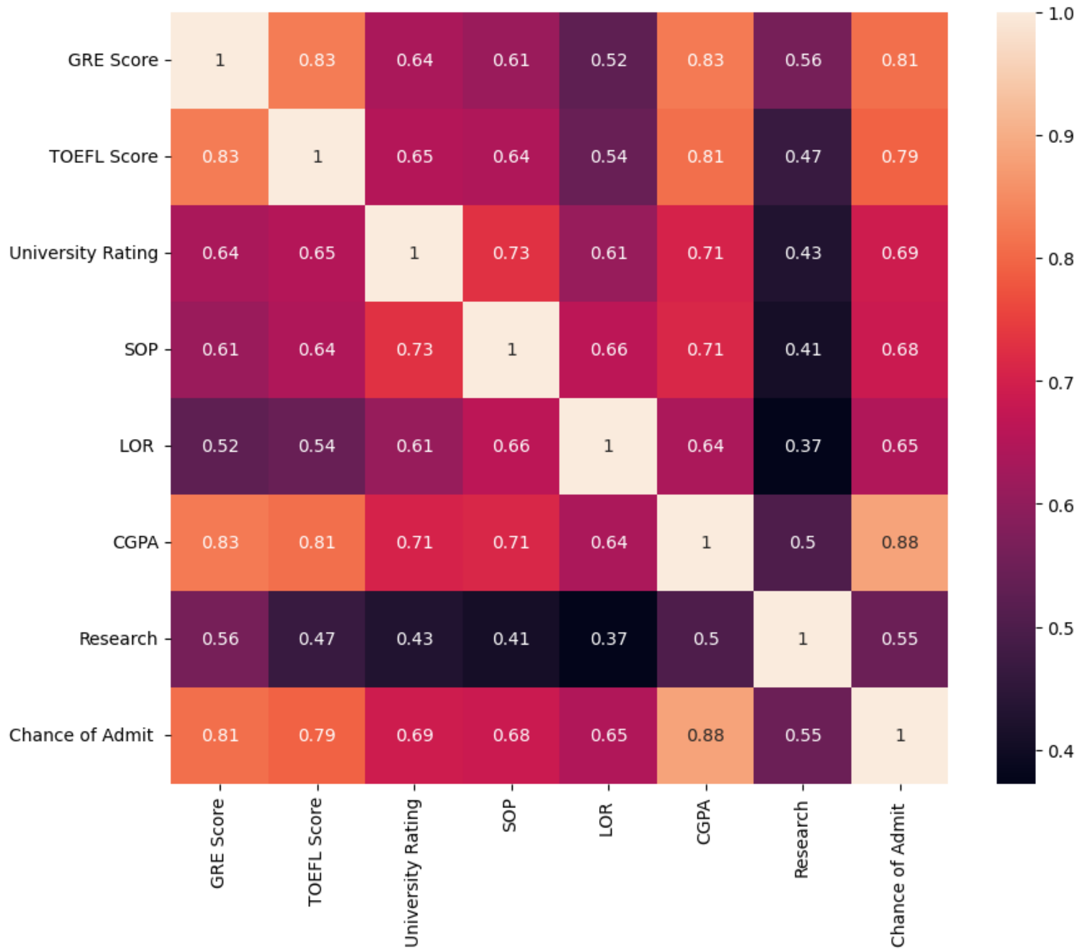


Independent continuous variables are also correlated with each other.

```
df.corr()
```

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
GRE Score	1.000000	0.827200	0.635376	0.613498	0.524679	0.825878	0.563398	0.810351
TOEFL Score	0.827200	1.000000	0.649799	0.644410	0.541563	0.810574	0.467012	0.792228
University Rating	0.635376	0.649799	1.000000	0.728024	0.608651	0.705254	0.427047	0.690132
SOP	0.613498	0.644410	0.728024	1.000000	0.663707	0.712154	0.408116	0.684137

```
plt.figure(figsize=(10,8))
sns.heatmap(df.corr(), annot=True)
plt.show()
```



2. Data Preprocessing

2.1 Duplicate value check, 2.2 Missing Value Treatement and 2.3 Outlier Treatment

```
# drop Serial NO. column
df = df.drop(columns=['Serial No.'], axis=1)
```

```
# check for duplicates
df.duplicated().sum()
```

```
0
```

There are no missing values, outliers and duplicates present in the dataset.

