Jamboree Education

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: Predict the chances of graduate admission based on the given features.

```
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("https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/839/original/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

```
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 present in the dataset.

```
cat_cols = ['University Rating', 'SOP', 'LOR ', 'Research']
num_cols = ['GRE Score', 'TOEFL Score', 'CGPA']
target = 'Chance of Admit '
```

```
df.describe()
```

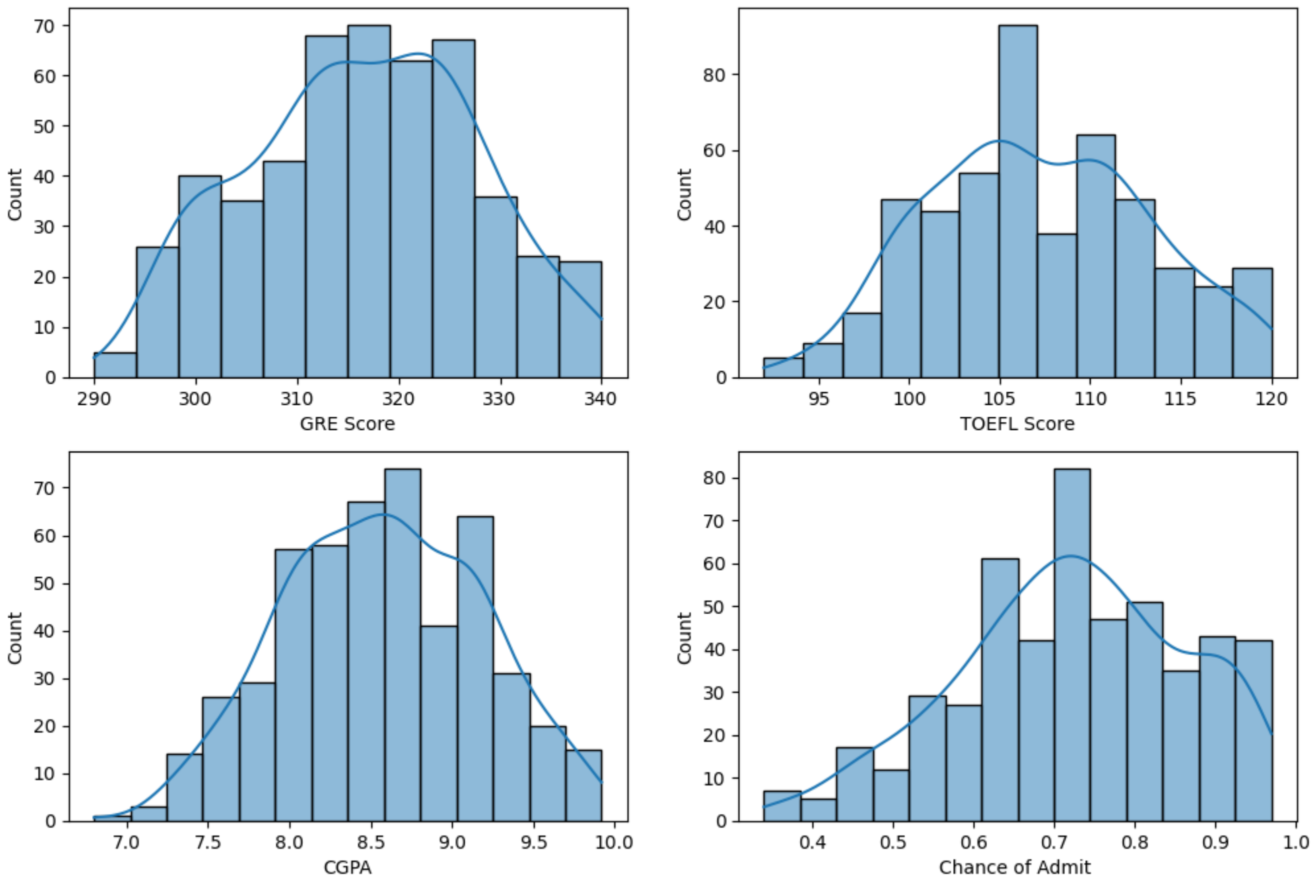
	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
count	500.000000	500.000000	500.000000	500.000000	500.000000	500.00000	500.000000	500.000000	500.00000
mean	250.500000	316.472000	107.192000	3.114000	3.374000	3.48400	8.576440	0.560000	0.72174
std	144.481833	11.295148	6.081868	1.143512	0.991004	0.92545	0.604813	0.496884	0.14114
min	1.000000	290.000000	92.000000	1.000000	1.000000	1.00000	6.800000	0.000000	0.34000
25%	125.750000	308.000000	103.000000	2.000000	2.500000	3.00000	8.127500	0.000000	0.63000

```
# check 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
```

