Jamboree Education - Linear Regression

In [ ]:

Importing Libraries

In [172…

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

Importing modules or packages for linear Regression.

In [173…

```
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
```

In [ ]:

Downloading Dataset

In [174…

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

Out[174]:

	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

In [ ]:

In [175…

```
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.

In [ ]:

In [176…

```
df.nunique()
```

Out[176]:

```
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
```

In [ ]:

In [177…

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

In [178…

```
df.describe()
```

Out[178]:

	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Resea
count	500.000000	500.000000	500.000000	500.000000	500.000000	500.00000	500.000000	500.000(
mean	250.500000	316.472000	107.192000	3.114000	3.374000	3.48400	8.576440	0.560(
std	144.481833	11.295148	6.081868	1.143512	0.991004	0.92545	0.604813	0.496;
min	1.000000	290.000000	92.000000	1.000000	1.000000	1.00000	6.800000	0.000(
25%	125.750000	308.000000	103.000000	2.000000	2.500000	3.00000	8.127500	0.000(
50%	250.500000	317.000000	107.000000	3.000000	3.500000	3.50000	8.560000	1.000(
75%	375.250000	325.000000	112.000000	4.000000	4.000000	4.00000	9.040000	1.000(
max	500.000000	340.000000	120.000000	5.000000	5.000000	5.00000	9.920000	1.000(

In [ ]:

In [179…

```
# check for missing values

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

Out[179]:

```
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
```

In [ ]:

Explorartory Data Analysis - Univariate,Bivariate and Multivariate analysis

Univariate Analysis

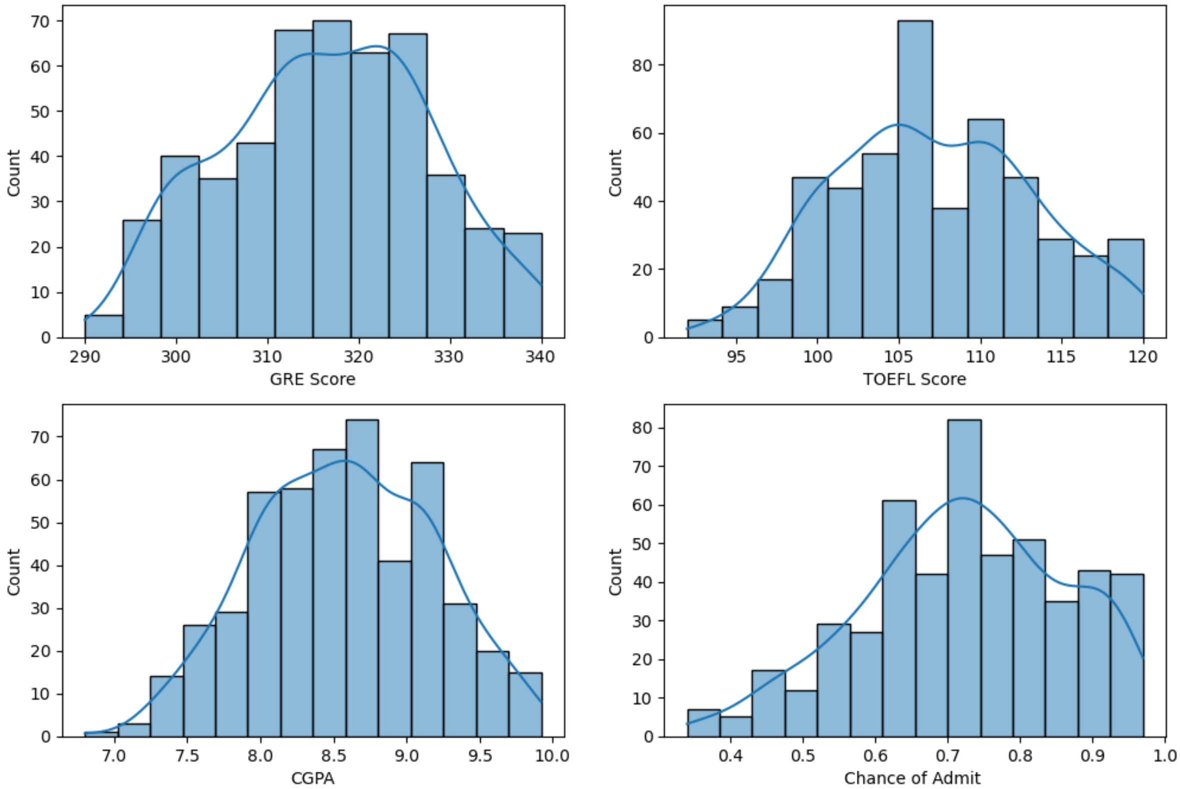
In [ ]:

In [180…

```
### 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()
```



In [ ]:

