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August 26, 2023

1 CHAPTER 1: DEFINITION OF THE PROBLEM STATEMENT AND EXPLORATORY DATE ANALYSIS

1.1 INTRODUCTION TO `JAMBOREE EDUCTION PRIVATE LIMETED`

`Jamboree` is India's leading and oldest institute for study abroad test preparation and admission counselling. It offers comprehensive classroom preparation programs for tests such as `GMAT, GRE, SAT, TOEFT and IELTS`. Jamboree has 35 centers located in India and Nepal. Each centre follows a uniform curriculum with same outstanding teaching standards & syllabus.

`Jamboree` was founded by the `Akrita Kalra` in the spring of 1993. `Vineet Gupta` is the Director and Operational head of the company.

1.2 DEFINITION OF PROBLEM

Jamboree has helped thousands of students who wants to 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.

This analysis will help Jamboree in understanding what factors are important in graduate admissions and how these factors are interrelated among themselves.

This analysis also predicts one's chances of admission given the rest of the variables.

1.3 IMPORTING THE LIBRARIES AND DATASET

1.3.1 Importing all the required libraries

[787]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from itertools import combinations,permutations
import math
import warnings
from sklearn.preprocessing import MinMaxScaler
```

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Ridge, Lasso,ElasticNet
from statsmodels.stats.outliers_influence import variance_inflation_factor
import statsmodels.api as sm
from scipy import stats
```

1.3.2 Importing the Dataset

[702]:
```
jamboree = pd.read_csv('Jamboree_admission.csv')
```

[703]:
```
# top 10 rows of the dataset
jamboree.head(10)
```

[703]:
```
   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
5           6        330          115                  5  4.5   3.0  9.34
6           7        321          109                  3  3.0   4.0  8.20
7           8        308          101                  2  3.0   4.0  7.90
8           9        302          102                  1  2.0   1.5  8.00
9          10        323          108                  3  3.5   3.0  8.60

   Research  Chance of Admit
0         1             0.92
1         1             0.76
2         1             0.72
3         1             0.80
4         0             0.65
5         1             0.90
6         1             0.75
7         0             0.68
8         0             0.50
9         0             0.45
```

[704]:
```
# Deleting the space in LOR_ and Chance of Admit_ to avoid Key error
jamboree.rename(columns = {"LOR ":"LOR","Chance of Admit ":"Chance of␣
 ↪Admit"},inplace = True)
```

1.3.3 Description regarding each column of the dataset

Column name	Description
Serial No.	Unique row ID representing unique student

Column name	Description
GRE Score	Score obtained by the student in GRE exam out of 340
TOEFL Score	Score obtained by the student in TOEFL exam out of 120
University Rating	Student's Undergraduate University/College rating out of 5, where 5 being the Best, 1 being the worst
SOP	Strength of Statement of Purpose calculated by some empirical formulae out of 5.0, where 5.0 being the Best, 1.0 being the worst
LOR__	Strength of Letter of Recommendation calculated by some empirical formulae out of 5.0, where 5.0 being the Best, 1.0 being the worst
CGPA	Student's Undergraduate Cumulative Grade Point Average out of 10 points
Research	Boolean column where 1 represents that student has Research Experience and 0 represents that student does not have Research Experience
Chance of Admit__	Probability of getting admission in IVY League colleges calculated using some empirical formulae consisting all the above columns(range - 0 to 1), where 1 being 100% sure of admission and 0 being 100% sure of no admission

1.4 ANALYSING BASIC METRICS OF DATASET

1.4.1 Shape of the data

[705]:
```
print(f"Number of rows in the dataset = {jamboree.shape[0]}")
print(f"Number of columns in the dataset = {jamboree.shape[1]}")
```

```
Number of rows in the dataset = 500
Number of columns in the dataset = 9
```

1.4.2 Datatypes of all the attributes

[706]:
```
jamboree.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
```

1.4.3 Missing value or Null Value Detection

[707]:
```
jamboree.isnull().sum()
```

[707]:
```
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
```

1.4.4 Descriptive Statistics regarding each column of dataset

[708]:
```
jamboree.describe()
```

[708]:
```
       Serial No.   GRE Score  TOEFL Score  University Rating         SOP  \
count  500.000000  500.000000   500.000000         500.000000  500.000000
mean   250.500000  316.472000   107.192000           3.114000    3.374000
std    144.481833   11.295148     6.081868           1.143512    0.991004
min      1.000000  290.000000    92.000000           1.000000    1.000000
25%    125.750000  308.000000   103.000000           2.000000    2.500000
50%    250.500000  317.000000   107.000000           3.000000    3.500000
75%    375.250000  325.000000   112.000000           4.000000    4.000000
max    500.000000  340.000000   120.000000           5.000000    5.000000

             LOR        CGPA    Research  Chance of Admit
count  500.00000  500.000000  500.000000        500.00000
mean     3.48400    8.576440    0.560000          0.72174
std      0.92545    0.604813    0.496884          0.14114
min      1.00000    6.800000    0.000000          0.34000
25%      3.00000    8.127500    0.000000          0.63000
```

```
50%      3.50000    8.560000    1.000000          0.72000
75%      4.00000    9.040000    1.000000          0.82000
max      5.00000    9.920000    1.000000          0.97000
```

1.4.5 Creating Separate column names' lists for categorical, numerical and Target

[709]:
```
cat_cols = ['University Rating','SOP','LOR','Research']
num_cols = ['GRE Score','TOEFL Score','CGPA','Chance of Admit']
target = 'Chance of Admit'
```

[710]:
```
jamboree.dtypes
```

[710]:
```
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
```

1.4.6 Conversion of Cat_cols to Categorical data type

[711]:
```
for i in cat_cols:
    jamboree[i] = pd.Categorical(jamboree[i],ordered = True)
```

[712]:
```
jamboree.dtypes
```

[712]:
```
Serial No.              int64
GRE Score               int64
TOEFL Score             int64
University Rating    category
SOP                  category
LOR                  category
CGPA                  float64
Research             category
Chance of Admit       float64
dtype: object
```

1.4.7 Number of unique values in each column of given dataset

[713]:
```
for i in jamboree.columns:
    print(i,":",jamboree[i].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
```

1.4.8 Unique values of columns whose nunique < 10

[714]:
```python
for i in jamboree.columns:
    if jamboree[i].nunique() < 10:
        print(i,sorted(jamboree[i].unique()),"",sep = "\n")
```

```
University Rating
[1, 2, 3, 4, 5]

SOP
[1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0]

LOR
[1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0]

Research
[0, 1]
```

1.4.9 Range of values for all numerical columns

[715]:
```python
for i in num_cols:
    print(f"Maximum of {i}",jamboree[i].max())
    print(f"Minimum of {i}",jamboree[i].min())
    print()
```

```
Maximum of GRE Score 340
Minimum of GRE Score 290

Maximum of TOEFL Score 120
Minimum of TOEFL Score 92

Maximum of CGPA 9.92
Minimum of CGPA 6.8

Maximum of Chance of Admit 0.97
Minimum of Chance of Admit 0.34
```

[716]:
```
print(f"Maximum of Chance of Admit ",jamboree[target].max())
print(f"Minimum of Chance of Admit ",jamboree[target].min())
```

```
Maximum of Chance of Admit  0.97
Minimum of Chance of Admit  0.34
```

1.4.10 Value counts of all categorical columns

[717]:
```
for i in cat_cols:
    print("Value Counts of {}".format(i),end="\n\n")
    print(jamboree[i].value_counts(),end="\n\n")
```

```
Value Counts of University Rating

3    162
2    126
4    105
5     73
1     34
Name: University Rating, dtype: int64

Value Counts of SOP

4.0    89
3.5    88
3.0    80
2.5    64
4.5    63
2.0    43
5.0    42
1.5    25
1.0     6
Name: SOP, dtype: int64

Value Counts of LOR

3.0    99
4.0    94
3.5    86
4.5    63
2.5    50
5.0    50
2.0    46
1.5    11
1.0     1
Name: LOR, dtype: int64

Value Counts of Research
```

```
1    280
0    220
Name: Research, dtype: int64
```

1.4.11 Observations:

No null values in the dataset

No Duplicated rows in the dataset

Serial No., University Rating, SOP, LOR , Research should be categorical type of variables as they have discrete and finite values

GRE Score, TOEFL Score, CGPA should be numerical type of variables as they have continuous type of values.

Chance of Admit is the Target column in this analysis.

University rating range is from 1 to 5 with step size = 1

Statement of Purpose range is from 1.0 to 5.0 with step size = 0.5

Letter of Recommendation range is from 1.0 to 5.0 with step size = 0.5

Research is Boolean type of column with value either 0 (no research) or 1 (Research)

Range of GRE Score in the given dataset = 290 to 340

Range of TOEFL Score in the given dataset = 92 to 120

Range of Student's CGPA in the given dataset = 6.8 to 9.92

Range of Target column - Chance of Admit in the given dataset = 0.34 to 0.97

Mean value of GRE Score = 316.472/340, TOEFL Score = 107.192/120, University Rating = 3.114/5, SOP = 3.374/5, LOR = 3.484/5, CGPA = 8.576/10, Research = 0.56/1, Chance of Admit = 0.721/ 1

Median value of GRE Score = 317/340, TOEFL Score = 107/120, University Rating = 3/5, SOP = 3.5/5, LOR = 3.5/5, CGPA = 8.56/10, Research = 1, Chance of Admit = 0.72/ 1

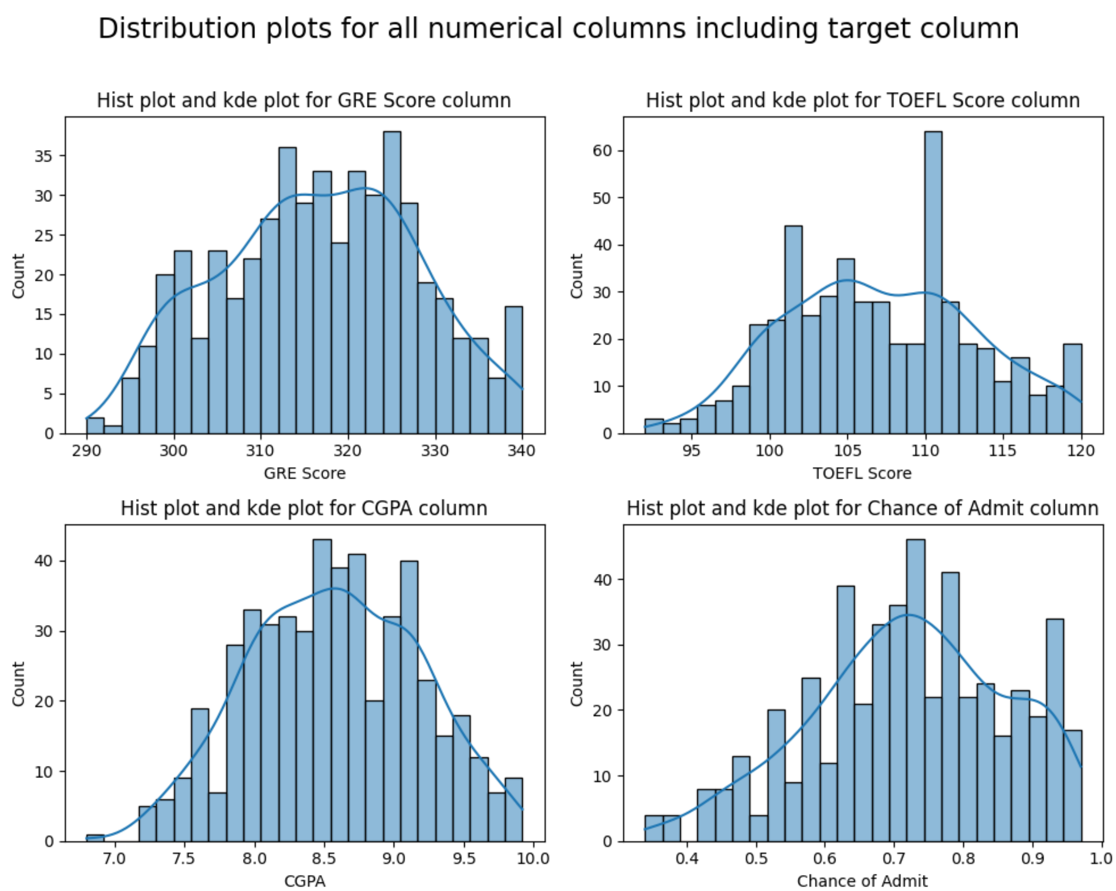
Mean and Median values are almost matched for every column

University ratings quantile values are 1,2,3,4,5. That means equal divisions are made for each University rating

1.5 UNIVARIATE ANALYSIS (DISTRIBUTION PLOTS OF ALL THE CONTINUOUS VARIABLES, BARPLOTS/COUNTPLOTS OF ALL THE CATEGORICAL VARIABLES)

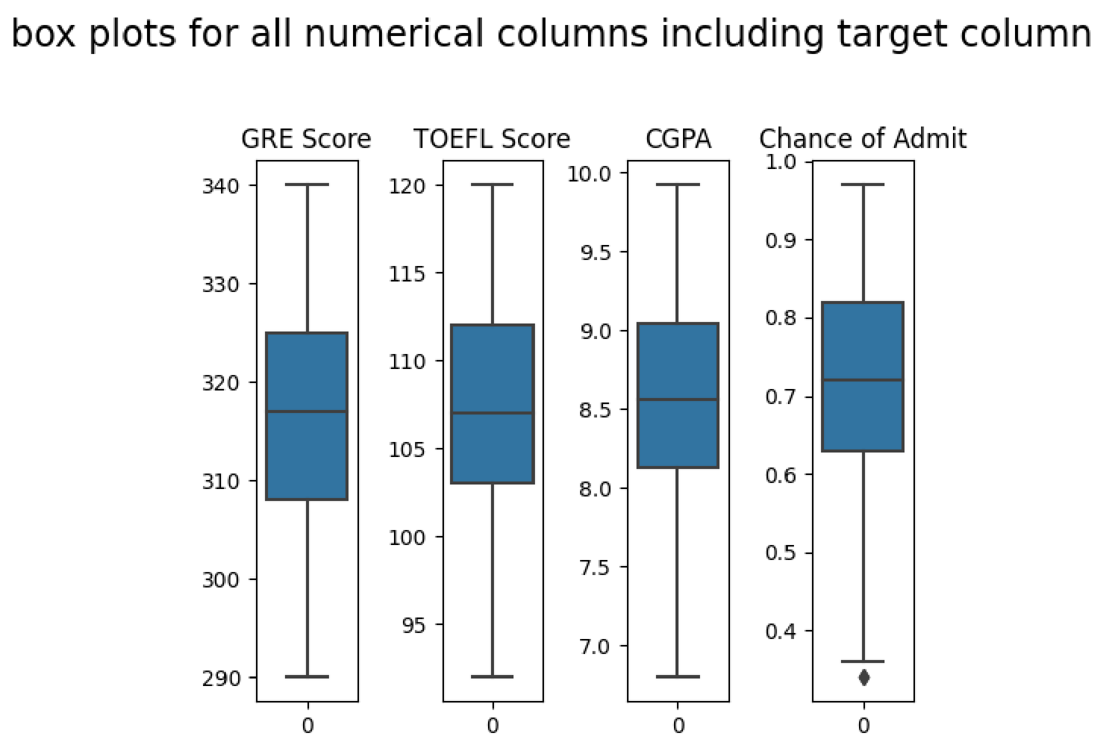
1.5.1 Distribution plots for all numerical columns

[718]:
```
fig = plt.figure(figsize = (10,8))
fig.suptitle("Distribution plots for all numerical columns including target␣
↪column \n",fontsize = "xx-large" )
k = 1
for i in num_cols:
    plt.subplot(2,2,k)
    plt.title("Hist plot and kde plot for {} column".format(i))
    sns.histplot(data=jamboree, x=i, kde=True,bins = 25)
    # plt.xticks(rotation = 90)
    k = k+1
plt.tight_layout()
plt.show()
```