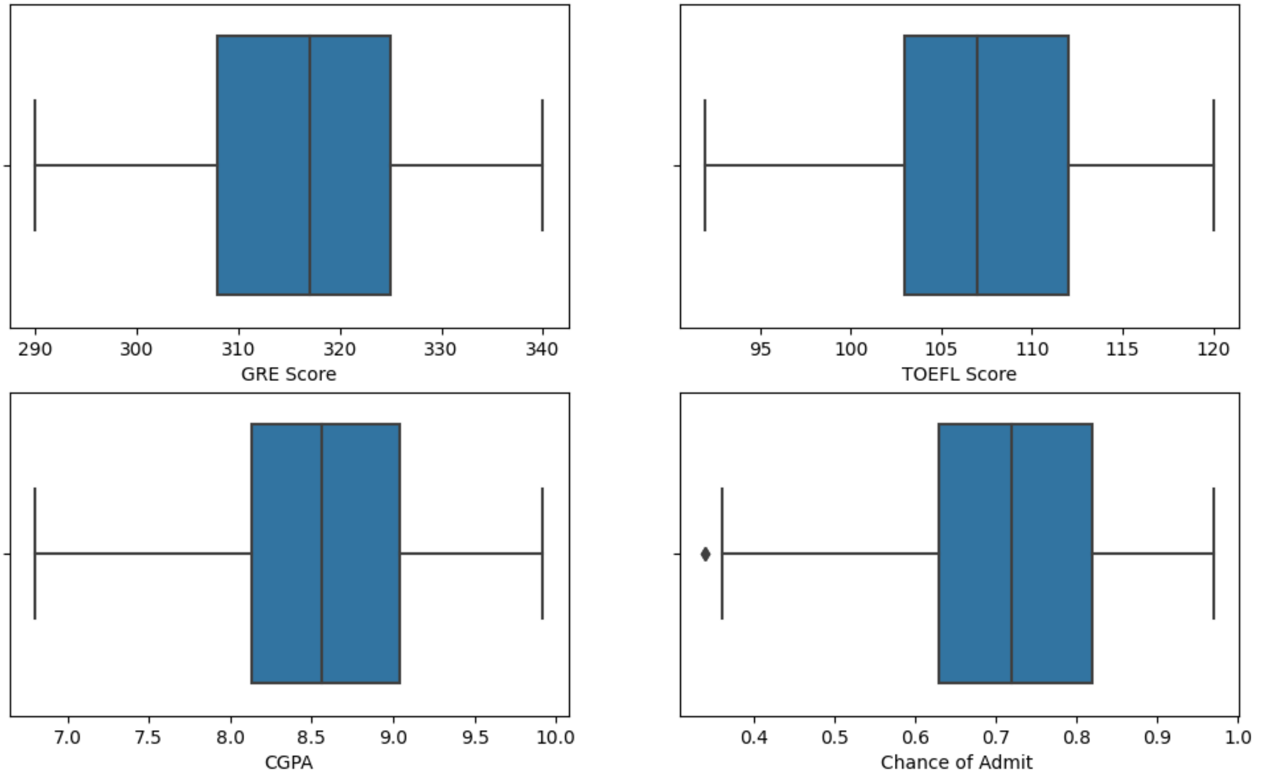
Univariate Analysis

```
# check distribution of each numerical variable
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()
```




```
# check 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()
```