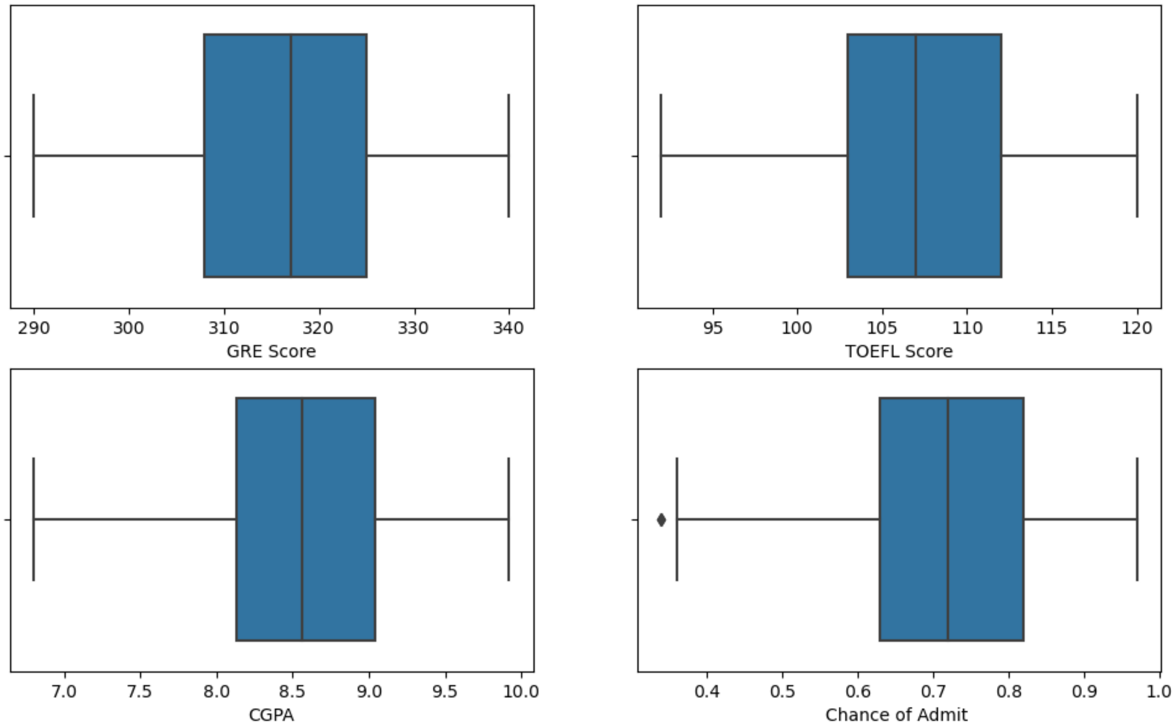
In [181…

```
# 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 in the dataset

In [ ]:

In [183…

```
# 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
```

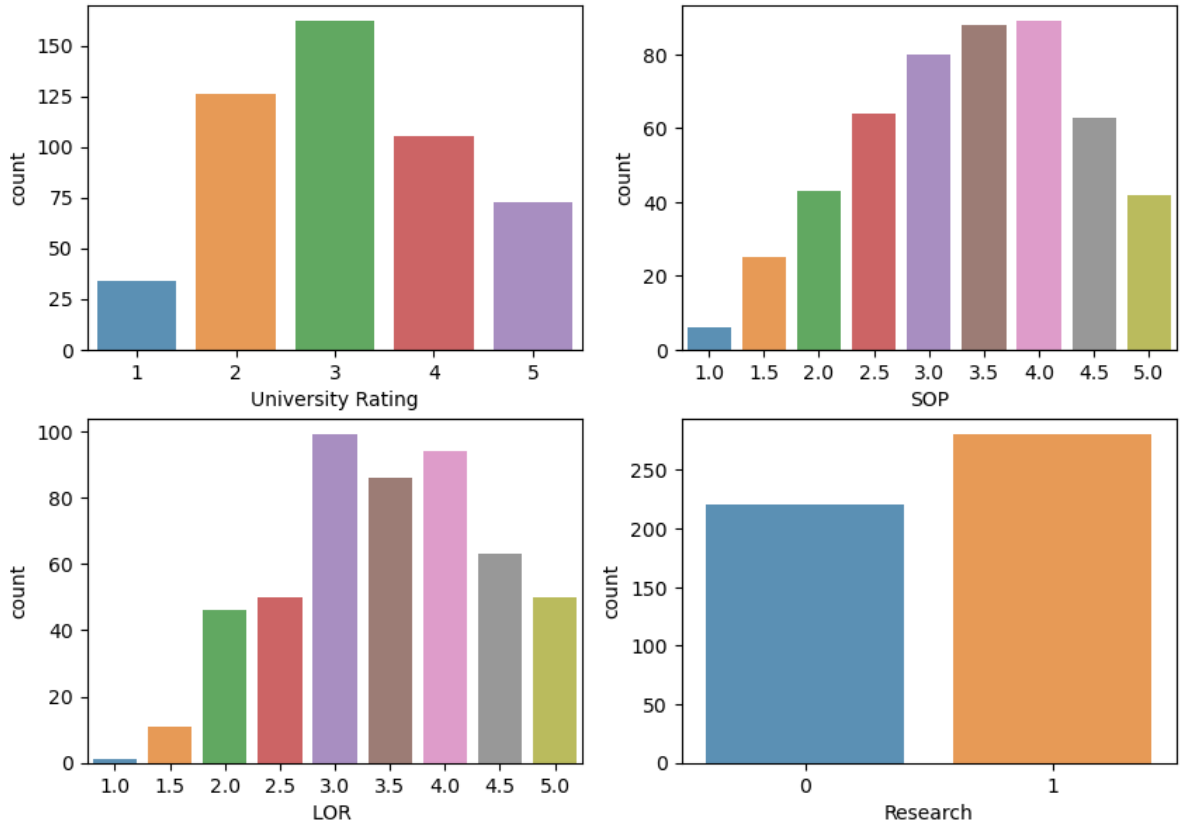
In [184…