2.4 Feature Engineering

Any additional features we dont need it, we can extract the valuable information from the given features itself

2.5 Data preparation for model building

```
X = df.drop(columns=[target])
y = df[target]
```

```
# Using standard scaler to get rid of the scale
sc = StandardScaler()
X = sc.fit_transform(X)
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=1)
```

```
print(X_train.shape, y_train.shape)
print(X_test.shape, y_test.shape)
```

```
(350, 7) (350,)
(150, 7) (150,)
```

3. Model Building

```
def adjusted_r2(r2, p, n):
    """
    n: no of samples
    p: no of predictors
    r2: r2 score
```

```
    """
    adj_r2 = 1 - ((1-r2)*(n-1) / (n-p-1))
    return adj_r2

def get_metrics(y_true, y_pred, p=None):
    n = y_true.shape[0]
    mse = np.sum((y_true - y_pred)**2) / n
    rmse = np.sqrt(mse)
    mae = np.mean(np.abs(y_true - y_pred))
    score = r2_score(y_true, y_pred)
    adj_r2 = None
    if p is not None:
        adj_r2 = adjusted_r2(score, p, n)

    res = {
        "mean_absolute_error": round(mae, 2),
        "rmse": round(rmse, 2),
        "r2_score": round(score, 2),
        "adj_r2": round(adj_r2, 2)
    }
    return res


def train_model(X_train, y_train, X_test, y_test,cols, model_name="linear", alpha=1.0):
    model = None
    if model_name == "lasso":
        model = Lasso(alpha=alpha)
    elif model_name == "ridge":
        model = Ridge(alpha=alpha)
    else:
        model = LinearRegression()

    model.fit(X_train, y_train)
    y_pred_train = model.predict(X_train)
    y_pred_test = model.predict(X_test)
    p = X_train.shape[1]
    train_res = get_metrics(y_train, y_pred_train, p)
    test_res = get_metrics(y_test, y_pred_test, p)

    print(f"\n----   {model_name.title()} Regression Model  ----\n")
    print(f"Train MAE: {train_res['mean_absolute_error']} Test MAE: {test_res['mean_absolute_error']}")
    print(f"Train RMSE: {train_res['rmse']} Test RMSE: {test_res['rmse']}")
    print(f"Train R2_score: {train_res['r2_score']} Test R2_score: {test_res['r2_score']}")
    print(f"Train Adjusted_R2: {train_res['adj_r2']} Test Adjusted_R2: {test_res['adj_r2']}")
    print(f"Intercept: {model.intercept_}")
    coef_df = pd.DataFrame({"Column": cols, "Coef": model.coef_})
    print(coef_df)
    print("-"*50)
    return model


train_model(X_train, y_train, X_test, y_test,df.columns[:-1], "linear")
train_model(X_train, y_train, X_test, y_test,df.columns[:-1], "ridge")
train_model(X_train, y_train, X_test, y_test,df.columns[:-1], "lasso", 0.001)
```

```
----   Linear Regression Model  ----

Train MAE: 0.04 Test MAE: 0.04
Train RMSE: 0.06 Test RMSE: 0.06
Train R2_score: 0.82 Test R2_score: 0.82
Train Adjusted_R2: 0.82 Test Adjusted_R2: 0.81
Intercept: 0.724978121476996
              Column      Coef
0          GRE Score  0.018657
1        TOEFL Score  0.023176
2  University Rating  0.011565
3                SOP -0.000999
4               LOR   0.012497
5               CGPA  0.064671
6           Research  0.013968
--------------------------------------------------

----   Ridge Regression Model  ----

Train MAE: 0.04 Test MAE: 0.04
Train RMSE: 0.06 Test RMSE: 0.06
Train R2_score: 0.82 Test R2_score: 0.82
Train Adjusted_R2: 0.82 Test Adjusted_R2: 0.81
Intercept: 0.7249823645841696
              Column      Coef
0          GRE Score  0.018902
1        TOEFL Score  0.023252
2  University Rating  0.011594
3                SOP -0.000798
4               LOR   0.012539
5               CGPA  0.064004
6           Research  0.013990
--------------------------------------------------

----   Lasso Regression Model  ----

Train MAE: 0.04 Test MAE: 0.04
Train RMSE: 0.06 Test RMSE: 0.06
Train R2_score: 0.82 Test R2_score: 0.82
Train Adjusted_R2: 0.82 Test Adjusted_R2: 0.81
Intercept: 0.7249659139557142
              Column      Coef
0          GRE Score  0.018671
1        TOEFL Score  0.022770
2  University Rating  0.010909
3                SOP  0.000000
4               LOR   0.011752
5               CGPA  0.064483
6           Research  0.013401
--------------------------------------------------
▾      Lasso
Lasso(alpha=0.001)
```