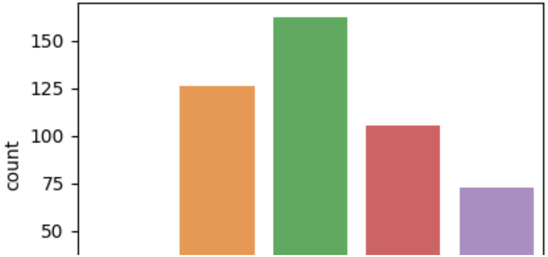


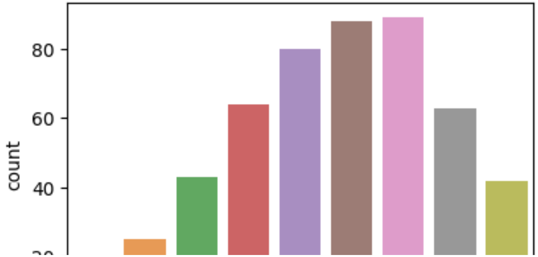
There are no outliers present in the dataset.

```
# 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
```

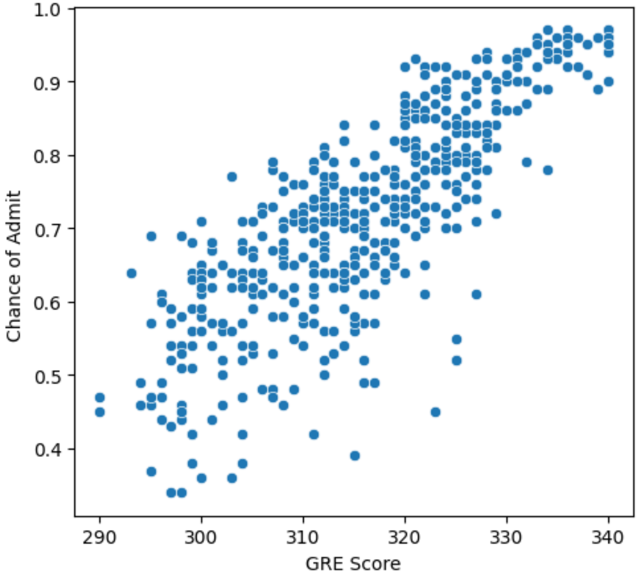
```
# countplots for categorical variables
cols, rows = 2, 2
fig, axs = plt.subplots(rows, cols, figsize=(10, 7))

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()
```