```
# 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()
```



In [ ]:

Bivariate Analysis

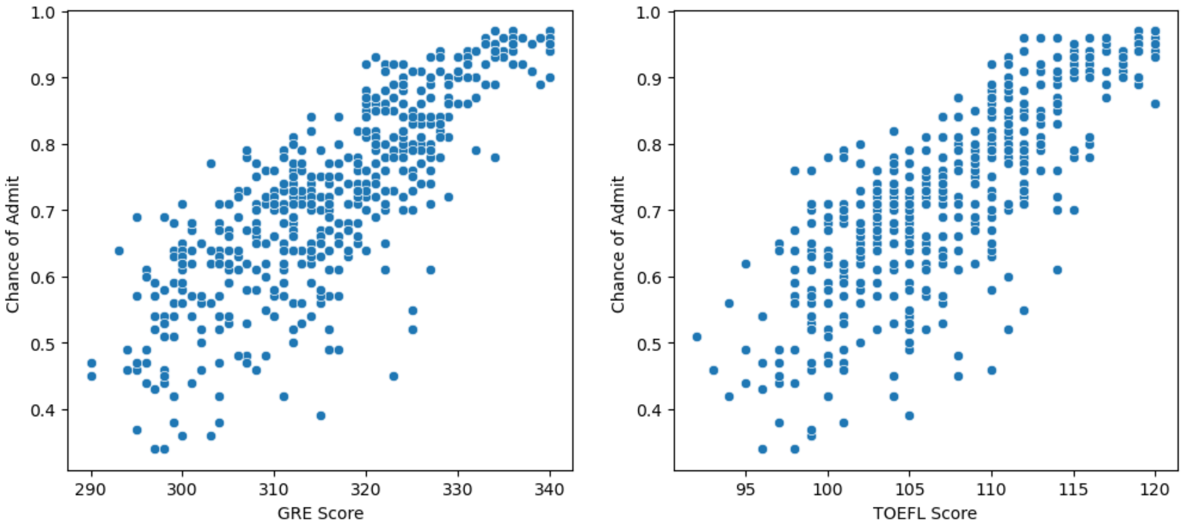
In [185…

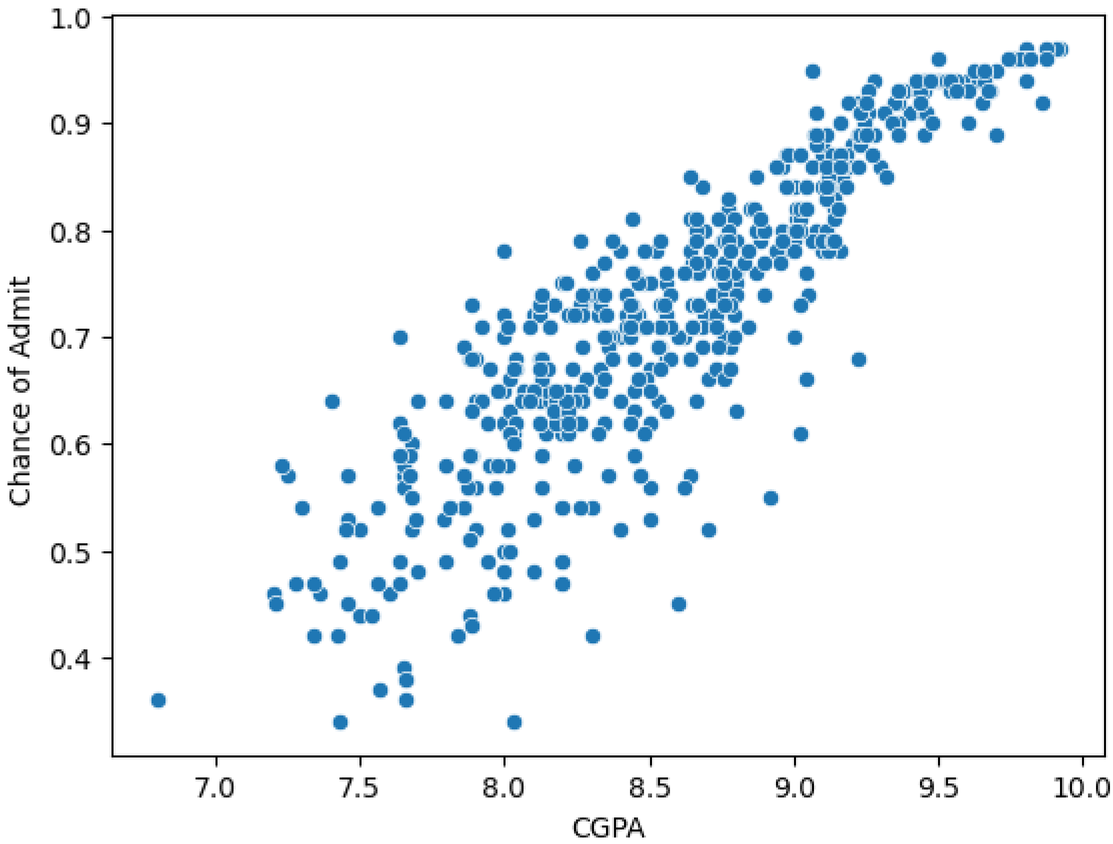
```
# check relation between continuous variables & target variable