- Since model is not overfitting, Results for Linear, Ridge and Lasso are the same.
- R2_score and Adjusted_r2 are almost the same. Hence there are no unnecessary independent variables in the data.

4. Testing the assumptions of the linear regression model

4.1 Multicollinearity check by VIF score

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

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

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

	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

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

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

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

```
res
```

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

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

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

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

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

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

	feature	VIF
0	CGPA	2.455008
1	Research	2.455008

```
# now again train the model with these only two features
X = df[['CGPA', 'Research']]
```

```
sc = StandardScaler()
X = sc.fit_transform(X)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=1)


model = train_model(X_train, y_train, X_test, y_test, ['CGPA', 'Research'], "linear")
train_model(X_train, y_train, X_test, y_test, ['CGPA', 'Research'], "ridge")
train_model(X_train, y_train, X_test, y_test, ['CGPA', 'Research'], "lasso", 0.001)
```

```
----   Linear Regression Model  ----

Train MAE: 0.05 Test MAE: 0.05
Train RMSE: 0.06 Test RMSE: 0.07
Train R2_score: 0.78 Test R2_score: 0.81
Train Adjusted_R2: 0.78 Test Adjusted_R2: 0.81
Intercept: 0.7247774222727991
     Column      Coef
0      CGPA  0.112050
1  Research  0.020205
--------------------------------------------------

----   Ridge Regression Model  ----

Train MAE: 0.05 Test MAE: 0.05
Train RMSE: 0.06 Test RMSE: 0.07
Train R2_score: 0.78 Test R2_score: 0.81
Train Adjusted_R2: 0.78 Test Adjusted_R2: 0.81
Intercept: 0.7247830300095277
     Column      Coef
0      CGPA  0.111630
1  Research  0.020362
--------------------------------------------------

----   Lasso Regression Model  ----

Train MAE: 0.05 Test MAE: 0.05
Train RMSE: 0.06 Test RMSE: 0.07
Train R2_score: 0.78 Test R2_score: 0.81
Train Adjusted_R2: 0.78 Test Adjusted_R2: 0.81
Intercept: 0.7247713356661623
     Column      Coef
0      CGPA  0.111344
1  Research  0.019571
--------------------------------------------------
▾      Lasso
Lasso(alpha=0.001)
```

After removing collinear features using VIF and using only two features. R2_score and Adjusted_r2 are still the same as before the testing dataset.