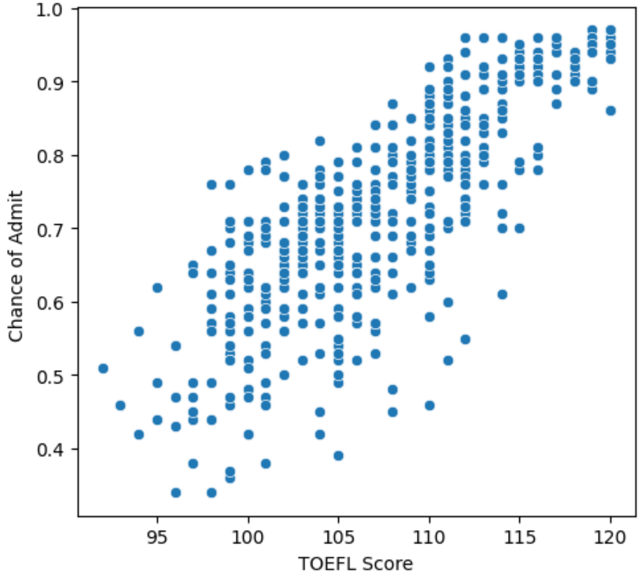




Bivariate Analysis

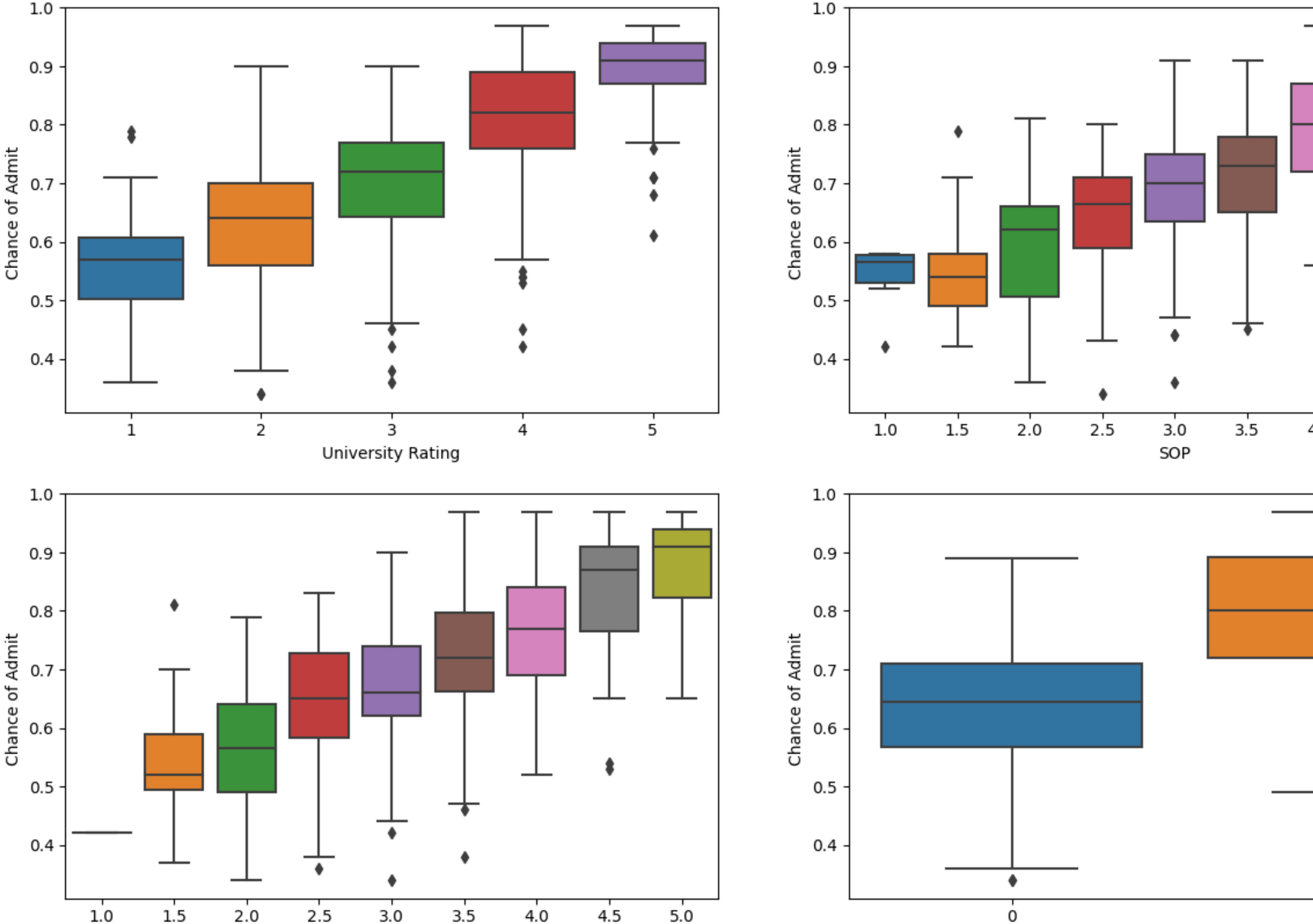
```
# check relation bw continuous variables & target variable
fig, axs = plt.subplots(1, 2, figsize=(12,5))

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
```

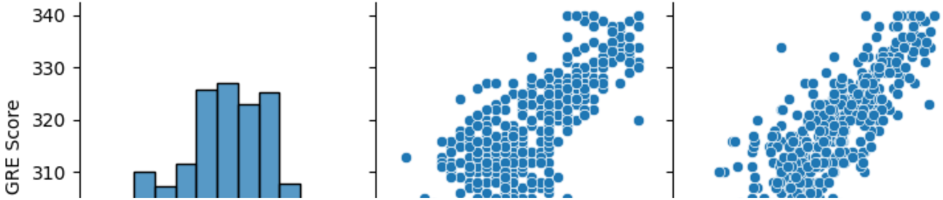


Chance of Admit
1.0
0.9
0.8
0.7
0.6
0.5
0.4
1
2
3
4
5
University Rating
Chance of Admit
1.0
1.5
2.0
2.5
3.0
3.5
SOP
Chance of Admit
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
Chance of Admit
0