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()
```





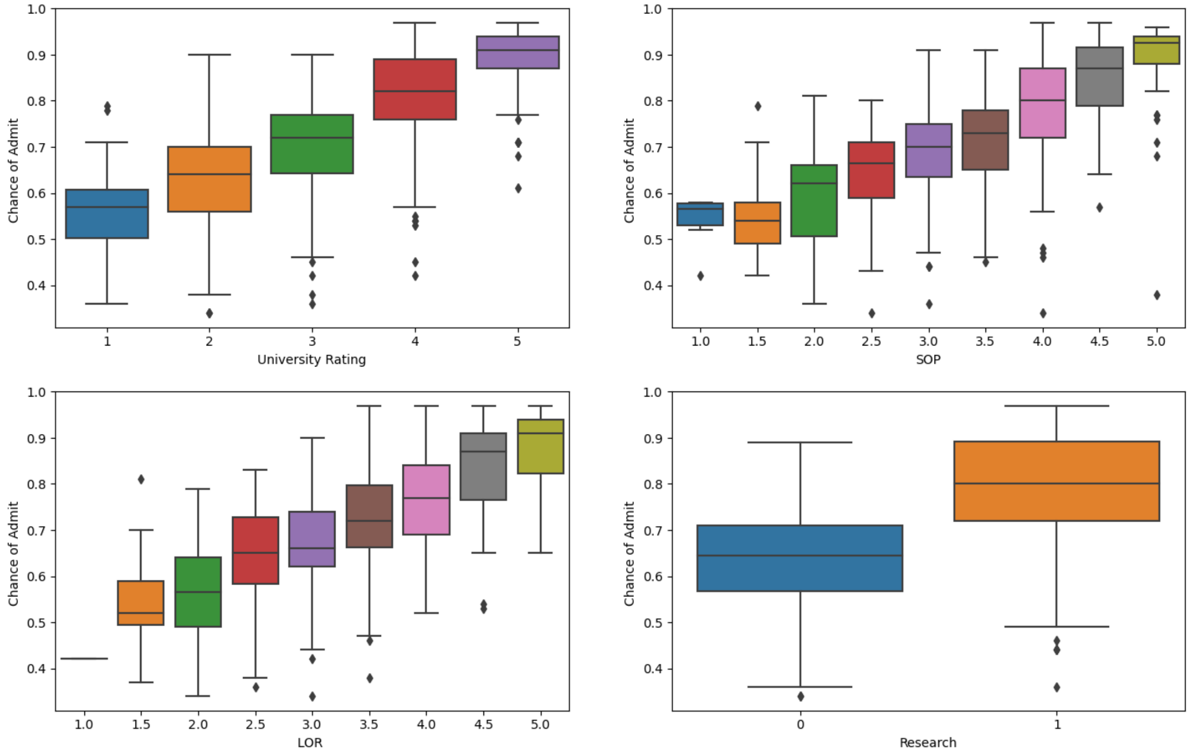
There is a linear correlation between the continuous variables and the target variable.

In [ ]:

In [186…

