Jamboree Education - Linear Regression

● Jamboree is a renowned educational institution that has successfully assisted numerous students in gaining admission to top colleges abroad. With their proven problem-solving methods, they have helped students achieve exceptional scores on exams like GMAT, GRE, and SAT with minimal effort.

● To further support students, Jamboree has recently introduced a new feature on their website. This feature enables students to assess their probability of admission to Ivy League colleges, considering the unique perspective of Indian applicants.

● This analysis will help Jamboree in understanding what factors are important in graduate admissions and how these factors are interrelated among themselves. It will also help predict one's chances of admission given the rest of the variables.

Data set link: https://drive.google.com/file/d/1UCnSk_NN02jlzj0bbSZ_j-gdGUDDJxy4/view

Column description:

● Serial No.: This column represents the unique row identifier for each applicant in the dataset.

● GRE Scores: This column contains the GRE (Graduate Record Examination) scores of the applicants, which are measured on a scale of 0 to 340.

● TOEFL Scores: This column includes the TOEFL (Test of English as a Foreign Language) scores of the applicants, which are measured on a scale of 0 to 120.

● University Rating: This column indicates the rating or reputation of the university that the applicants are associated with.The rating is based on a scale of 0 to 5, with 5 representing the highest rating.

● SOP: This column represents the strength of the applicant's statement of purpose, rated on a scale of 0 to 5, with 5 indicating a strong and compelling SOP.

● LOR: This column represents the strength of the applicant's letter of recommendation, rated on a scale of 0 to 5, with 5 indicating a strong and compelling LOR.

● CGPA: This column contains the undergraduate Grade Point Average (GPA) of the applicants, which is measured on a scale of 0 to 10.

● Research: This column indicates whether the applicant has research experience (1) or not (0).

● Chance of Admit: This column represents the estimated probability or chance of admission for each applicant, ranging from 0 to 1.

These columns provide relevant information about the applicants' academic qualifications, test scores, university ratings, and other factors that may influence their chances of admission.

import numpy as np import pandas as pd import matplotlib.pyplot as plt import seaborn as sns from sklearn.linear_model import LinearRegression from sklearn.model_selection import train_test_split

Loading Jamboree Data

```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler, MinMaxScaler
import statsmodels.api as sm
from sklearn.linear_model import LinearRegression
import warnings
warnings.filterwarnings("ignore")

data = pd.read_csv('Jamboree_Admission.csv')

data
```

```
     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
..          ...        ...          ...                ...  ...   ...
...
495         496        332          108                  5  4.5   4.0
9.02
496         497        337          117                  5  5.0   5.0
9.87
497         498        330          120                  5  4.5   5.0
9.56
498         499        312          103                  4  4.0   5.0
8.43
499         500        327          113                  4  4.5   4.5
9.04

     Research  Chance of Admit
0           1             0.92
1           1             0.76
2           1             0.72
3           1             0.80
4           0             0.65
..        ...              ...
495         1             0.87
```

```
496          1              0.96
497          1              0.93
498          0              0.73
499          0              0.84

[500 rows x 9 columns]
```

```
data.shape
```

```
(500, 9)
```

```
data.dtypes
```

```
Serial No.              int64
GRE Score               int64
TOEFL Score             int64
University Rating       int64
SOP                   float64
LOR                   float64
CGPA                  float64
Research                int64
Chance of Admit       float64
dtype: object
```

```
data.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
```

Insight: No null values.

```
#We donot need 'Serial No.' column for the analysis.So dropping that
column
data.drop('Serial No.', axis=1, inplace=True)
```