- As you can see from the graphs, as tge rating increases the `Chance of Admit` also increases.
- 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()
```

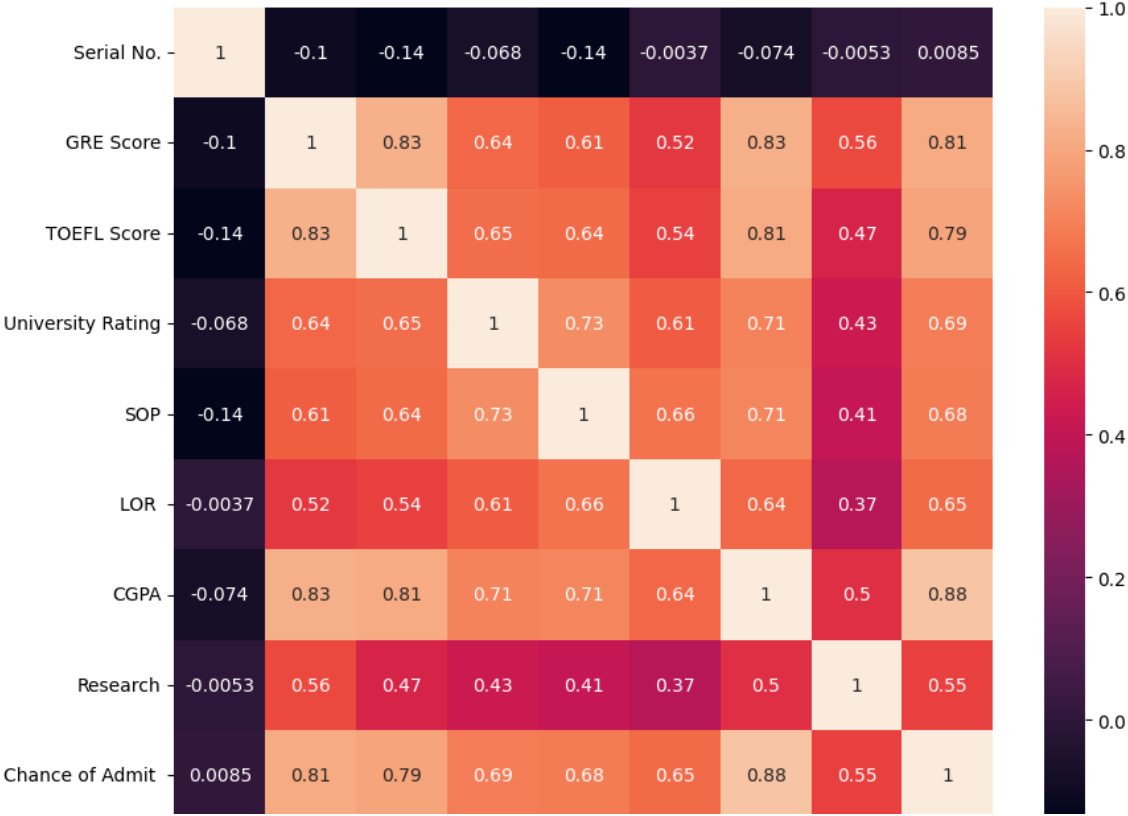


Independent continuous variables are also correlated with each other.

```
df.corr()
```

	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
Serial No.	1.000000	-0.103839	-0.141696	-0.067641	-0.137352	-0.003694	-0.074289	-0.005332	0.008505
GRE Score	-0.103839	1.000000	0.827200	0.635376	0.613498	0.524679	0.825878	0.563398	0.810351
TOEFL Score	-0.141696	0.827200	1.000000	0.649799	0.644410	0.541563	0.810574	0.467012	0.792228
University Rating	-0.067641	0.635376	0.649799	1.000000	0.728024	0.608651	0.705254	0.427047	0.690132
SOP	-0.137352	0.613498	0.644410	0.728024	1.000000	0.663707	0.712154	0.408116	0.684137
LOR	-0.003694	0.524679	0.541563	0.608651	0.663707	1.000000	0.637469	0.372526	0.645365
CGPA	-0.074289	0.825878	0.810574	0.705254	0.712154	0.637469	1.000000	0.501311	0.882413
Research	-0.005332	0.563398	0.467012	0.427047	0.408116	0.372526	0.501311	1.000000	0.545871
Chance of Admit	0.008505	0.810351	0.792228	0.690132	0.684137	0.645365	0.882413	0.545871	1.000000

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



Data Preprocessing

```
# 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.