```
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
```



From the above graphs,we can see that as the target 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.

In [ ]:

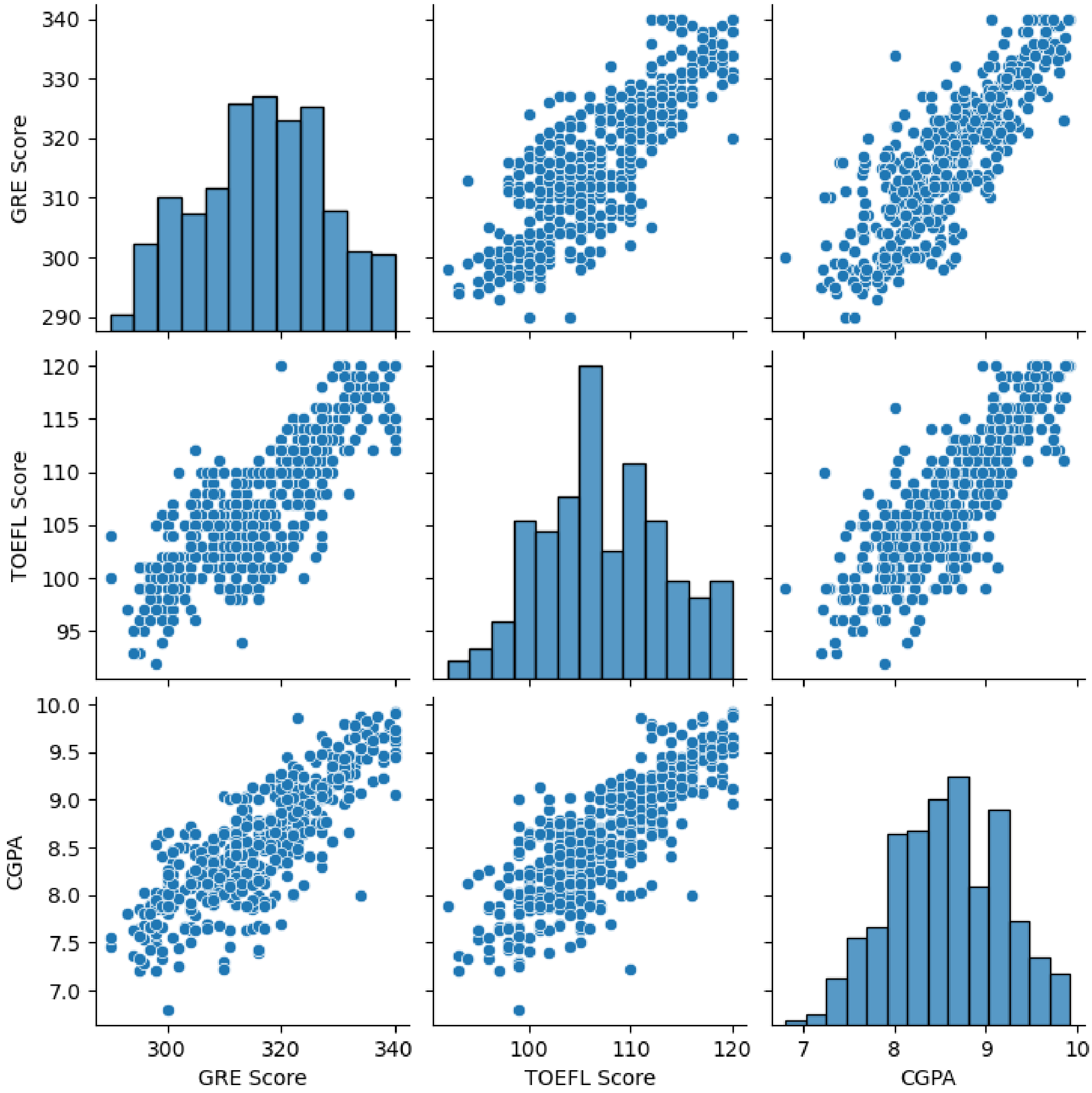
```

```

Multivariate Analysis

In [187…

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



Independent continuous variables are also correlated with each other.

In [ ]:

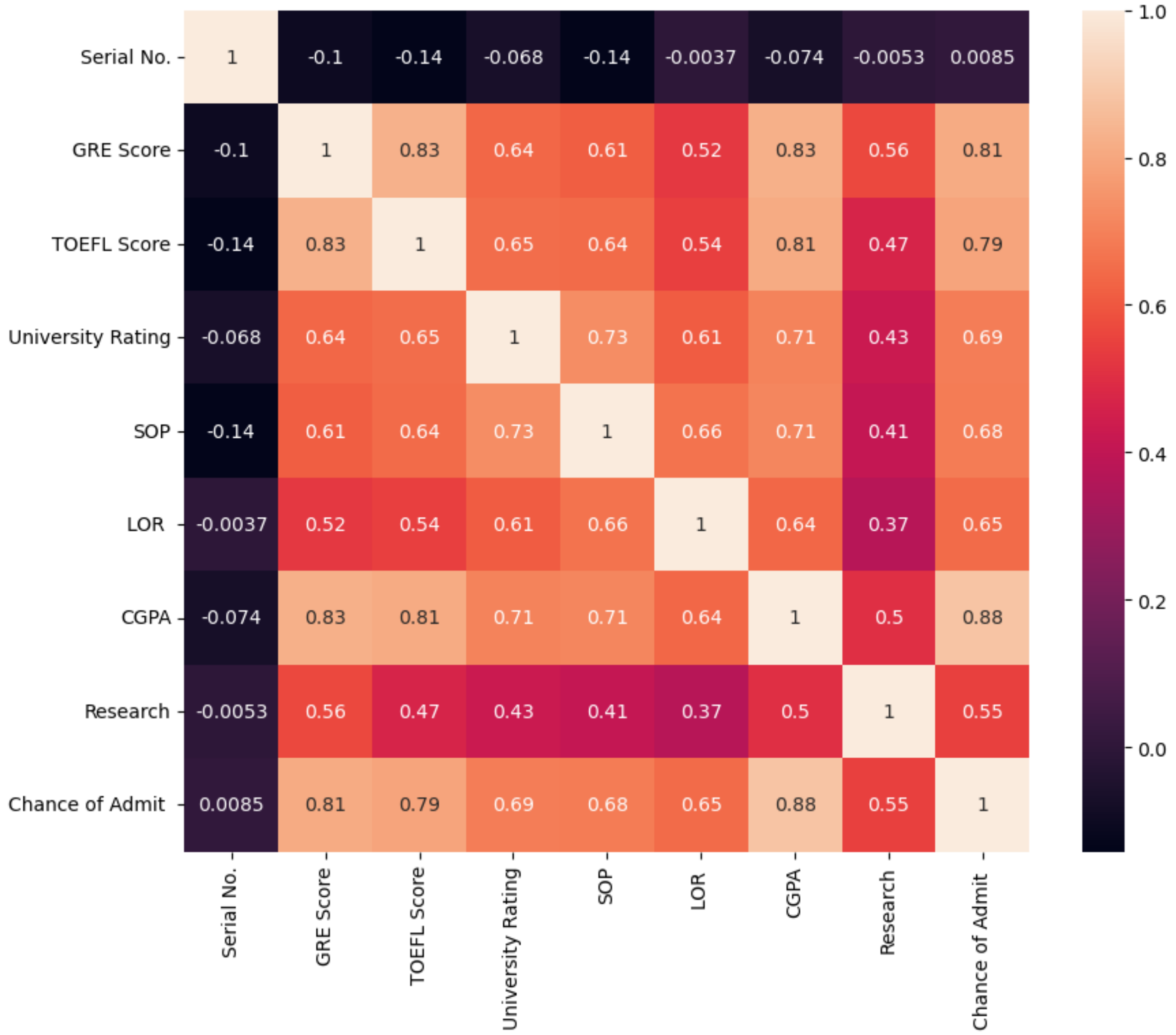
In [188…
```
df.corr()
```

Out[188]:

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

In [189…

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



In [ ]:

Data Preprocessing

In [190…
```
# drop 'Serial NO.' column