4.2 Mean of Residuals

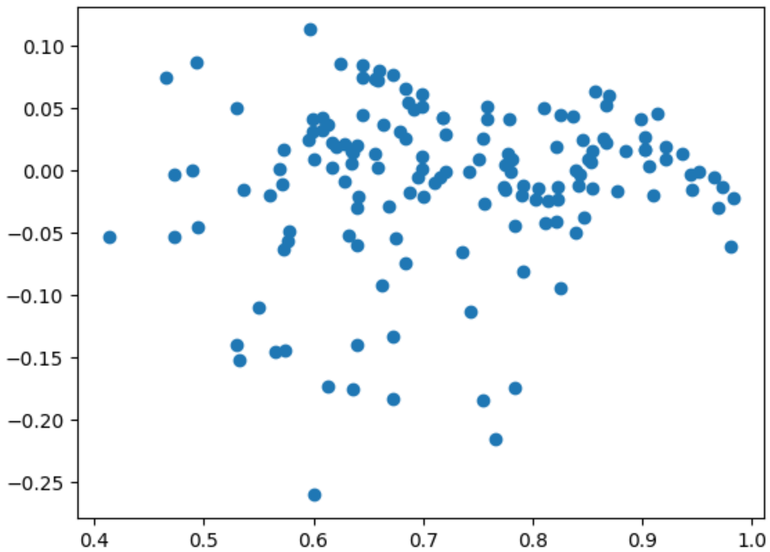
It is clear from RMSE that Mean of Residuals is almost zero.

4.3 Linearity of variables

It is quite clear from EDA that independent variables are linearly dependent on the target variables.

4.4 Test for Homoscedasticity

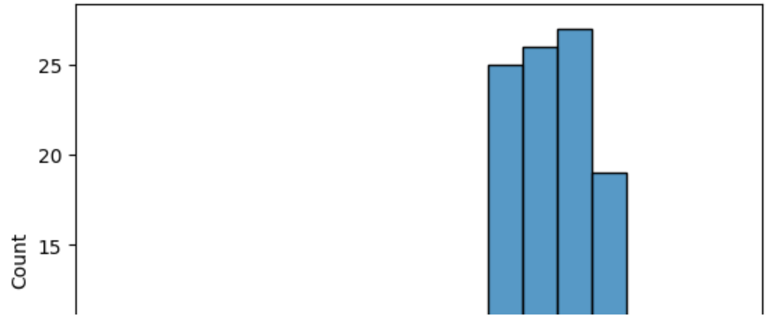
```
y_pred = model.predict(X_test)
residuals = (y_test - y_pred)
plt.scatter(y_pred, residuals)
plt.show()
```



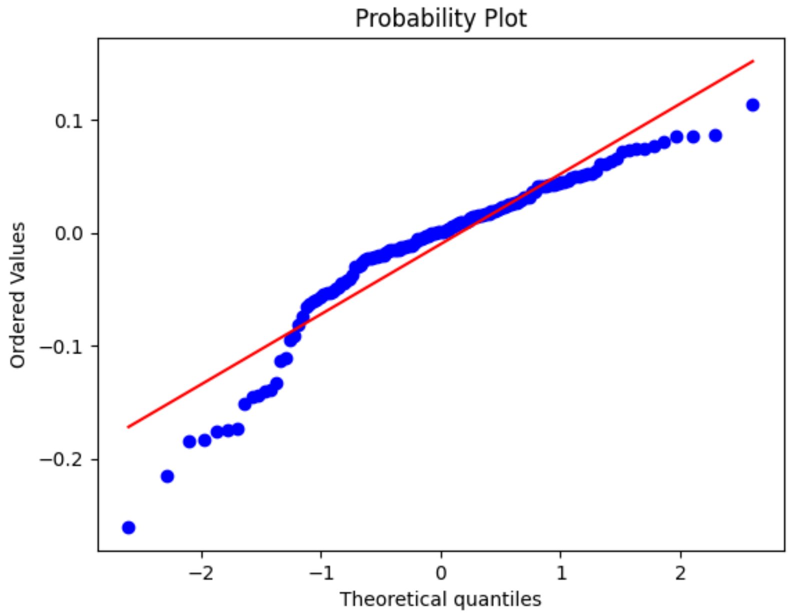
Since the plot is not creating a cone type shape. Hence there is no homoscedasticity present in the data.

4.5 Normality of Residuals

```
sns.histplot(residuals)
plt.show()
```




```
stats.probplot(residuals, plot=plt)
plt.show()
```



5. Model performance evaluation

Metrics checked - MAE, RMSE, R2, Adj R2

Train and test performances are checked

Comments on the performance measures and if there is any need to improve the model or not

All these related data has been performed above

0s completed at 4:30 PM