Jamboree

has helped thousands of students 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.

Problem Statement:

1. To understand what factors are important in graduate admissions and how these factors are interrelated among themselves
2. To predict one's chances of admission, given the rest of the variables

In [1]:
```
# Importing required packages for analysis
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
# Importing stats functions
from scipy.stats import chi2_contingency,ttest_ind,levene,f_oneway,mannwhitneyu,pearsonr,spearmanr,kruskal,normaltest
```

In [3]:
```
# Importing ML related functions
from sklearn.linear_model import LinearRegression,Lasso,Ridge
from sklearn.preprocessing import MinMaxScaler, StandardScaler, PolynomialFeatures
from sklearn.model_selection import train_test_split, KFold, StratifiedKFold,GridSearchCV
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error, median_absolute_error
from sklearn.pipeline import Pipeline, make_pipeline
import statsmodels.api as sm
```

In [4]:
```
# Initial pandas & matplotlib setup
pd.options.display.max_rows = 30
pd.options.display.max_columns = 30
np.set_printoptions(precision=2,suppress=True)

import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
```

In [5]:
```
# To increase jupyter notebook cell width
from IPython.display import display, HTML
display(HTML("<style>.container { width:100% !important; }</style>"))
```

In [6]:
```
# To plot clear graphs
import matplotlib_inline
matplotlib_inline.backend_inline.set_matplotlib_formats('svg')
```

In [7]:
```
# Importing the given dataset to pandas dataframe
data = pd.read_csv("../input/Jamboree_Admission.csv")
data.drop(columns="Serial No.",inplace=True)
df = data.copy()
df.head(5)
```

Out[7]:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
0	337	118	4	4.5	4.5	9.65	1	0.92
1	324	107	4	4.0	4.5	8.87	1	0.76
2	316	104	3	3.0	3.5	8.00	1	0.72
3	322	110	3	3.5	2.5	8.67	1	0.80
4	314	103	2	2.0	3.0	8.21	0	0.65

Column Profiling:

1. Serial No. (Unique row ID)
2. GRE Scores (out of 340)
3. TOEFL Scores (out of 120)
4. University Rating (out of 5)
5. Statement of Purpose and Letter of Recommendation Strength (out of 5)
6. Undergraduate GPA (out of 10)
7. Research Experience (either 0 or 1)
8. Chance of Admit (ranging from 0 to 1)

In [8]:
```
# To get the shape of the dataset
print(f"Number of records : {df.shape[0]}")
print(f"Total Features:  {df.shape[1]}")
```

```
Number of records : 500
Total Features:  8
```

In [9]:
```
# Check for duplicates
df.loc[df.duplicated(),:]
```

Out[9]:

GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit

In [10]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 8 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   GRE Score          500 non-null    int64  
 1   TOEFL Score        500 non-null    int64  
 2   University Rating  500 non-null    int64  
 3   SOP                500 non-null    float64
 4   LOR                500 non-null    float64
 5   CGPA               500 non-null    float64
 6   Research           500 non-null    int64  
 7   Chance of Admit    500 non-null    float64
dtypes: float64(4), int64(4)
memory usage: 31.4 KB
```

Insights:

1. There are 500 records with 8 different columns sans Serial No.
2. There are no duplicates or missing values in any of the columns
3. Datatypes of Research, and University Rating can be changed to object for analysis

In [11]:
```
# Remove unwanted spaces and rename the column & index names to make analysis easier
df.columns = ["_".join(col.strip().split(" ")) for col in df.columns]
df.columns
```

Out[11]:
```
Index(['GRE_Score', 'TOEFL_Score', 'University_Rating', 'SOP', 'LOR', 'CGPA',
       'Research', 'Chance_of_Admit'],
      dtype='object')
```

In [12]:
```
# Change datatype of Research, and University Rating columns
df["University_Rating"] = df["University_Rating"].astype("object")
df["Research"] = df["Research"].astype("object")
```

In [13]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 8 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   GRE_Score          500 non-null    int64  
 1   TOEFL_Score        500 non-null    int64  
 2   University_Rating  500 non-null    object 
 3   SOP                500 non-null    float64
 4   LOR                500 non-null    float64
 5   CGPA               500 non-null    float64
 6   Research           500 non-null    object 
 7   Chance_of_Admit    500 non-null    float64
dtypes: float64(4), int64(2), object(2)
memory usage: 31.4+ KB
```

In [14]:
```
# Create two lists of Categorical & Numerical features
cat_cols = df.select_dtypes(include=["object"]).columns.tolist()
num_cols = df.select_dtypes(include=["int","float"]).columns.tolist()

print(f"Categorical Columns: {cat_cols}")
print(f"Numerical Columns: {num_cols}")
```

```
Categorical Columns: ['University_Rating', 'Research']
Numerical Columns: ['GRE_Score', 'TOEFL_Score', 'SOP', 'LOR', 'CGPA', 'Chance_of_Admit']
```

In [15]:
```
df.describe()
```

Out[15]:

	GRE_Score	TOEFL_Score	SOP	LOR	CGPA	Chance_of_Admit
count	500.000000	500.000000	500.000000	500.00000	500.000000	500.00000
mean	316.472000	107.192000	3.374000	3.48400	8.576440	0.72174
std	11.295148	6.081868	0.991004	0.92545	0.604813	0.14114
min	290.000000	92.000000	1.000000	1.00000	6.800000	0.34000
25%	308.000000	103.000000	2.500000	3.00000	8.127500	0.63000
50%	317.000000	107.000000	3.500000	3.50000	8.560000	0.72000
75%	325.000000	112.000000	4.000000	4.00000	9.040000	0.82000
max	340.000000	120.000000	5.000000	5.00000	9.920000	0.97000

Insights:

1. Based on mean & median values of above columns, it doesn't look like there are many outliers
2. Also, data seem to comply with the ranges provided in column profiling

In [16]:
```python
def print_unique_values_and_counts(cols_list,df):

    """
    Given a list of columns & dataframe, print unique values and counts

    """
    print("Unique Values & Unique Value Counts:")
    print()

    for column in cols_list:
        print(f"{column} :\n Unique Values: {df[column].unique()},\n Unique Value Counts: {df[column].nunique()}")
        print("----------------------------XXX---------------------------")
        print()

    return

# Calling the above function with categorical columns list & data
print_unique_values_and_counts(cat_cols,df)
```

```
Unique Values & Unique Value Counts:

University_Rating :
 Unique Values: [4 3 2 5 1],
 Unique Value Counts: 5
----------------------------XXX---------------------------

Research :
 Unique Values: [1 0],
 Unique Value Counts: 2
----------------------------XXX---------------------------
```

Insights:

1. Unique values of University_Rating & Research match with ranges provided in column profiling

In [17]:
```python
def print_value_counts(cols_list):

    """
    Given list of columns, counts of first 10 different categories

    """
    for col in cols_list:
        print(col,":")
        print()
        print(df.loc[:,col].value_counts().head(10))
        print()
        print("----------------------------XXX---------------------------")
        print()

    return
# Call above function with the list of categorical columns
print_value_counts(cat_cols)
```

```
University_Rating :

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

----------------------------XXX---------------------------

Research :

1    280
0    220
Name: Research, dtype: int64

----------------------------XXX---------------------------
```

Insights:

1. There are more students from universities with University_Rating 3, closely followed by students from Univesity_Rating 2
2. More than 50% of students are/were doing research

In [18]:
```
from math import inf
def calculate_quartiles(df,column,unit= None,minCap=-inf,):

    """
    Given a dataframe and numerical column, calculate quartiles, IQR

    """
    quartile1 = np.percentile(df[column],25)
    quartile3 = np.percentile(df[column],75)
    IQR = quartile3-quartile1
    minimum = max(quartile1-1.5*IQR,minCap)
    maximum = quartile3+1.5*IQR

    print(f"Quartile 1:  {unit}{quartile1}")
    print(f"Quartile 3:  {unit}{quartile3}")
    print(f"IQR (Inter Quartile Range): {unit}{np.round(quartile3-quartile1)}")
    print(f"Minimum {column}: {unit}{minimum}\nMaximum {column}: {unit}{maximum}")

    return minimum, maximum
```

In [19]:
```python
# Calculating the quartiles and percentage of outliers

for column in num_cols:
    print(f"{column}:")
    print()
    lower_limit, upper_limit = calculate_quartiles(df,column,unit='',minCap= 0)

    outliers = df.loc[(df[column] > upper_limit) | (df[column] < lower_limit),column]
    outliers_percentage = outliers.shape[0]*100/df[column].shape[0]

    print(f"Total count of Outliers: {outliers.shape[0]} out of {df.shape[0]} records")
    print(f"Percentage of Outliers in the dataset: {np.round(outliers_percentage,2)}%")

    print()
    print("----------------------------XXX---------------------------")
    print()
```

```
GRE_Score:

Quartile 1:  308.0
Quartile 3:  325.0
IQR (Inter Quartile Range): 17.0
Minimum GRE_Score: 282.5
Maximum GRE_Score: 350.5
Total count of Outliers: 0 out of 500 records
Percentage of Outliers in the dataset: 0.0%

----------------------------XXX---------------------------

TOEFL_Score:

Quartile 1:  103.0
Quartile 3:  112.0
IQR (Inter Quartile Range): 9.0
Minimum TOEFL_Score: 89.5
Maximum TOEFL_Score: 125.5
Total count of Outliers: 0 out of 500 records
Percentage of Outliers in the dataset: 0.0%

----------------------------XXX---------------------------

SOP:

Quartile 1:  2.5
Quartile 3:  4.0
IQR (Inter Quartile Range): 2.0
Minimum SOP: 0.25
Maximum SOP: 6.25
Total count of Outliers: 0 out of 500 records
Percentage of Outliers in the dataset: 0.0%

----------------------------XXX---------------------------

LOR:

Quartile 1:  3.0
Quartile 3:  4.0
IQR (Inter Quartile Range): 1.0
Minimum LOR: 1.5
Maximum LOR: 5.5
Total count of Outliers: 1 out of 500 records
Percentage of Outliers in the dataset: 0.2%

----------------------------XXX---------------------------

CGPA:

Quartile 1:  8.127500000000001
Quartile 3:  9.04
IQR (Inter Quartile Range): 1.0
Minimum CGPA: 6.7587500000000045
Maximum CGPA: 10.408749999999996
Total count of Outliers: 0 out of 500 records
Percentage of Outliers in the dataset: 0.0%

----------------------------XXX---------------------------

Chance_of_Admit:

Quartile 1:  0.63
Quartile 3:  0.82
IQR (Inter Quartile Range): 0.0
Minimum Chance_of_Admit: 0.3450000000000001
Maximum Chance_of_Admit: 1.105
Total count of Outliers: 2 out of 500 records
Percentage of Outliers in the dataset: 0.4%

----------------------------XXX---------------------------
```

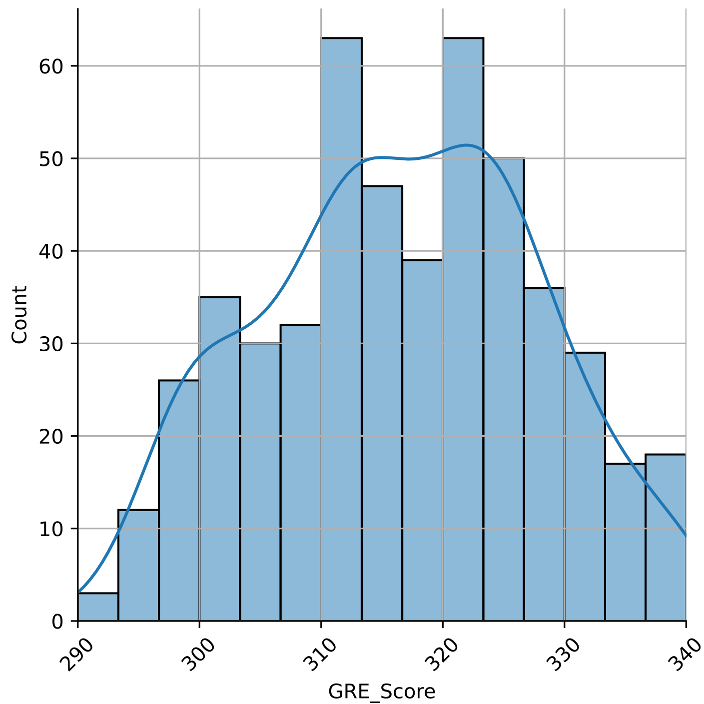
Insights:

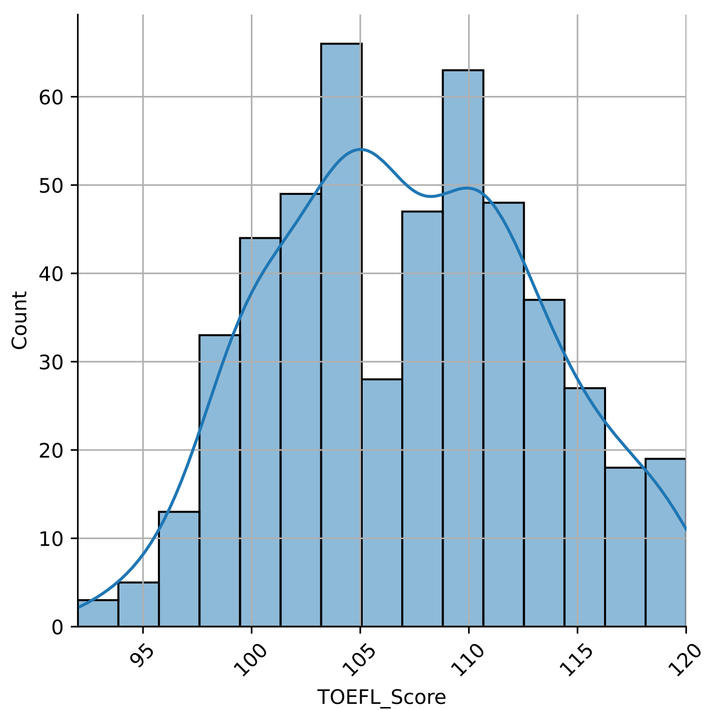
1. Outliers exist in Chance_of_Admit, and LOR columns but very small percentage.
2. Other columns do not have any outliers

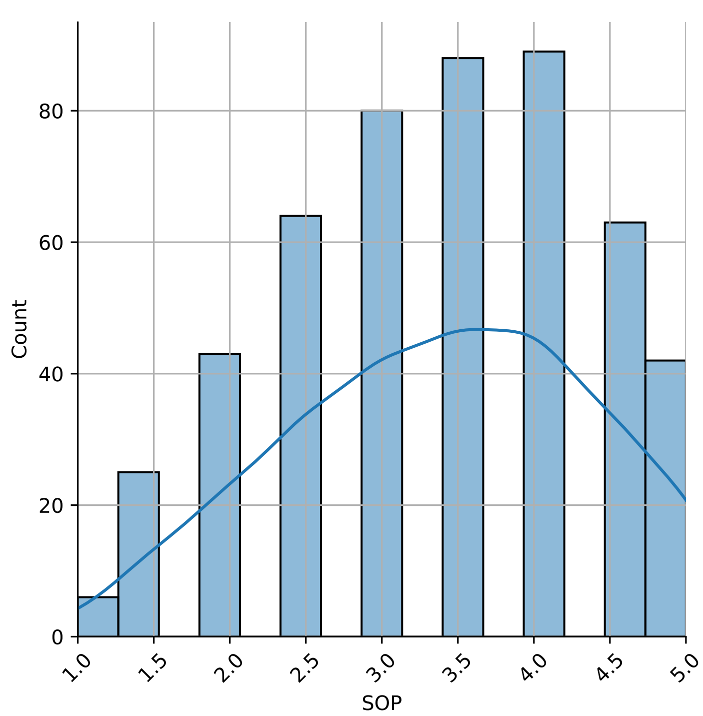
Visual Analysis:

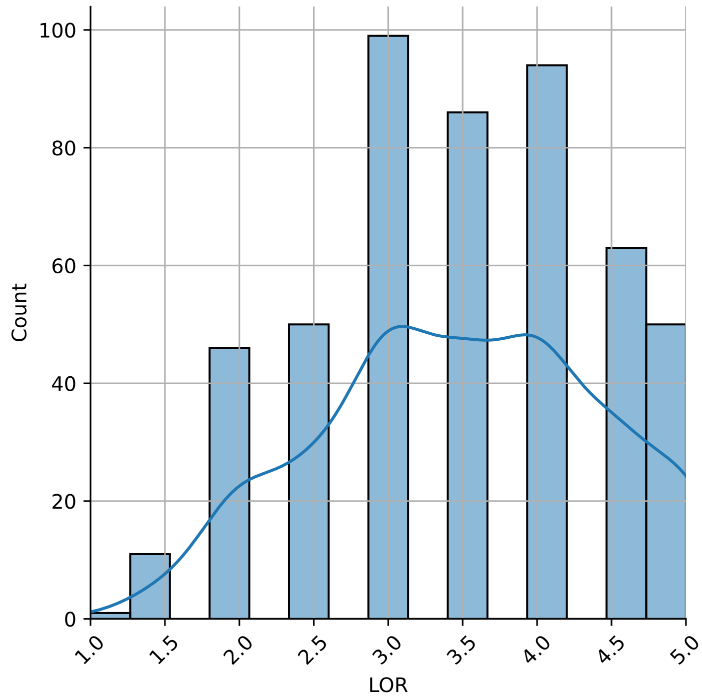
Univariate Analysis:

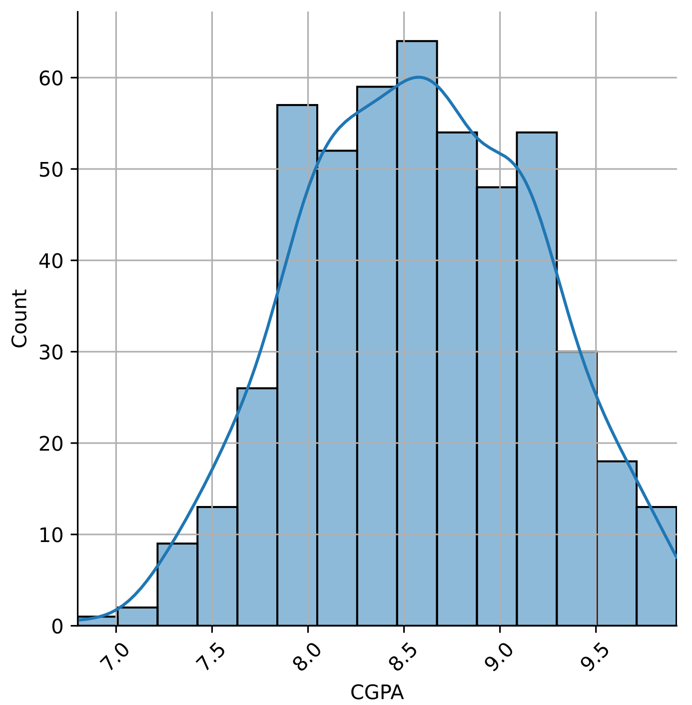
In [20]:
```
# To plot the Kernel density distribution and histogram of numerical columns
for column in num_cols:
    sns.displot(df[column],kde=True,bins = 15)
    plt.xlim((df[column].min(),df[column].max()))
    plt.xticks(rotation=45)
    plt.grid(True)
    plt.show()
```

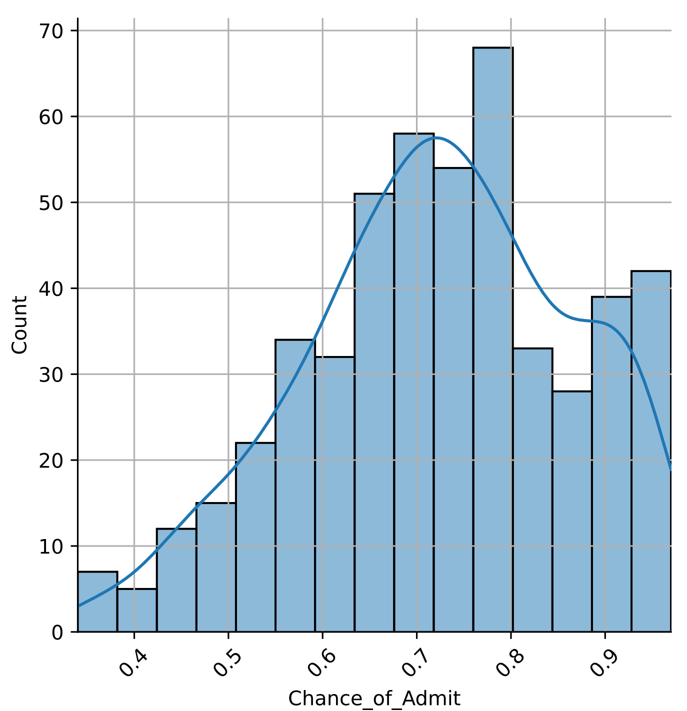










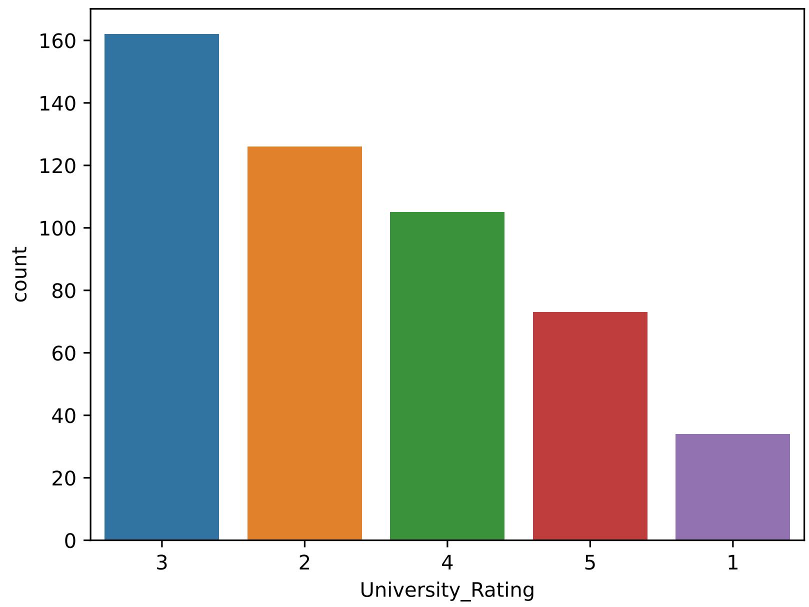


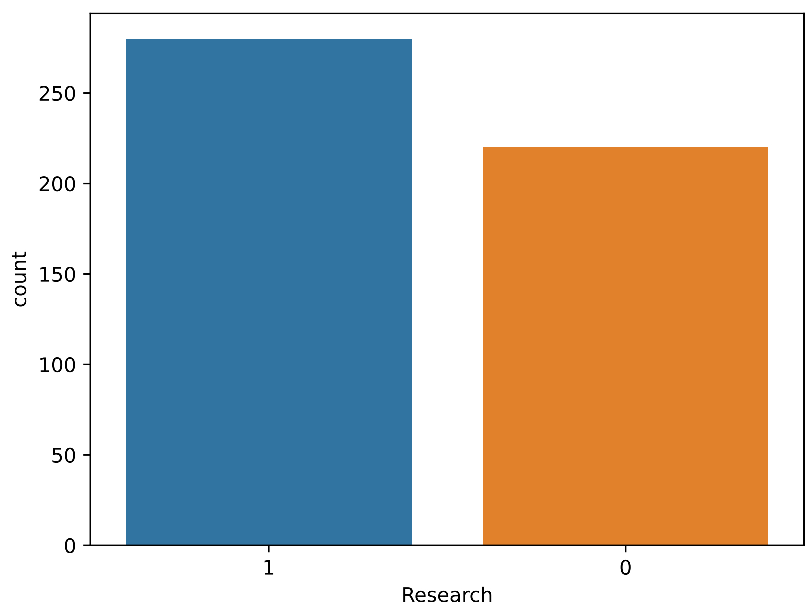
Insights:

1. GRE_Score & TOEFL_Score have bimodal distributions
2. CGPS is close to Guassian. Rest of them including Chance_of_Admit, are left skewed.

In [21]:
```
def print_count_plots(df,cols_list,limit=50):

    """
    Given the dataframe, categorical columns list, returns the count plots for all
    Caveat: If there are more than 100 unique categories for a column, it is skipped

    """
    for col in cat_cols:
        if df[col].nunique() <= limit:
            sns.countplot(data=df,x=col,order=df[col].value_counts().index)
            plt.show()

    return
```

In [22]:
```
# To generate count plots for all categorical variables
print_count_plots(df,cat_cols)
```

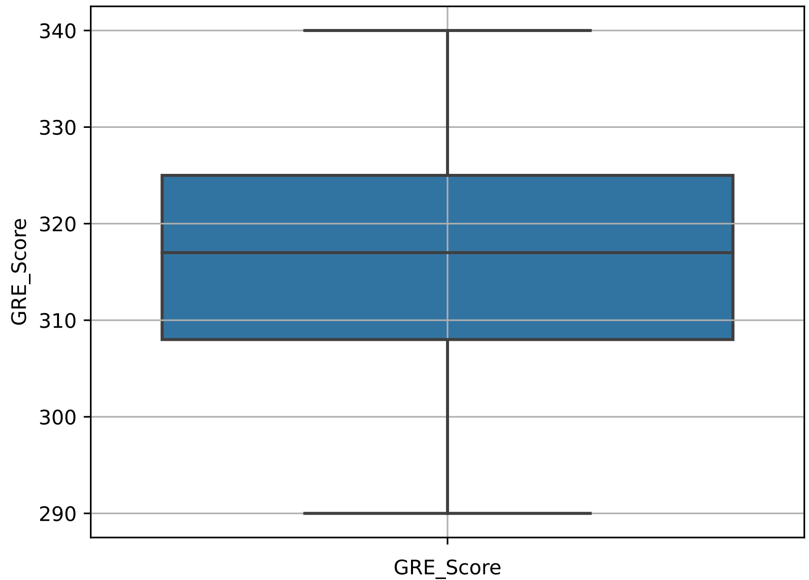


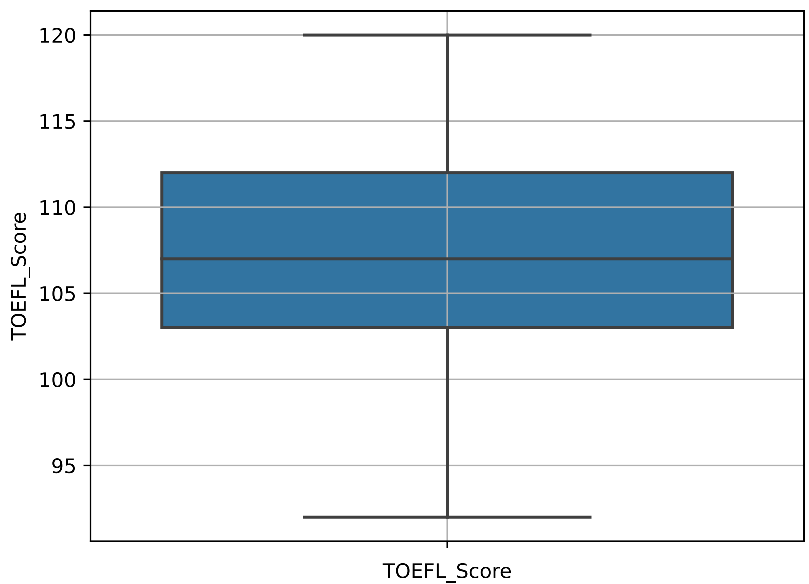


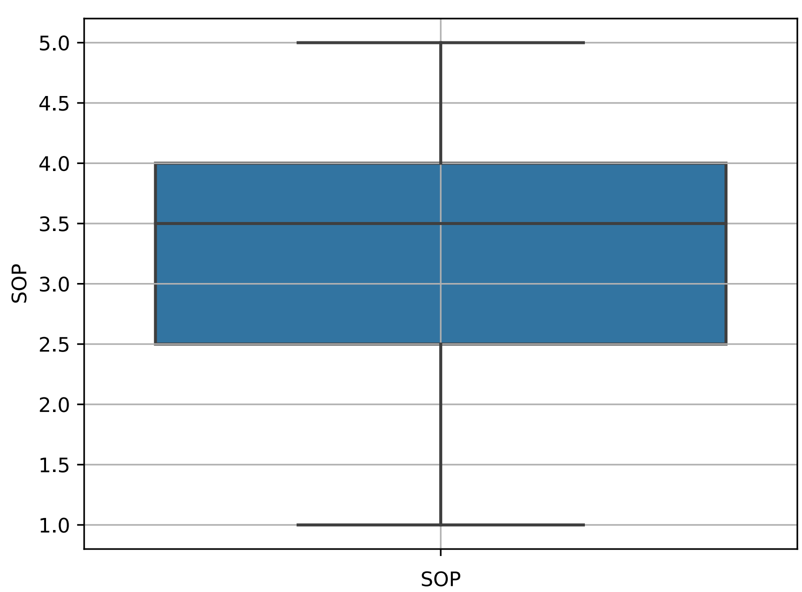
Insights:

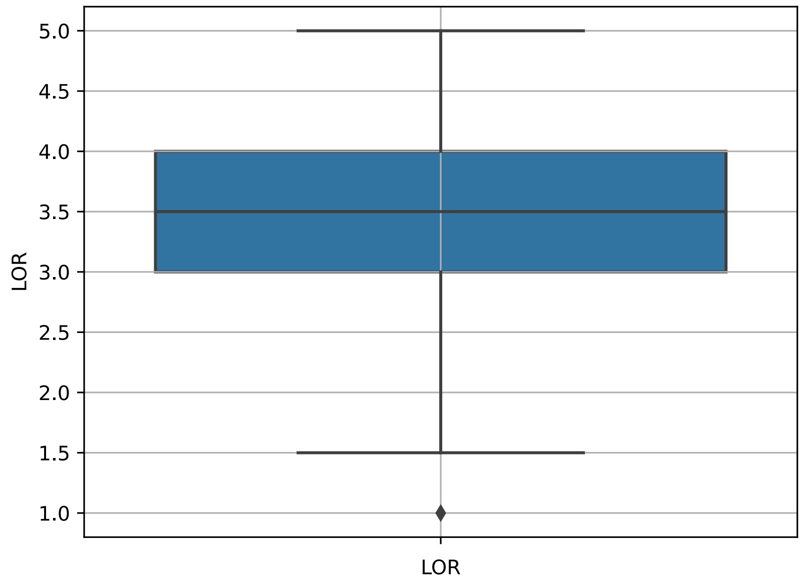
1. As seen earlier, there are more students from universities with University_Rating of 3
2. More than 50% students have research experience

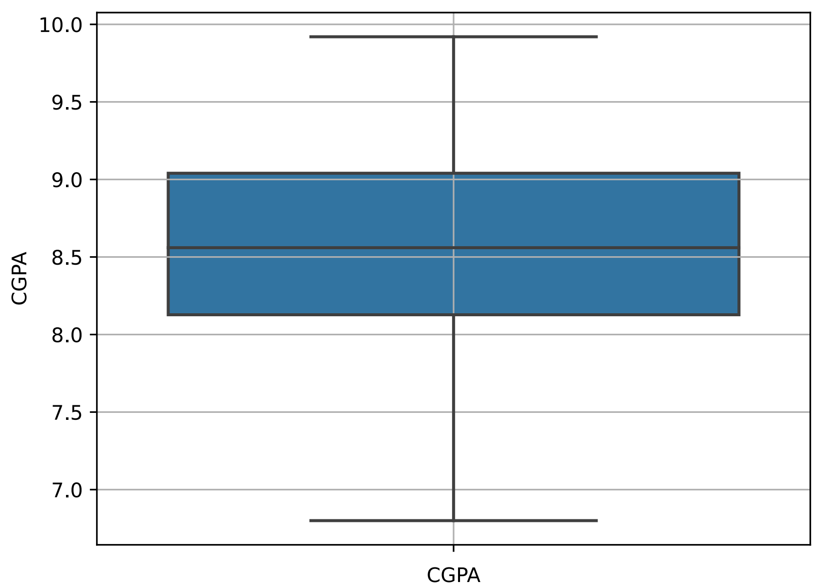
In [23]:
```python
# Generate box plots for all numerical columns
for column in num_cols:
    sns.boxplot(data=df,y=column)
    plt.xlabel(column)
    plt.grid(True)
    plt.show()
```

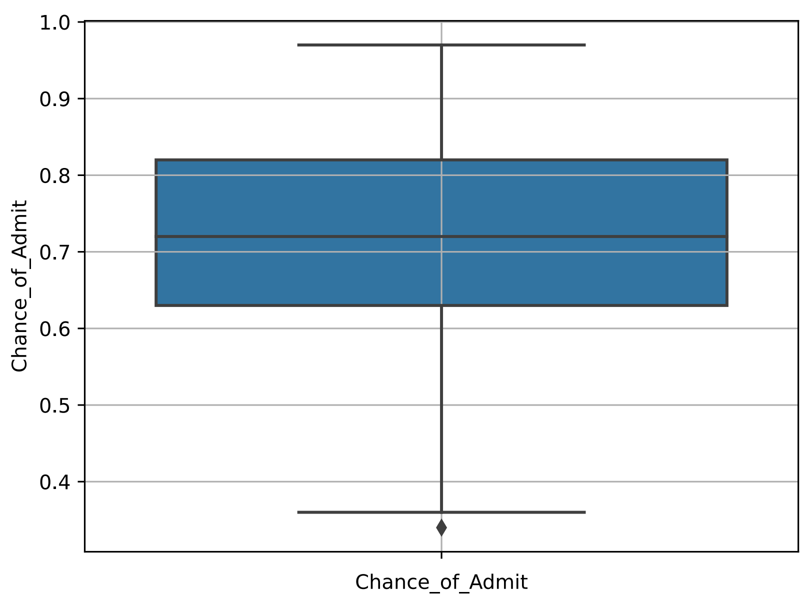










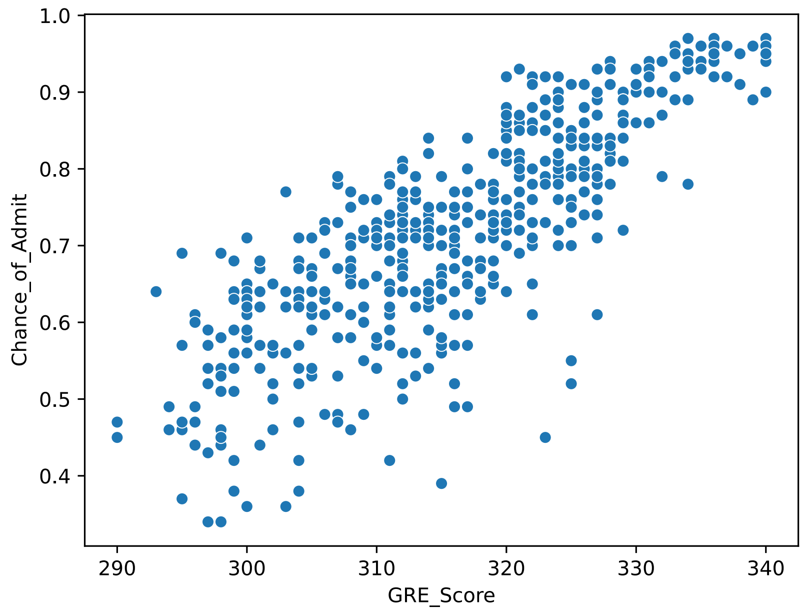


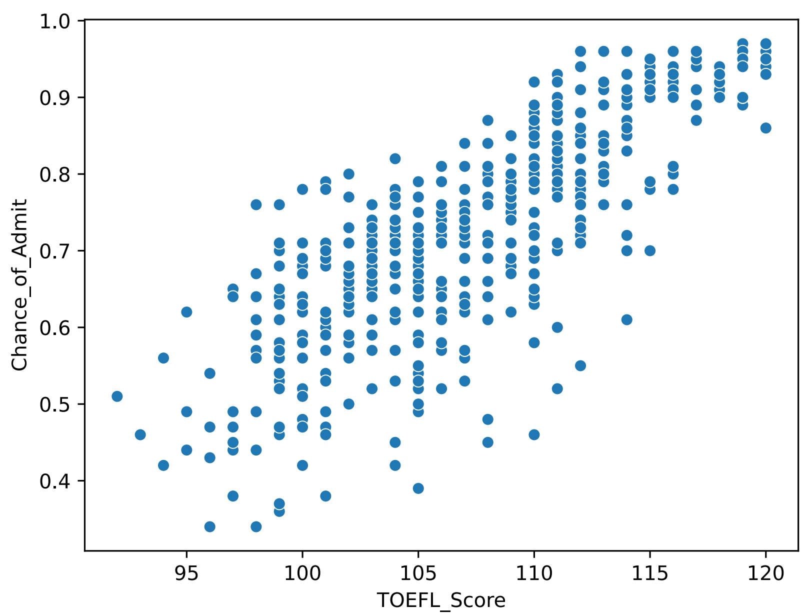
Insights:

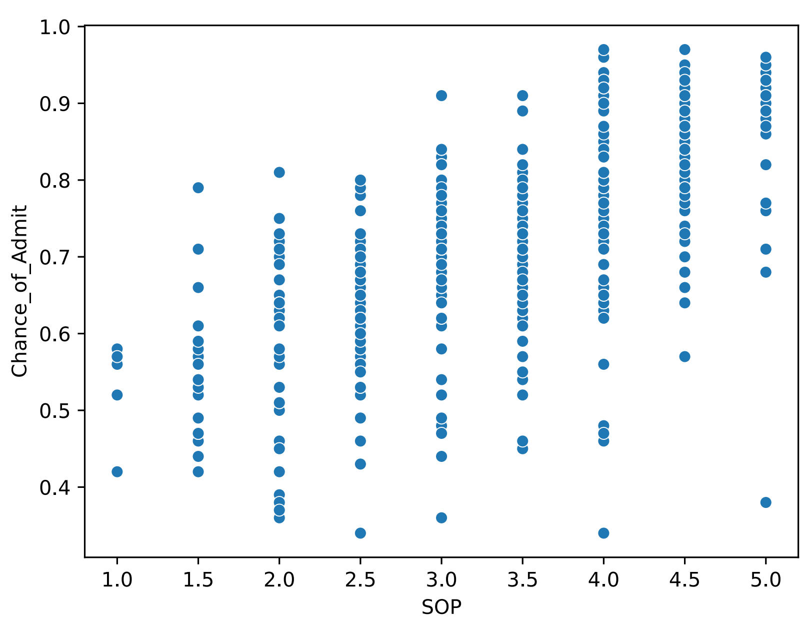
1. Median SOP, LOR scores are 3.5.Median GRE_Score & TOEFL_Score ~318, ~107 respectively
2. 50% of students have Chance_of_Admit between ~0.6 to ~0.8

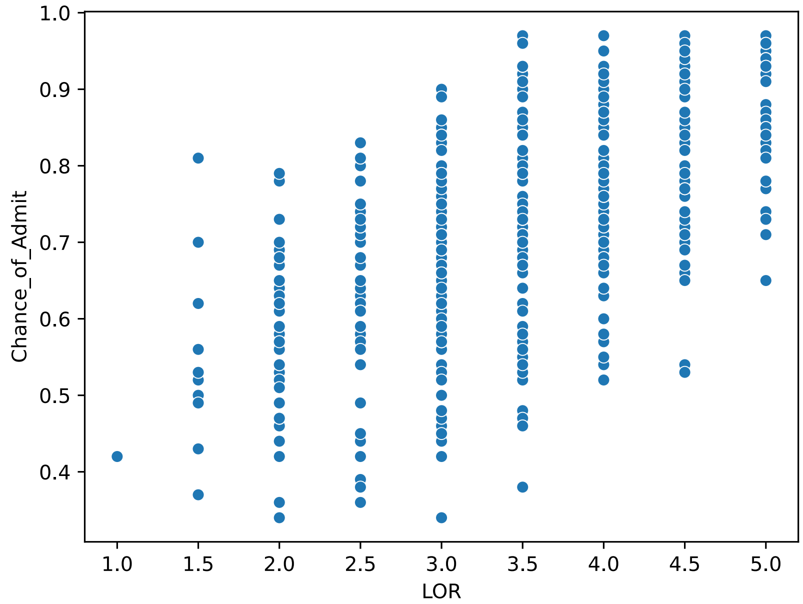
Bivariate Analysis:

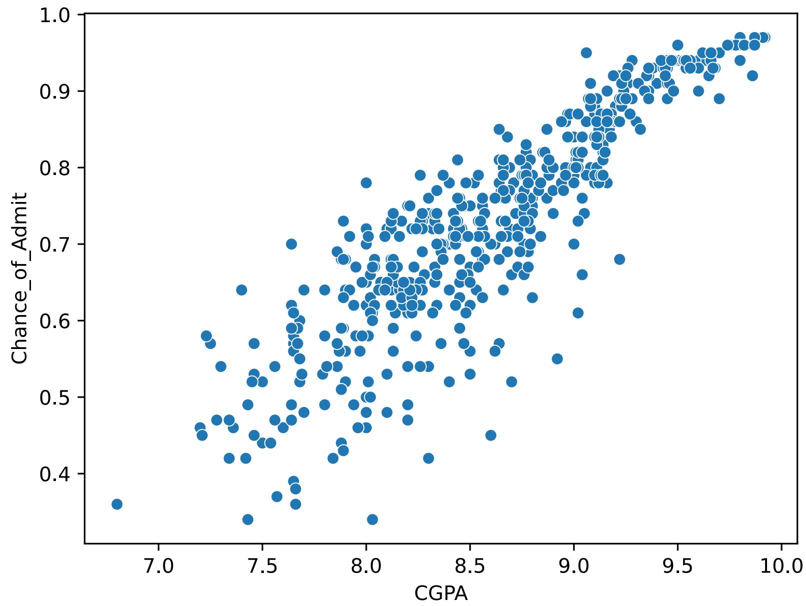
In [24]:
```
for col in num_cols:
    if col != "Chance_of_Admit":
        sns.scatterplot(x=df[col], y=df["Chance_of_Admit"])
        plt.show()
```







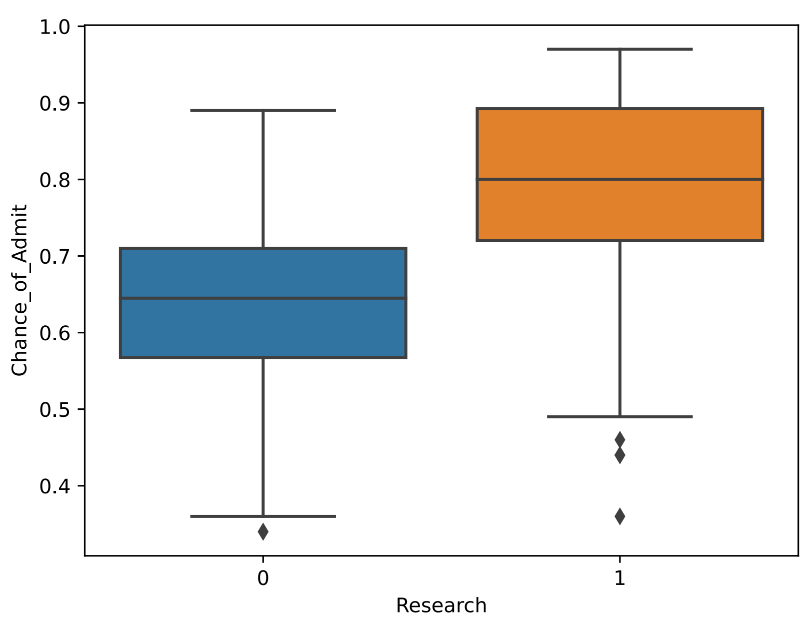




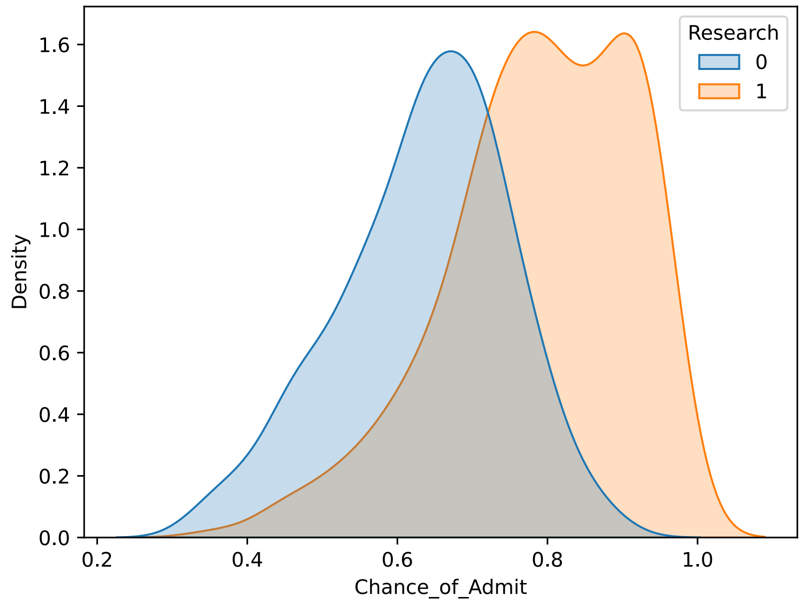
Insights:

1. TOEFL_Score, GRE_Score, CGPA seem to have a positive correlaton with Chance_of_Admit
2. As SOP & LOR rating increase, chances of admit seem to increase but not as correlated as other features
3. TOEFL_Score, GRE_Score, and CGPA seem to be positively correlated as well

In [25]:
```
# Plot boxplot
sns.boxplot(x=df["Research"],y=df["Chance_of_Admit"])
plt.show()
```



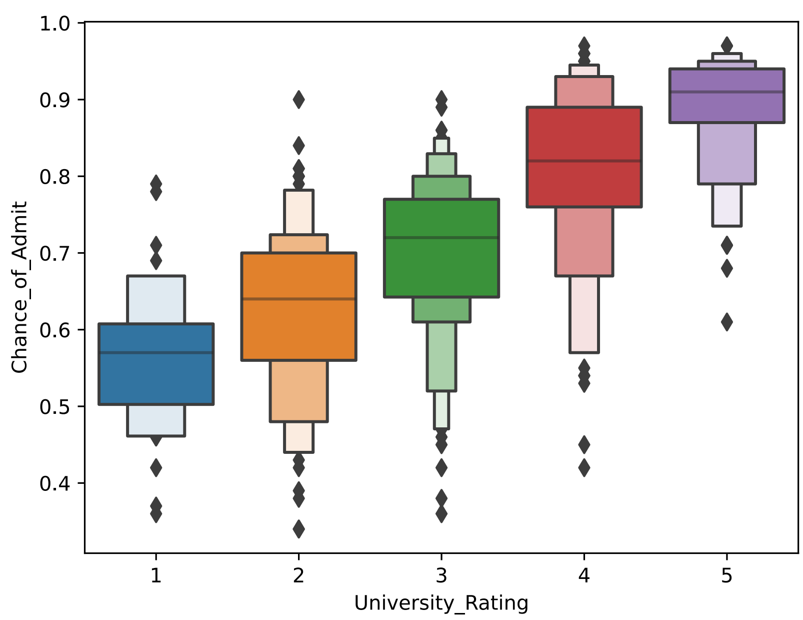
In [26]:
```
sns.kdeplot(hue=df["Research"],x=df["Chance_of_Admit"],fill=True)
plt.show()
```



Insights:

1. Median Chance of Admit is higher for students with research experience when compared to students without research experience
2. Chance_of_Admit distribution for students, with research experience, is slighlty towards right of that of students without research experience. Is it significant is something to check as part of inferencial analysis

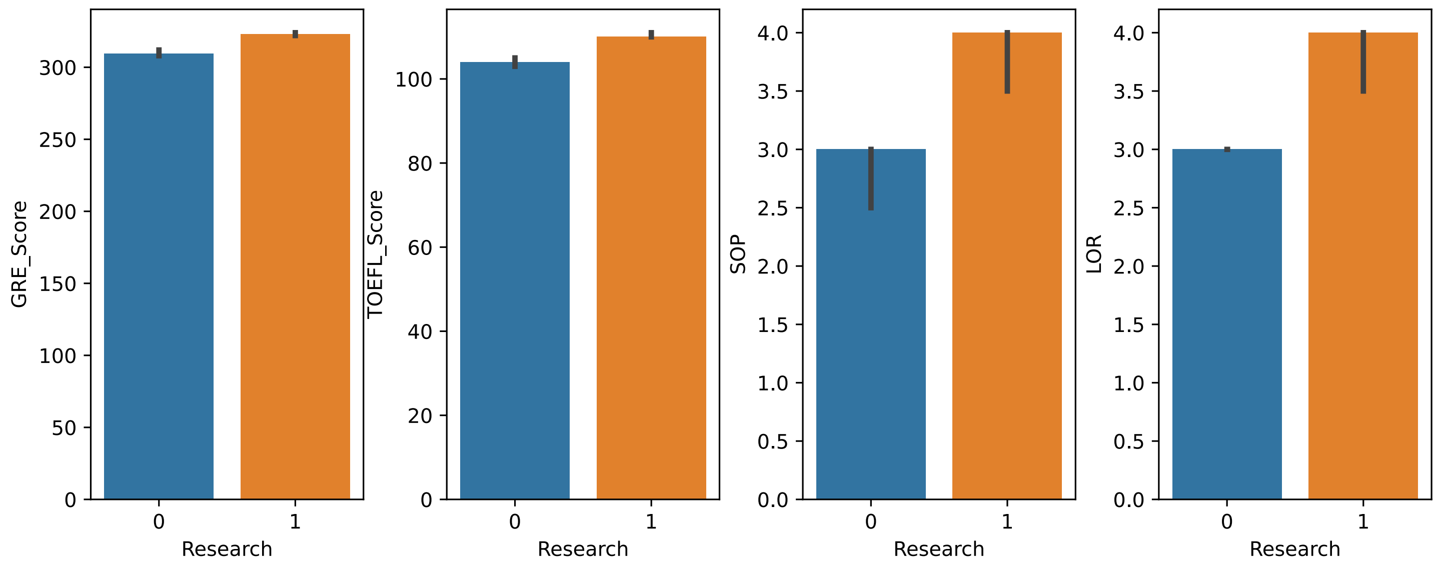
In [27]:
```
# Plot boxplot
sns.boxenplot(x=df["University_Rating"],y=df["Chance_of_Admit"])
plt.show()
```



Insights:

1. Median Chance of Admit is higher for students from better universities. There are some exceptions however
2. Chance_of_Admit distributions overlap for students from different university ratings. Greater the rating, more left skewed the distributions
3. Is there significant difference in mean/median Chance_of_Admit ? - to check as part of inferencial analysis

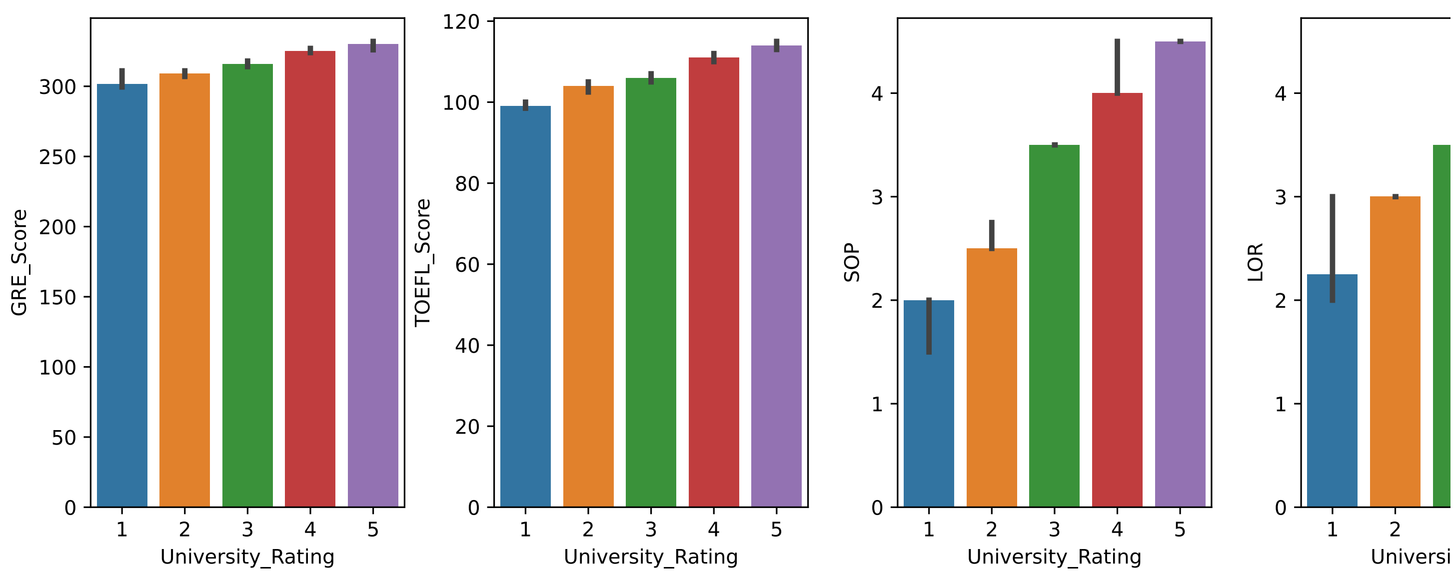
In [28]:
```python
fig,axes = plt.subplots(nrows=1,ncols=6,figsize=(15,4))
fig.tight_layout(h_pad=3)

for i,col in enumerate(num_cols):
    sns.barplot(x=df["Research"],y=df[col],n_boot=1000,errorbar=('ci',95),ax=axes[i],estimator="median")
plt.show()
```