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

In [191…
```
# check for duplicates

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

Out[191]:
```
0
```

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

In [ ]:

Data preparation for model building

In [195…
```
X = df.drop(columns=[target])
y = df[target]
```

In [202…
```
X.shape,y.shape
```

Out[202]:
```
((500, 7), (500,))
```

In [218…
```
# standardize the dataset using train_test_split

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_sta

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

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

In [219…
```
model = LinearRegression()

model.fit(X_train, y_train)
```

Out[219]:
```
▾ LinearRegression
LinearRegression()
```

In [215…
```
# weights

model.coef_
```

Out[215]:
```
array([ 0.01865693,  0.02317626,  0.01156475, -0.00099944,  0.01249708,
        0.06467088,  0.01396816])
```

In [223…
```
model.intercept_
```

Out[223]: 0.7249781214769964

Model Building

In [225…

```
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
```

In [226…

```
def train_model(X_train, y_train, X_test, y_test,cols, model_name="linear", alpha=1
    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['mear
    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_sc
    print(f"Train Adjusted_R2: {train_res['adj_r2']} Test Adjusted_R2: {test_res['a
    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
```

In [227…

```
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: 0.7249781214769964
              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: 0.7249823645841699
              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: 0.7249659139557144
              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
--------------------------------------------------
```

Out[227]:

```
▾      Lasso
Lasso(alpha=0.001)
```

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.

In [ ]:

Linear Regression Model - Assumption Test

1. Mutlicollinearity Check

In [160…

```
def vif(newdf):
    vif_data = pd.DataFrame() # VIF 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
```

In [161…

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

Out[161]:

	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 [ ]:

In [162…

```
# drop GRE Score and again calculate the VIF

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

Out[162]:

	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

In [163…

```
# drop TOEFL Score and again calculate the VIF

res = vif(df.iloc[:,2:-1])
res
```

Out[163]:

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

In [164…

```
# Now lets drop the SOP and again calculate VIF

res = vif(df.iloc[:,2:-1].drop(columns=['SOP']))
res
```

Out[164]:

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

In [165…

```
# 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
```

Out[165]:

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

In [166…

```
# drop the University Rating

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

Out[166]:

	feature	VIF
0	CGPA	2.455008
1	Research	2.455008

In [ ]:

```

```

In [167…

```
# 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_sta
```

In [168…

```
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
--------------------------------------------------
```