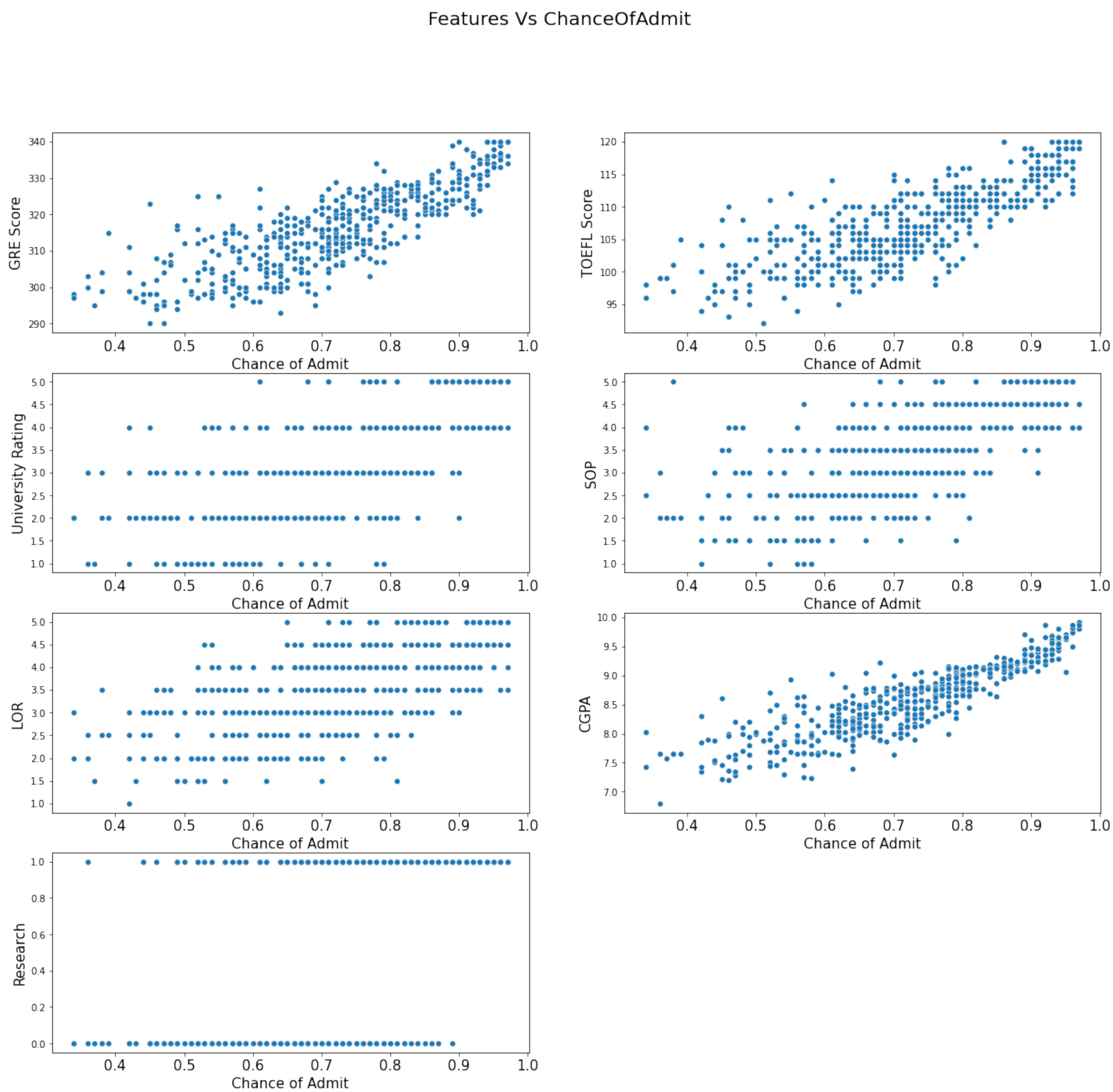
```
data.describe()
```

```
        GRE Score  TOEFL Score  University Rating         SOP
LOR   \
count  500.000000   500.000000         500.000000  500.000000
500.00000
mean   316.472000   107.192000           3.114000    3.374000
3.48400
```

```
std      11.295148     6.081868           1.143512    0.991004
0.92545
min     290.000000    92.000000           1.000000    1.000000
1.00000
25%     308.000000   103.000000           2.000000    2.500000
3.00000
50%     317.000000   107.000000           3.000000    3.500000
3.50000
75%     325.000000   112.000000           4.000000    4.000000
4.00000
max     340.000000   120.000000           5.000000    5.000000
5.00000

             CGPA    Research  Chance of Admit
count  500.000000  500.000000        500.00000
mean     8.576440    0.560000          0.72174
std      0.604813    0.496884          0.14114
min      6.800000    0.000000          0.34000
25%      8.127500    0.000000          0.63000
50%      8.560000    1.000000          0.72000
75%      9.040000    1.000000          0.82000
max      9.920000    1.000000          0.97000
```

Insight:

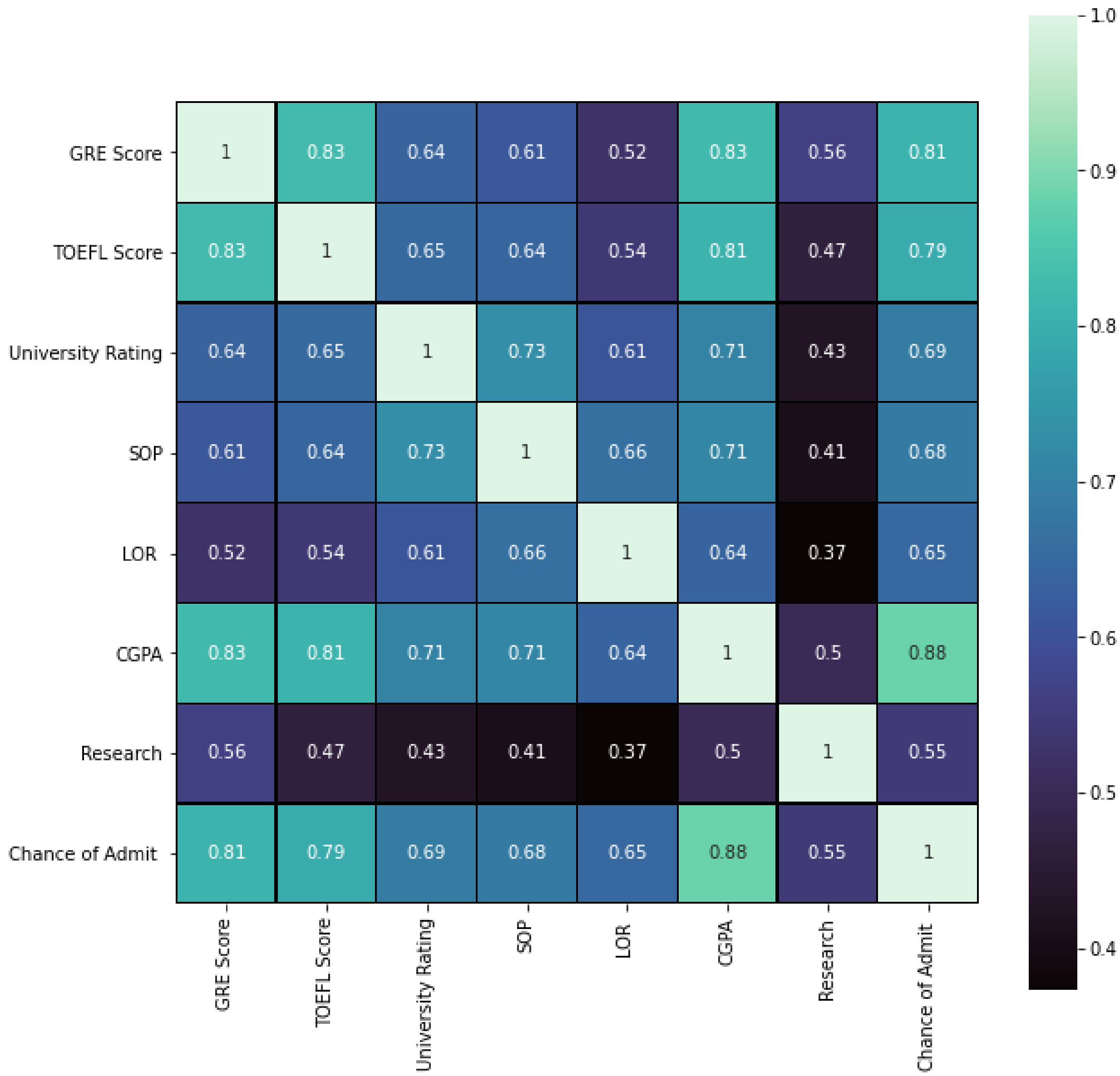
```
Range of columnsin given data:

    GRE Score---------[290.0, 340.0]
    TOEFL Score-------[92.0,120.0]
    University Rating-[1, 5]
    SOP---------------[1, 5]
    LOR---------------[1, 5]
    CGPA--------------[6.8, 9.92]
    Research----------[0, 1]
    Chance of Admit---[0.34, 0.97]

columns = ['GRE Score', 'TOEFL Score', 'University Rating', 'SOP',
'LOR ', 'CGPA',
       'Research']

fig = plt.figure(figsize=(20,18))
for i,col in enumerate(columns):
    plt.subplot(len(columns)/2 +1,2,i+1)
    sns.scatterplot(x=data['Chance of Admit '], y = data[col])
    plt.xlabel('Chance of Admit' , fontsize= 15, color = 'black')
    plt.ylabel(col,fontsize= 15, color = 'black')
    plt.xticks(fontsize = 15)
fig.suptitle("Features Vs ChanceOfAdmit",fontsize= 20, color =
'black')
plt.show()
```



Insight:

From the above plots we can observe that there is a linear correlation between GRE Score, Tofel Score, CGPA which are continuous and Chance to Admit. For the other columns SOP,LOR,University Rating as the rating increases the chance to get admission also increases. On the other hand there is high chance of getting admission for research people.

```
plt.figure(figsize=(10,10))
sns.heatmap(data.corr(), annot = True, cmap = 'mako', linewidths =
0.1, square= True, linecolor = 'Black')
plt.yticks(rotation=0)
plt.show()
```



Insights:

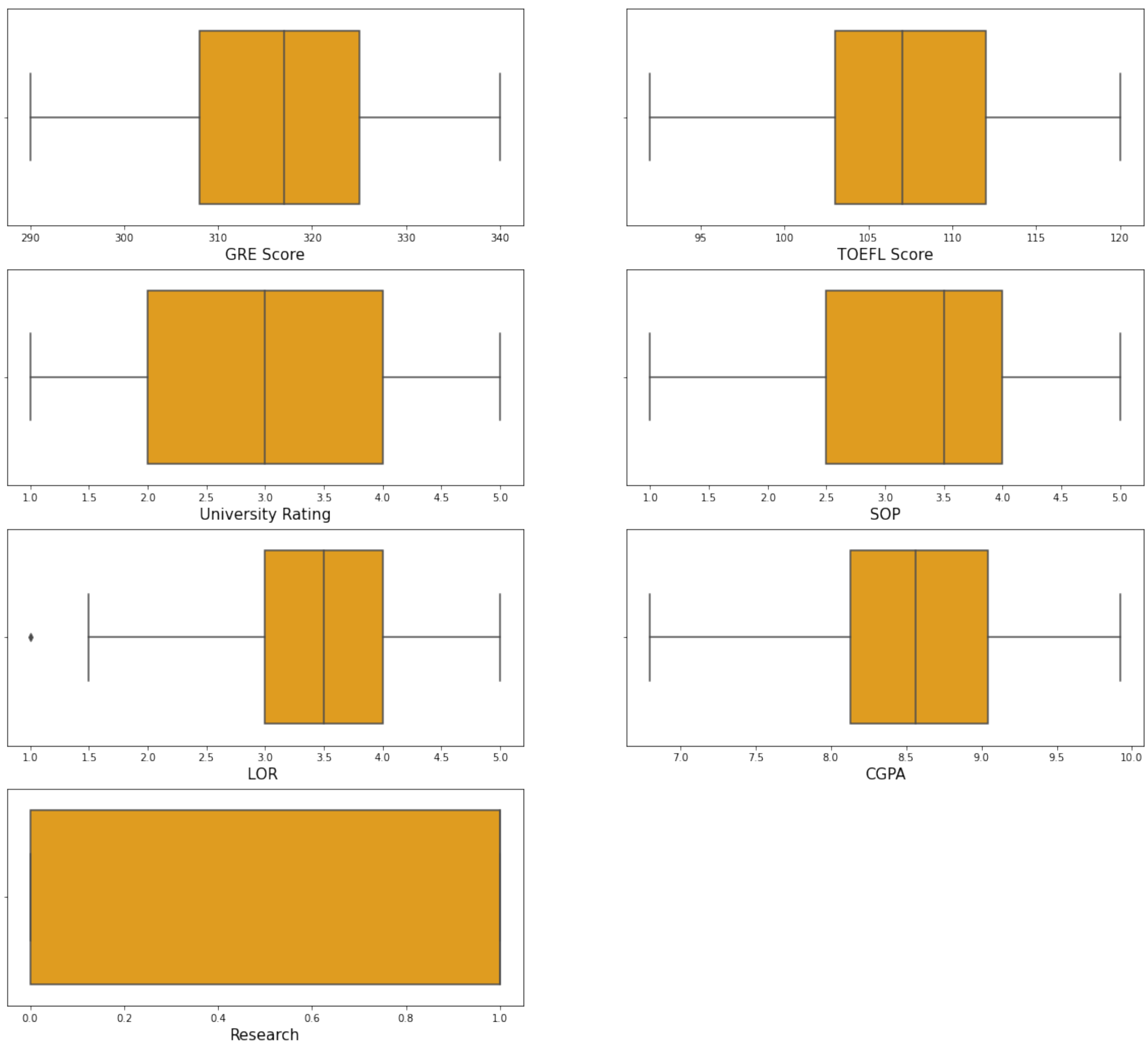
```
From the above fig it is known that GRE Score and CGPA are more
correlated to Chance of Admit.But there are no other features that are
highly correlated. So there is no need to drop any feature for now.
```

Data Preprocessing

```
data.duplicated().sum()

0
```

Insight:

```
No duplicate records found.

fig = plt.figure(figsize=(20,18))
for i,col in enumerate(columns):
    plt.subplot(len(columns)/2 +1,2,i+1)
    sns.boxplot(data = data,x= col, color = 'orange')
    plt.xlabel(col, fontsize=15)
    #plt.xticks(fontsize = 15)
#fig.suptitle("Features Vs ChanceOfAdmit",fontsize= 20, color =
'black')
plt.show()
```



Insights:

```
Other than LOR there no outliers found in other features. And there is
no need for treating LOR as it is one of the ratings given on scale 0-
5.
```

Preparing the data for modeling

STEP-1: Encoding

```
As our data has no categorical variables there is no need for
encoding.
```

STEP-2: Feature and Target split

```
Splitting entire data to two parts, one contains data of 'Chance of
Admit' which is the target column
for our analysis and the other part contains all the other features.

y = data['Chance of Admit ']
data.drop('Chance of Admit ', axis=1, inplace= True)
X = data

X.shape, y.shape

((500, 7), (500,))
```

STEP-3: Train-test split

```
Splitting data ito train and test data in 80/20 ratio.

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

print(f"X_train:{X_train.shape},X_test:{X_test.shape}, y_train:
{y_train.shape}, y_test:{y_test.shape}")

X_train:(400, 7),X_test:(100, 7), y_train:(400,), y_test:(100,)
```

STEP-4: Data Normalization/Standardization

```
Data normalization helps in scaling the whole data under one scale.We
use StandardScaler for Normalizing data.

scaler = StandardScaler()
#scaler = MinMaxScaler()
X_train = pd.DataFrame(scaler.fit_transform(X_train),
columns=X_train.columns)
X_train.head()
```

```
   GRE Score  TOEFL Score  University Rating       SOP      LOR
CGPA  \
0   0.389986     0.602418          -0.098298  0.126796  0.564984
0.415018
1  -0.066405     0.602418           0.775459  0.633979  1.651491 -
0.067852
2  -1.253022    -0.876917          -0.098298  0.126796 -0.521524 -
0.134454
3  -0.248961    -0.055064          -0.972054 -0.887570  0.564984 -
0.517420
4  -0.796631    -0.219435          -0.098298  0.126796 -1.064777 -
0.617324

   Research
0  0.895434
1 -1.116777
2 -1.116777
3 -1.116777
4  0.895434
```

```
X_test = pd.DataFrame(scaler.transform(X_test), columns =
X_test.columns)
X_test.head()
```

```
   GRE Score  TOEFL Score  University Rating       SOP      LOR
CGPA  \
0   1.576604     1.424271           0.775459  0.633979  0.021730
1.597217
1  -0.248961     0.109306           0.775459  1.141162  0.564984
0.764683
2  -0.157683    -0.383805          -0.972054 -1.394754 -1.064777 -
1.549762
3  -0.431518     0.273677          -0.098298 -0.380387 -0.521524
0.181909
4   0.846378     0.766789          -0.098298  0.126796 -0.521524
0.781333

   Research
0  0.895434
1  0.895434
2 -1.116777
3 -1.116777
4  0.895434
```

```
X_train
```

```
     GRE Score  TOEFL Score  University Rating       SOP      LOR
CGPA  \
0     0.389986     0.602418          -0.098298  0.126796  0.564984
0.415018
```

```
1    -0.066405     0.602418           0.775459  0.633979  1.651491 -
0.067852
2    -1.253022    -0.876917          -0.098298  0.126796 -0.521524 -
0.134454
3    -0.248961    -0.055064          -0.972054 -0.887570  0.564984 -
0.517420
4    -0.796631    -0.219435          -0.098298  0.126796 -1.064777 -
0.617324
..         ...          ...                ...       ...       ...
...
395   1.120212     0.602418           0.775459  1.141162  1.108237
0.997792
396  -0.979187    -0.383805          -0.972054 -0.887570 -0.521524 -
0.600673
397  -1.344300    -1.370029          -1.845810 -1.394754 -1.608031 -
2.215790
398  -0.705353    -0.383805          -0.972054 -0.887570  0.564984 -
1.499810
399  -0.248961    -0.219435          -0.972054  0.633979  0.021730 -
0.550721

     Research
0    0.895434
1   -1.116777
2   -1.116777
3   -1.116777
4    0.895434
..        ...
395  0.895434
396  0.895434
397 -1.116777
398 -1.116777
399 -1.116777

[400 rows x 7 columns]
```

```
y_train = y_train.reset_index(drop=True)
y_train
```

```
0      0.77
1      0.71
2      0.62
3      0.72
4      0.75
       ...
395    0.87
396    0.72
397    0.57
398    0.55
```

```
399    0.62
Name: Chance of Admit , Length: 400, dtype: float64
```

Building Linear Regression model using Statsmodel lib

```
X_sm = sm.add_constant(X_train)

X_train.shape,y_train.shape,X_sm.shape

((400, 7), (400,), (400, 8))

model = sm.OLS(y_train, X_sm)
results = model.fit()


# statstical summary of the model
print(results.summary())

                            OLS Regression Results

======================================================================
========
Dep. Variable:       Chance of Admit    R-squared:
0.821
Model:                           OLS    Adj. R-squared:
0.818
Method:                Least Squares    F-statistic:
257.0
Date:               Wed, 14 Feb 2024    Prob (F-statistic):
3.41e-142
Time:                       18:55:22    Log-Likelihood:
561.91
No. Observations:                400    AIC:
-1108.
Df Residuals:                    392    BIC:
-1076.
Df Model:                          7

Covariance Type:           nonrobust

======================================================================
===============
                        coef    std err          t      P>|t|
[0.025      0.975]
----------------------------------------------------------------------
---------------
const                 0.7242      0.003    241.441      0.000
```

```
0.718       0.730
GRE Score               0.0267      0.006      4.196      0.000
0.014       0.039
TOEFL Score             0.0182      0.006      3.174      0.002
0.007       0.030
University Rating       0.0029      0.005      0.611      0.541      -
0.007       0.012
SOP                     0.0018      0.005      0.357      0.721      -
0.008       0.012
LOR                     0.0159      0.004      3.761      0.000
0.008       0.024
CGPA                    0.0676      0.006     10.444      0.000
0.055       0.080
Research                0.0119      0.004      3.231      0.001
0.005       0.019
======================================================================
========
Omnibus:                       86.232   Durbin-Watson:
2.050
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
190.099
Skew:                          -1.107   Prob(JB):
5.25e-42
Kurtosis:                       5.551   Cond. No.
5.65
======================================================================
========

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

Insights:

```
From the above summary we can say that CGPA and GRE score are more
important features as they
have more weights.
The adj R2_score is descent value of 0.81.
```

Assumptions of linear regression.

1. No multicolinearity:

   Multicollinearity check by VIF(Variance Inflation Factor) score. Variables are dropped one-by-one till none has a VIF>5.

2. Mean of residuals should be close to zero.

3. Linear relationship between independent & dependent variables.

   This can be checked using the following methods: ■ Scatter plots ■ Regression plots ■ Pearson Correlation

4. Test for Homoscedasticity

   ■ Create a scatterplot of residuals against predicted values. ■ Perform a Goldfeld-Quandt test to check the presence of Heteroscedasticity in the data. ■ If the obtained p-value>0.05, there is no strong evidence of heteroscedas

5. Normality of residuals

   ■ Almost bell-shaped curve in residuals distribution.

6. Impact of outliers

Assumption-1: Multicolinearity

```
from statsmodels.stats.outliers_influence import
variance_inflation_factor

data.columns

Index(['GRE Score', 'TOEFL Score', 'University Rating', 'SOP', 'LOR ',
'CGPA',
       'Research'],
      dtype='object')

X_t = pd.DataFrame(X_train, columns=data.columns)

vif = pd.DataFrame()

vif['Features'] = X_t.columns
vif['VIF'] = [variance_inflation_factor(X_t.values, i) for i in
range(X_t.shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif

            Features   VIF
5               CGPA  4.65
0          GRE Score  4.49
1        TOEFL Score  3.66
3                SOP  2.79
2  University Rating  2.57
4               LOR   1.98
6           Research  1.52
```

Insights:

```
As the Variance Inflation Factor(VIF) score is less than 5 for all the features we can say that there is
no much multicolinearity between the features.
```

```
model = LinearRegression()
model.fit(X_t, y_train)
```

```
LinearRegression()
```

```
model.score(X_t, y_train)
```

```
0.8210671369321554
```

Insights:

```
The R2-score for this model is 0.82 considering all the features. Let us see if there is a difference in the
model score after removing CGPA assuming it is correlational.
```

```
X_t1 = X_t.drop(columns = ['CGPA'])
```

```
vif = pd.DataFrame()

vif['Features'] = X_t1.columns
vif['VIF'] = [variance_inflation_factor(X_t1.values, i) for i in range(X_t1.shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

	Features	VIF
0	GRE Score	3.71
1	TOEFL Score	3.42
3	SOP	2.68
2	University Rating	2.53
4	LOR	1.88
5	Research	1.52

Insights:

```
The VIF values decreased a little but there is no drastic change in them. Let us check if the model score
improves without CGPA
```

```
model1 = LinearRegression()
model1.fit(X_t1, y_train)
```

```
LinearRegression()
```

```
model1.score(X_t1, y_train)
```

```
0.7712805222402632
```

Insight:

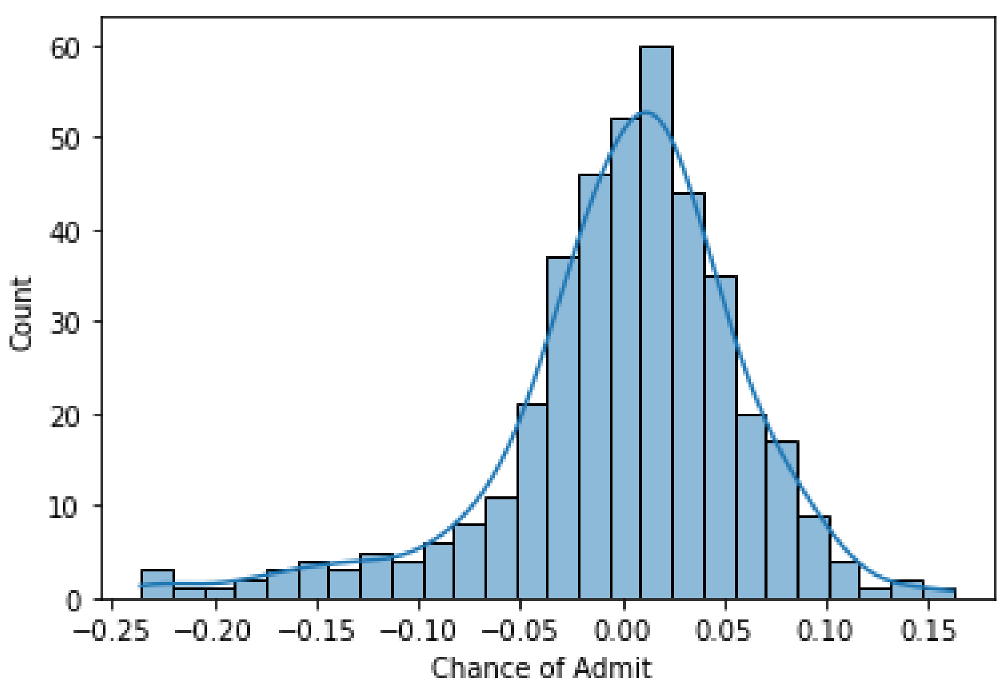
```
The model score got reduced without CGPA indicating that it is an
important feature.
```

Assumption-2: Normality of Residuals

```
y_hat = model.predict(X_t)

errs = y_train - y_hat
errs[:5]
```

```
0   -0.023197
1   -0.035079
2   -0.024015
3    0.047252
4    0.099054
Name: Chance of Admit , dtype: float64
```

```
sns.histplot(errs, kde= True)
plt.show()
```



Insights:

```
Mean of residuals is distributed  around zero from the above plot. So this assumptions holds true for the
given data.
```

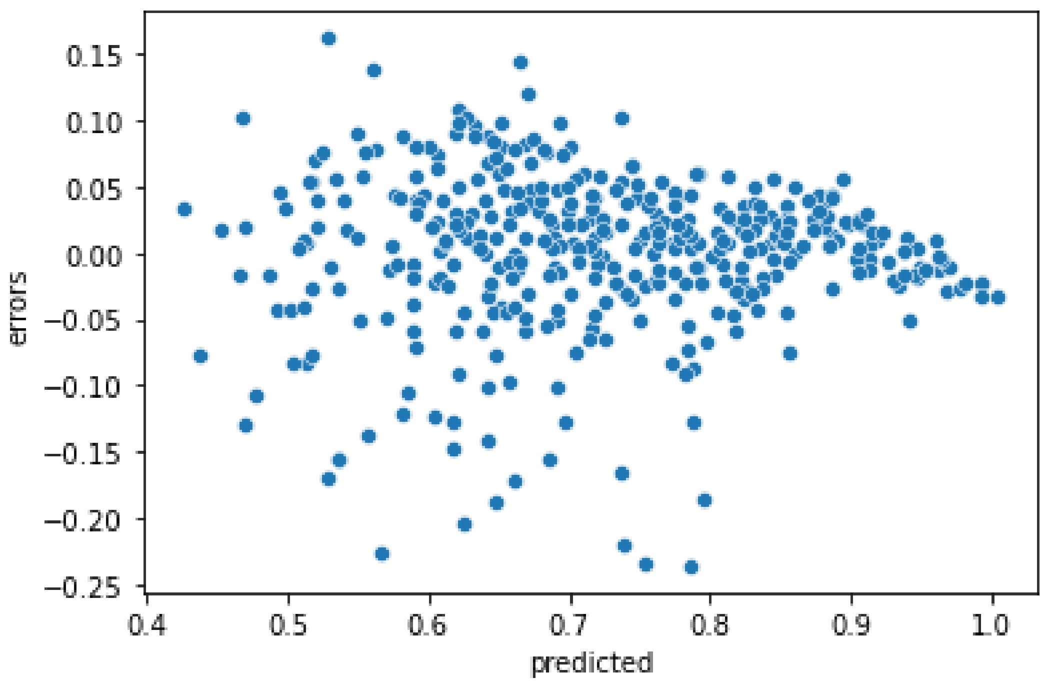
Assumption-3: Linear Relationship

Insights:

```
From the scatter plot in the bivariate analysis we can say that there is linear relationship
between dependent variable and independent variables.
```

Assumption-4: Homoscedasticity

```
sns.scatterplot(x = y_hat, y= errs)
plt.xlabel("predicted")
plt.ylabel("errors")
plt.show()
```

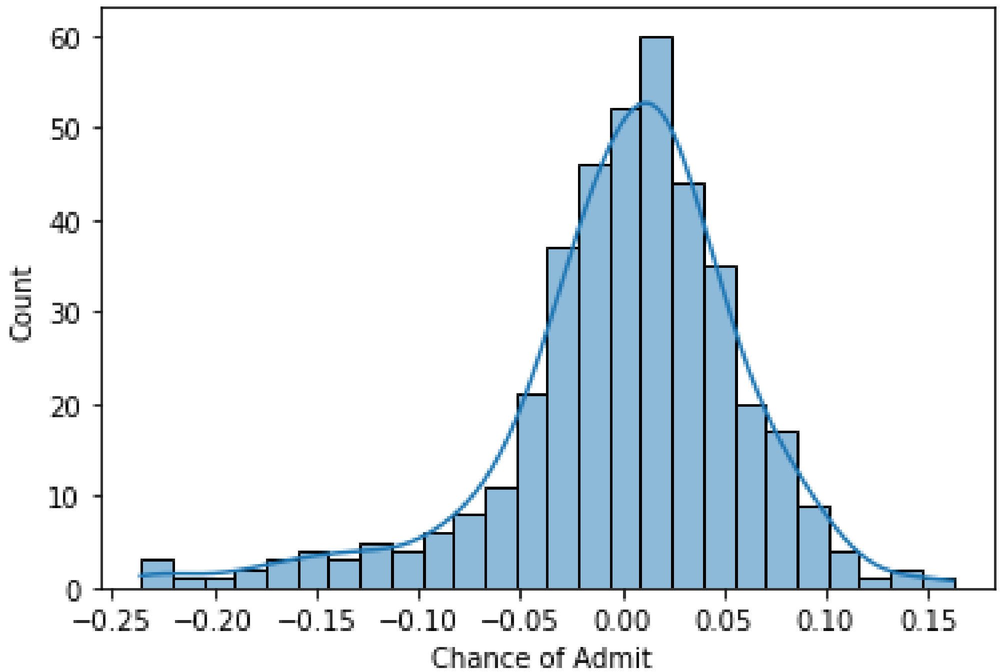


Insights:

There is no homoscedasticity as there is no cone shape pattern in the plot.Assumption for homscedasticity holds true for given data.

Assumption-5: Normality of residuals

```
sns.histplot(errs, kde=True)
plt.show()
```



Insights:

```
The plot for residuals nearly is normally distributed which indicates
the errors are mostly
concentrated nearer to zero. Assumption of normality holds true for
the given data.
```

Assumption-6: Impact of outliers

As there are no outliers in our data there is no impact of outliers.

```
from sklearn.metrics import mean_absolute_error
mae = mean_absolute_error(y_train, y_hat)
print("MAE train:", mae)

MAE train: 0.04253334061164314

mae = mean_absolute_error(y_test, model.predict(X_test))
print("MAE test:", mae)

MAE test: 0.0427226542770537
```

```python
from sklearn.metrics import mean_squared_error

rmse = np.sqrt(mean_squared_error(y_train, y_hat))
print("RMSE train:", rmse)
```

```
RMSE train: 0.059384808482100516
```

```python
rmse = np.sqrt(mean_squared_error(y_test, model.predict(X_test)))
print("RMSE test:", rmse)
```

```
RMSE test: 0.060865880415783134
```

```python
R2_score_train = model.score(X_train,y_train)
print("R2_score train:", R2_score_train)
```

```
R2_score train: 0.8210671369321554
```

```python
R2_score_test = model.score(X_test,y_test)
print("R2_score test:", R2_score_test)
```

```
R2_score test: 0.8188432567829628
```

```python
n,d = X_train.shape
adj_r2 = 1 - ((1- R2_score_train)*(n-1)/(n-d-1))
print("Adj R2_score train:",adj_r2)
```

```
Adj R2_score train: 0.8178719072345153
```

```python
n,d = X_test.shape
adj_r2 = 1 - ((1- R2_score_test)*(n-1)/(n-d-1))
print("Adj R2_score test:",adj_r2)
```

```
Adj R2_score test: 0.8050595915381882
```

Insights:

```
Taking
Adj R2_score: 0.821,
MAE: 0.042
RSME: 0.059
into consideration the model has decent performance with minimum
errors.
```