1.5.2 Box plots for all numerical columns

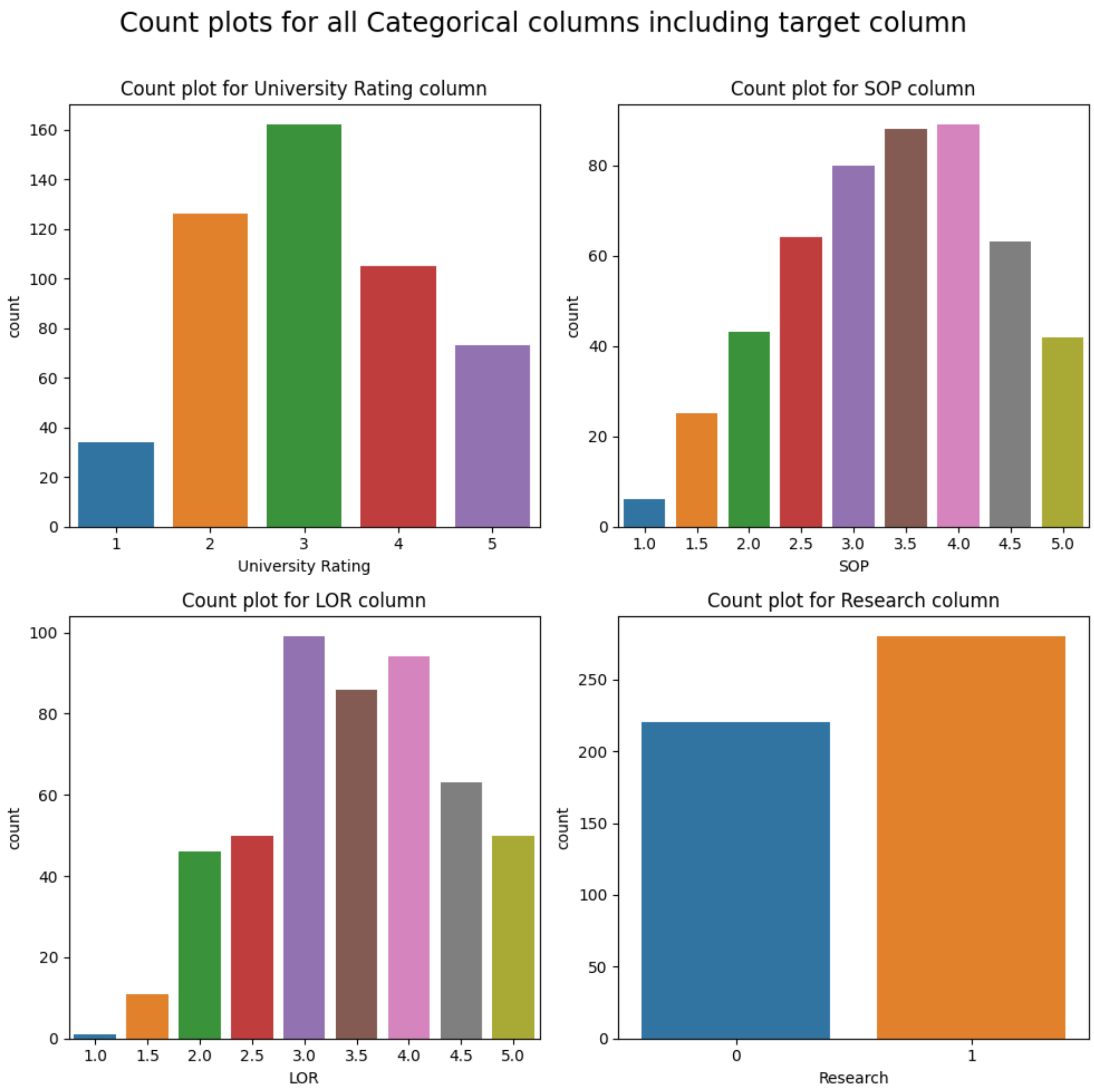
[719]:
```
fig = plt.figure(figsize = (5,5))
fig.suptitle("box plots for all numerical columns including target column␣
↪\n",fontsize = "xx-large" )
k = 1
for i in num_cols:
    plt.subplot(1,4,k)
    plt.title("{}".format(i))
    sns.boxplot(data=jamboree[i])
    k = k+1
plt.tight_layout()
plt.show()
```



1.5.3 Count plots for all categorical columns

[720]:
```
fig = plt.figure(figsize = (10,10))
fig.suptitle("Count plots for all Categorical columns including target column␣
↪\n",fontsize = "xx-large" )
k = 1
for i in cat_cols:
    plt.subplot(2,2,k)
    plt.title("Count plot for {} column".format(i))
```

```
    sns.countplot(data=jamboree, x=i)
    # plt.xticks(rotation = 90)
    k = k+1
plt.tight_layout()
plt.show()
```



1.5.4 Observations

GRE Score, TOEFL Score and CGPA are looking like approximate normal distribution

Chance of Admit is looking like Right skewed Normal Distribution. May be outliers at lower whisker of Chance of Admit.

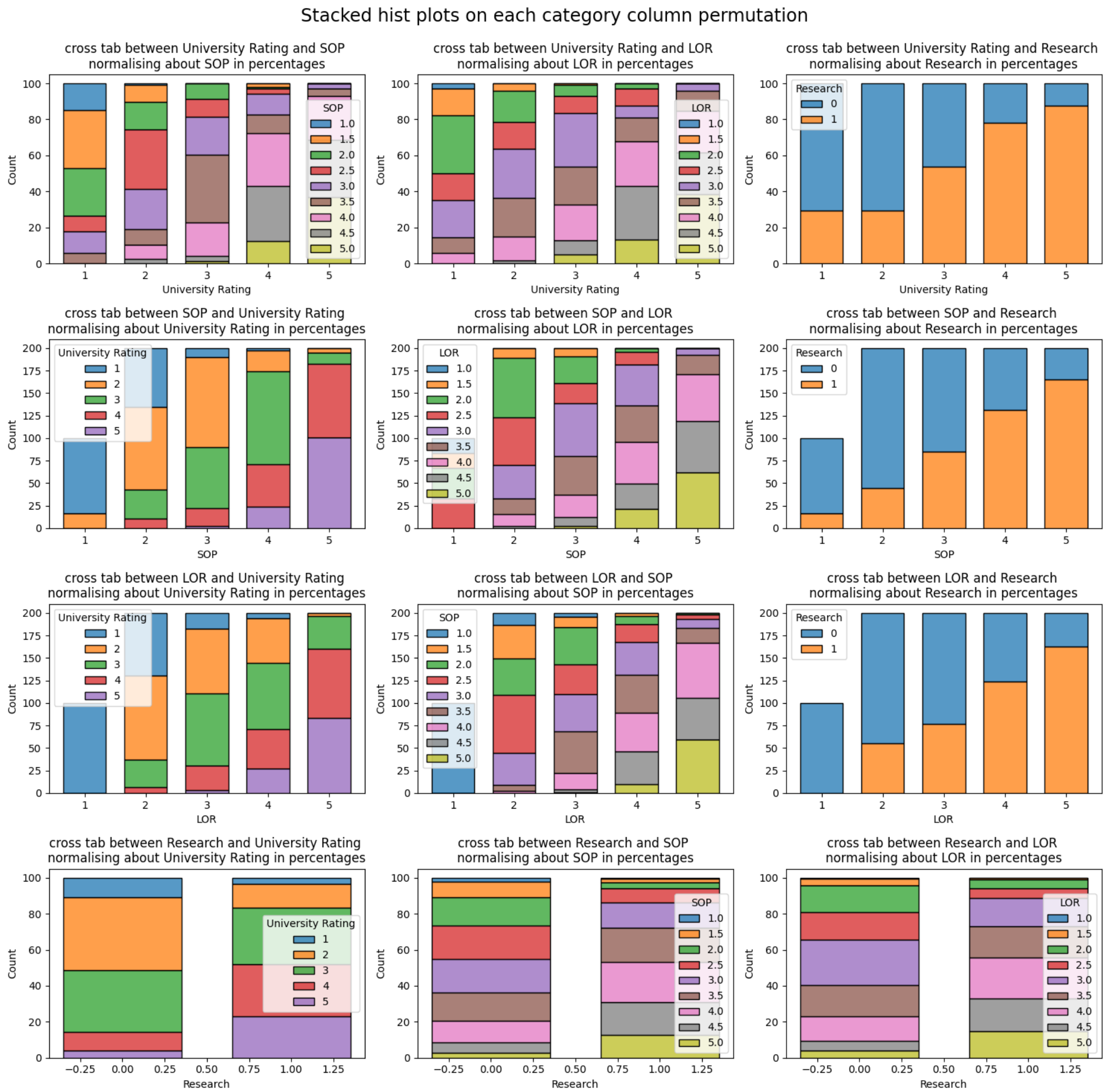
Some outliers may present in Chance of Admit column according to box plots

1.6 BIVARIATE ANALYSIS (RELATIONSHIPS BETWEEN IMPORTANT VARIABLES SUCH AS WORKDAY AND COUNT, SEASON AND COUNT, WEATHER AND COUNT)

1.6.1 Categorical Vs Categorical

[721]:
```
cat_perm = list(permutations(cat_cols,2))
cat_comb = list(combinations(cat_cols,2))
```

[722]:
```
fig = plt.figure(figsize = (15,15))
plt.suptitle("Stacked hist plots on each category column␣
↪permutation\n",fontsize="xx-large")
k = 1
for p,q in cat_perm:
    plt.subplot(math.ceil(len(cat_perm)/3),3,k)
    plt.title(f"cross tab between {p} and {q} \nnormalising about {q} in␣
↪percentages")
    k += 1
    plot = jamboree.groupby([p])[q].value_counts(normalize=True).mul(100).
↪reset_index(name='percentage')
    sns.histplot(x = p , hue = q, weights= 'percentage',
                 multiple = 'stack',data=plot,shrink = 0.7)
    warnings.filterwarnings('ignore')
plt.tight_layout()
plt.subplots_adjust(top=0.92)
plt.show()
warnings.filterwarnings('ignore')
```

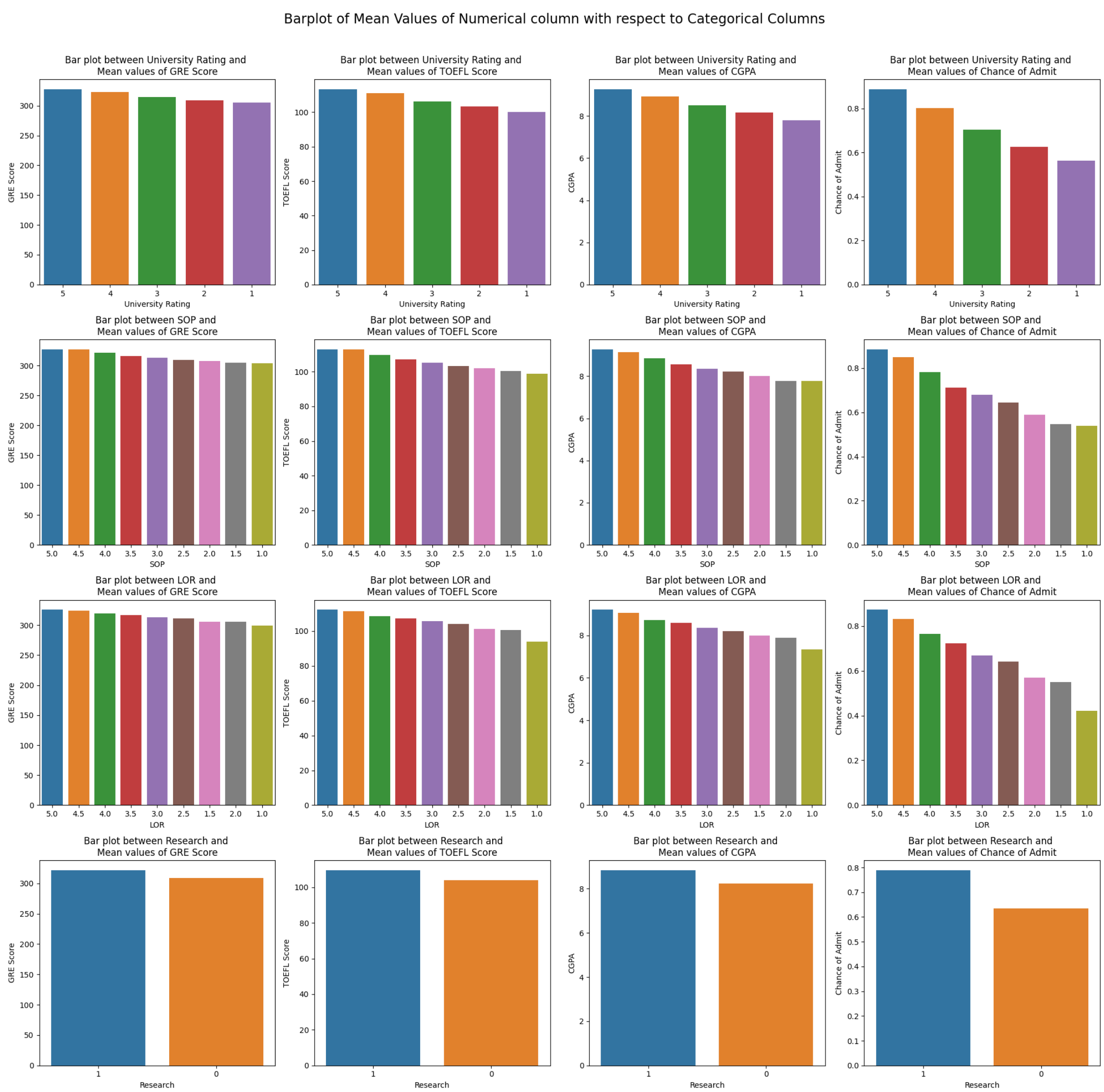


[723]:

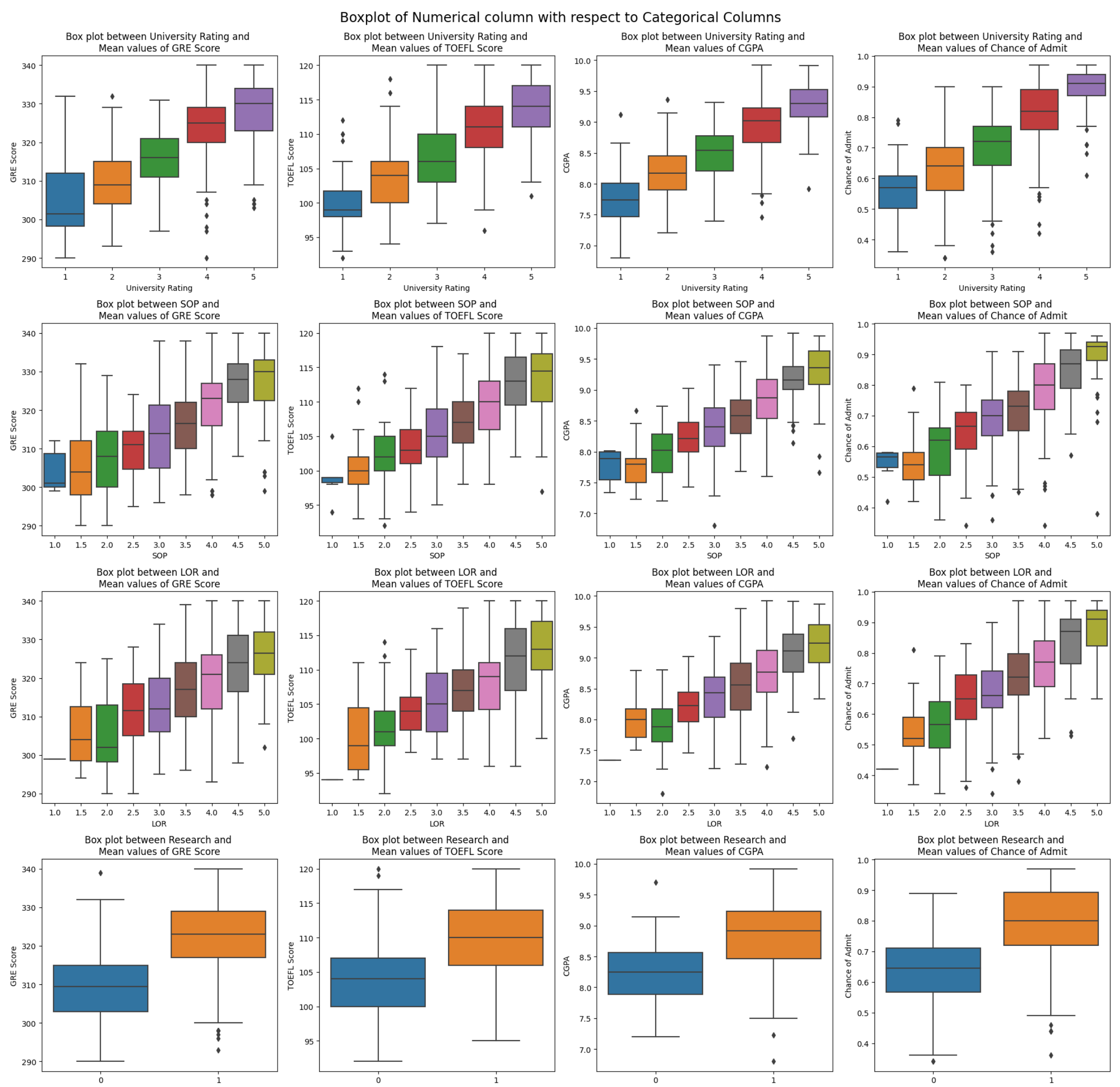
```python
Cat_Vs_Num = []
for i in range(len(cat_cols)):
    for j in range(len(num_cols)):
        Cat_Vs_Num.append((cat_cols[i], num_cols[j]))
print(Cat_Vs_Num)
print(len(Cat_Vs_Num))
```

```
[('University Rating', 'GRE Score'), ('University Rating', 'TOEFL Score'),
('University Rating', 'CGPA'), ('University Rating', 'Chance of Admit'), ('SOP',
'GRE Score'), ('SOP', 'TOEFL Score'), ('SOP', 'CGPA'), ('SOP', 'Chance of
Admit'), ('LOR', 'GRE Score'), ('LOR', 'TOEFL Score'), ('LOR', 'CGPA'), ('LOR',
'Chance of Admit'), ('Research', 'GRE Score'), ('Research', 'TOEFL Score'),
('Research', 'CGPA'), ('Research', 'Chance of Admit')]
16
```

[724]:
```python
fig = plt.figure(figsize = (20,20))
plt.suptitle("Barplot of Mean Values of Numerical column with respect to Categorical Columns\n",fontsize = "xx-large")
k = 1
for p,q in Cat_Vs_Num:
    plt.subplot(math.ceil(len(Cat_Vs_Num)/4),4,k)
    plt.title(f"Bar plot between {p} and \nMean values of {q}")
    k += 1
    df = pd.DataFrame(jamboree.groupby([p])[[q]].mean().reset_index())
    sns.barplot(data = df,x = p,y= q,order = df.sort_values(q,ascending = False)[p])
plt.tight_layout()
plt.subplots_adjust(top=0.92)
plt.show()
warnings.filterwarnings('ignore')
```

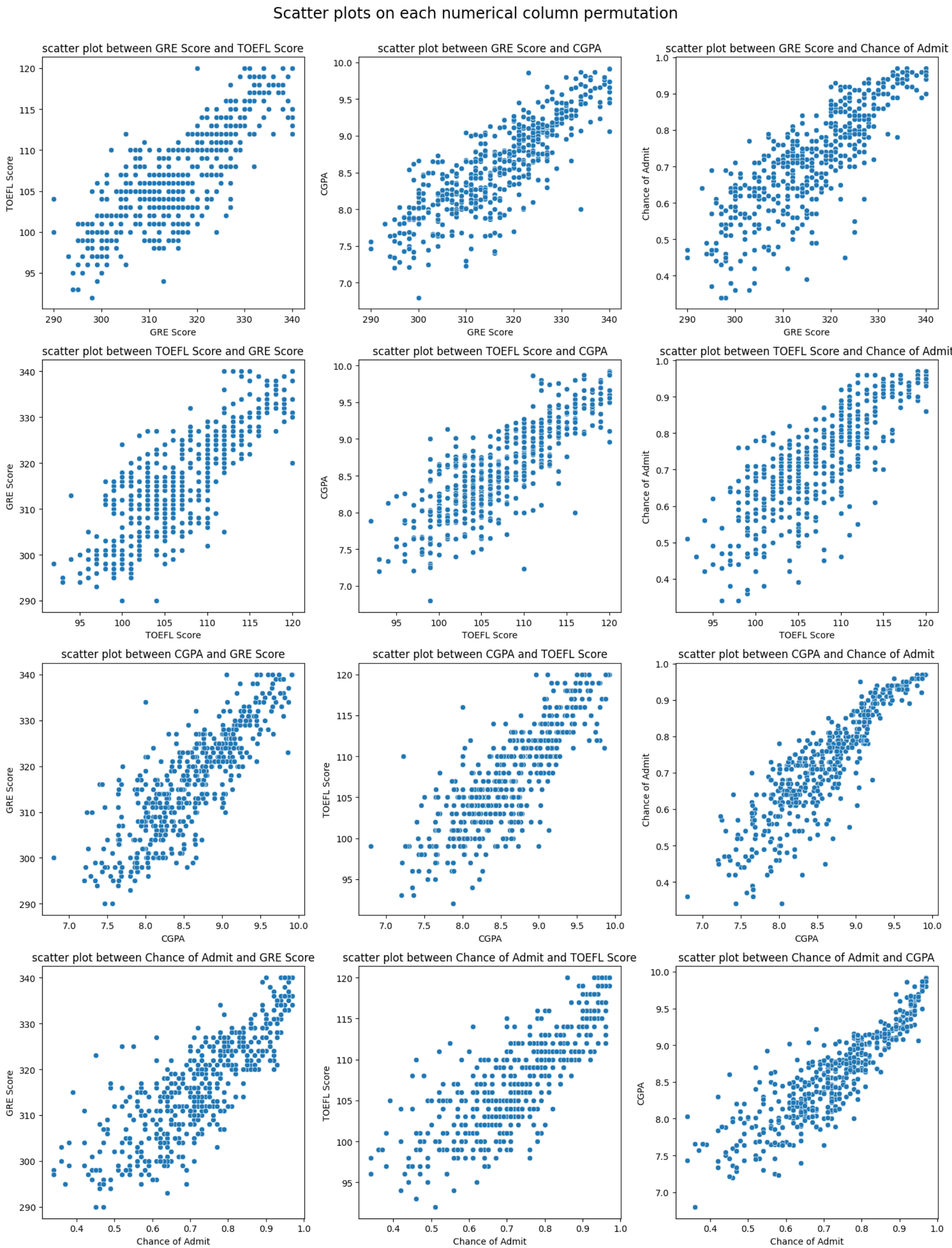


```
[725]: fig = plt.figure(figsize = (20,20))
       plt.suptitle("Boxplot of Numerical column with respect to Categorical␣
        ↪Columns",fontsize = "xx-large")
       k = 1
       for p,q in Cat_Vs_Num:
           plt.subplot(math.ceil(len(Cat_Vs_Num)/4),4,k)
           plt.title(f"Box plot between {p} and \nMean values of {q}")
           k += 1
           sns.boxplot(data = jamboree,x = p,y= q)
       plt.tight_layout()
       plt.subplots_adjust(top=0.94)
       plt.show()
       warnings.filterwarnings('ignore')
```



[726]:
```
num_perm = list(permutations(num_cols,2))
num_comb = list(combinations(num_cols,2))
```

[727]:
```
fig = plt.figure(figsize = (15,20))
plt.suptitle("Scatter plots on each numerical column␣
↪permutation\n",fontsize="xx-large")
k = 1
for p,q in num_perm:
    plt.subplot(math.ceil(len(cat_perm)/3),3,k)
    plt.title(f"scatter plot between {p} and {q}")
    k += 1
    sns.scatterplot(data=jamboree,x=p,y=q)
    warnings.filterwarnings('ignore')
plt.tight_layout()
plt.subplots_adjust(top=0.94)
plt.show()
warnings.filterwarnings('ignore')
```



[728]:

```
#combinations of three in such a way that first two are numerical columns and␣
↪third is categorical col
Num_Num_Cat = []
```

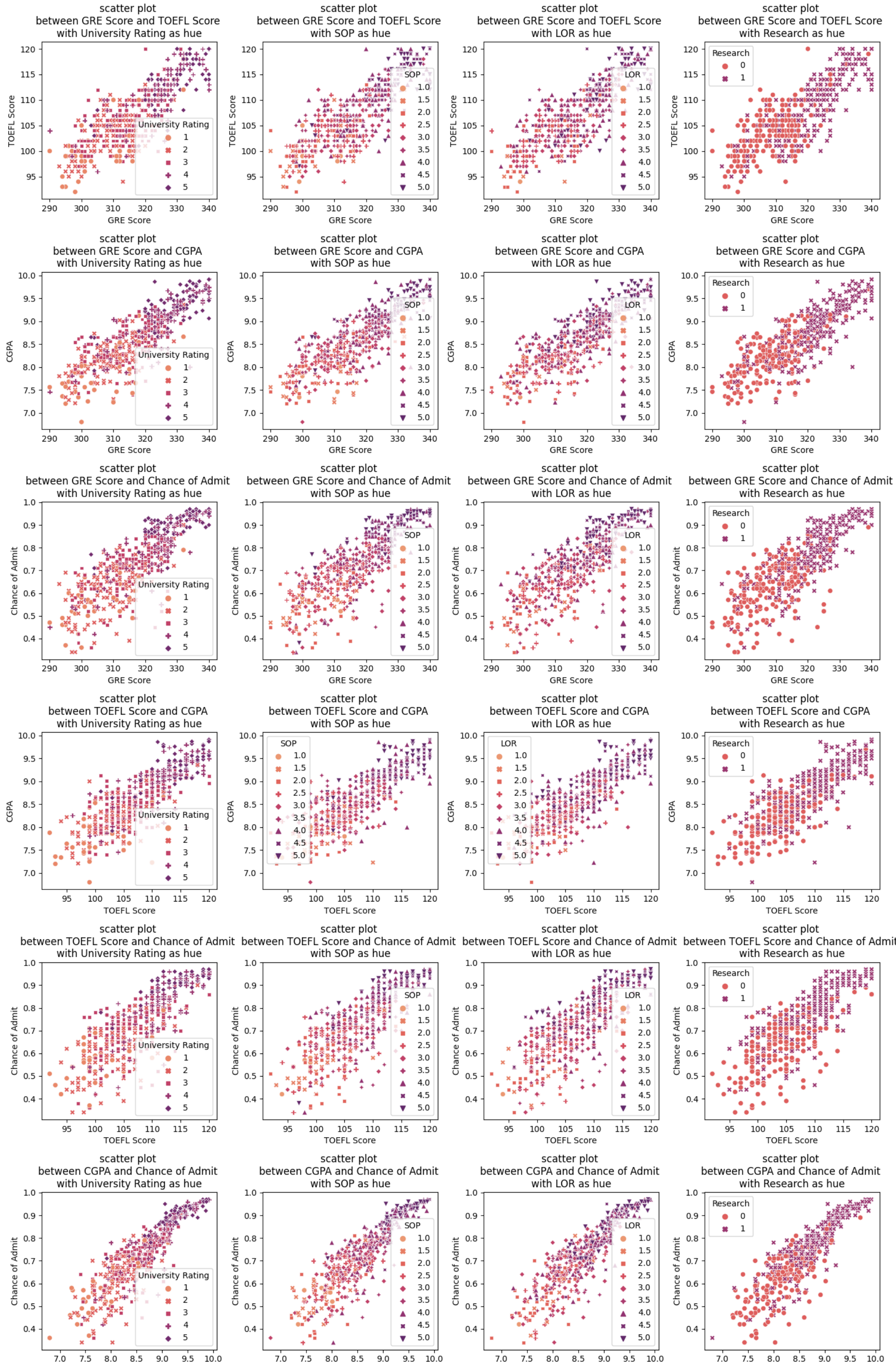
```
for i in range(len(num_comb)):
    for j in range(len(cat_cols)):
        Num_Num_Cat.append(list(num_comb[i])+[cat_cols[j]])
print(Num_Num_Cat)
print(len(Num_Num_Cat))
```

```
[['GRE Score', 'TOEFL Score', 'University Rating'], ['GRE Score', 'TOEFL Score',
'SOP'], ['GRE Score', 'TOEFL Score', 'LOR'], ['GRE Score', 'TOEFL Score',
'Research'], ['GRE Score', 'CGPA', 'University Rating'], ['GRE Score', 'CGPA',
'SOP'], ['GRE Score', 'CGPA', 'LOR'], ['GRE Score', 'CGPA', 'Research'], ['GRE
Score', 'Chance of Admit', 'University Rating'], ['GRE Score', 'Chance of
Admit', 'SOP'], ['GRE Score', 'Chance of Admit', 'LOR'], ['GRE Score', 'Chance
of Admit', 'Research'], ['TOEFL Score', 'CGPA', 'University Rating'], ['TOEFL
Score', 'CGPA', 'SOP'], ['TOEFL Score', 'CGPA', 'LOR'], ['TOEFL Score', 'CGPA',
'Research'], ['TOEFL Score', 'Chance of Admit', 'University Rating'], ['TOEFL
Score', 'Chance of Admit', 'SOP'], ['TOEFL Score', 'Chance of Admit', 'LOR'],
['TOEFL Score', 'Chance of Admit', 'Research'], ['CGPA', 'Chance of Admit',
'University Rating'], ['CGPA', 'Chance of Admit', 'SOP'], ['CGPA', 'Chance of
Admit', 'LOR'], ['CGPA', 'Chance of Admit', 'Research']]
24
```

[729]:

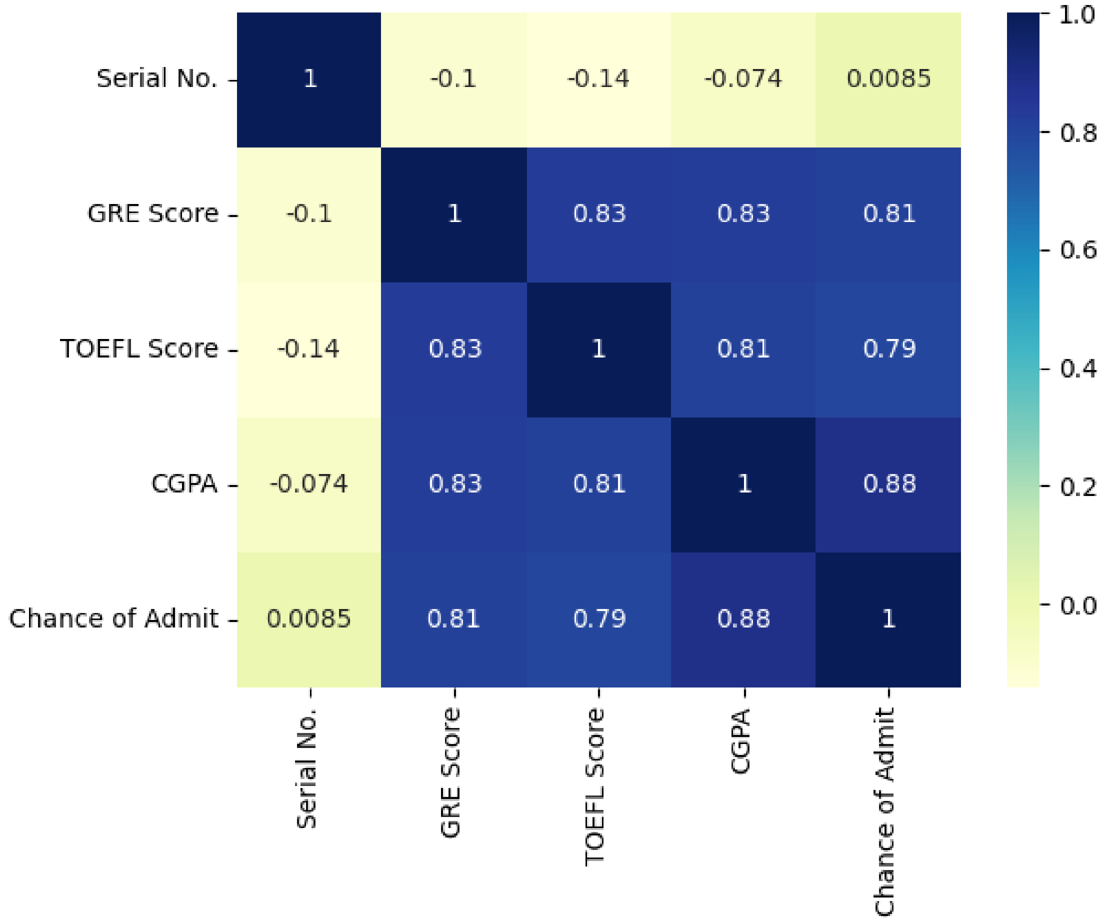
```
fig = plt.figure(figsize = (15,24))
plt.suptitle("Scatter plots on each numerical column␣
↪permutation\n",fontsize="xx-large")
k = 1
for p,q,r in Num_Num_Cat:
    plt.subplot(math.ceil(len(Num_Num_Cat)/4),4,k)
    plt.title(f"scatter plot \nbetween {p} and {q} \nwith {r} as hue")
    k += 1
    sns.scatterplot(data=jamboree,x=p,y=q,hue = r,style = r, palette = "flare")
    warnings.filterwarnings('ignore')
plt.tight_layout()
plt.subplots_adjust(top=0.94)
plt.show()
warnings.filterwarnings('ignore')
```

Scatter plots on each numerical column permutation



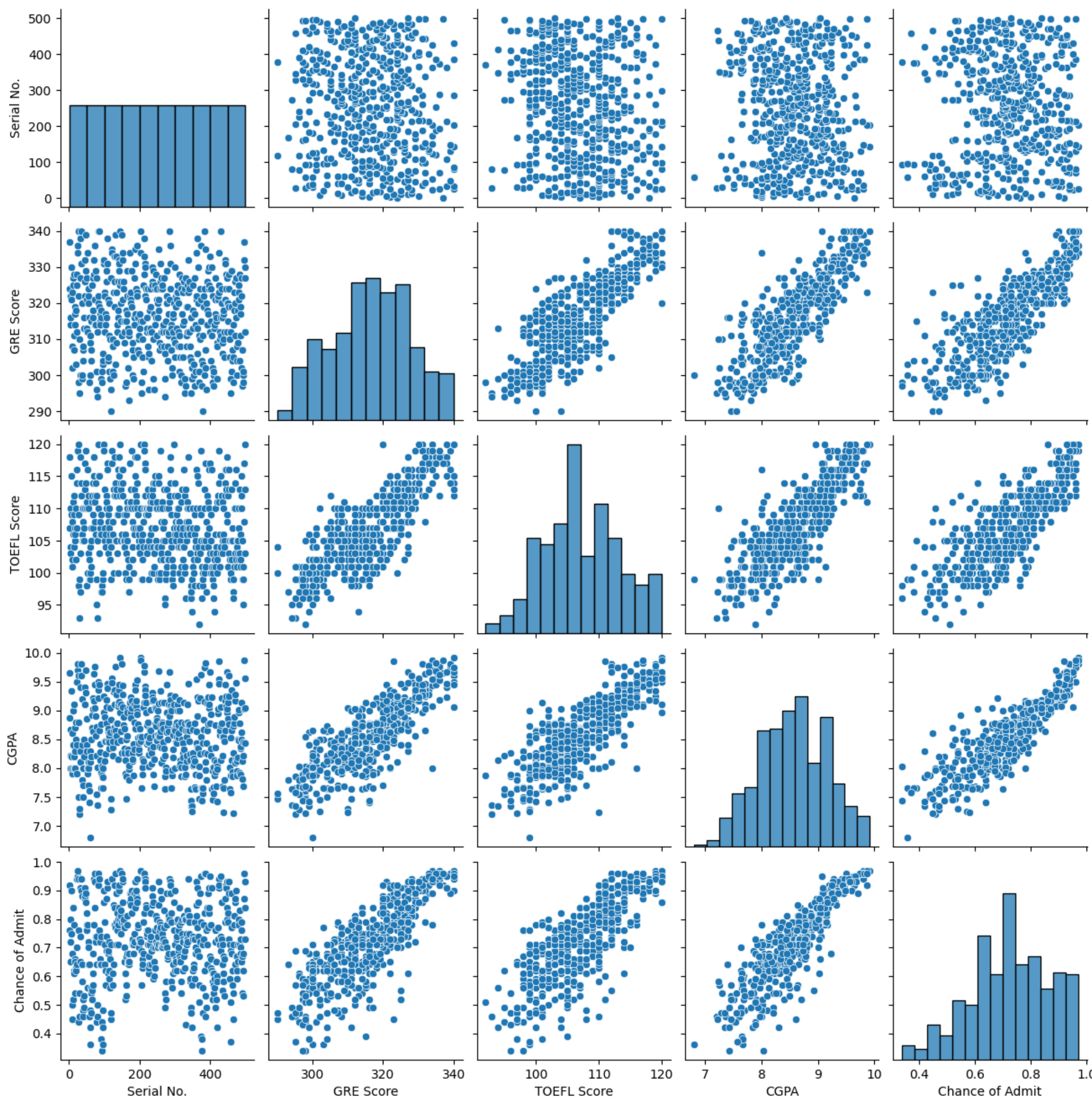
```
[730]: sns.heatmap(jamboree.corr(), cmap="YlGnBu", annot=True)
```

```
[730]: <Axes: >
```




```
[731]: sns.pairplot(data = jamboree)
```

```
[731]: <seaborn.axisgrid.PairGrid at 0x1b345310610>
```



2 CHAPTER 2: DATA PREPROCESSING

2.1 DUPLICATE VALUE CHECK

[732]:
```
jamboree.duplicated().sum()
```

[732]: 0

No duplicated rows

2.2 MISSING VALUE TREATMENT

No Missing values in the data

2.3 OUTLIER TREATMENT

Very minimal outliers present in the data. So neglecting them.

2.4 FEATURE ENGINEERING

No need of creating new features.

All availabe columns act as features

2.5 DATA PREPARATION FOR MODELING

2.5.1 Separating the Target variable from dataset and delete the Serial Number column from Train dataset

[733]:
```
# y is the target variable
y = jamboree["Chance of Admit"]

# X is Feature dataset
X = jamboree.drop(["Serial No.","Chance of Admit"],axis = 1)

# Shape of target and feature datasets
y.shape,X.shape
```

[733]:
```
((500,), (500, 7))
```

Jamboree has * "Chance of Admit" as target variable * 8 input features

2.5.2 Splitting the given dataset to Train,test data

using 80:20 ratio to split: * 80% for training = 400 rows * 20% for testing = 100 rows

[734]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size = 0.2,
 ↪random_state = 1)
```

[735]:
```
type(X_test)
```

[735]:
```
pandas.core.frame.DataFrame
```

[736]:
```
X_train.shape, y_train.shape
```

[736]:
```
((400, 7), (400,))
```

[737]:
```
X_test.shape, y_test.shape
```

[737]:
```
((100, 7), (100,))
```

2.5.3 Scaling the data

[738]:
```
scaler = MinMaxScaler()
X_train_scaled = pd.DataFrame(scaler.fit_transform(X_train),columns = X_train.
 ↪columns)
X_test_scaled = pd.DataFrame(scaler.transform(X_test),columns = X_test.columns)
```

[739]:
```
X_train_scaled.head()
```

[739]:
```
   GRE Score  TOEFL Score  University Rating    SOP       LOR      CGPA  \
0       0.40     0.428571                0.5  0.250  0.571429  0.503205
1       0.56     0.642857                0.0  0.375  0.571429  0.557692
2       0.20     0.321429                0.5  0.625  0.285714  0.346154
3       0.20     0.250000                0.0  0.500  0.142857  0.000000
4       0.64     0.428571                0.5  0.625  0.714286  0.653846

   Research
0       0.0
1       1.0
2       0.0
3       1.0
4       1.0
```

[740]:
```
X_test_scaled.head()
```

[740]:
```
   GRE Score  TOEFL Score  University Rating    SOP       LOR      CGPA  \
0       0.46     0.500000               0.25  0.375  0.142857  0.522436
1       0.44     0.535714               0.50  0.500  0.428571  0.532051
2       0.98     0.964286               1.00  0.875  0.714286  0.929487
3       0.52     0.535714               0.25  0.625  0.571429  0.589744
4       0.70     0.642857               0.75  0.875  0.714286  0.692308

   Research
0       0.0
1       1.0
2       0.0
3       1.0
4       1.0
```

3 CHAPTER 3: MODEL BUILDING

3.1 BUILD THE LINEAR REGRESSION MODEL AND COMMENT ON THE MODEL STATISTICS

[741]:
```
model = LinearRegression()
model.fit(X_train_scaled,y_train)
```

[741]:
```
LinearRegression()
```

[742]:
```
model.coef_
```

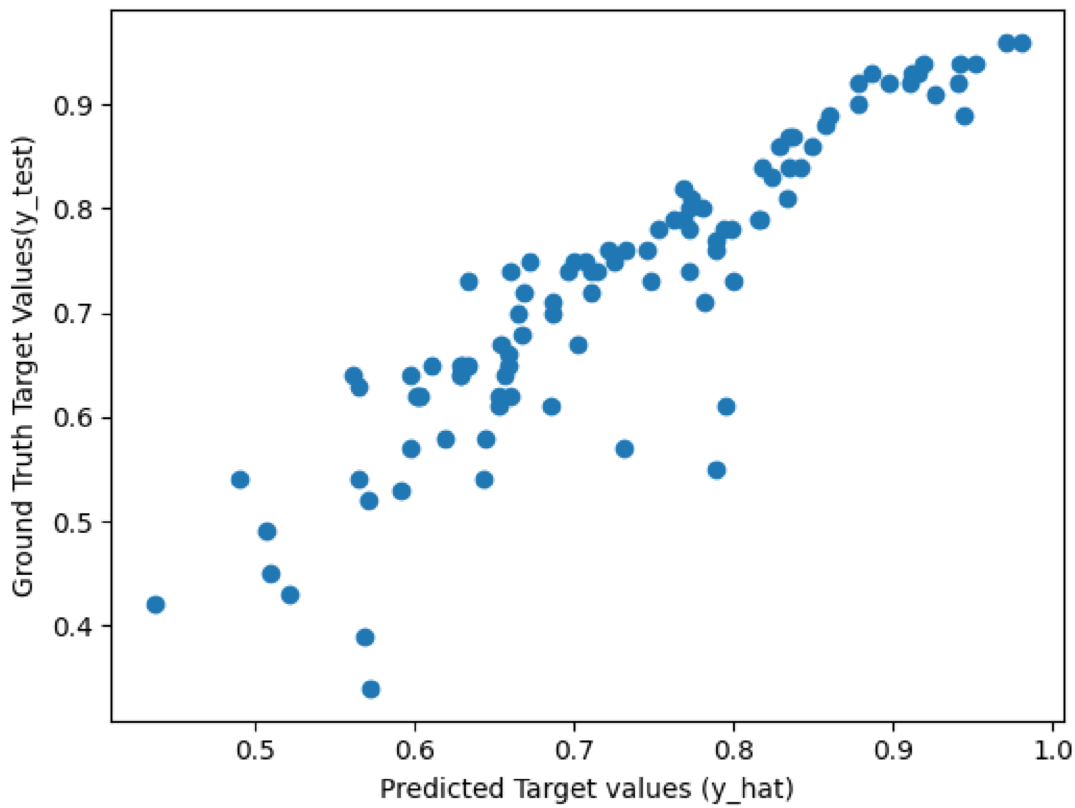
[742]:
```
array([0.09161221, 0.08887002, 0.02451543, 0.01202031, 0.05049382,
       0.36411739, 0.01988978])
```

[743]:
```
model.intercept_
```

[743]:
```
0.35899013133207913
```

Model intercept is bias value. If we put all weights = 0, y_hat = model intercept. This implies that it is the intersection of hyperplane with the y_hat axis.

[744]:
```
fig = plt.figure()
y_hat = model.predict(X_test_scaled)
plt.scatter(y_hat,y_test)
plt.xlabel("Predicted Target values (y_hat)")
plt.ylabel("Ground Truth Target Values(y_test)")
plt.show()
```



[745]:
```
def mean_absolute_error(y_test, y_hat):
    return np.mean(np.abs(y_test - y_hat))

def mean_squared_error(y_test, y_hat):
    return np.mean((y_test - y_hat)**2)

def root_mean_squared_error(y_test, y_hat):
    return np.sqrt(mean_squared_error(y_test, y_hat))

def r2_score(y_test, y_hat):
    ss_residual = np.sum((y_test - y_hat)**2)
    ss_total = np.sum((y_test - np.mean(y_test))**2)
    r2 = 1 - (ss_residual / ss_total)
    return r2

def adjusted_r2_score(r2, n_samples, n_features):
    adj_r2 = 1 - (((1 - r2) * (n_samples - 1)) / (n_samples - n_features - 1))
    return adj_r2

mae = mean_absolute_error(y_test, y_hat)
mse = mean_squared_error(y_test, y_hat)
```

```
rmse = root_mean_squared_error(y_test, y_hat)
r2 = r2_score(y_test, y_hat)
adj_r2 = adjusted_r2_score(r2, len(X_test), len(X_test.columns))

print("Mean Absolute Error:", mae)
print("Mean Squared Error:", mse)
print("Root Mean Squared Error:", rmse)
print("R-squared Score:", r2)
print("Adjusted R-squared Score:", adj_r2)
```

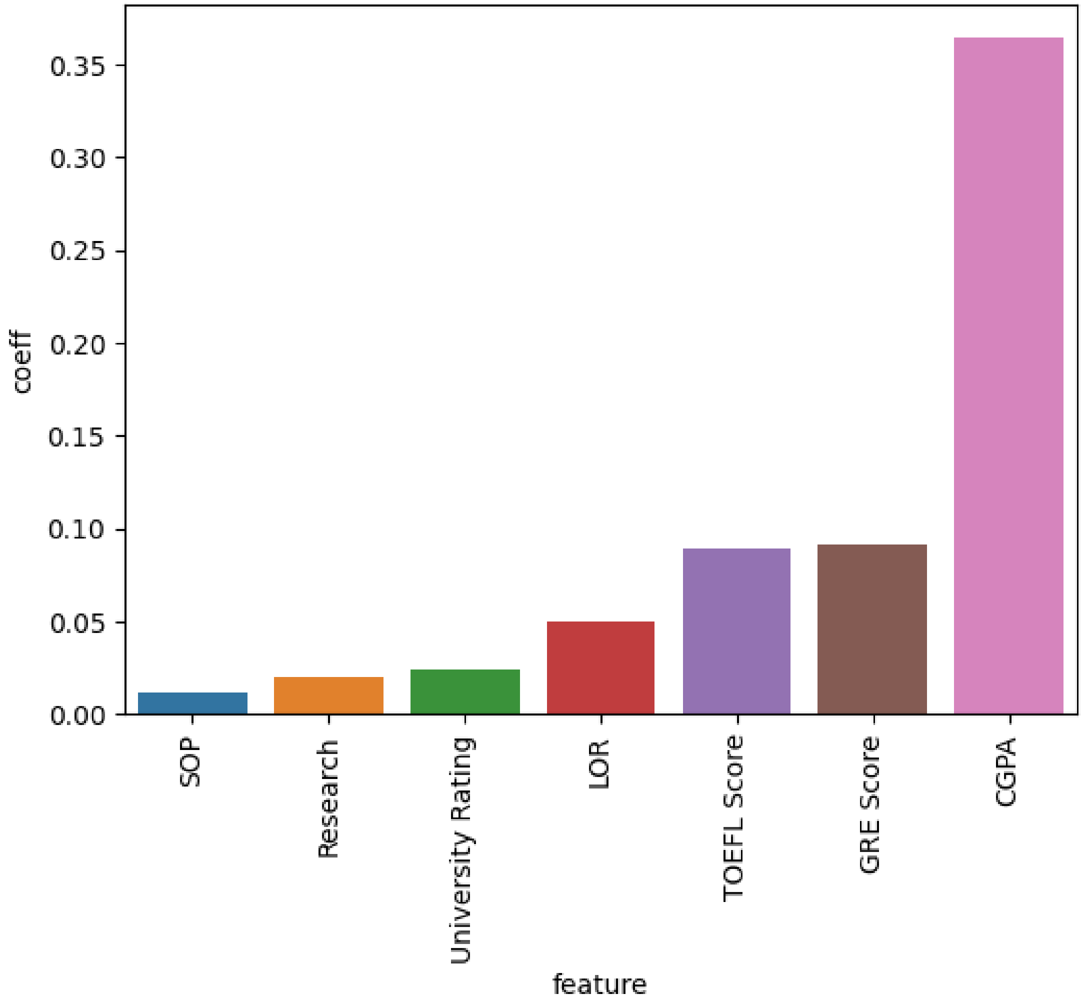
```
Mean Absolute Error: 0.040200193804157944
Mean Squared Error: 0.0034590988971363824
Root Mean Squared Error: 0.05881410457650769
R-squared Score: 0.8208741703103732
Adjusted R-squared Score: 0.8072450310948581
```

General Linear Regression model uses Ordinary Least Squares method to fit the weights to given dataset

3.2 DISPLAY MODEL COEFFICIENTS WITH COLUMN NAMES

[746]:

```
feature_coeff = pd.DataFrame(list(zip(X_train_scaled.columns,model.coef_)),
                    columns=['feature', 'coeff'])
sns.barplot(x='feature', y='coeff', data=feature_coeff,order = feature_coeff.
 ↪sort_values("coeff").feature)
plt.xticks(rotation=90)
plt.show()
```



CGPA has highest coeffcient implies that CGPA feature has more importance.

SOP has lowest coeffcient implies that SOP feature has less importance

3.3 TRY OUT RIDGE AND LASSO REGRESSION

3.3.1 L1 Regularisation or Lasso Regression

[747]:
```
lasso = Lasso(alpha = 0.001)
lasso.fit(X_train_scaled,y_train)
```

[747]:
```
Lasso(alpha=0.001)
```

[748]:
```
print(lasso.coef_)
```

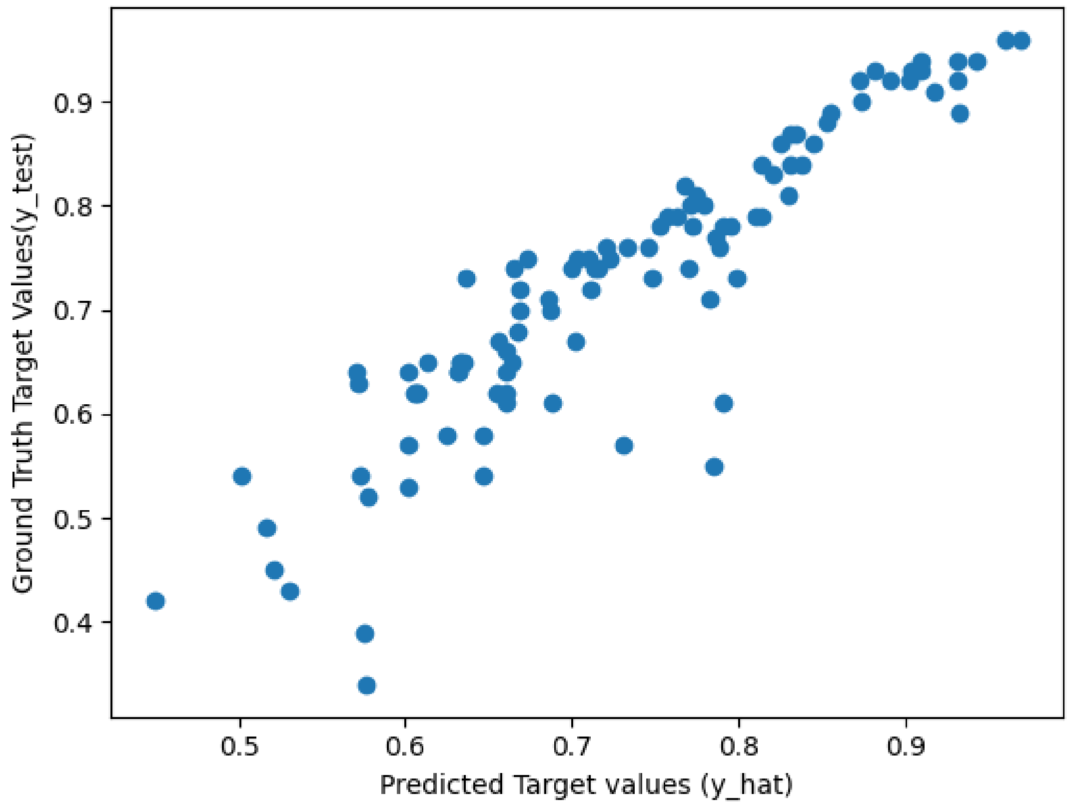
```
[0.08963466 0.08455098 0.02802097 0.0094516  0.04769436 0.34232003
 0.02173095]
```

[749]:
```
print(lasso.intercept_)
```

```
0.37500346903568066
```

[750]:
```
y_hat = lasso.predict(X_test_scaled)
```

[751]:
```
fig = plt.figure()
plt.scatter(y_hat,y_test)
plt.xlabel("Predicted Target values (y_hat)")
plt.ylabel("Ground Truth Target Values(y_test)")
plt.show()
```



[752]:
```
mae = mean_absolute_error(y_test, y_hat)
mse = mean_squared_error(y_test, y_hat)
rmse = root_mean_squared_error(y_test, y_hat)
r2 = r2_score(y_test, y_hat)
adj_r2 = adjusted_r2_score(r2, len(X_test), len(X_test.columns))

print("Mean Absolute Error:", mae)
print("Mean Squared Error:", mse)
print("Root Mean Squared Error:", rmse)
```

```
print("R-squared Score:", r2)
print("Adjusted R-squared Score:", adj_r2)
```

```
Mean Absolute Error: 0.04057015310599113
Mean Squared Error: 0.003505640777196343
Root Mean Squared Error: 0.0592084519067704
R-squared Score: 0.8184640475792894
Adjusted R-squared Score: 0.8046515294603223
```

3.3.2 L2 Regularisation or Ridge Regression

[753]:
```
ridge = Ridge(alpha = 1.0)
ridge.fit(X_train_scaled,y_train)
```

[753]:
```
Ridge()
```

[754]:
```
ridge.coef_
```

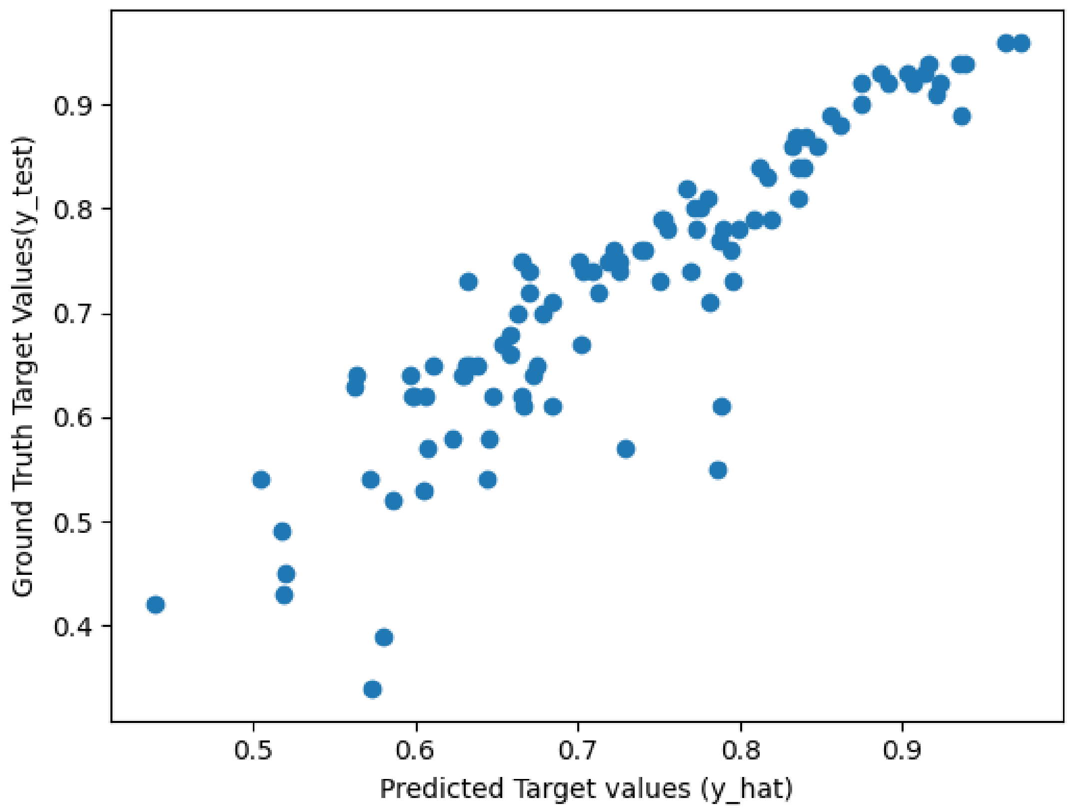
[754]:
```
array([0.1084213 , 0.09997178, 0.03160706, 0.02311355, 0.05562673,
       0.29302587, 0.02197611])
```

[755]:
```
ridge.intercept_
```

[755]:
```
0.3701847983439584
```

[756]:
```
y_hat = ridge.predict(X_test_scaled)
```

[757]:
```
fig = plt.figure()
plt.scatter(y_hat,y_test)
plt.xlabel("Predicted Target values (y_hat)")
plt.ylabel("Ground Truth Target Values(y_test)")
plt.show()
```



[758]:
```
mae = mean_absolute_error(y_test, y_hat)
mse = mean_squared_error(y_test, y_hat)
rmse = root_mean_squared_error(y_test, y_hat)
r2 = r2_score(y_test, y_hat)
adj_r2 = adjusted_r2_score(r2, len(X_test), len(X_test.columns))

print("Mean Absolute Error:", mae)
print("Mean Squared Error:", mse)
print("Root Mean Squared Error:", rmse)
print("R-squared Score:", r2)
print("Adjusted R-squared Score:", adj_r2)
```

```
Mean Absolute Error: 0.04093430970906569
Mean Squared Error: 0.003526280548973887
Root Mean Squared Error: 0.05938249362374307
R-squared Score: 0.8173952385182597
Adjusted R-squared Score: 0.8035013979707359
```

3.3.3 Elastic net regularisation

[759]:
```
elasticnet = ElasticNet(alpha = 0.001)
elasticnet.fit(X_train_scaled,y_train)
```

[759]:
```
ElasticNet(alpha=0.001)
```

[760]:
```
elasticnet.coef_
```

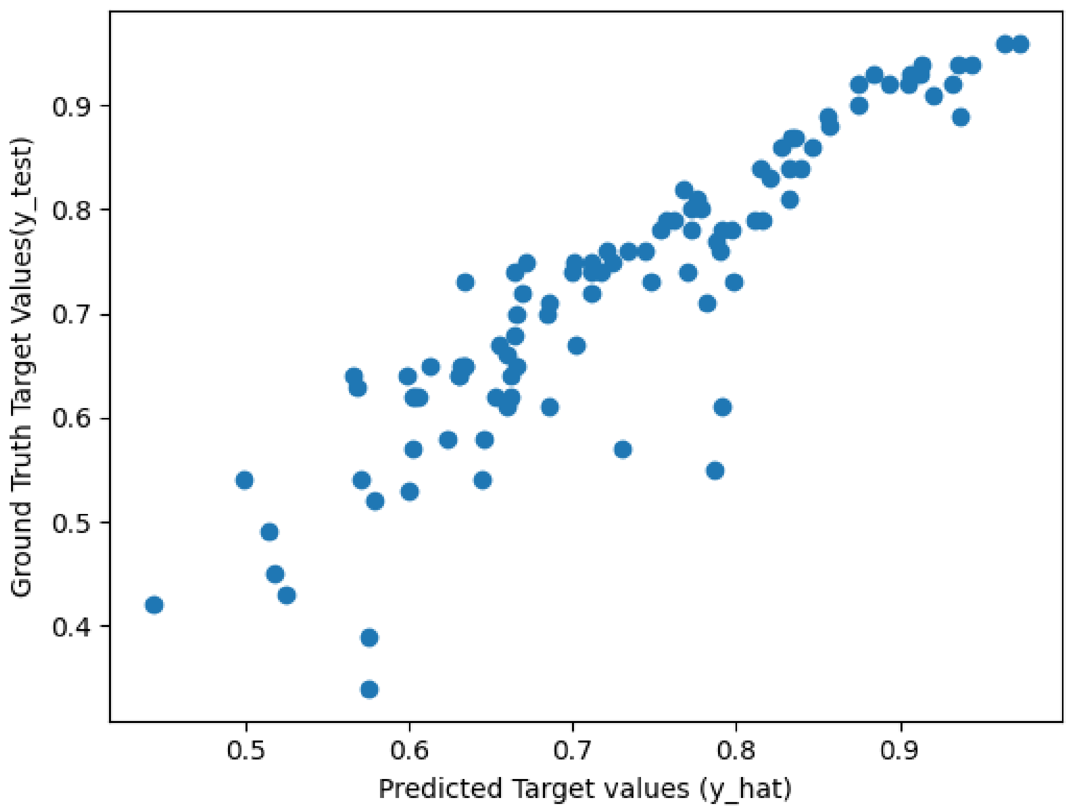
[760]:
```
array([0.09524095, 0.0896154 , 0.02779894, 0.01343073, 0.05038349,
       0.33579987, 0.02121245])
```

[761]:
```
elasticnet.intercept_
```

[761]:
```
0.36954114253282005
```

[762]:
```
y_hat = elasticnet.predict(X_test_scaled)
```

[763]:
```
fig = plt.figure()
plt.scatter(y_hat,y_test)
plt.xlabel("Predicted Target values (y_hat)")
plt.ylabel("Ground Truth Target Values(y_test)")
plt.show()
```



[764]:
```
mae = mean_absolute_error(y_test, y_hat)
mse = mean_squared_error(y_test, y_hat)
rmse = root_mean_squared_error(y_test, y_hat)
r2 = r2_score(y_test, y_hat)
adj_r2 = adjusted_r2_score(r2, len(X_test), len(X_test.columns))

print("Mean Absolute Error:", mae)
print("Mean Squared Error:", mse)
print("Root Mean Squared Error:", rmse)
print("R-squared Score:", r2)
print("Adjusted R-squared Score:", adj_r2)
```

```
Mean Absolute Error: 0.04053178187336964
Mean Squared Error: 0.003489961231819844З
Root Mean Squared Error: 0.05907589383005427
R-squared Score: 0.8192759964880201
Adjusted R-squared Score: 0.8055252570903695
```

As there is no overfitting, Evaluation metrics of Normal Linear Regression model, Lasso Regression model, Ridge Regression model and Elastic Net model are almost similar.

4 CHAPTER 4: TESTING THE ASSUMPTIONS OF THE LINEAR REGRESSION MODEL **

4.1 MULTI-COLLINEARITY CHECK BY VIF SCORE (VARIABLES ARE DROPPED ONE BY ONE TILL NONE HAS VIF>5)

Statsmodel implementation of Linear Regression

[765]:
```
X_train_sm = sm.add_constant(X_train)  #Statmodels default is without␣
↪intercept, to add intercept we need to add constant

sm_model = sm.OLS(y_train, X_train_sm).fit()

print(sm_model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:        Chance of Admit   R-squared:                       0.822
Model:                            OLS   Adj. R-squared:                  0.818
Method:                 Least Squares   F-statistic:                     257.7
Date:                Sun, 27 Aug 2023   Prob (F-statistic):          2.10e-142
Time:                        00:07:56   Log-Likelihood:                 559.27
No. Observations:                 400   AIC:                            -1103.
Df Residuals:                     392   BIC:                            -1071.
Df Model:                           7
```

```
Covariance Type:            nonrobust
==============================================================================
=====
                       coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
-----
const               -1.2887      0.118    -10.890      0.000      -1.521
-1.056
GRE Score            0.0018      0.001      3.135      0.002       0.001
0.003
TOEFL Score          0.0032      0.001      3.156      0.002       0.001
0.005
University Rating    0.0061      0.004      1.387      0.166      -0.003
0.015
SOP                  0.0030      0.005      0.591      0.555      -0.007
0.013
LOR                  0.0144      0.005      3.105      0.002       0.005
0.024
CGPA                 0.1167      0.011     10.743      0.000       0.095
0.138
Research             0.0199      0.007      2.668      0.008       0.005
0.035
============================================================================
Omnibus:                       80.594   Durbin-Watson:                   1.932
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              167.116
Skew:                          -1.064   Prob(JB):                     5.14e-37
Kurtosis:                       5.346   Cond. No.                     1.31e+04
============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 1.31e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

When one or more input variables exhibit strong correlation, One among them is enough to be part of the model

[766]:

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

[766]:
```
              Features      VIF
0            GRE Score  1371.11
1          TOEFL Score  1266.69
5                 CGPA   941.67
3                  SOP    34.73
4                  LOR    30.89
2    University Rating    21.45
6             Research     2.80
```

Removing the variable with highest VIF

[767]:
```
cols = vif["Features"][1:].values
X_train_2 = X_train[cols]

X_train_2_sm = sm.add_constant(X_train_2)  #Statmodels default is without␣
 ↪intercept, to add intercept we need to add constant
sm_model = sm.OLS(y_train, X_train_2_sm).fit()
print(sm_model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:        Chance of Admit   R-squared:                       0.817
Model:                            OLS   Adj. R-squared:                  0.814
Method:                 Least Squares   F-statistic:                     292.5
Date:                Sun, 27 Aug 2023   Prob (F-statistic):          1.49e-141
Time:                        00:07:56   Log-Likelihood:                 554.32
No. Observations:                 400   AIC:                            -1095.
Df Residuals:                     393   BIC:                            -1067.
Df Model:                           6
Covariance Type:            nonrobust
================================================================================
=====
                        coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
-----
const                -0.9933      0.072    -13.728      0.000      -1.136
-0.851
TOEFL Score           0.0048      0.001      5.421      0.000       0.003
0.006
CGPA                  0.1298      0.010     12.801      0.000       0.110
0.150
SOP                   0.0017      0.005      0.323      0.747      -0.008
0.012
LOR                   0.0140      0.005      2.982      0.003       0.005
0.023
University Rating     0.0073      0.004      1.631      0.104      -0.001
0.016
```

```
Research               0.0266      0.007      3.690      0.000      0.012
0.041
==============================================================================
Omnibus:                       69.467   Durbin-Watson:                   1.922
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              125.834
Skew:                          -0.984   Prob(JB):                     4.74e-28
Kurtosis:                       4.918   Cond. No.                     2.56e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 2.56e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

[768]:

```python
vif = pd.DataFrame()
vif['Features'] = X_train_2.columns
vif['VIF'] = [variance_inflation_factor(X_train_2.values, i) for i in range(X_train_2.shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

[768]:

	Features	VIF
1	CGPA	721.92
0	TOEFL Score	641.91
2	SOP	32.93
3	LOR	30.59
4	University Rating	20.59
5	Research	2.78

Lets try removing one more variable

[769]:

```python
cols = vif["Features"][1:].values
X_train_3 = X_train[cols]

X_train_3_sm = sm.add_constant(X_train_3)  #Statmodels default is without intercept, to add intercept we need to add constant
sm_model = sm.OLS(y_train, X_train_3_sm).fit()
print(sm_model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:         Chance of Admit   R-squared:                       0.741
Model:                             OLS   Adj. R-squared:                  0.737
Method:                  Least Squares   F-statistic:                     225.1
Date:                 Sun, 27 Aug 2023   Prob (F-statistic):          4.30e-113
Time:                         00:07:56   Log-Likelihood:                 484.62
```

```
No. Observations:                 400   AIC:                            -957.2
Df Residuals:                     394   BIC:                            -933.3
Df Model:                           5
Covariance Type:            nonrobust
================================================================================
=====
                        coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
-----
const                -0.6820      0.081     -8.418      0.000      -0.841
-0.523
TOEFL Score           0.0111      0.001     12.946      0.000       0.009
0.013
SOP                   0.0131      0.006      2.178      0.030       0.001
0.025
LOR                   0.0257      0.005      4.685      0.000       0.015
0.036
University Rating     0.0170      0.005      3.256      0.001       0.007
0.027
Research              0.0421      0.008      4.974      0.000       0.025
0.059
==============================================================================
Omnibus:                       55.399   Durbin-Watson:                   1.926
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               81.722
Skew:                          -0.901   Prob(JB):                     1.80e-18
Kurtosis:                       4.286   Cond. No.                     2.40e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 2.4e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

[770]:

```
vif = pd.DataFrame()
vif['Features'] = X_train_3.columns
vif['VIF'] = [variance_inflation_factor(X_train_3.values, i) for i in range(X_train_3.shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

[770]:

	Features	VIF
1	SOP	32.54
2	LOR	29.70
0	TOEFL Score	21.10

```
3  University Rating  20.48
4           Research   2.77
```

Lets try removing One more variable

```
[771]: cols = vif["Features"][1:].values
X_train_4 = X_train[cols]

X_train_4_sm = sm.add_constant(X_train_4)  #Statmodels default is without␣
 ↪intercept, to add intercept we need to add constant
sm_model = sm.OLS(y_train, X_train_4_sm).fit()
print(sm_model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:        Chance of Admit   R-squared:                       0.738
Model:                            OLS   Adj. R-squared:                  0.735
Method:                 Least Squares   F-statistic:                     277.6
Date:                Sun, 27 Aug 2023   Prob (F-statistic):          2.54e-113
Time:                        00:07:56   Log-Likelihood:                 482.22
No. Observations:                 400   AIC:                            -954.4
Df Residuals:                     395   BIC:                            -934.5
Df Model:                           4
Covariance Type:            nonrobust
================================================================================
=====
                        coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
-----
const                -0.7130      0.080     -8.897      0.000      -0.871
-0.555
LOR                   0.0298      0.005      5.769      0.000       0.020
0.040
TOEFL Score           0.0116      0.001     13.725      0.000       0.010
0.013
University Rating     0.0219      0.005      4.621      0.000       0.013
0.031
Research              0.0426      0.008      5.007      0.000       0.026
0.059
==============================================================================
Omnibus:                       50.073   Durbin-Watson:                   1.921
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               70.438
Skew:                          -0.852   Prob(JB):                     5.06e-16
Kurtosis:                       4.149   Cond. No.                     2.36e+03
==============================================================================

Notes:
```

```
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 2.36e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

[772]:

```python
vif = pd.DataFrame()
vif['Features'] = X_train_4.columns
vif['VIF'] = [variance_inflation_factor(X_train_4.values, i) for i in␣
 ↪range(X_train_4.shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

[772]:

	Features	VIF
0	LOR	25.88
1	TOEFL Score	19.27
2	University Rating	15.30
3	Research	2.75

[773]:

```python
cols = vif["Features"][1:].values
X_train_5 = X_train[cols]

X_train_5_sm = sm.add_constant(X_train_5)  #Statmodels default is without␣
 ↪intercept, to add intercept we need to add constant
sm_model = sm.OLS(y_train, X_train_5_sm).fit()
print(sm_model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:        Chance of Admit   R-squared:                       0.716
Model:                            OLS   Adj. R-squared:                  0.713
Method:                 Least Squares   F-statistic:                     332.0
Date:                Sun, 27 Aug 2023   Prob (F-statistic):          1.08e-107
Time:                        00:07:56   Log-Likelihood:                 466.04
No. Observations:                 400   AIC:                            -924.1
Df Residuals:                     396   BIC:                            -908.1
Df Model:                           3
Covariance Type:            nonrobust
================================================================================
=====
                        coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
-----
const                -0.7632      0.083     -9.212      0.000      -0.926
-0.600
TOEFL Score           0.0127      0.001     14.863      0.000       0.011
0.014
```

```
University Rating      0.0331      0.004      7.384      0.000      0.024
0.042
Research               0.0434      0.009      4.907      0.000      0.026
0.061
==============================================================================
Omnibus:                       54.249   Durbin-Watson:                   1.893
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               77.733
Skew:                          -0.904   Prob(JB):                     1.32e-17
Kurtosis:                       4.182   Cond. No.                     2.35e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 2.35e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

[774]:

```
vif = pd.DataFrame()
vif['Features'] = X_train_5.columns
vif['VIF'] = [variance_inflation_factor(X_train_5.values, i) for i in␣
 ↪range(X_train_5.shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

[774]:

	Features	VIF
1	University Rating	11.55
0	TOEFL Score	9.98
2	Research	2.75

[775]:

```
cols = vif["Features"][1:].values
X_train_6 = X_train[cols]

X_train_6_sm = sm.add_constant(X_train_6)  #Statmodels default is without␣
 ↪intercept, to add intercept we need to add constant
sm_model = sm.OLS(y_train, X_train_6_sm).fit()
print(sm_model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:        Chance of Admit   R-squared:                       0.676
Model:                            OLS   Adj. R-squared:                  0.675
Method:                 Least Squares   F-statistic:                     414.8
Date:                Sun, 27 Aug 2023   Prob (F-statistic):           5.66e-98
Time:                        00:07:56   Log-Likelihood:                 440.24
No. Observations:                 400   AIC:                            -874.5
Df Residuals:                     397   BIC:                            -862.5
Df Model:                           2
```

```
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -1.0546      0.078    -13.592      0.000      -1.207      -0.902
TOEFL Score    0.0163      0.001     21.865      0.000       0.015       0.018
Research       0.0546      0.009      5.884      0.000       0.036       0.073
==============================================================================
Omnibus:                       48.320   Durbin-Watson:                   1.920
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               64.561
Skew:                          -0.865   Prob(JB):                     9.57e-15
Kurtosis:                       3.940   Cond. No.                     2.07e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 2.07e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

[776]:

```
vif = pd.DataFrame()
vif['Features'] = X_train_6.columns
vif['VIF'] = [variance_inflation_factor(X_train_6.values, i) for i in␣
 ↪range(X_train_6.shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

[776]:

	Features	VIF
0	TOEFL Score	2.37
1	Research	2.37

Lets use Regularisation on modified dataset

[777]:

```
X = jamboree[['TOEFL Score', 'Research']]
y = jamboree["Chance of Admit"]
scaler = MinMaxScaler()
X = scaler.fit_transform(X)

X_train_m, X_test_m, y_train_m, y_test_m = train_test_split(X, y, test_size=0.
 ↪2, random_state=1)
```

[778]:

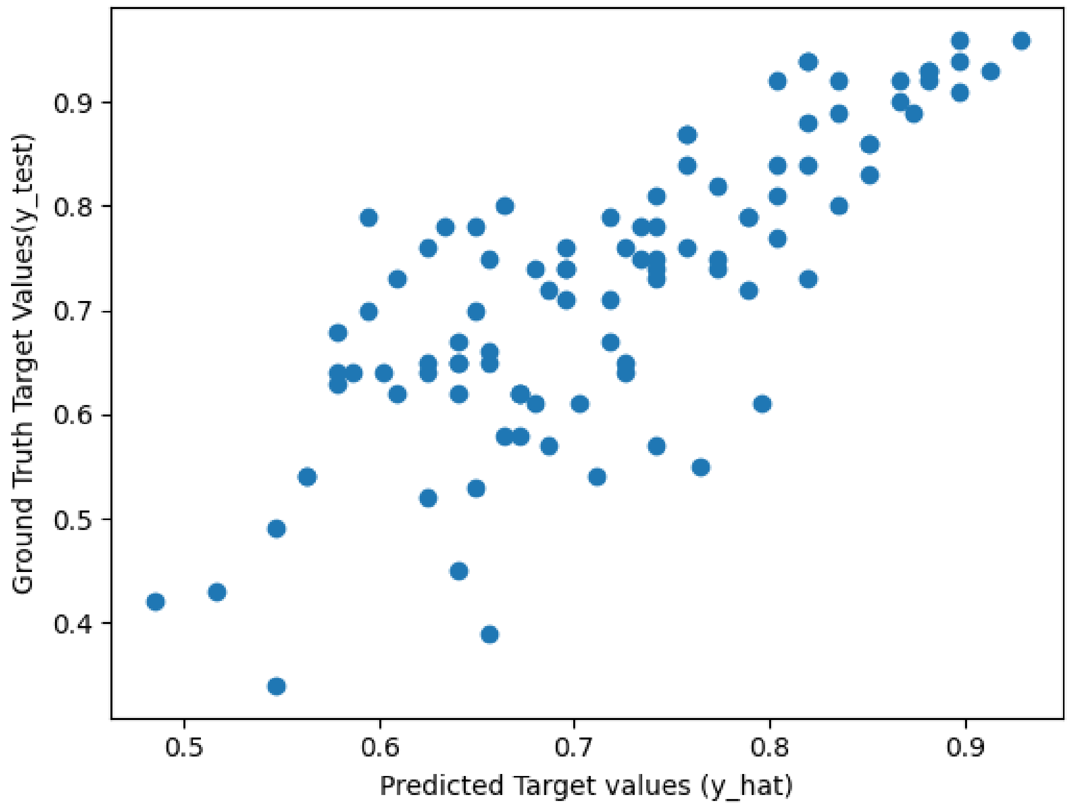
```
X_test_m = pd.DataFrame(X_test_m)
```

[779]:

```
lasso = Lasso(alpha = 0.001)
lasso.fit(X_train_m,y_train_m)
print("Lasso Coefficients are:",lasso.coef_)
print("Lasso intercept is:",lasso.intercept_)
```

```
y_hat = lasso.predict(X_test_m)
fig = plt.figure()
plt.scatter(y_hat,y_test_m)
plt.xlabel("Predicted Target values (y_hat)")
plt.ylabel("Ground Truth Target Values(y_test)")
plt.show()
```

```
Lasso Coefficients are: [0.43490898 0.05500989]
Lasso intercept is: 0.4541667753121399
```



[780]:
```
mae = mean_absolute_error(y_test_m, y_hat)
mse = mean_squared_error(y_test_m, y_hat)
rmse = root_mean_squared_error(y_test_m, y_hat)
r2 = r2_score(y_test_m, y_hat)
adj_r2 = adjusted_r2_score(r2, len(X_test_m), len(X_test_m.columns))

print("Mean Absolute Error:", mae)
print("Mean Squared Error:", mse)
print("Root Mean Squared Error:", rmse)
print("R-squared Score:", r2)
print("Adjusted R-squared Score:", adj_r2)
```

```
Mean Absolute Error: 0.0652676258742749
Mean Squared Error: 0.007266123004342548
Root Mean Squared Error: 0.08524155679211019
R-squared Score: 0.6237313963884549
Adjusted R-squared Score: 0.6159732808500724
```

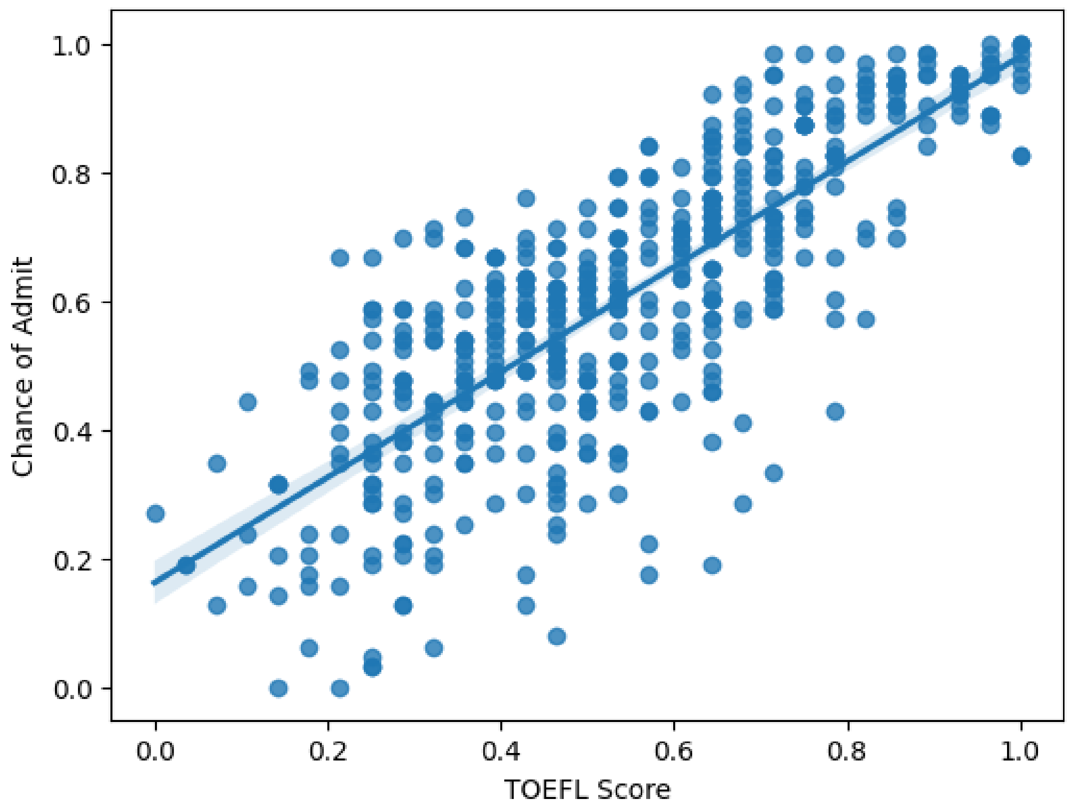
Clearly The R2 Score and Adjusted R2 Score are decreasing because of deletion of the features due to VIF>5.

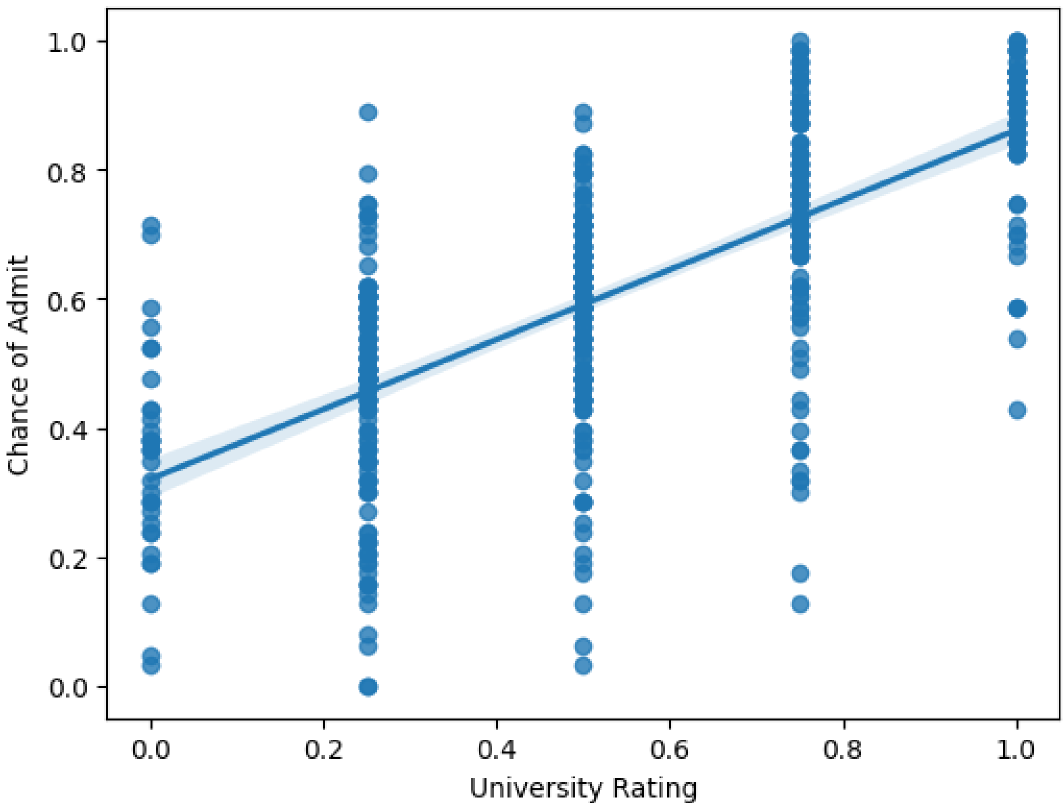
So it is not good to delete the features as Higher R2 Score indicates the Better model

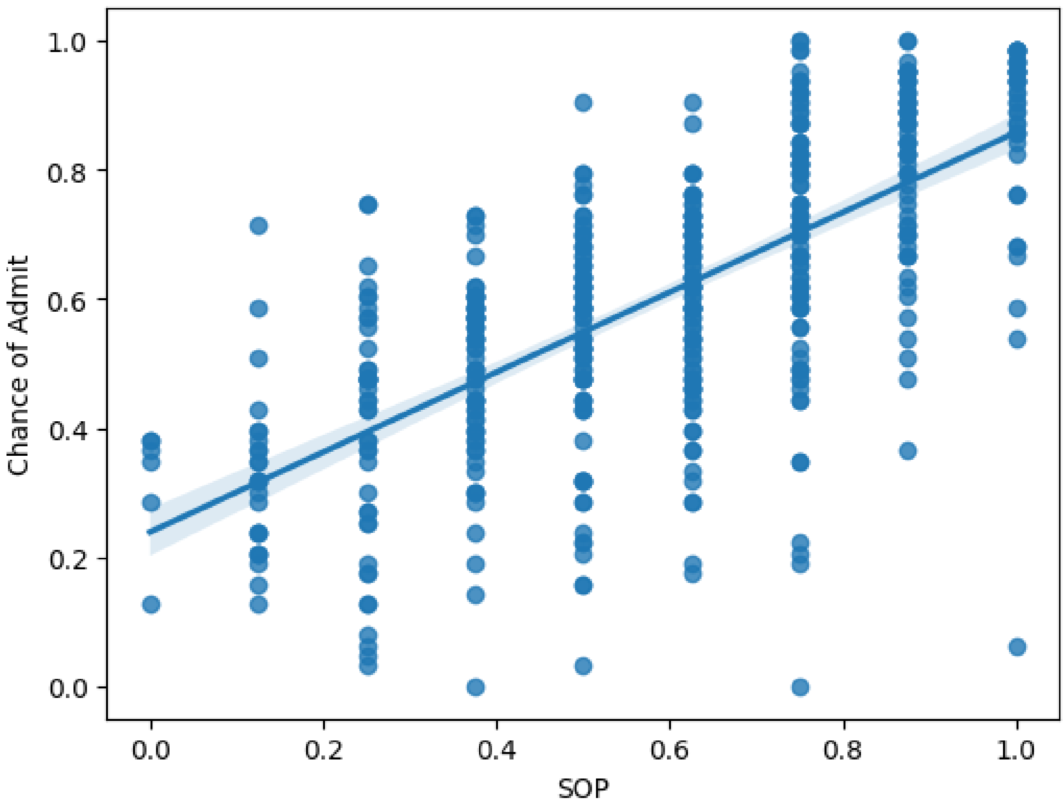
Regularisation techniques, Feature Engineering or handling, Dimensionality Reduction or Collecting More data can mitigate the multi collinearity problem

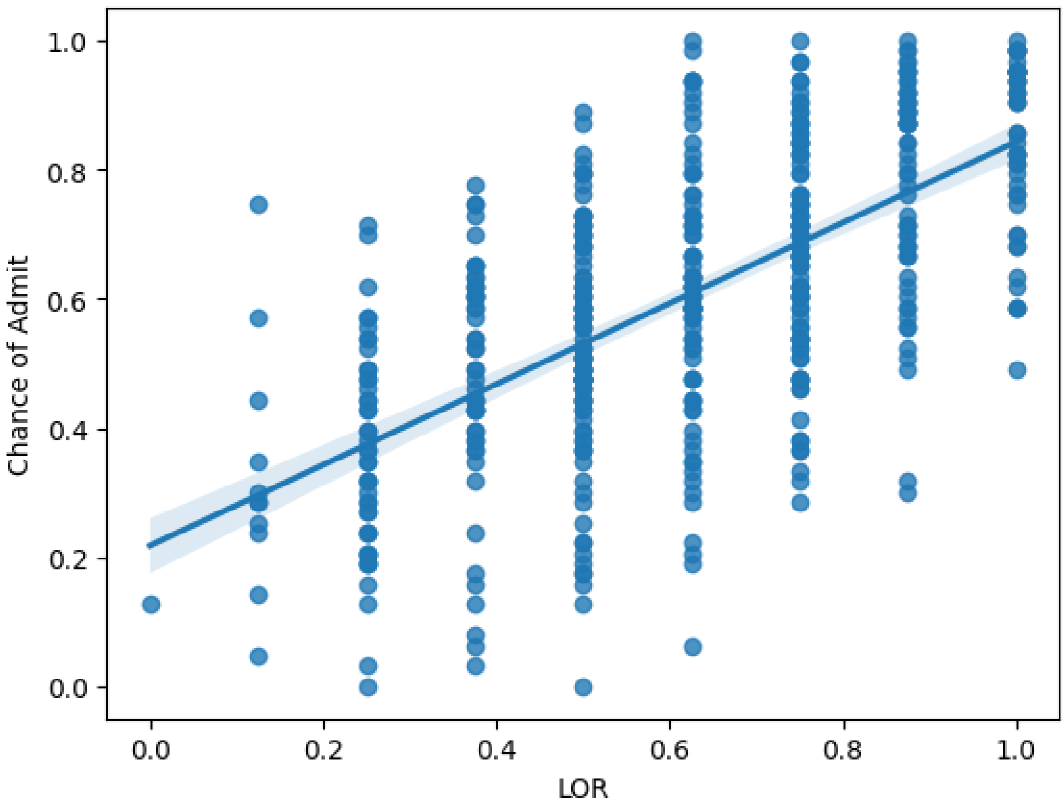
4.2 LINEARITY OF VARIABLES (NO PATTERN IN THE RESIDUAL PLOT)

[802]:
```python
for i in jamboree_scaled.columns[2:-1]:
    sns.regplot(x = i,y ="Chance of Admit",data = jamboree_scaled)
    plt.show()
```

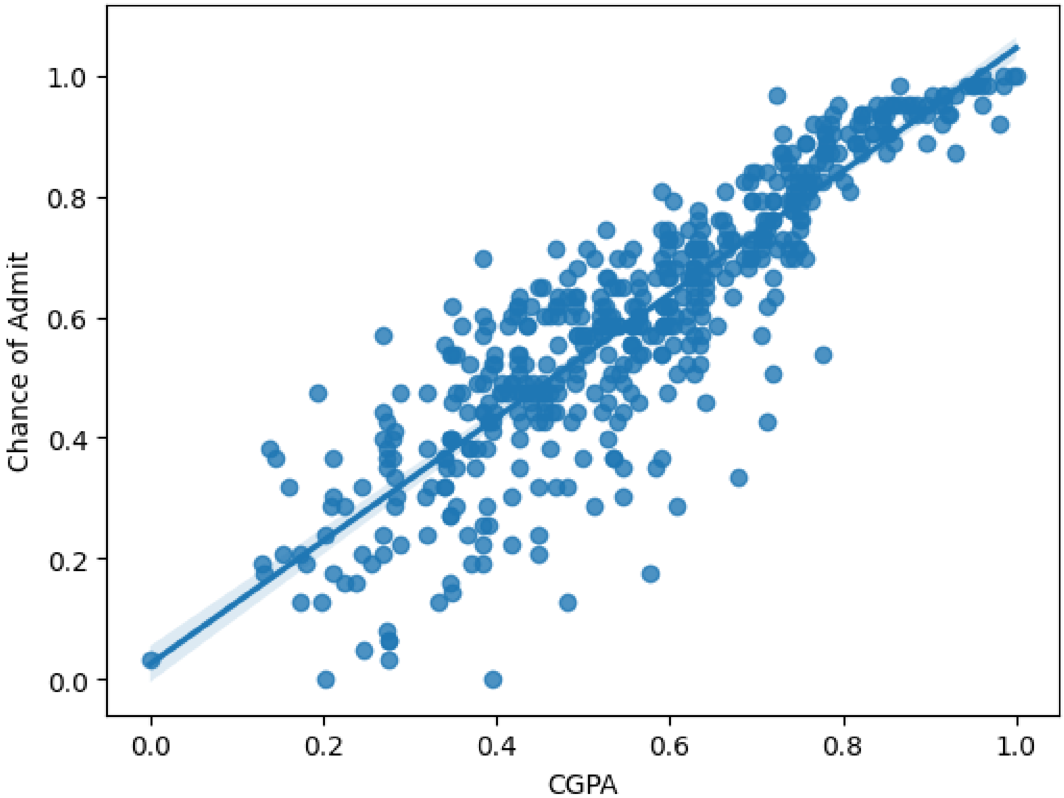


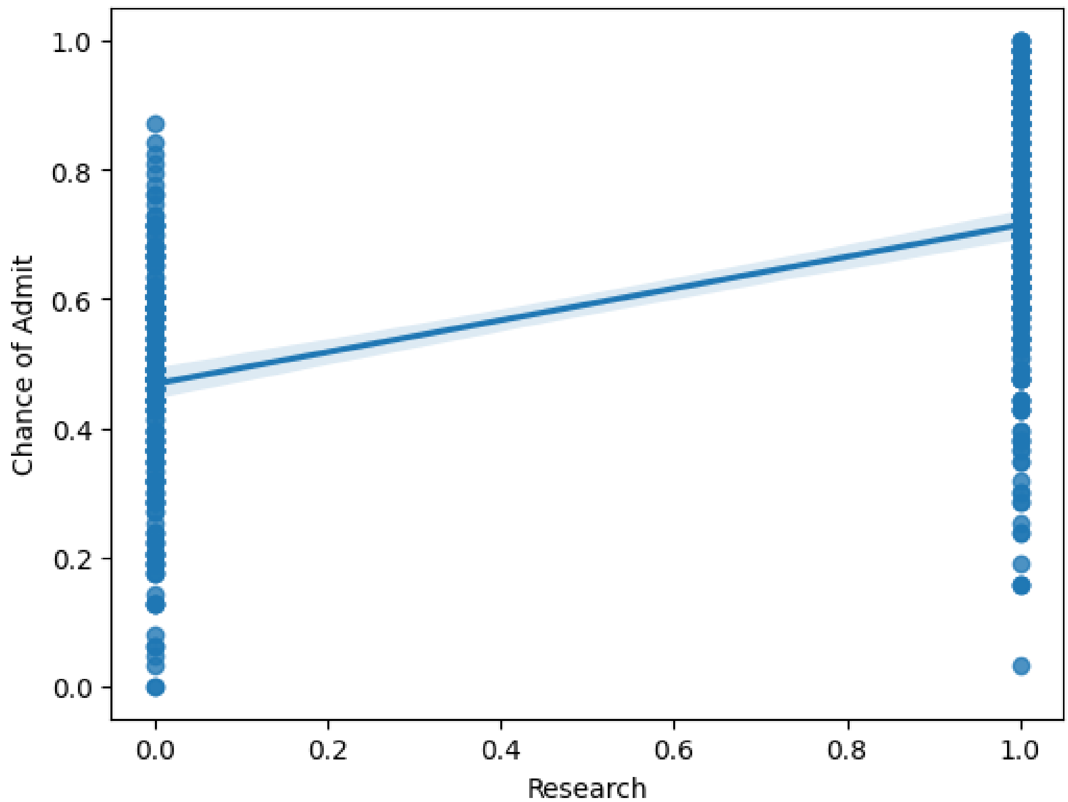

1.0
0.8
0.6
0.4
0.2
0.0
Chance of Admit
0.0
0.2
0.4
0.6
0.8
1.0
University Rating


Chance of Admit
SOP
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0



1.0
0.8
0.6
0.4
0.2
0.0
Chance of Admit
0.0
0.2
0.4
0.6
0.8
1.0
LOR


Chance of Admit
CGPA
0.0
0.2
0.4
0.6
0.8
1.0



Almost all the features are have Linear dependent on Target Variable

4.3 NORMALITY OF RESIDUALS (ALMOST BELL SHAPED CURVE IN RESIDUALS DISTRIBUTION, POINTS IN QQ PLOT ARE ALMOST ALL ON THE TIME)

[781]:
```
scaler = MinMaxScaler()
jamboree_scaled = pd.DataFrame(scaler.fit_transform(jamboree),columns =␣
 ↪jamboree.columns)
y = jamboree_scaled["Chance of Admit"]
X = jamboree_scaled.drop(["Serial No.","Chance of Admit"],axis = 1)
X_train_new, X_test_new, y_train_new, y_test_new =␣
 ↪train_test_split(X,y,test_size = 0.2, random_state = 1)
X_train_sm_new = sm.add_constant(X_train_new)  #Statmodels default is without␣
 ↪intercept, to add intercept we need to add constant
sm_model = sm.OLS(y_train_new, X_train_sm_new).fit()
print(sm_model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:        Chance of Admit   R-squared:                       0.822
```

```
Model:                            OLS   Adj. R-squared:                  0.818
Method:                 Least Squares   F-statistic:                     257.7
Date:                Sun, 27 Aug 2023   Prob (F-statistic):          2.10e-142
Time:                        00:08:19   Log-Likelihood:                 374.46
No. Observations:                 400   AIC:                            -732.9
Df Residuals:                     392   BIC:                            -701.0
Df Model:                           7
Covariance Type:            nonrobust
================================================================================
=====
                        coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
-----
const                 0.0187      0.016      1.155      0.249      -0.013
0.051
GRE Score             0.1454      0.046      3.135      0.002       0.054
0.237
TOEFL Score           0.1411      0.045      3.156      0.002       0.053
0.229
University Rating     0.0389      0.028      1.387      0.166      -0.016
0.094
SOP                   0.0191      0.032      0.591      0.555      -0.044
0.083
LOR                   0.0916      0.029      3.105      0.002       0.034
0.150
CGPA                  0.5780      0.054     10.743      0.000       0.472
0.684
Research              0.0316      0.012      2.668      0.008       0.008
0.055
==============================================================================
Omnibus:                       80.594   Durbin-Watson:                   1.932
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              167.116
Skew:                          -1.064   Prob(JB):                     5.14e-37
Kurtosis:                       5.346   Cond. No.                         23.4
==============================================================================

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

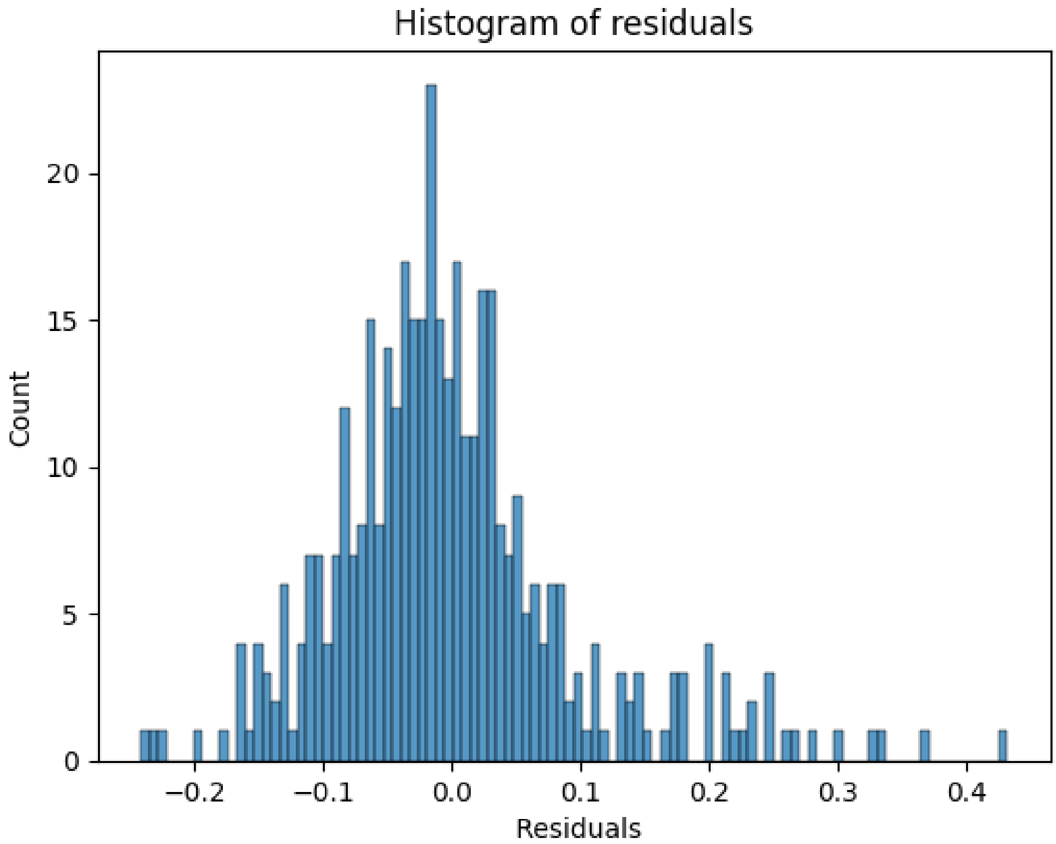
[783]:

```
y_hat = sm_model.predict(X_train_sm_new)
errors = y_hat - y_train_new
```

[785]:

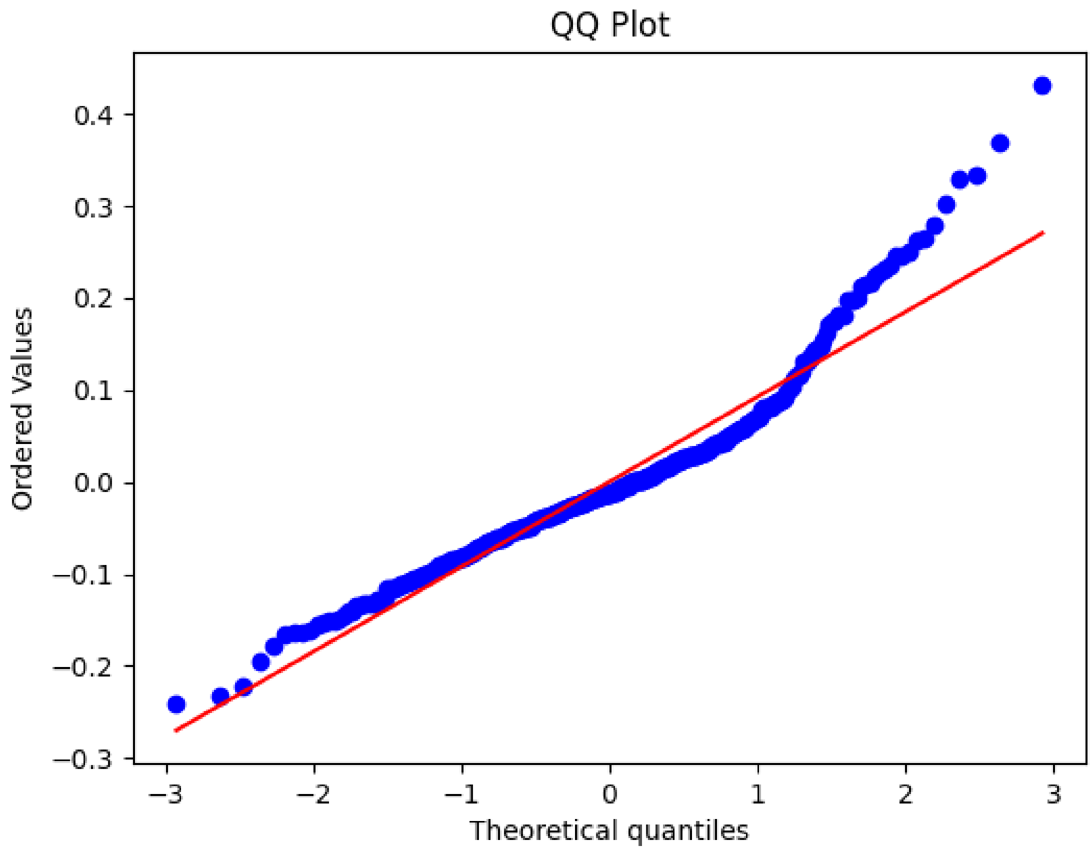
```
sns.histplot(errors,bins = 100)
plt.xlabel(" Residuals")
plt.title("Histogram of residuals")
```

[785]: Text(0.5, 1.0, 'Histogram of residuals')



QQ plot of errors

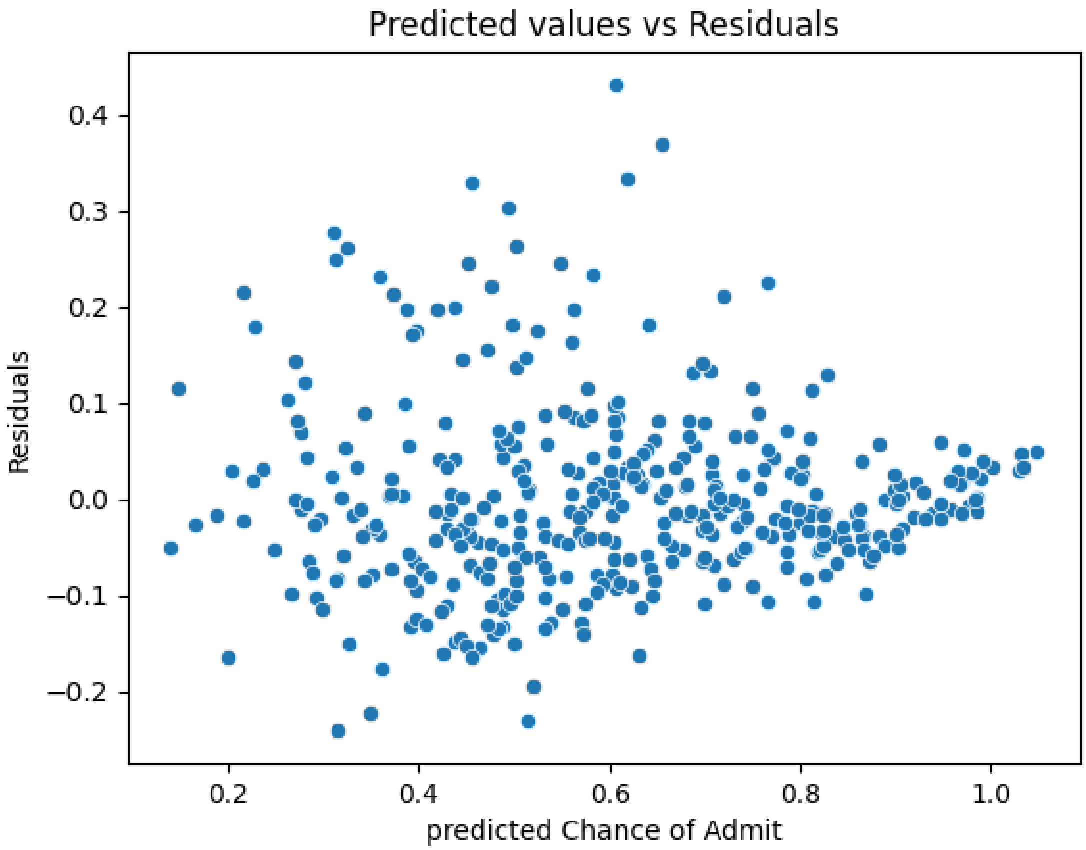
[788]:
```
stats.probplot(errors, plot=plt)
plt.title("QQ Plot")
plt.show()
```



4.4 TEST FOR HOMOSCEDASTICITY

[790]:
```
sns.scatterplot(x=y_hat,y=errors)
plt.xlabel("predicted Chance of Admit")
plt.ylabel("Residuals")
plt.title("Predicted values vs Residuals")
```

[790]:
```
Text(0.5, 1.0, 'Predicted values vs Residuals')
```



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

4.5 THE MEAN OF RESIDUALS IS NEARLY ZERO

[792]:
```
np.mean(errors)
```

[792]:
```
7.216449660063518e-16
```

Mean of residuals is very near to zero

5 CHAPTER 5: MODEL PERFORMANCE EVALUATION

5.1 METRICS CHECKED - MAE, RMSE, R2, Adj R2

[803]:
```
elasticnet = ElasticNet(alpha = 0.001)
elasticnet.fit(X_train_scaled,y_train)
y_hat = elasticnet.predict(X_test_scaled)
mae = mean_absolute_error(y_test, y_hat)
mse = mean_squared_error(y_test, y_hat)
```

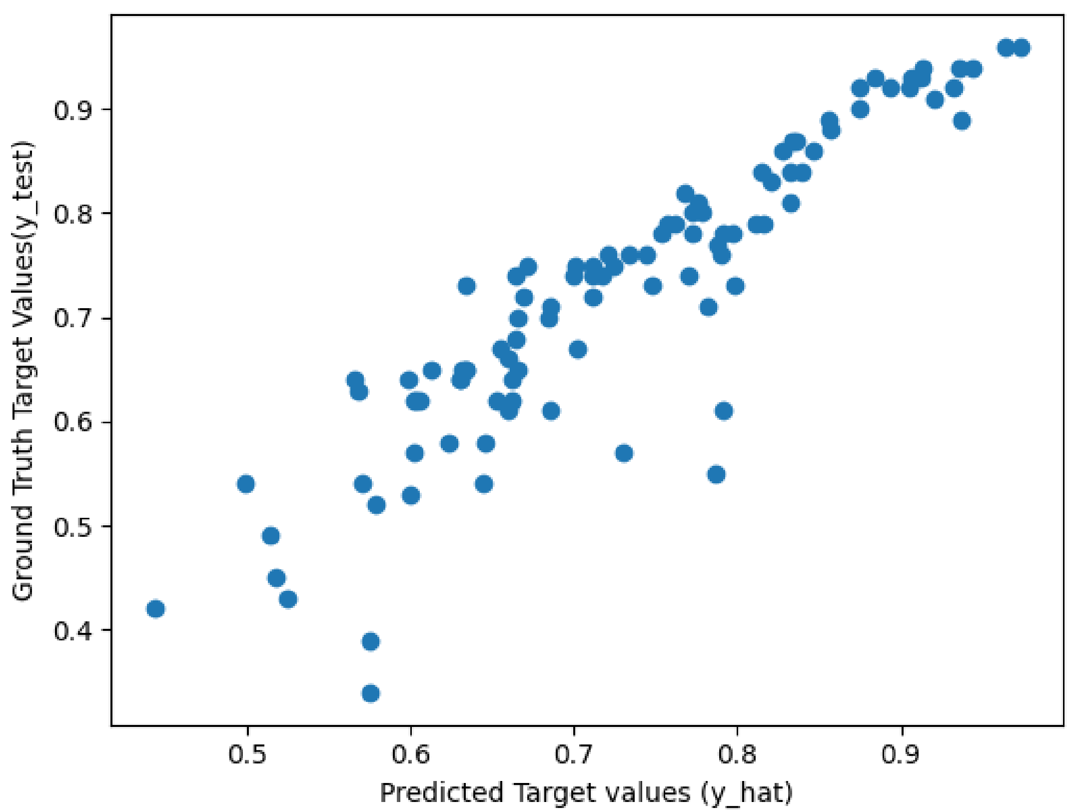
```
rmse = root_mean_squared_error(y_test, y_hat)
r2 = r2_score(y_test, y_hat)
adj_r2 = adjusted_r2_score(r2, len(X_test), len(X_test.columns))

print("Mean Absolute Error:", mae)
print("Mean Squared Error:", mse)
print("Root Mean Squared Error:", rmse)
print("R-squared Score:", r2)
print("Adjusted R-squared Score:", adj_r2)
```

```
Mean Absolute Error: 0.04053178187336964
Mean Squared Error: 0.0034899612318198443
Root Mean Squared Error: 0.05907589383005427
R-squared Score: 0.8192759964880201
Adjusted R-squared Score: 0.8055252570903695
```

5.2 TRAIN AND TEST PERFORMANCES ARE CHECKED

[804]:
```
fig = plt.figure()
plt.scatter(y_hat,y_test)
plt.xlabel("Predicted Target values (y_hat)")
plt.ylabel("Ground Truth Target Values(y_test)")
plt.show()
```



5.3 COMMENTS ON THE PERFORMANCES MEASURES AND IF THERE IS ANY NEED TO IMPROVE THE MODEL OR NOT

elastic net provides best R square score and adjusted R square score.

No need to delete the features due to multicollinearity as they are decreasing the R2 square

6 CHAPTER 6: ACTIONABLE INSIGHTS & RECOMMENDATIONS

6.1 INSIGHTS

CGPA is highest important feature according to weights

SOP is least important feature according to weights

On deletion of Features due to VIF, Lastly remained features are TOEFL score and Research. This implies that these two feature independent and very important in predicting the target variable

6.2 RECOMMENDATIONS

Multicollinearity present in the data. So It should be handled by increasing the data

Deleting the features reduces the R2 square values. So it is not preferable.

All independent variables are linearly correlated with dependent variable

TOEFL Score and REsearch are two important variables which are important in making the prediction

Following are best Evaluation metrics

Mean Absolute Error: 0.040531781873369 64 Mean Squared Error: 0.0034899612318198443 Root Mean Squared Error: 0.05907589383005427 R-squared Score: 0.8192759964880201 Adjusted R-squared Score: 0.8055252570903695