Data preparation for model building

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

```
# standardize the dataset
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,)
```

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)
```

```python
    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
```

```python
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_}")
    #print(len(df.columns), len(model.coef_))
    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
```

- 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.

Linear Regression Model - Assumption Test

Train RMSE: 0.06 Test RMSE: 0.06

Mutlicollinearity Check

Column Coef

```
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
```

Train MAE: 0.04 Test MAE: 0.04

```
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

```
# 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)
```

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.

```
Train R2_score: 0.78 Test R2_score: 0.81
```

Mean of Residuals

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

Linearity of variables

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

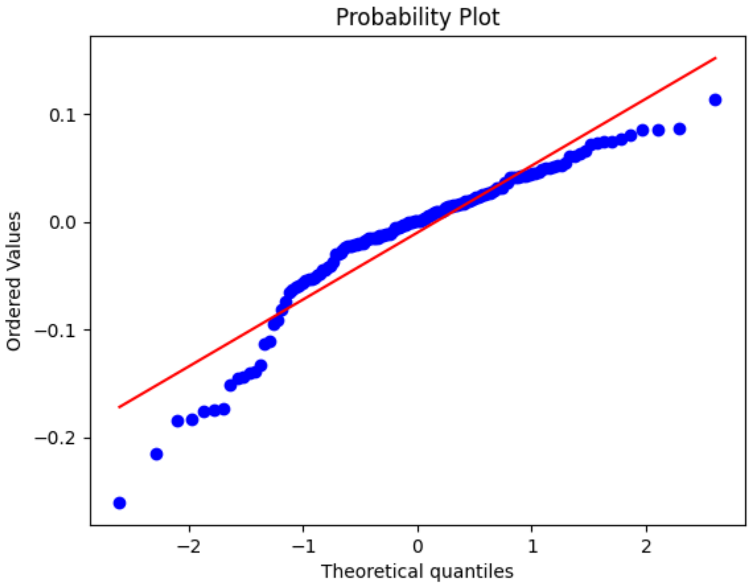
```
Train RMSE: 0.06 Test RMSE: 0.07
```

Normality of Residuals

```
Column      Coef
```

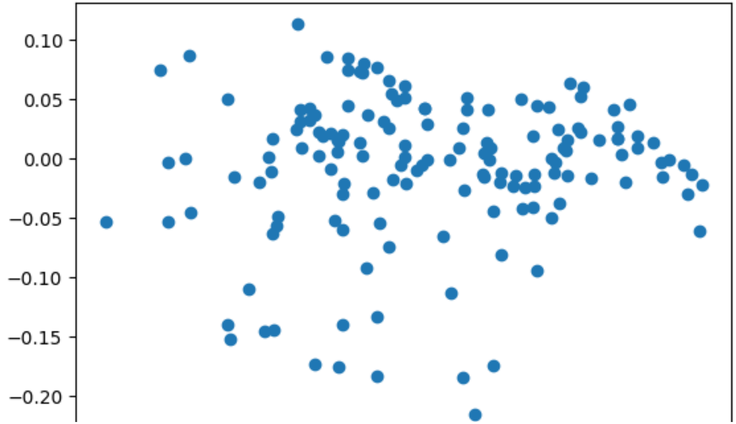
```
y_pred = model.predict(X_test)
residuals = (y_test - y_pred)
sns.histplot(residuals)
plt.show()
```


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



Test for Homoscedasticity

```
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.

Insights

1. Multicollinearity is present in the data.
2. After removing collinear features there are only two variables which are important in making predictions for the target variables.
3. Indepedent variables are linearly correlated with dependent variables.

Recommendations

1. `CGPA and Research` are the only two variables which are important in making the prediction for `Chance of Admit`.
2. `CGPA` is the most important varibale in making the prediction for the `Chance of Admit`.
3. Following are the final model results on the test data:
    - **RMSE:** 0.07
    - **MAE:** 0.05
    - **R2_score:** 0.81
    - **Adjusted_R2:** 0.81