Insights:

1. Estimated Median SOP, LOR, Chance of Admit of students with research experience is higher than their counterpart
2. For GRE_Score, TOEFL_Score, and CGPA - Difference of estimated median is lower

In [29]:
```python
fig,axes = plt.subplots(nrows=1,ncols=6,figsize=(17,4))
fig.tight_layout(h_pad=3)

for i,col in enumerate(num_cols):
    sns.barplot(x=df["University_Rating"],y=df[col],n_boot=1000,errorbar=('ci',95),ax=axes[i],estimator="median")
plt.show()
```

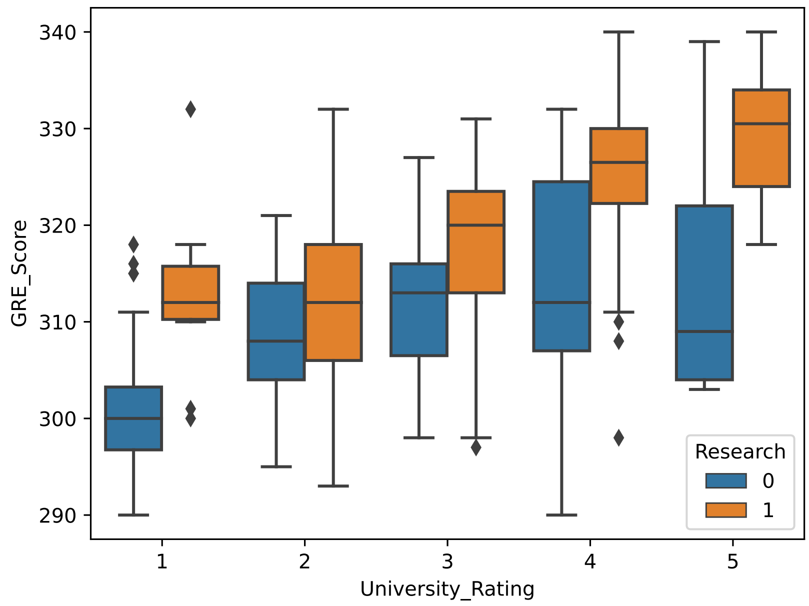


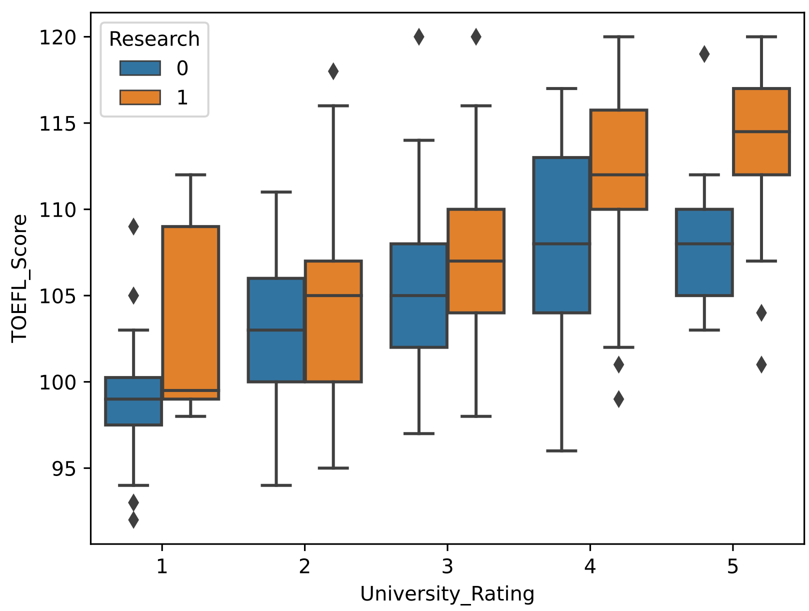
Insights:

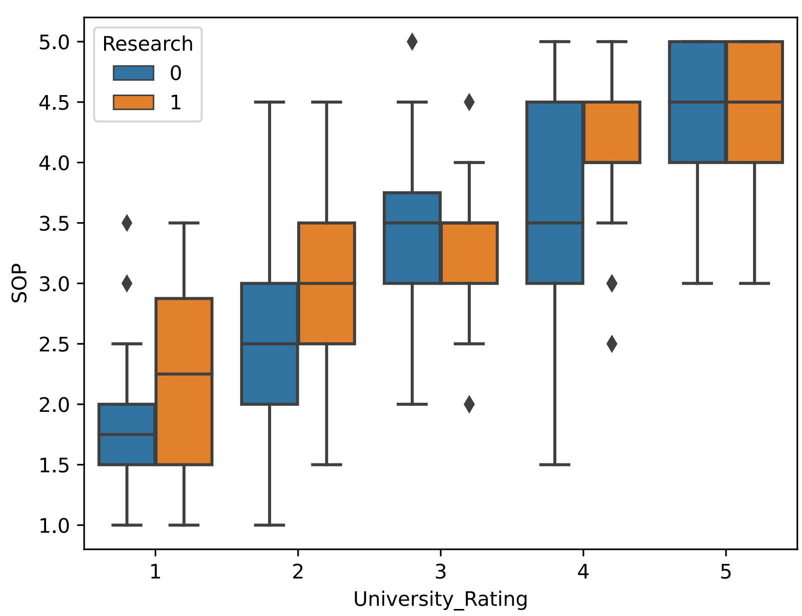
1. Estimated Median SOP,LOR,CGPA, and Chance_of_Admit values of students from highly rated universities are higher
2. Estimated Median GRE_Score, TOEFL_Score are only slighly higher for students from universities of high rating

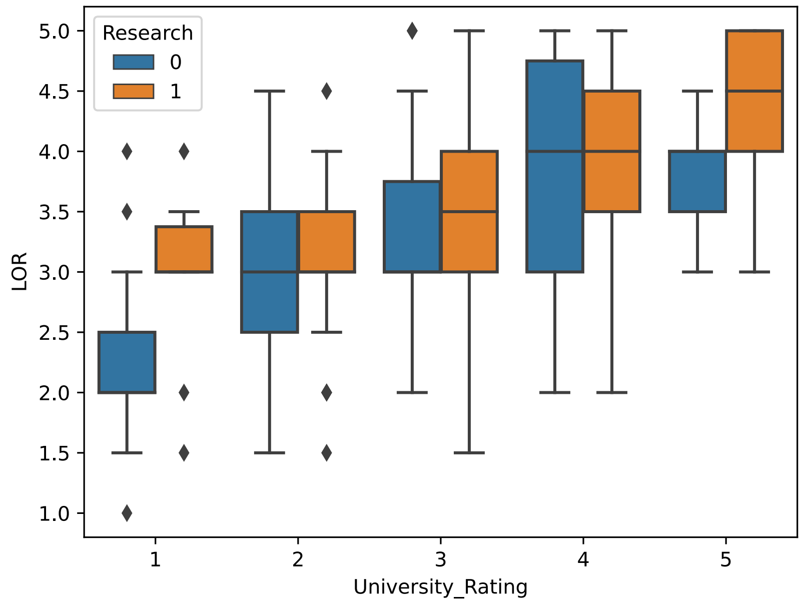
Multivariate Analysis:

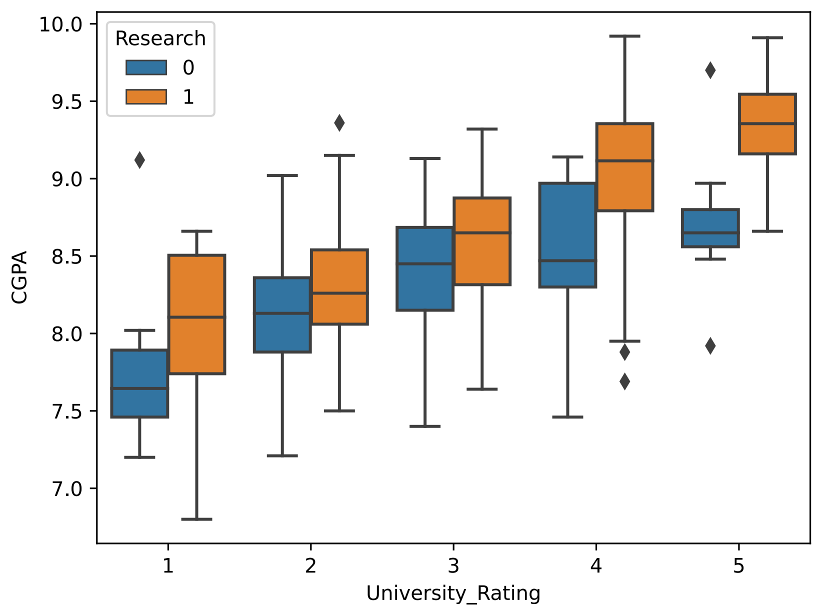
In [30]:
```
# Plot boxplot
for col in num_cols:
    sns.boxplot(x=df["University_Rating"],y=df[col],hue=df["Research"])
    plt.show()
```

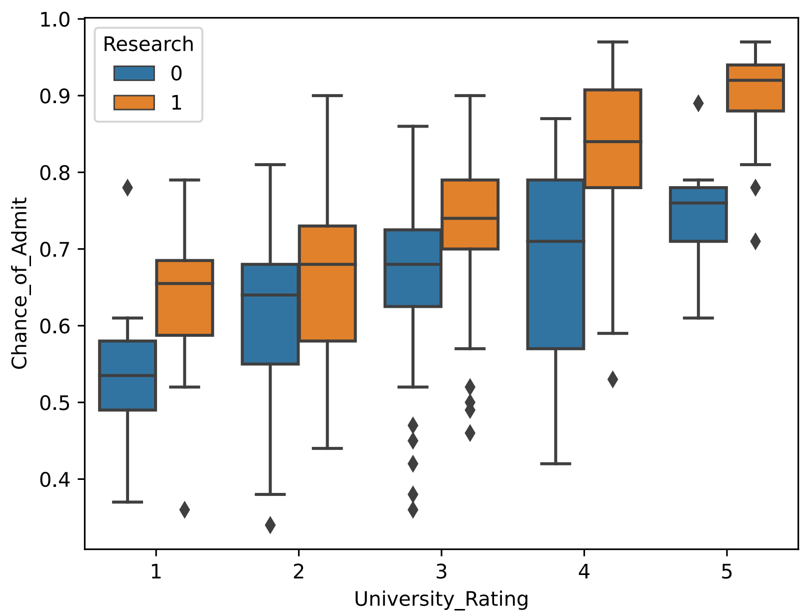








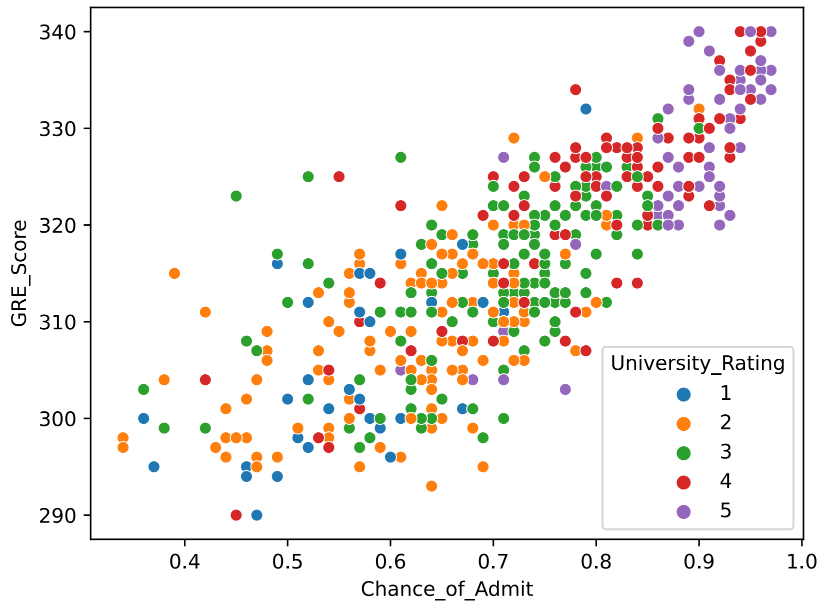


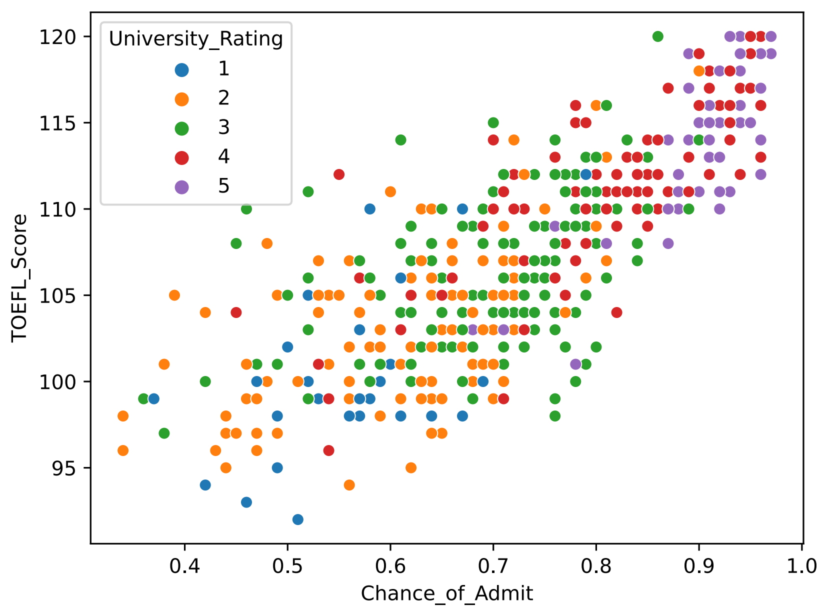


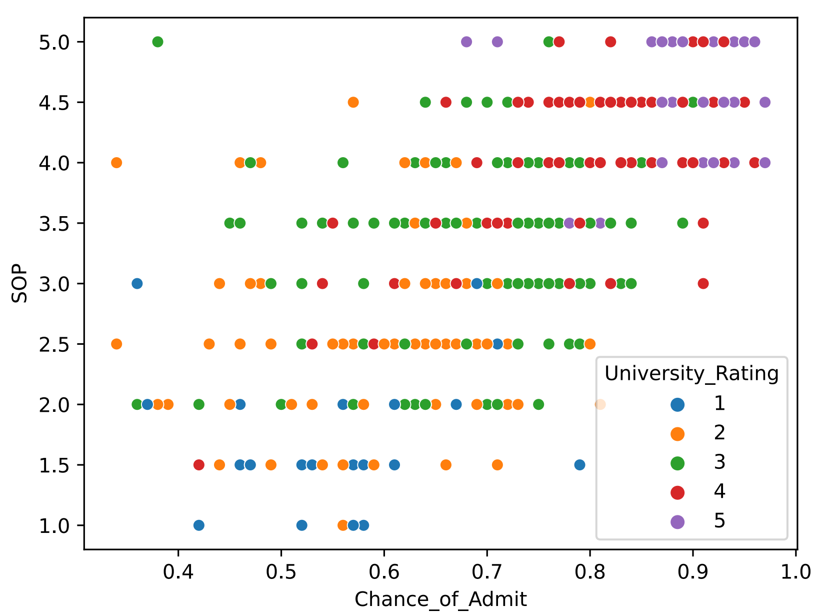
Insights:

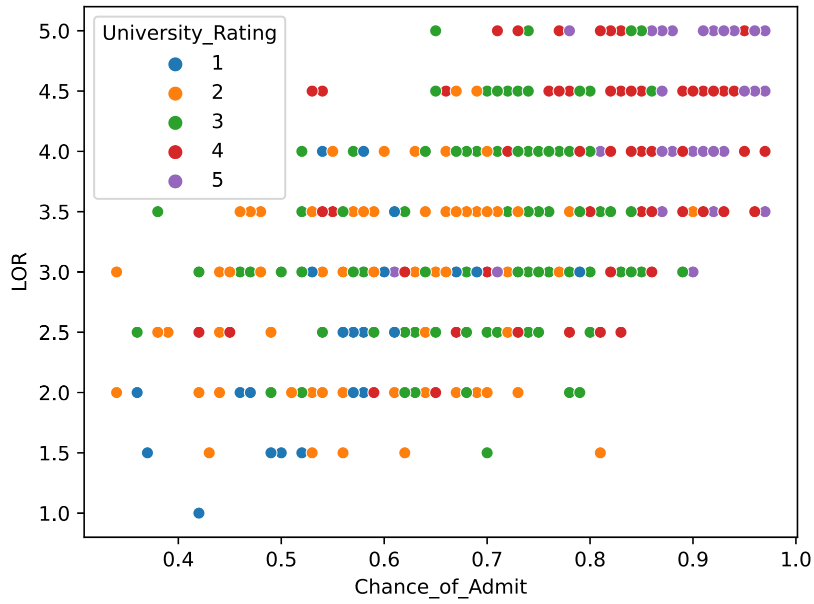
1. Regardless of the University_Rating, students with research experience seem to have higher median TOEFL_Score,GRE_Score, and Chance_of_Admit than their counterparts
2. Above holds true for SOP, and LOR scores as well with some exceptions.
    - Median SOP scores of students with research experience of University_Rating 3 is lesser than their counterparts
    - Median SOP scores of students with research experience of University_Rating 5 is equal to that of students without research experience
3. Median LOR score of students with experience (University_Rating 4) is equal to that of students without research experience

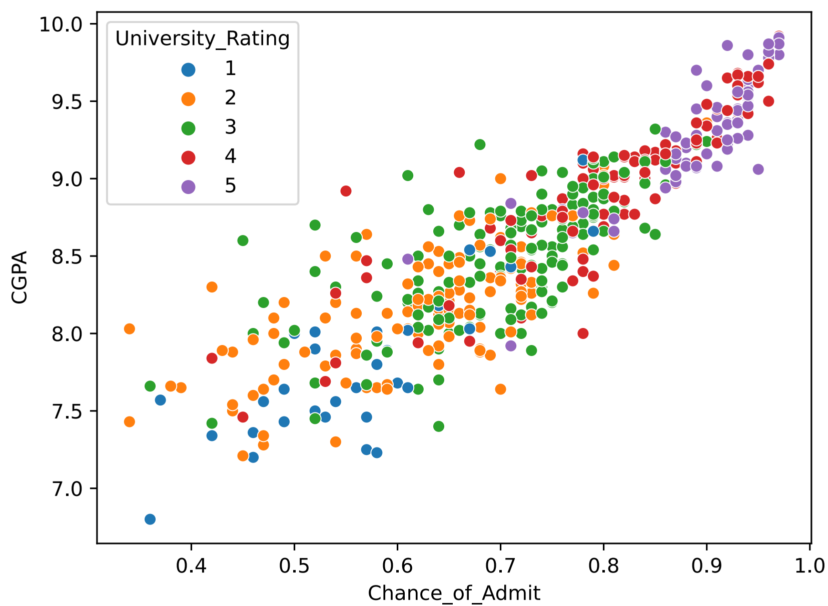
In [31]:
```
for col in num_cols:
    if col != "Chance_of_Admit":
        sns.scatterplot(y=df[col], x=df["Chance_of_Admit"],hue=df["University_Rating"],palette=sns.color_palette(n_co
        plt.show()
```







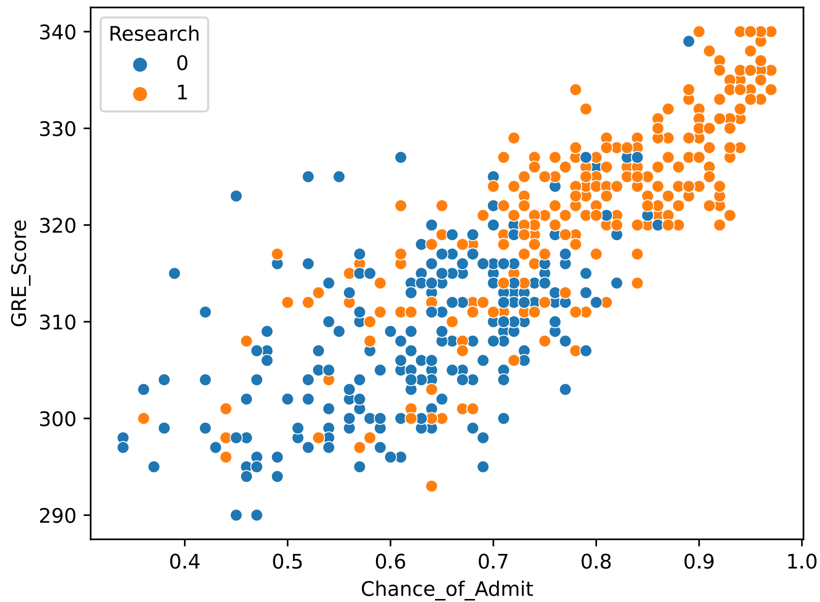


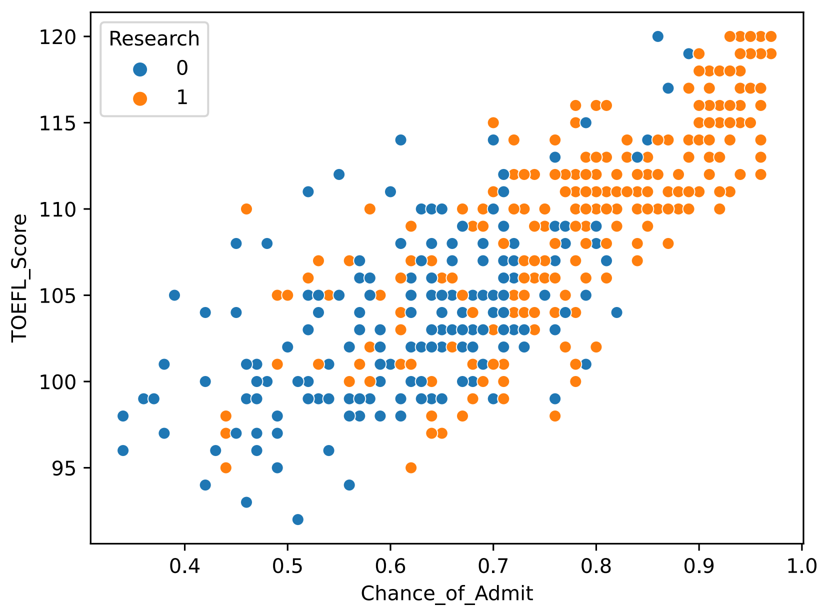


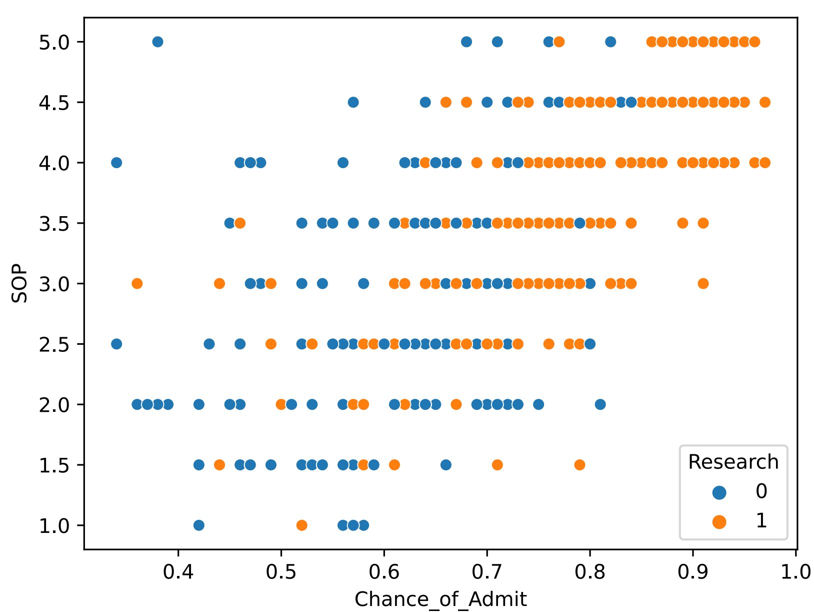
Insights:

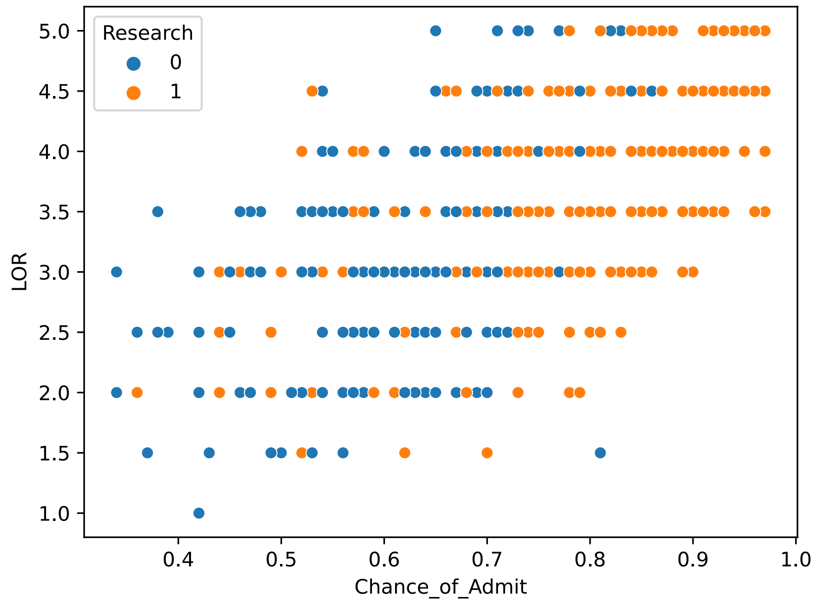
1. As expected, majority of students, from high rating universities, are on higher end of the spectrum in all scores

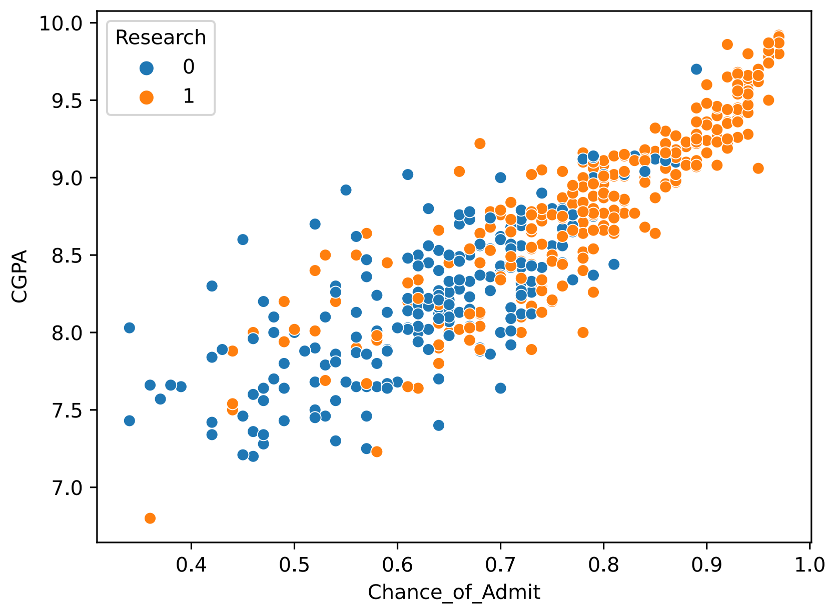
In [32]:
```
for col in num_cols:
    if col != "Chance_of_Admit":
        sns.scatterplot(y=df[col], x=df["Chance_of_Admit"],hue=df["Research"],palette=sns.color_palette(n_colors=2))
        plt.show()
```









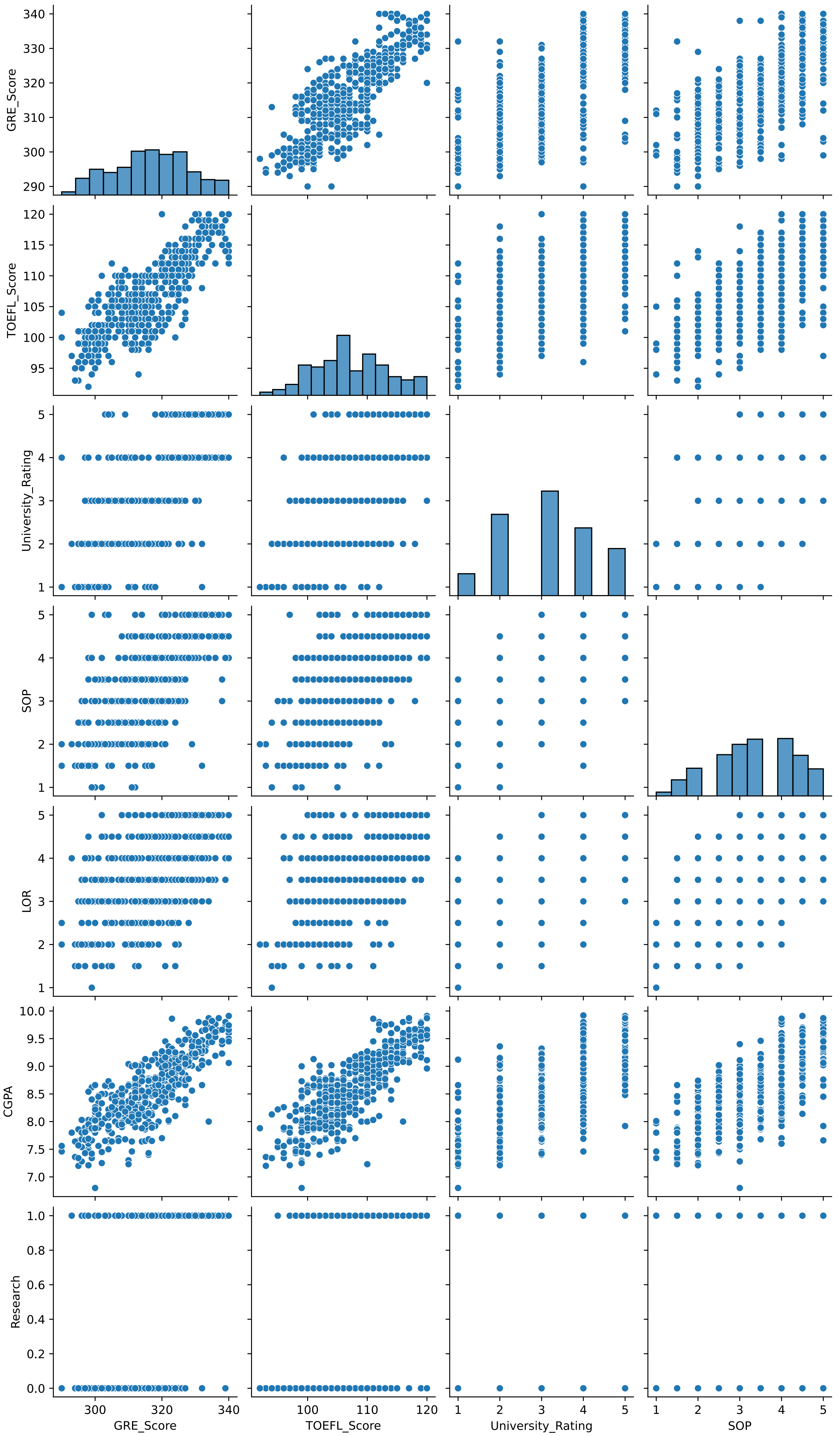


Insights:

1. As expected, majority of research experienced students are on higher end of the spectrum in all scores

In [33]:

```
# To see how features relate with other features
sns.pairplot(df.drop(columns=["Chance_of_Admit"]))
plt.show()
```

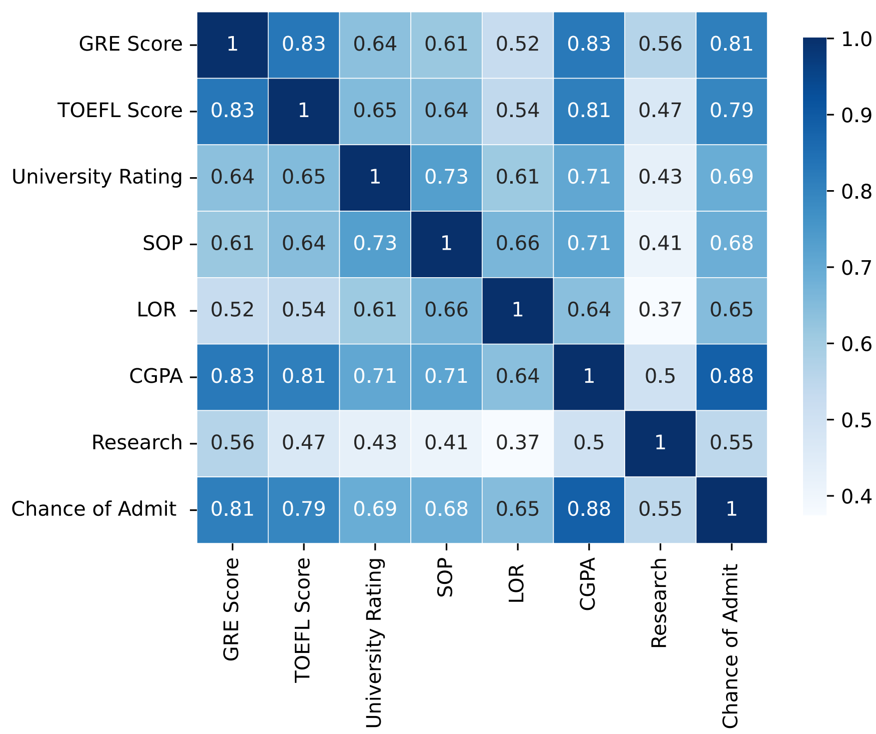


Insights:

1. Higher CGPA students also have higher TOEFL_Score, GRE_Score and vice versa
2. However, there are student's CGPA, TOEFL_Score, and GRE_Score seem to vary even though they have similar SOP, LOR scores

Correlation:

In [34]:
```
#Heatmap of correlation between different features:
sns.heatmap(data= data.corr(method="pearson",numeric_only=True)
            ,cbar_kws={"shrink": .9},linewidths=0.4,cmap="Blues",annot=True,
           )
plt.yticks(rotation = 0)
plt.show()
```



Insights:

1. Evidently, features are highly correlated with Chance of Admit as well as with each other
2. CGPA, and GRE_Score are highly correlated features with Chance of Admit. Closely followed by TOEFL_Score
3. GRE_Score, TOEFL_Score, and CGPA has correlation of above 0.8
4. There is a possiblity of multi-collinearity in the features as well

Inferential Stats:

Based on the exploratory data analysis, here are couple of hypothesis to see if same can be inferred about the population:

1. Are research & University_Ratings associated ?
2. Students with research experience, regardless of their university rating, have higher mean/median TOEFL, GRE scores, CGPA, Chance_of_Admit compared to their counterparts ?
3. Are mean/median GRE, TOEFL scores, CGPA, LOR, SOP of students, from different university rating, are different ?

Hypothesis 1: Are research & University_Ratings associated ?

In [35]:
```
# More Students from Universities with ratings 3 & above, seem to have research experience
# Lets see if this association is significant using chi2_contingency
pd.crosstab(index=df["Research"],columns= df["University_Rating"],margins=True,normalize="columns")
```

Out[35]:

University_Rating	1	2	3	4	5	All
Research						
0	0.705882	0.706349	0.462963	0.219048	0.123288	0.44
1	0.294118	0.293651	0.537037	0.780952	0.876712	0.56

In [36]:
```
# Assumptios:
# All assumptions related to Chisquare are met.
# Mutually exclusive, two categorical variables, and more than 5 frequency in each group

# Null Hypothesis H0: There is no association between Research and University_Rating
# Alternate Hypothesis Ha: There is association between Research and University_Rating

chi2_contingency(pd.crosstab(index=df["Research"],columns= df["University_Rating"]))
```

Out[36]:
```
Chi2ContingencyResult(statistic=96.90000948490646, pvalue=4.4936229585994394e-20, dof=4, expected_freq=array([[14.
96, 55.44, 71.28, 46.2 , 32.12],
       [19.04, 70.56, 90.72, 58.8 , 40.88]]))
```

Insights:

1. With significance level of 0.05, we have enough evidence to reject H0 and accept Ha - Research & University_Rating are associated

In [37]:
```
def check_normality(data, alpha = 0.05):

    # Null Hypothesis, H0: Given data comes from normal distribution
    # Alternate Hypothesis, Ha: Given data does not come normal distribution

    from scipy.stats import normaltest

    teststatistic, pvalue = normaltest(data)

#     print("Null Hypothesis, H0: Given data comes from normal distribution")
#     print("Alternate Hypothesis, Ha: Given data does not come from normal distribution")

    print("Result: ", end=" ")
    if pvalue < alpha:
        print("Reject H0. Therefore, Given data does not come normal distribution")
    else:
        print("Unable to reject H0. Therefore, Given data comes from normal distribution")

#     print()
#     print("----------------------------XXX----------------------------")
#     print()

    print("Hypothesis test performed: ", normaltest.__name__)
    print(f"TestStatistic:{np.round(teststatistic,4)}, Pvalue:{np.round(pvalue,4)}")
```

In [38]:
```
def check_equal_variance(*samples, normality = True, alpha=0.05):

    # Null Hypothesis, H0:  samples come from populations with equal variances
    # Alternate Hypothesis, Ha: samples do NOT come from populations with equal variances

    from scipy.stats import levene

#   'median': recommended for skewed distributions.
#   'mean': recommended for symmetric, moderate-tailed distributions.
#   'trimmed': recommended for heavy-tailed distributions.

    if normality:
        center = "mean"
    else:
        center = "median"

    teststatistic, pvalue = levene(*samples,center = center)


#     print("Null Hypothesis, H0:  samples come from populations with equal variances ")
#     print("Alternate Hypothesis, Ha: samples do NOT come from populations with equal variances ")


    print("Result: ", end=" ")
    if pvalue < alpha:
        print("Reject H0. Samples do NOT come from populations with equal variances")
    else:
        print("Unable to reject H0. Therefore,samples come from populations with equal variances")

#     print()
#     print("----------------------------XXX----------------------------")
#     print()

    print("Hypothesis test performed: ", levene.__name__)
    print(f"TestStatistic:{np.round(teststatistic,4)}, Pvalue:{np.round(pvalue,4)}")
```

In [39]:
```python
def compare_two_means(sample1, sample2, normality = True, equal_var = True, alpha = 0.05, alternative = "greater"):
    '''
    Conducts ttest_ind or mannwhitneyu test based on normality and variance of the samples
    By providing alternative value, either one sided or two sided test can be conducted

    '''

    if alternative not in ["two-sided","less","greater"]:
        print("selected alternative is incorrect")
        return

    from scipy.stats import ttest_ind, mannwhitneyu


    if normality and equal_var:
        func = ttest_ind
    else:
        func = mannwhitneyu


    teststatistic, pvalue = func(sample1, sample2, alternative = alternative)

    if alternative == "greater":

#         print("Null Hypothesis,H0: sample1 mean/median (mu1) <= sample2 mean/median (mu2)")
#         print("Alternate Hypothesis,Ha: mu1 > mu2")

        print("Result: ", end=" ")
        if pvalue < alpha:
            print("Reject H0. mu1 > mu2")
        else:
            print("Unable to reject H0, mu1 <= mu2")

    print("Hypothesis test performed: ", func.__name__)
    print(f"TestStatistic:{np.round(teststatistic,4)}, Pvalue:{np.round(pvalue,4)}")
```

Hypothesis 2: Students with research experience, regardless of their university rating, have higher mean/median TOEFL, GRE scores, CGPA compared to their counterparts ?

In [40]:
```python
# Split the data into two. Research & Non-Research students
cond = (df["Research"] == 1)
research = df.loc[cond,:]
non_research = df.loc[~(cond),:]
```

Test Assumptions of Normality, Equal Variance before proceeding with above Hypothesis test:

Test for Normality:

- Null Hypothesis, H0: samples come from populations with equal variances
- Alternate Hypothesis, Ha: samples do NOT come from populations with equal variances

In [41]:
```python
for col in num_cols:
    print(f"{col}:")
    check_normality(research[col])
    print("------------------XXXX--------------------")
```

```
GRE_Score:
Result:  Reject H0. Therefore, Given data does not come normal distribution
Hypothesis test performed:  normaltest
TestStatistic:12.2635, Pvalue:0.0022
------------------XXXX--------------------
TOEFL_Score:
Result:  Reject H0. Therefore, Given data does not come normal distribution
Hypothesis test performed:  normaltest
TestStatistic:10.6977, Pvalue:0.0048
------------------XXXX--------------------
SOP:
Result:  Reject H0. Therefore, Given data does not come normal distribution
Hypothesis test performed:  normaltest
TestStatistic:11.7487, Pvalue:0.0028
------------------XXXX--------------------
LOR:
Result:  Reject H0. Therefore, Given data does not come normal distribution
Hypothesis test performed:  normaltest
TestStatistic:12.0061, Pvalue:0.0025
------------------XXXX--------------------
CGPA:
Result:  Reject H0. Therefore, Given data does not come normal distribution
Hypothesis test performed:  normaltest
TestStatistic:8.4713, Pvalue:0.0145
------------------XXXX--------------------
Chance_of_Admit:
Result:  Reject H0. Therefore, Given data does not come normal distribution
Hypothesis test performed:  normaltest
TestStatistic:22.1576, Pvalue:0.0
------------------XXXX--------------------
```

In [42]:
```
for col in num_cols:
    print(f"{col}:")
    check_normality(non_research[col])
    print("------------------XXXX--------------------")
```

```
GRE_Score:
Result:  Unable to reject H0. Therefore, Given data comes from normal distribution
Hypothesis test performed:  normaltest
TestStatistic:1.8814, Pvalue:0.3903
------------------XXXX--------------------
TOEFL_Score:
Result:  Unable to reject H0. Therefore, Given data comes from normal distribution
Hypothesis test performed:  normaltest
TestStatistic:5.1852, Pvalue:0.0748
------------------XXXX--------------------
SOP:
Result:  Reject H0. Therefore, Given data does not come normal distribution
Hypothesis test performed:  normaltest
TestStatistic:7.6444, Pvalue:0.0219
------------------XXXX--------------------
LOR:
Result:  Unable to reject H0. Therefore, Given data comes from normal distribution
Hypothesis test performed:  normaltest
TestStatistic:4.3074, Pvalue:0.1161
------------------XXXX--------------------
CGPA:
Result:  Unable to reject H0. Therefore, Given data comes from normal distribution
Hypothesis test performed:  normaltest
TestStatistic:1.275, Pvalue:0.5286
------------------XXXX--------------------
Chance_of_Admit:
Result:  Reject H0. Therefore, Given data does not come normal distribution
Hypothesis test performed:  normaltest
TestStatistic:6.1402, Pvalue:0.0464
------------------XXXX--------------------
```

Test for equal variance:

- Null Hypothesis, H0: samples come from populations with equal variances
- Alternate Hypothesis, Ha: samples do NOT come from populations with equal variances

In [43]:
```
for col in num_cols:
    print(f"{col}:")
    check_equal_variance(research[col],non_research[col],normality=False)
    print("------------------XXXX--------------------")
```

```
GRE_Score:
Result:  Unable to reject H0. Therefore,samples come from populations with equal variances
Hypothesis test performed:  levene
TestStatistic:1.1331, Pvalue:0.2876
------------------XXXX--------------------
TOEFL_Score:
Result:  Reject H0. Samples do NOT come from populations with equal variances
Hypothesis test performed:  levene
TestStatistic:9.2632, Pvalue:0.0025
------------------XXXX--------------------
SOP:
Result:  Unable to reject H0. Therefore,samples come from populations with equal variances
Hypothesis test performed:  levene
TestStatistic:1.3571, Pvalue:0.2446
------------------XXXX--------------------
LOR:
Result:  Unable to reject H0. Therefore,samples come from populations with equal variances
Hypothesis test performed:  levene
TestStatistic:0.0292, Pvalue:0.8645
------------------XXXX--------------------
CGPA:
Result:  Reject H0. Samples do NOT come from populations with equal variances
Hypothesis test performed:  levene
TestStatistic:7.8503, Pvalue:0.0053
------------------XXXX--------------------
Chance_of_Admit:
Result:  Unable to reject H0. Therefore,samples come from populations with equal variances
Hypothesis test performed:  levene
TestStatistic:2.2916, Pvalue:0.1307
------------------XXXX--------------------
```

Test to compare median/mean scores:

- Null Hypothesis,H0: sample1 mean/median (mu1) <= sample2 mean/median (mu2)
- Alternate Hypothesis,Ha: mu1 > mu2

In [44]:
```
for col in num_cols:
    print(f"{col}:")
    compare_two_means(research[col],non_research[col],normality=False,equal_var=False,alternative="greater")
    print("------------------XXXX--------------------")
```

```
GRE_Score:
Result:  Reject H0. mu1 > mu2
Hypothesis test performed:  mannwhitneyu
TestStatistic:51515.5, Pvalue:0.0
------------------XXXX--------------------
TOEFL_Score:
Result:  Reject H0. mu1 > mu2
Hypothesis test performed:  mannwhitneyu
TestStatistic:47777.0, Pvalue:0.0
------------------XXXX--------------------
SOP:
Result:  Reject H0. mu1 > mu2
Hypothesis test performed:  mannwhitneyu
TestStatistic:45303.0, Pvalue:0.0
------------------XXXX--------------------
LOR:
Result:  Reject H0. mu1 > mu2
Hypothesis test performed:  mannwhitneyu
TestStatistic:44111.0, Pvalue:0.0
------------------XXXX--------------------
CGPA:
Result:  Reject H0. mu1 > mu2
Hypothesis test performed:  mannwhitneyu
TestStatistic:49043.0, Pvalue:0.0
------------------XXXX--------------------
Chance_of_Admit:
Result:  Reject H0. mu1 > mu2
Hypothesis test performed:  mannwhitneyu
TestStatistic:51060.0, Pvalue:0.0
------------------XXXX--------------------
```

Insights:

1. Performed a non-parametric mannwhitneyu to compare median values of all features for students with research experience and without.
2. With alpha as 0.05, it is evident that median scores of students with research experience is significantly higher than their counterparts

Hypothesis Test 3: Mean/Median GRE, TOEFL scores, CGPA, LOR, SOP of students, from different university rating, are different ?

- Null Hypothesis,H0: All samples have same mean/median values
- Alternate Hypothesis,Ha: Atleast one sample have a different mean/median value

In [45]:
```
# Split the students based on their university ratings
university_students = {}
for i in sorted(df["University_Rating"].unique()):
    cond = (df["University_Rating"] == i)
    university_students[i] = df.loc[cond,:]
```

In [46]:
```
# Assuming that assumptions of Anova aren't met, perform non parametric Kruskal test
alpha = 0.05
for col in num_cols:
    print(f"{col}:")
    teststatistic, pvalue =  kruskal(university_students[1][col],university_students[2][col],university_students[3][c

    print("Result: ", end=" ")
    if pvalue > alpha:
        print(f"Students from differently rated universities, have same mean/median {col}")
    else:
        print(f"Students from differently rated universities, do not have same mean/median {col}. Atleast one is dif

    print("Hypothesis test performed: ", kruskal.__name__)
    print(f"TestStatistic:{np.round(teststatistic,4)}, Pvalue:{np.round(pvalue,4)}")

    print("------------------XXXX--------------------")
```

```
GRE_Score:
Result:  Students from differently rated universities, do not have same mean/median GRE_Score. Atleast one is diff
erent
Hypothesis test performed:  kruskal
TestStatistic:208.7246, Pvalue:0.0
------------------XXXX--------------------
TOEFL_Score:
Result:  Students from differently rated universities, do not have same mean/median TOEFL_Score. Atleast one is di
fferent
Hypothesis test performed:  kruskal
TestStatistic:211.0893, Pvalue:0.0
------------------XXXX--------------------
SOP:
Result:  Students from differently rated universities, do not have same mean/median SOP. Atleast one is different
Hypothesis test performed:  kruskal
TestStatistic:266.8391, Pvalue:0.0
------------------XXXX--------------------
LOR:
Result:  Students from differently rated universities, do not have same mean/median LOR. Atleast one is different
Hypothesis test performed:  kruskal
TestStatistic:183.3783, Pvalue:0.0
------------------XXXX--------------------
CGPA:
Result:  Students from differently rated universities, do not have same mean/median CGPA. Atleast one is different
Hypothesis test performed:  kruskal
TestStatistic:248.8257, Pvalue:0.0
------------------XXXX--------------------
Chance_of_Admit:
Result:  Students from differently rated universities, do not have same mean/median Chance_of_Admit. Atleast one i
s different
Hypothesis test performed:  kruskal
TestStatistic:250.4582, Pvalue:0.0
------------------XXXX--------------------
```

Insights:

1. Performed non-parametric Kruskal test to compare if mean/median scores & chances of admit of students from different university rating are same
2. With significance level of 0.05, it is evident that scores & chances of admit are different

Data Preparation for Modelling:

In [47]:
```
def split_train_test(X,y,train_size=0.8,test_size=0.2):

    """
    Given features X and label y as dataframes, split them into train & test sets
    and save them as two csv files. By default, train_size is set to 80%

    """

    X_train,X_test,y_train,y_test = train_test_split(X,y,train_size=0.8,test_size=0.2,random_state=23)

    # Concat features & labels back
    train = pd.concat((X_train,y_train), axis=1)
    test = pd.concat((X_test,y_test), axis=1 )

    # Save the train & test set as separate csv files
    train.to_csv("../input/train.csv",index=False)
    test.to_csv("../input/test.csv",index=False)

    return train, test
```

In [48]:
```
def prepocessing(filePath):

    df = pd.read_csv(filepath_or_buffer="../input/Jamboree_Admission.csv")
    df = df.drop(columns="Serial No.")

    # Remove unwanted spaces and rename the column & index names to make analysis easier
    df.columns = ["_".join(col.strip().split(" ")) for col in df.columns]
    df.to_csv(path_or_buf= "../input/cleaned_data.csv", index=False)

    return df
```

In [49]:
```python
def create_kfolds(filePath,folds):

    """
    Given the filePath of the data, split the data into folds
    based on the inputparameter folds. Saves the new dataframe as csv

    """
    df = pd.read_csv(filepath_or_buffer= filePath)
    df["kfold"] =-1

    df = df.sample(frac=1,random_state=23).reset_index(drop=True)
    kf = KFold(n_splits = folds)

    for fold,(train_idx,valid_idx) in enumerate(kf.split(X=df)):
        df.loc[valid_idx,"kfold"] = fold

    df.to_csv("../input/train_folds.csv",index=False)
```

In [50]:
```python
def create_skfolds(filePath,folds,label):

    """
    Uses binning on label column to split the data into multiple folds
    Note: Warns if folds are too high to bin the data correctly
    Also, saves the dataframe with new column folds as csv file

    """

    df = pd.read_csv(filepath_or_buffer= filePath )
    df["kfold"] =-1

    df = df.sample(frac=1,random_state=23).reset_index(drop=True)

    # Associate each datapoint to a bin
    df.loc[:,"bins"] = pd.cut(df[label], bins = folds, labels = False)

    kf = StratifiedKFold(n_splits = folds)

    for fold,(train_idx,valid_idx) in enumerate(kf.split(X=df,y=df["bins"].values)):
        df.loc[valid_idx,"kfold"] = fold

    df = df.drop(columns="bins")

    df.to_csv("../input/train_folds.csv",index=False)
```

Building a simple Multivariate Linear Regression Model:

Linear Regression:

In [51]:
```python
# Drops Serial No. & fix the unwanted spaces in feature names
# Saves the cleaned df
df = prepocessing("../input/Jamboree_Admission.csv")
df.head(5)
```

Out[51]:

	GRE_Score	TOEFL_Score	University_Rating	SOP	LOR	CGPA	Research	Chance_of_Admit
0	337	118	4	4.5	4.5	9.65	1	0.92
1	324	107	4	4.0	4.5	8.87	1	0.76
2	316	104	3	3.0	3.5	8.00	1	0.72
3	322	110	3	3.5	2.5	8.67	1	0.80
4	314	103	2	2.0	3.0	8.21	0	0.65

In [52]:
```python
features = df.columns.drop("Chance_of_Admit").to_list()
label = "Chance_of_Admit"

print(f"Features: {features}")
print(f"Label: {label}")
```

```
Features: ['GRE_Score', 'TOEFL_Score', 'University_Rating', 'SOP', 'LOR', 'CGPA', 'Research']
Label: Chance_of_Admit
```

In [53]:
```python
# Split the data into train & test sets
train, test = split_train_test(X=df[features],y=df[[label]])
```

In [198]:
```python
# Separate features from the label of train set

X_train = train[features]
y_train = train[[label]]

# Scale the train & valid set features
scaler = StandardScaler()
scaled_X_train = scaler.fit_transform(X_train)
```

In [199]:
```python
# Add constant to the features
scaled_X_train_with_constant = sm.add_constant(scaled_X_train)
```

In [200]:
```python
# Fit the OLS model on training data

model = sm.OLS(y_train,scaled_X_train_with_constant)
results = model.fit()
```

In [201]:
```
print(results.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:        Chance_of_Admit   R-squared:                       0.820
Model:                            OLS   Adj. R-squared:                  0.817
Method:                 Least Squares   F-statistic:                     255.5
Date:                Wed, 14 Jun 2023   Prob (F-statistic):          8.73e-142
Time:                        04:28:12   Log-Likelihood:                 555.80
No. Observations:                 400   AIC:                            -1096.
Df Residuals:                     392   BIC:                            -1064.
Df Model:                           7
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.7211      0.003    236.761      0.000       0.715       0.727
x1             0.0210      0.006      3.282      0.001       0.008       0.034
x2             0.0171      0.006      2.826      0.005       0.005       0.029
x3             0.0074      0.005      1.427      0.154      -0.003       0.018
x4             0.0034      0.005      0.654      0.513      -0.007       0.014
x5             0.0111      0.004      2.593      0.010       0.003       0.019
x6             0.0744      0.007     11.310      0.000       0.062       0.087
x7             0.0105      0.004      2.810      0.005       0.003       0.018
==============================================================================
Omnibus:                      103.536   Durbin-Watson:                   1.969
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              262.618
Skew:                          -1.259   Prob(JB):                     9.40e-58
Kurtosis:                       6.068   Cond. No.                         5.60
==============================================================================

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

Insights:

1. R-squared & Adj. R-squared are ~0.8 and are close. Tells us that there are no unnecessary dimensions used in model building
2. Given that Prob (F-statistic) is very close to 0, suggest that there is a significant linear relationship between dependent and independent variables
3. It doesn't matter if we scale or not scale the data as Oridnary Least Squares doesn't depend on gradient descent

In [202]:
```
# Predict the values for train data
y_train_pred = results.predict(scaled_X_train_with_constant)
```

In [203]:
```
# Separate features & label for test dataset
X_test = test[features]
y_test = test[[label]]

scaled_X_test = scaler.transform(X_test)
```

In [204]:
```
# Add constant to the features for intercept
scaled_X_test_with_constant = sm.add_constant(scaled_X_test)
```

In [205]:
```
# Predict the values for test data
y_test_pred = results.predict(scaled_X_test_with_constant)
```

In [206]:
```
# Showing actual Chance_of_Admit of test data & predicted y_test_hat side
np.hstack((y_test.values, y_test_pred.reshape(-1,1)))[4:10]
```

Out[206]:
```
array([[0.81, 0.77],
       [0.61, 0.79],
       [0.77, 0.76],
       [0.89, 0.85],
       [0.85, 0.83],
       [0.71, 0.74]])
```

Model Performance Evaluation:

Training set:

In [207]:
```
# Calculate R2square for train dataset
r2_score(y_train,y_train_pred)
```

Out[207]: 0.8202047364283864

In [208]:
```
# Calculate MAE for train dataset
mean_absolute_error(y_train,y_train_pred)
```

Out[208]: 0.04267592384199064

In [209]:
```
# Calculate Median Absolute Error for train dataset
median_absolute_error(y_train,y_train_pred)
```

Out[209]: 0.02898048447555407

In [210]:
```
# Calculate mean squared error for train dataset
mean_squared_error(y_train,y_train_pred)
```

Out[210]: 0.0036360165833867393

In [211]:
```
# Calculate root mean squared error for train dataset
np.sqrt(mean_squared_error(y_train,y_train_pred))
```
Out[211]: 0.06029939123562309

Test set:

In [212]:
```
# Calculate R2square for test dataset
r2_score(y_test,y_test_pred)
```
Out[212]: 0.8258557445209804

In [213]:
```
# Calculate MAE for test dataset
mean_absolute_error(y_test,y_test_pred)
```
Out[213]: 0.041332508041023085

In [214]:
```
# Calculate Median Absolute Error for test dataset
median_absolute_error(y_test,y_test_pred)
```
Out[214]: 0.029997657390810673

In [215]:
```
# Calculate mean squared error for test dataset
mean_squared_error(y_test,y_test_pred)
```
Out[215]: 0.003222128467196326

In [216]:
```
# Calculate root mean squared error for test dataset
np.sqrt(mean_squared_error(y_test,y_test_pred))
```
Out[216]: 0.05676379539104416

In [217]:
```
# Update the features names
weights = results.params
weights.index = ["const"] + features
weights = np.round(weights,3)

# Parameters/Coefficients of the model
weights
```
Out[217]:
```
const                0.721
GRE_Score            0.021
TOEFL_Score          0.017
University_Rating    0.007
SOP                  0.003
LOR                  0.011
CGPA                 0.074
Research             0.010
dtype: float64
```

Insights:

1. Based on the weights associated with features, CGPA, GRE_Score seem to have higher weightage, followed by Research, TOEFL_Score, and LOR
2. R-squared for train & test sets are close to ~0.8 suggesting a decent fit

Test Assumptions for Linear Regression:

Multicollinearity Check by VIF Score:

In [218]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

In [219]:
```
vif = pd.DataFrame()
X_t = scaled_X_train_with_constant[:,1:]
vif['Features'] = features
vif['VIF'] = [variance_inflation_factor(X_t, i) for i in range(X_t.shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```
Out[219]:

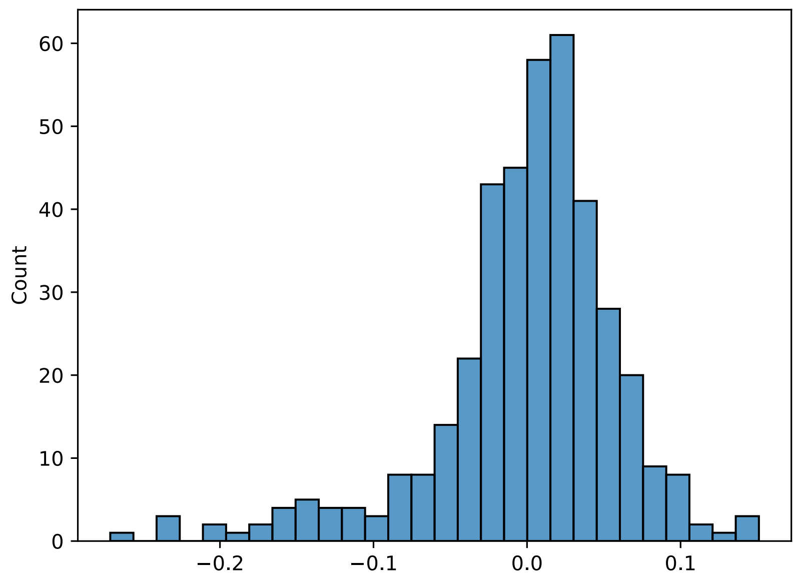
	Features	VIF
5	CGPA	4.67
0	GRE_Score	4.42
1	TOEFL_Score	3.97
3	SOP	2.97
2	University_Rating	2.92
4	LOR	1.97
6	Research	1.50

Insights:

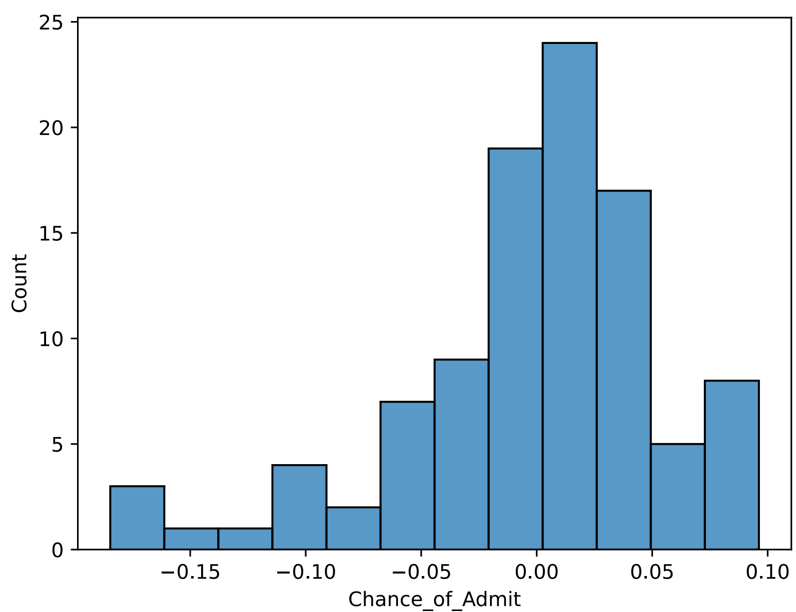
1. Features with VIF > 10 are considered to be very highly multicollinear. VIF value between 5 and 10 are considered to be highly collinear.
2. In our set of features, CGPA & GRE_Score have VIF close to 5 but not > 5. Rest all features have VIF 4 and below. No high multicollinearity in the features

Mean of residuals is close to zero:

In [76]:
```
# Get the residuals of the above OLS regression model
residuals = results.resid

# Plot a density plot to view the distribution
sns.histplot(residuals)
plt.show()
```



In [228]:
```
# Get the test data residuals
test_residuals = test[label] - y_test_pred

# Plot a density plot to view the distribution
sns.histplot(test_residuals)
plt.show()
```



In [226]:
```
# Check the mean of the residuals
round(np.mean(residuals),2)
```

Out[226]: -0.0

In [227]:
```
# Check the mean of the residuals
round(np.mean(test_residuals),2)
```

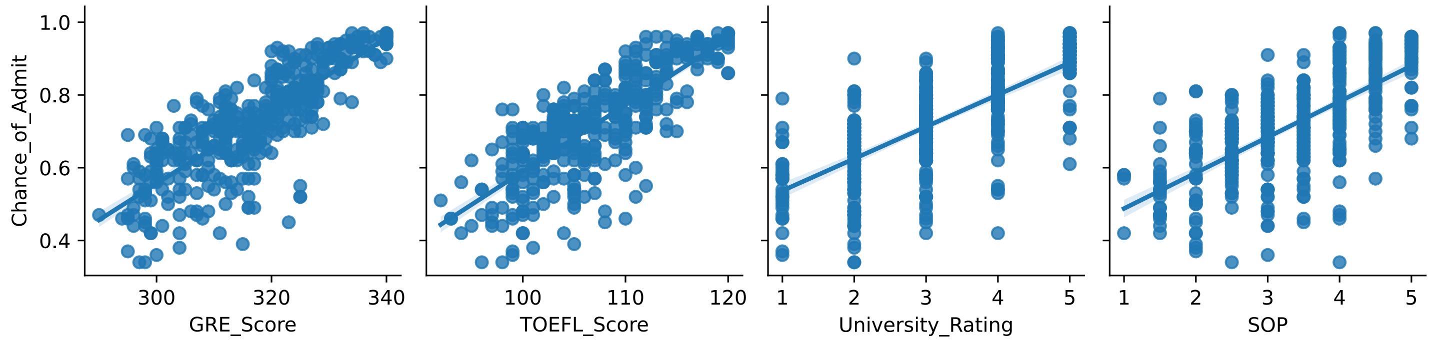
Out[227]: -0.0

Insights:

1. Mean of the residuals of both training and test data is close to the zero. This assumption of Linear Regression holds true

Linearity of variables:

In [79]:
```
sns.pairplot(y_vars="Chance_of_Admit",data=train,kind="reg")
plt.show()
```



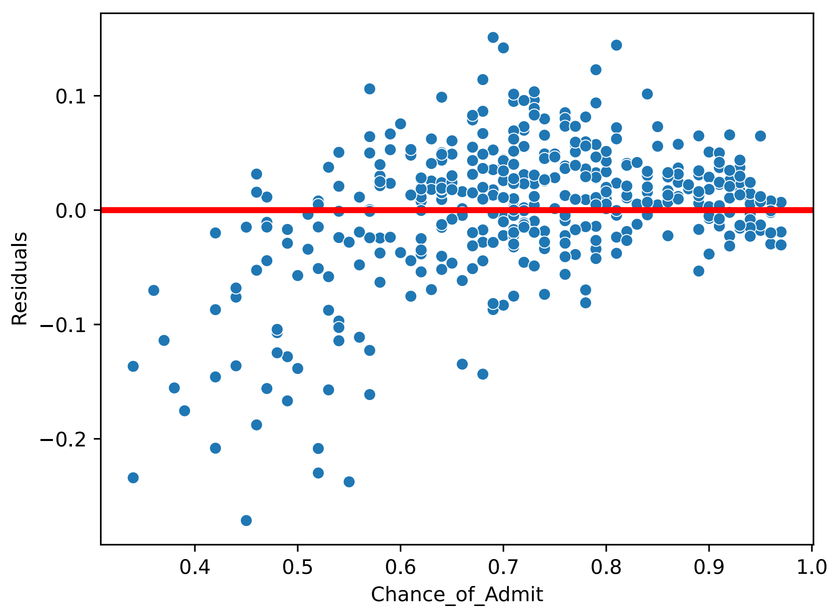
Insights:

1. As per the plots above, there exists a linear relationship between dependent and independent variables

Test for Homoscedasticity:

Train Data:

In [234]:
```
# Residuals plot od training data
sns.scatterplot(x=train["Chance_of_Admit"].values,y=residuals.values)
plt.axhline(y=0,color ="red",linewidth=3)
plt.xlabel("Chance_of_Admit")
plt.ylabel("Residuals")
plt.show()
```

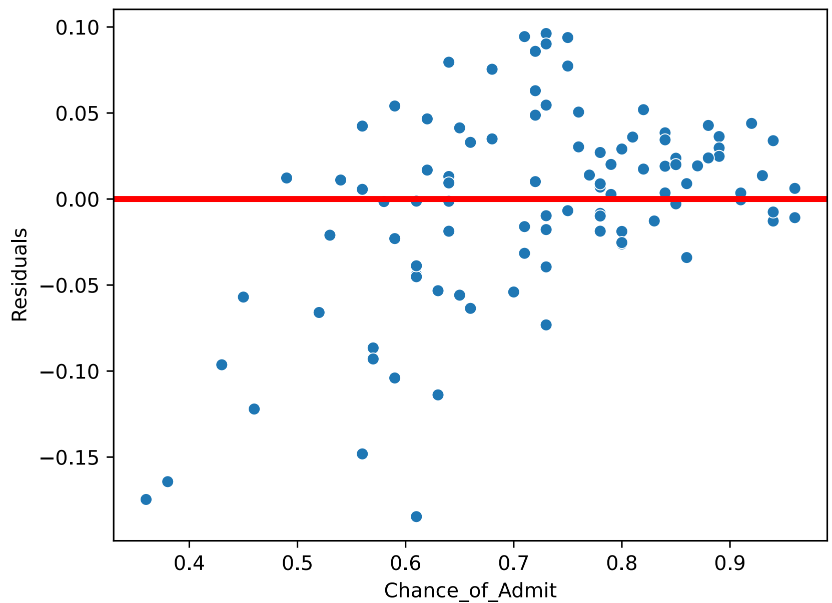


In [232]:
```
#H0: There is no heteroskedasticity in the residuals
#Ha: There is no heteroskedasticity in the residuals

from statsmodels.stats.diagnostic import het_breuschpagan

bp_test = het_breuschpagan(residuals, scaled_X_train_with_constant)

# Extract the test statistics and p-values
test_statistic = bp_test[0]
p_value = bp_test[1]

# Print the test results
print("Breusch-Pagan Test:")
print("Test statistic:", test_statistic)
print("p-value:", p_value)
```

```
Breusch-Pagan Test:
Test statistic: 20.4624484856879
p-value: 0.00465281341145511
```

Test Data:

In [233]:
```
# Residuals plot of test data
sns.scatterplot(x=test["Chance_of_Admit"].values,y=test_residuals.values)
plt.axhline(y=0,color ="red",linewidth=3)
plt.xlabel("Chance_of_Admit")
plt.ylabel("Residuals")
plt.show()
```



In [231]:
```
#H0: There is no heteroskedasticity in the residuals
#Ha: There is no heteroskedasticity in the residuals

from statsmodels.stats.diagnostic import het_breuschpagan

bp_test = het_breuschpagan(test_residuals, scaled_X_test_with_constant)

# Extract the test statistics and p-values
test_statistic = bp_test[0]
p_value = bp_test[1]

# Print the test results
print("Breusch-Pagan Test:")
print("Test statistic:", test_statistic)
print("p-value:", p_value)
```

```
Breusch-Pagan Test:
Test statistic: 16.86830894807262
p-value: 0.01826537347379551
```

Insights:

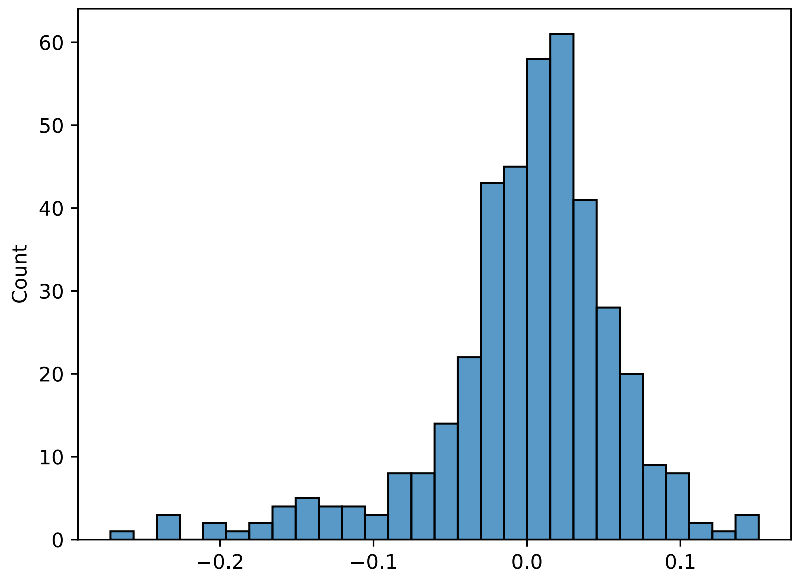
1. From the residuals plot & the above statisitical test, it is evident that there is heteroskedasticity in the residuals
2. Could be because of left skewed Chance_of_Admit too
3. Tried different transformation for dependent variable & tried using weighted least sqares regression. But it didn't work

Normality of residuals

In [82]:
```
# Null hypothesis H0: x comes from a normal distribution
# Alternate hypothesis Ha: x does not come from a normal distribution
alpha = 0.05

test_statistic, p_value = normaltest(residuals)
print(f"Test-statistic: {test_statistic}, p-value: {p_value}")

if p_value < alpha:
    print("The null hypothesis can be rejected")
else:
    print("The null hypothesis cannot be rejected")
```

```
Test-statistic: 103.53596929993317, p-value: 3.291924963275956e-23
The null hypothesis can be rejected
```

In [83]:
```python
# plot the density plot for residuals
sns.histplot(residuals)
plt.show()
```



Insights:

1. At significance level of 0.05, Residuals are not normally distributed. Skewed to the left like the label's distribution
2. However, they are close to normal even though the normality test says otherwise

Build a regularized model with cross validation

Lasso/L1 Regression:

In [84]:
```python
train = pd.read_csv("../input/train.csv")
test  = pd.read_csv("../input/test.csv")
```

In [85]:
```python
# Create a pipeline that generates polynomial features, scales the data, and fits Lasso regressor
model = Pipeline(steps = [("poly", PolynomialFeatures())
                          ,("scaler", StandardScaler())
                          ,("regressor", Lasso(max_iter=10000))]
                )
```

In [86]:
```python
# Below are the hyperparameters for GridSearchCV

params = {"poly__degree" : np.arange(0,6)
         ,"regressor__alpha" : [0.0001,0.001,0.01,0.1,1,10,100,1000]
         }
```

In [87]:
```python
# Get the GridSearchCV ready with scoring as "r2" and using KFold CV
search = GridSearchCV( estimator = model
             , param_grid = params
             , scoring= "r2"
             , n_jobs= -1
             , cv = KFold(n_splits=5,random_state=20,shuffle=True)
             , return_train_score= True
             )
```

In [88]:
```python
search.fit(train[features],train[[label]])
```

Out[88]:
```
▸ GridSearchCV
▸ estimator: Pipeline
▸ PolynomialFeatures
▸ StandardScaler
▸ Lasso
```

In [89]:
```python
print(f"Best Hyperparameters: {search.best_params_}")
print(f"Best R2score on validation set: {np.round(search.best_score_,2)}")
```

```
Best Hyperparameters: {'poly__degree': 2, 'regressor__alpha': 0.001}
Best R2score on validation set: 0.81
```

In [90]:
```
# Using the hyperparameters above, train the model on entire training dataset
model = Pipeline(steps = [("poly", PolynomialFeatures(degree=2))
                 ,("scaler", StandardScaler())
                 ,("regressor", Lasso(alpha =0.001 ,max_iter=1000))]
                 )

model.fit(X=train[features],y=train[[label]])
```

Out[90]:
```
Pipeline
  PolynomialFeatures
  StandardScaler
  Lasso
```

In [108]:
```
# R2score of model on training dataset
y_train_pred = model.predict(train[features])
print(f" R2Score on train set: {np.round(r2_score(train[[label]],y_train_pred),2)}")
```

```
 R2Score on train set: 0.82
```

In [150]:
```
# Predict using the above model on test data
y_test_pred = model.predict(test[features])
print(f"R2Score on test set: {np.round(r2_score(test[label],y_test_pred),2)}")
```

```
R2Score on test set: 0.83
```

Model Performance Evaluation:

Training set:

In [151]:
```
# Calculate mean absolute error
mean_absolute_error(train[label],y_train_pred)
```

Out[151]: 0.04144482683522679

In [152]:
```
# Calculate median absolute error
median_absolute_error(train[label],y_train_pred)
```

Out[152]: 0.029790220700906866

In [153]:
```
# Calculate mean squared error
mse = mean_squared_error(train[label],y_train_pred)
mse
```

Out[153]: 0.00344317733288388

In [117]:
```
# Calculate root mean squared error
rmse = np.sqrt(mse)
rmse
```

Out[117]: 0.06000636103281431

Test set:

In [154]:
```
# Calculate mean absolute error
mean_absolute_error(test[label],y_test_pred)
```

Out[154]: 0.04067237362711504

In [155]:
```
# Calculate median absolute error
median_absolute_error(test[label],y_test_pred)
```

Out[155]: 0.027533679130756994

In [156]:
```
# Calculate mean squarred error
mse = mean_squared_error(test[label],y_test_pred)
mse
```

Out[156]: 0.003094905626025386

In [157]:
```
# Calculate root mean squared error
rmse = np.sqrt(mse)
rmse
```

Out[157]: 0.055631875988729575

Insights:

1. Using CV & GridSearchCV, Hyperparameters found are alpha = 0.001, and degree = 2 with the best R2score on validation set as 0.82
2. With those hyperparameters, trained the model on entire training data yielding R2score of 0.82
3. On test dataset, R2score is 0.83. Also calcuated different metrics on training and test sets

Ridge/L2 Regularization:

In [158]:
```
# Create a pipiline that generates polynomial features, scales the data, and fits Ridge regressor
model = Pipeline(steps = [("poly", PolynomialFeatures())
                 ,("scaler", StandardScaler())
                 ,("regressor", Ridge(max_iter=10000))]
                 )
```

In [159]:
```
# Below are the hyperparameters for GridSearchCV
params = {"poly__degree" : np.arange(0,6,1)
         ,"regressor__alpha" : [0.001,0.01,0.1,1,10,100,1000]
         }
```

In [160]:
```
# Get the GridSearchCV ready with scoring as "r2" and using KFold CV
search = GridSearchCV( estimator = model
              , param_grid = params
              , scoring= "r2"
              , n_jobs= -1
              , cv = KFold(n_splits=5,random_state=23,shuffle=True)
              , return_train_score= True
                     )
```

In [161]:
```
search.fit(train[features],train[[label]])
```

Out[161]:
```
▸ GridSearchCV
▸ estimator: Pipeline
▸ PolynomialFeatures
▸ StandardScaler
▸ Ridge
```

In [162]:
```
print(f"Best Hyperparameters: {search.best_params_}")
print(f"Best R2score on validation set: {np.round(search.best_score_,2)}")
```

```
Best Hyperparameters: {'poly__degree': 2, 'regressor__alpha': 1}
Best R2score on validation set: 0.81
```

In [163]:
```
# Using the hyperparameters above, train the model on entire training dataset
model = Pipeline(steps = [("poly", PolynomialFeatures(degree=2))
                 ,("scaler", StandardScaler())
                 ,("regressor", Ridge(alpha =1 ,max_iter=1000))]
                 )
```

In [164]:
```
model.fit(X=train[features],y=train[[label]])
```

Out[164]:
```
▸ Pipeline
▸ PolynomialFeatures
▸ StandardScaler
▸ Ridge
```

In [165]:
```
# R2score of model on training dataset
print(f" R2Score on train set: {np.round(r2_score(train[[label]],model.predict(train[features])),2)}")
```

```
 R2Score on train set: 0.83
```

In [166]:
```
# Predict using the above model on test data
y_test_pred = model.predict(X=test[features])
print(f"R2Score on test set: {np.round(r2_score(test[label],y_test_pred),2)}")
```

```
R2Score on test set: 0.83
```

Model Performance Evaluation:

Training set:

In [167]:
```
# Predict on training data
y_train_pred = model.predict(train[features])
y_train = train[label]
```

In [168]:
```
# Calculate R2square for train dataset
r2_score(y_train,y_train_pred)
```

Out[168]: 0.8297403320660772

In [169]:
```
# Calculate MAE for train dataset
mean_absolute_error(y_train,y_train_pred)
```

Out[169]: 0.04144482683522679

In [170]:
```
# Calculate Median Absolute Error for train dataset
median_absolute_error(y_train,y_train_pred)
```

Out[170]: 0.029790220700906866

In [171]:
```
# Calculate mean squared error for train dataset
mean_squared_error(y_train,y_train_pred)
```
Out[171]: 0.00344317733288388

In [172]:
```
# Calculate root mean squared error for train dataset
np.sqrt(mean_squared_error(y_train,y_train_pred))
```
Out[172]: 0.05867859348079059

Test set:

In [173]:
```
# Calculate r2_score
r2_score(test[label],y_test_pred,)
```
Out[173]: 0.8327316736408757

In [174]:
```
# Calculate R2square for test dataset
y_test = test[label]
r2_score(y_test,y_test_pred)
```
Out[174]: 0.8327316736408757

In [175]:
```
# Calculate MAE for test dataset
mean_absolute_error(y_test,y_test_pred)
```
Out[175]: 0.04067237362711504

In [176]:
```
# Calculate Median Absolute Error for test dataset
median_absolute_error(y_test,y_test_pred)
```
Out[176]: 0.027533679130756994

In [177]:
```
# Calculate mean squared error for test dataset
mean_squared_error(y_test,y_test_pred)
```
Out[177]: 0.003094905626025386

In [178]:
```
# Calculate root mean squared error for test dataset
np.sqrt(mean_squared_error(y_test,y_test_pred))
```
Out[178]: 0.055631875988729575

Insights:

1. Using CV & GridSearchCV, Hyperparameters found are alpha = 1, and degree = 2 with the best R2score on validation set as 0.81
2. With those hyperparameters, trained the model on entire training data yielding R2score of 0.83
3. On test dataset, R2score is 0.83.

WLS (Weighted Least Squares)

In [179]:
```
# Separate features from the label of train set

X_train = train[features]
y_train = train[[label]]

# Scale the train & valid set features
scaler = StandardScaler()
scaled_X_train = scaler.fit_transform(X_train)

# Add constant to the features
scaled_X_train_with_constant = sm.add_constant(scaled_X_train)
```

In [180]:
```
# Fit the WLS model on training data

model = sm.WLS(y_train,scaled_X_train_with_constant)
results = model.fit()
```

In [181]:
```
print(results.summary())
```

```
                            WLS Regression Results                            
==============================================================================
Dep. Variable:        Chance_of_Admit   R-squared:                       0.820
Model:                            WLS   Adj. R-squared:                  0.817
Method:                 Least Squares   F-statistic:                     255.5
Date:                Wed, 14 Jun 2023   Prob (F-statistic):          8.73e-142
Time:                        04:23:34   Log-Likelihood:                 555.80
No. Observations:                 400   AIC:                            -1096.
Df Residuals:                     392   BIC:                            -1064.
Df Model:                           7                                         
Covariance Type:            nonrobust                                         
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.7211      0.003    236.761      0.000       0.715       0.727
x1             0.0210      0.006      3.282      0.001       0.008       0.034
x2             0.0171      0.006      2.826      0.005       0.005       0.029
x3             0.0074      0.005      1.427      0.154      -0.003       0.018
x4             0.0034      0.005      0.654      0.513      -0.007       0.014
x5             0.0111      0.004      2.593      0.010       0.003       0.019
x6             0.0744      0.007     11.310      0.000       0.062       0.087
x7             0.0105      0.004      2.810      0.005       0.003       0.018
==============================================================================
Omnibus:                      103.536   Durbin-Watson:                   1.969
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              262.618
Skew:                          -1.259   Prob(JB):                     9.40e-58
Kurtosis:                       6.068   Cond. No.                         5.60
==============================================================================

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

In [182]:
```
# Predict the label values for train  data
y_train_pred = results.predict(scaled_X_train_with_constant)
```

In [183]:
```
# Separate features & label for test dataset
X_test = test[features]
y_test = test[[label]]

scaled_X_test = scaler.transform(X_test)
```

In [184]:
```
# Add constant to the features for intercept
scaled_X_test_with_constant = sm.add_constant(scaled_X_test)
```

In [185]:
```
# Predict the values for test data
y_test_pred = results.predict(scaled_X_test_with_constant)
```

In [186]:
```
# Showing actual Chance_of_Admit of test data & predicted y_test_hat side
np.hstack((y_test.values, y_test_pred.reshape(-1,1)))[5:10]
```

Out[186]:
```
array([[0.61, 0.79],
       [0.77, 0.76],
       [0.89, 0.85],
       [0.85, 0.83],
       [0.71, 0.74]])
```

In [187]:
```
# Calculate R2score for test data
print(f"R2Score for test data: {np.round(r2_score(y_test,y_test_pred),2)}")
```

```
R2Score for test data: 0.83
```

Model Performance Evaluation:

Training set:

In [188]:
```
# Calculate R2square for train dataset
r2_score(y_train,y_train_pred)
```

Out[188]:
```
0.8202047364283864
```

In [189]:
```
# Calculate MAE for train dataset
mean_absolute_error(y_train,y_train_pred)
```

Out[189]:
```
0.04267592384199064
```

In [190]:
```
# Calculate Median Absolute Error for train dataset
median_absolute_error(y_train,y_train_pred)
```

Out[190]:
```
0.02898048447555407
```

In [191]:
```
# Calculate mean squared error for train dataset
mean_squared_error(y_train,y_train_pred)
```

Out[191]:
```
0.003636016583386739З
```

In [192]:
```
# Calculate root mean squared error for train dataset
np.sqrt(mean_squared_error(y_train,y_train_pred))
```

Out[192]:
```
0.06029939123562309
```

Test set:

In [193]:
```
# Calculate R2square for test dataset
r2_score(y_test,y_test_pred)
```
Out[193]: 0.8258557445209804

In [194]:
```
# Calculate MAE for test dataset
mean_absolute_error(y_test,y_test_pred)
```
Out[194]: 0.041332508041023085

In [195]:
```
# Calculate Median Absolute Error for test dataset
median_absolute_error(y_test,y_test_pred)
```
Out[195]: 0.029997657390810673

In [196]:
```
# Calculate mean squared error for test dataset
mean_squared_error(y_test,y_test_pred)
```
Out[196]: 0.003222128467196326

In [197]:
```
# Calculate root mean squared error for test dataset
np.sqrt(mean_squared_error(y_test,y_test_pred))
```
Out[197]: 0.05676379539104416

Insights:

1. Regardless of using WLS, or GLS , couldn't get the R2score on test set above 0.83

Final Insights:

1. CGPA, GRE Score, TOEFL Score have a very high correlation with Chance of Admit. Same can be inferred from the weights of the Linear Regression model as well
2. GRE Score, TOEFL Score are very highly correlated with CGPA
3. Math Aptitude & English skills of students from higher rated universities seem to be better
4. Students from university with higher rating, have better chances of admission into Ivy schools
5. Using Linear Regression with/without regularization, best perfomed model has an r2score of 0.83 -- improvement is required

Inferences:

1. Median GRE score, TOEFL Score, CGPA, LOR, SOP of students from universities with university ratings are different
2. University rating & Research are associated.
3. Students with research experience has higher median/mean CGPA, GRE Score, and TOEFL Scores. Their median chances of admission is also higher than that of students without experience

Recommendations:

1. Recommend collecting more datapoints and balanced data to have more/better data for training
2. Collecting more datapoints like Years of work experience, Current Discipline, Targeted discipline at the Ivy School, Research papers published, IELTS Score, and others would help improve the model predictions
3. Recommend using non-parametric Machine Learning Models to predict the Chances of admission - to improve model

Potential Business Benefits:

1. Jamboree can do targeted ads for students with less/mediocre chances of admission into Ivy League. To enroll into Jamboree to improve GMAT/GRE/SAT Scores and increase their admission chances
2. As the model gets improved, it gives competitive edge to Jamboree over the competition and leads to more website traffic & enrollments

In [ ]:
```

```