Out[168]:

```
▾        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.

In [ ]:

2. Mean of Residuals

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

In [ ]:

3. Linearity of variables

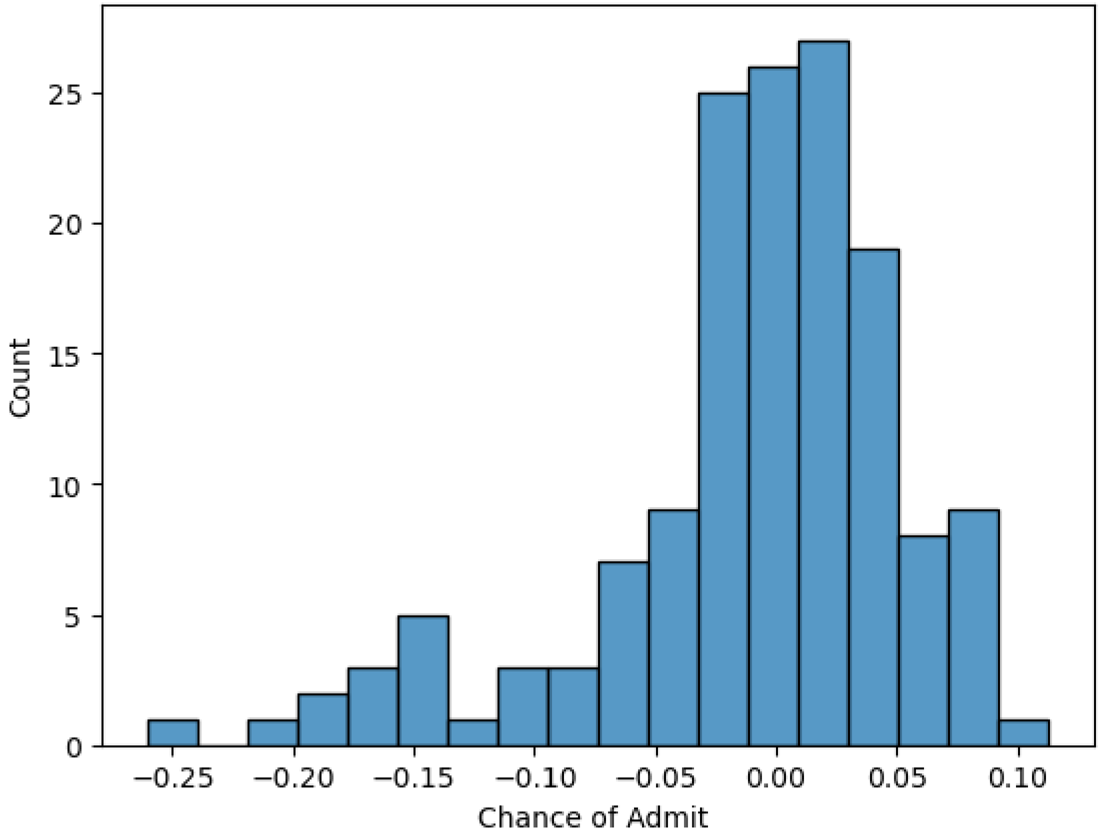
It is quite clear from EDA that independent variables are linearly dependent on the target variables.

In [ ]:

4. Normality of Residuals

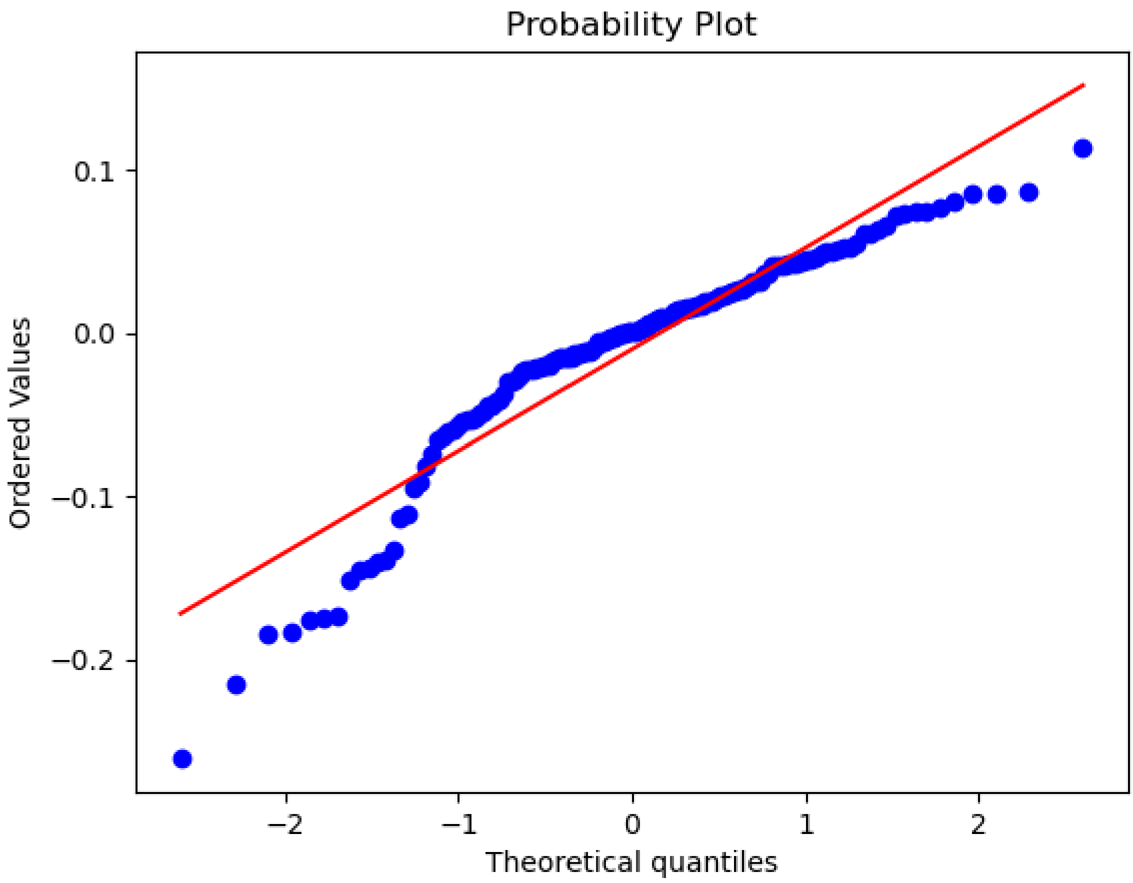
In [169…

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



In [170…

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

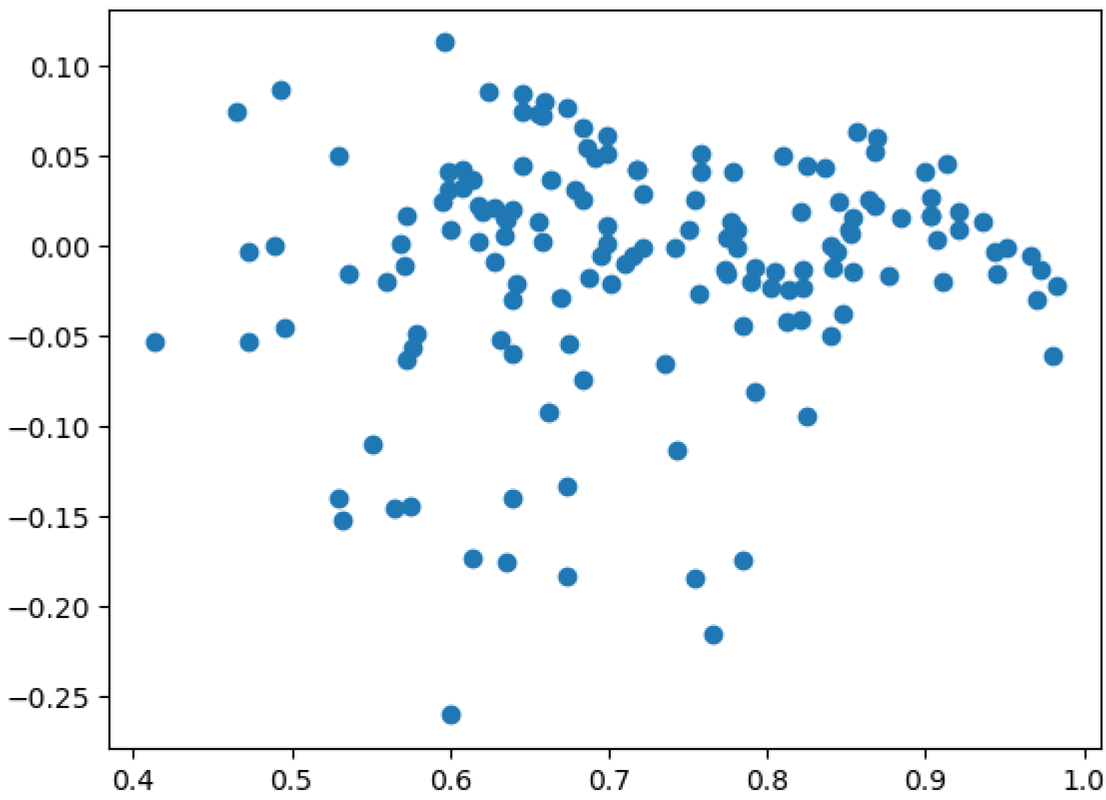


In [ ]:

5. Homoscedasticity

In [171…

```
plt.scatter(y_pred, residuals)
plt.show()
```



As the above plot is not creating any cone type shape,there is no homoscedasticity present in the data.

In [ ]:

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. Independent variables are linearly correlated with dependent variables.

In [ ]:

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 variable 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

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]: