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Roll No. - 17

Topic - Predictive Data Analytics on the US Graduate Admissions

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Introduction

In this Project , I utilized the U.S. graduate schools admission dataset from the Kaggle datasets in order to predict admission from important parameters within the dataset.

The goal is accomplished through extracting all data insights and salient features out of the admission dataset through useful data manipulation as well as visualization methods by leveraging Python libraries, modules and other tools for numerical computation and Data visualization accompanied by deriving practical hints as to how increase your chance of admission into top-tier Graduate schools in the United States.

Start With Analysis

Importing Libraries

```
In [1]: 1 import warnings
        2 warnings.filterwarnings('ignore')

In [2]: 1 import pandas as pd
        2 import numpy as np
        3
        4 from IPython.display import display
        5
        6 #Visualization
        7 import seaborn as sns
        8 import matplotlib
        9 import matplotlib.pyplot as plt
       10 import plotly.express as px
       11
       12 import scipy.stats as stats
       13 from scipy.stats.mstats import winsorize
       14
       15 from statsmodels.stats.outliers_influence import variance_inflation_factor
       16 from statsmodels.tools.tools import add_constant
       17
       18 from sklearn.model_selection import train_test_split
       19
       20 from sklearn.linear_model import LinearRegression,Lasso,Ridge
       21 from sklearn.tree import DecisionTreeRegressor
       22 from sklearn.ensemble import RandomForestRegressor
       23 from sklearn.neighbors import KNeighborsRegressor
       24 from sklearn.svm import SVR
       25 from sklearn.ensemble import AdaBoostRegressor,GradientBoostingRegressor
       26 from xgboost import XGBRegressor
       27
       28 from sklearn.metrics import r2_score, mean_absolute_error,mean_absolute_percentage_error,mean_squared_error
```

Loading Data

```
In [3]: 1 data = pd.read_csv("Admission_Predict_Ver1.1.csv")

In [4]: 1 df = data.copy()
```

Data PreProcessing and Cleaning

```
In [5]: 1 df
```

Out[5]:

	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
0	1	337	118	4	4.5	4.5	9.65	1	0.92
1	2	324	107	4	4.0	4.5	8.87	1	0.76
2	3	316	104	3	3.0	3.5	8.00	1	0.72
3	4	322	110	3	3.5	2.5	8.67	1	0.80
4	5	314	103	2	2.0	3.0	8.21	0	0.65
...	...	...	...	...	...	...	...	...	...
495	496	332	108	5	4.5	4.0	9.02	1	0.87
496	497	337	117	5	5.0	5.0	9.87	1	0.96
497	498	330	120	5	4.5	5.0	9.56	1	0.93
498	499	312	103	4	4.0	5.0	8.43	0	0.73
499	500	327	113	4	4.5	4.5	9.04	0	0.84

500 rows × 9 columns

```
In [6]: 1 df.head()
```

Out[6]:

	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
0	1	337	118	4	4.5	4.5	9.65	1	0.92
1	2	324	107	4	4.0	4.5	8.87	1	0.76
2	3	316	104	3	3.0	3.5	8.00	1	0.72
3	4	322	110	3	3.5	2.5	8.67	1	0.80
4	5	314	103	2	2.0	3.0	8.21	0	0.65

```
In [7]: 1 with pd.option_context('display.max_rows',500):
2       display(df)
```

	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
0	1	337	118	4	4.5	4.5	9.65	1	0.92
1	2	324	107	4	4.0	4.5	8.87	1	0.76
2	3	316	104	3	3.0	3.5	8.00	1	0.72
3	4	322	110	3	3.5	2.5	8.67	1	0.80
4	5	314	103	2	2.0	3.0	8.21	0	0.65
5	6	330	115	5	4.5	3.0	9.34	1	0.90
6	7	321	109	3	3.0	4.0	8.20	1	0.75
7	8	308	101	2	3.0	4.0	7.90	0	0.68
8	9	302	102	1	2.0	1.5	8.00	0	0.50
9	10	323	108	3	3.5	3.0	8.60	0	0.45
10	11	325	106	3	3.5	4.0	8.40	1	0.52

```
In [8]: 1 df.columns
```

Out[8]: Index(['Serial No.', 'GRE Score', 'TOEFL Score', 'University Rating', 'SOP', 'LOR ', 'CGPA', 'Research', 'Chance of Admit '], dtype='object')

Removing leading and trailing spaces from the column names

```
In [9]: 1 df.columns = df.columns.str.strip()
2       df.columns
```

Out[9]: Index(['Serial No.', 'GRE Score', 'TOEFL Score', 'University Rating', 'SOP', 'LOR', 'CGPA', 'Research', 'Chance of Admit'], dtype='object')

Using the Serial No. column as the index for dataframe to address the redundancy issue

```
In [10]: 1 df.set_index('Serial No.', inplace=True)
2         df
3         # df.drop(['Serial No.'],axis = 1,inplace =True)
4         # df
```

Out[10]:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
Serial No.								
1	337	118	4	4.5	4.5	9.65	1	0.92
2	324	107	4	4.0	4.5	8.87	1	0.76
3	316	104	3	3.0	3.5	8.00	1	0.72
4	322	110	3	3.5	2.5	8.67	1	0.80
5	314	103	2	2.0	3.0	8.21	0	0.65
...	...	...	...	...	...	...	...	...
496	332	108	5	4.5	4.0	9.02	1	0.87
497	337	117	5	5.0	5.0	9.87	1	0.96
498	330	120	5	4.5	5.0	9.56	1	0.93
499	312	103	4	4.0	5.0	8.43	0	0.73
500	327	113	4	4.5	4.5	9.04	0	0.84

500 rows × 8 columns

```
In [11]: 1 with pd.option_context('display.max_rows', 500):
2         display(df)
```

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
Serial No.								
1	337	118	4	4.5	4.5	9.65	1	0.92
2	324	107	4	4.0	4.5	8.87	1	0.76
3	316	104	3	3.0	3.5	8.00	1	0.72
4	322	110	3	3.5	2.5	8.67	1	0.80
5	314	103	2	2.0	3.0	8.21	0	0.65
6	330	115	5	4.5	3.0	9.34	1	0.90
7	321	109	3	3.0	4.0	8.20	1	0.75
8	308	101	2	3.0	4.0	7.90	0	0.68
9	302	102	1	2.0	1.5	8.00	0	0.50
10	323	108	3	3.5	3.0	8.60	0	0.45

```
In [12]: 1 df.shape
```

Out[12]: (500, 8)

```
In [13]: 1 df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 500 entries, 1 to 500
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: 35.2 KB
```

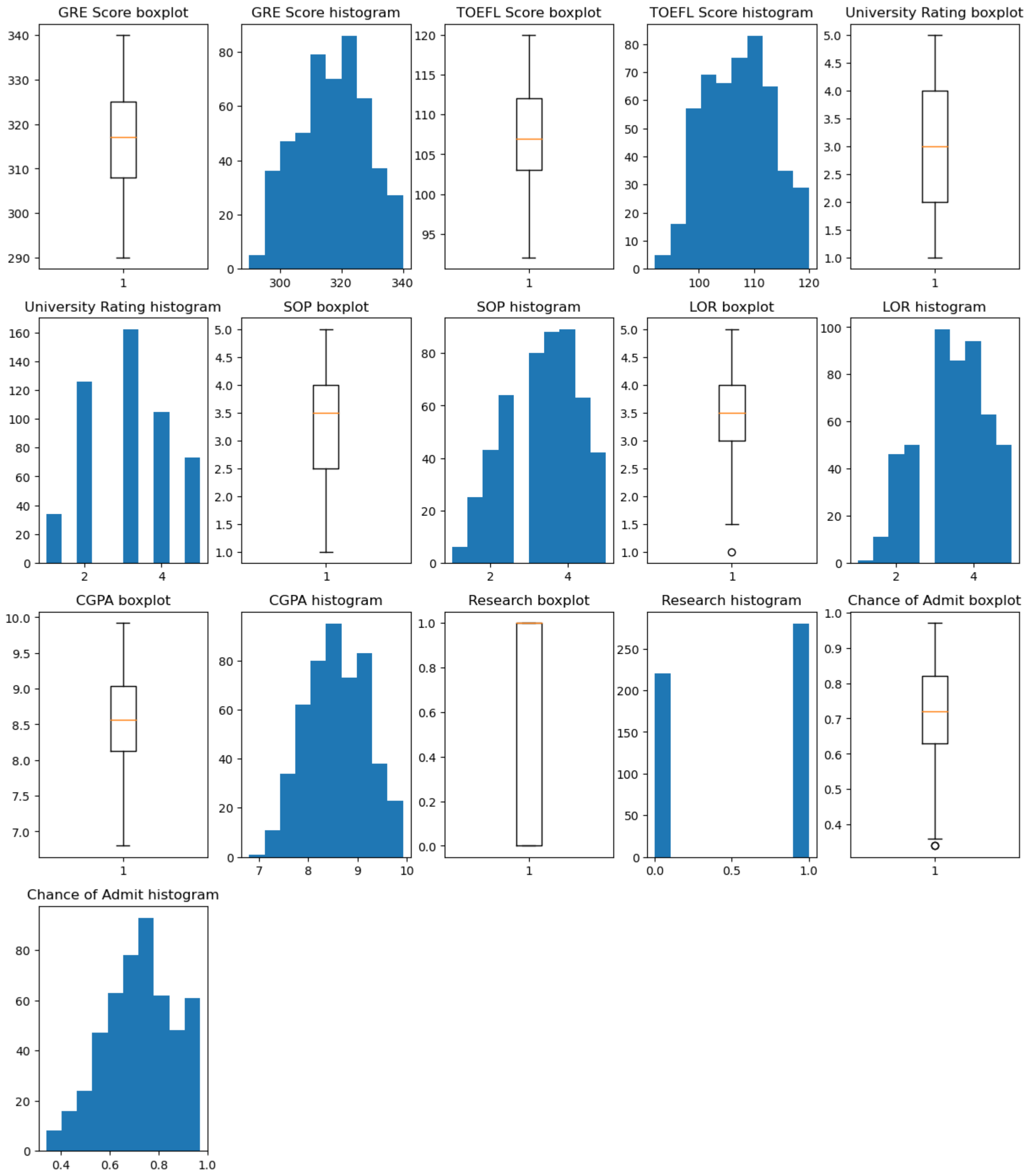
No Missing Values are present

Outlier Analysis

```
In [14]: 1 def outliers_visual(data):
2         plt.figure(figsize=(15, 40))
3         i = 0
4         for col in list(data.columns):
5             i += 1
6             plt.subplot(9, 5, i)
7             plt.boxplot(data[col])
8             plt.title('{} boxplot'.format(col))
9             i += 1
10            plt.subplot(9, 5, i)
11            plt.hist(data[col])
12            plt.title('{} histogram'.format(col))
13            plt.show()
```

```
In [15]: 1 def outlier_count(col, data=df):
2         print(15*'-' + col + 15*'-' )
3         q75, q25 = np.percentile(data[col], [75, 25])
4         iqr = q75 - q25
5         min_val = q25 - (iqr*1.5)
6         max_val = q75 + (iqr*1.5)
7         outlier_count = len(np.where((data[col] > max_val) | (data[col] < min_val))[0])
8         outlier_percent = round(outlier_count/len(data[col])*100, 2)
9         print('Number of outliers: {}'.format(outlier_count))
10        print('Percent of data that is outlier: {}'.format(outlier_percent))
11        print(50*'=')
```

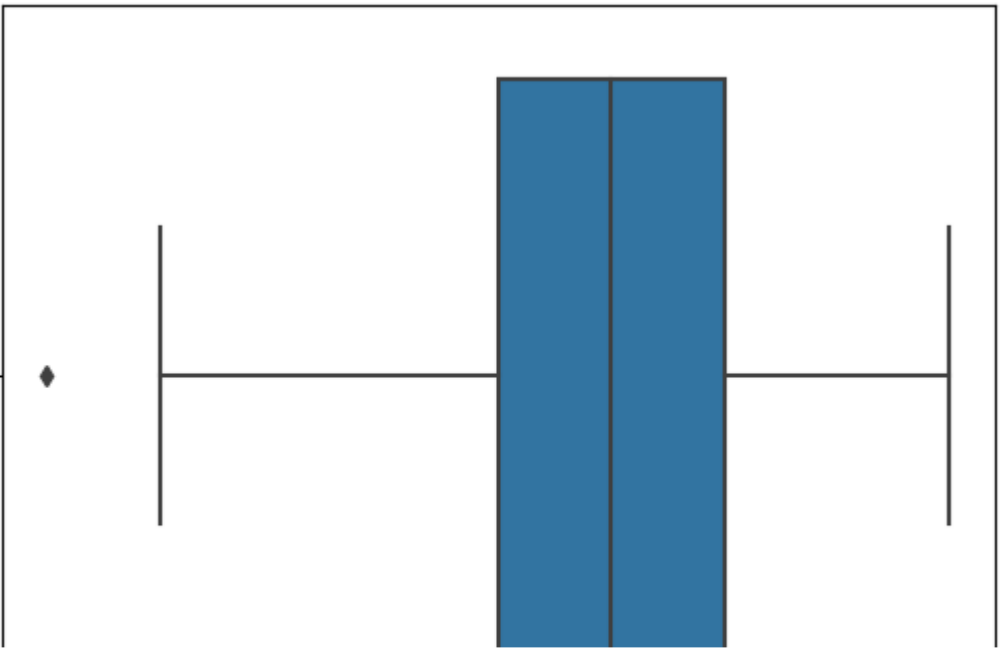
```
In [16]: 1 outliers_visual(df)
```



```
In [17]: 1 for col in df.columns:
2         outlier_count(col)
```

```
-----GRE Score-----
Number of outliers: 0
Percent of data that is outlier: 0.0%
=====
-----TOEFL Score-----
Number of outliers: 0
Percent of data that is outlier: 0.0%
=====
-----University Rating-----
Number of outliers: 0
Percent of data that is outlier: 0.0%
=====
-----SOP-----
Number of outliers: 0
Percent of data that is outlier: 0.0%
=====
-----LOR-----
Number of outliers: 1
Percent of data that is outlier: 0.2%
=====
-----CGPA-----
Number of outliers: 0
Percent of data that is outlier: 0.0%
=====
-----Research-----
Number of outliers: 0
Percent of data that is outlier: 0.0%
=====
-----Chance of Admit-----
Number of outliers: 2
Percent of data that is outlier: 0.4%
=====
```

```
In [18]: 1 sns.boxplot(data=df,x=df['LOR']);
```



```
In [19]: 1 Q1=df['LOR'].quantile(0.25)
2 Q3=df['LOR'].quantile(0.75)
3 IQR=Q3-Q1
4 print(Q1)
5 print(Q3)
6 print(IQR)
7 Lower_Whisker = Q1-(1.5*IQR)
8 Upper_Whisker = Q3+(1.5*IQR)
9 print(Lower_Whisker, Upper_Whisker)
```

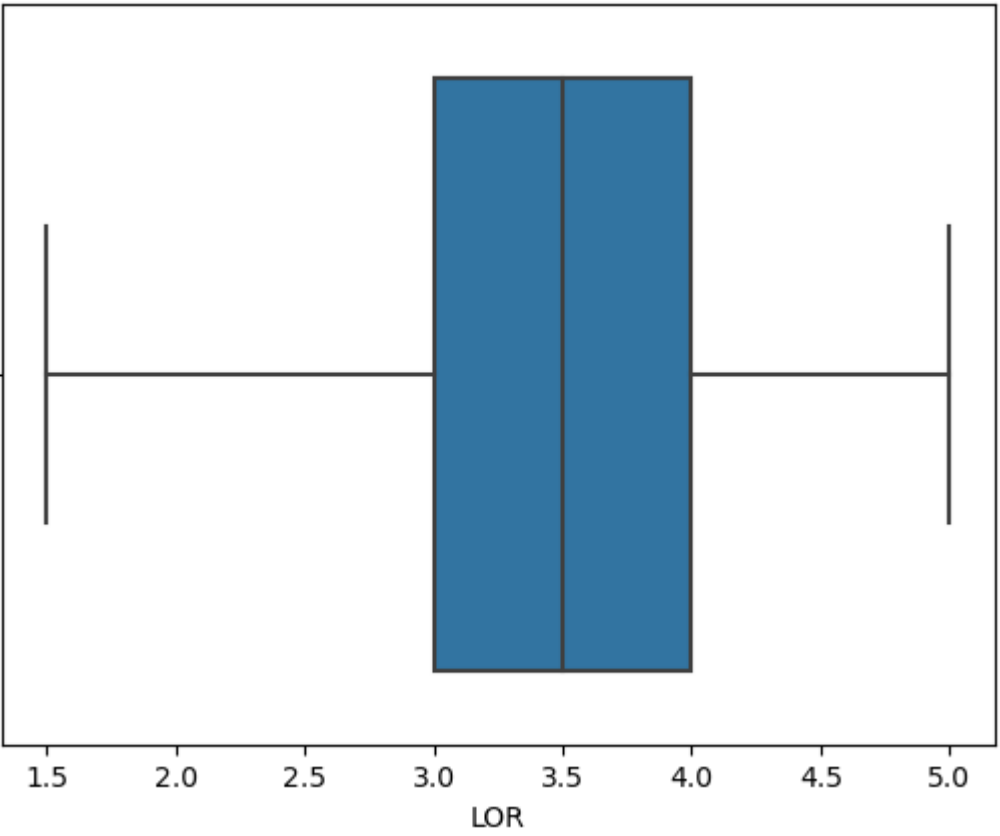
```
3.0
4.0
1.0
1.5 5.5
```

```
In [20]: 1 #Explore different quantiles at the Lower end
2 print('10% quantile : ', df['LOR'].quantile(0.10))
3 print('7.5% quantile : ', df['LOR'].quantile(0.075))
4 print('5% quantile : ', df['LOR'].quantile(0.05))
5 print('2.5% quantile : ', df['LOR'].quantile(0.025))
6 print('1% quantile : ', df['LOR'].quantile(0.01))
7 print('0.5% quantile : ', df['LOR'].quantile(0.005))
8 print('0.1% quantile : ', df['LOR'].quantile(0.001))
```

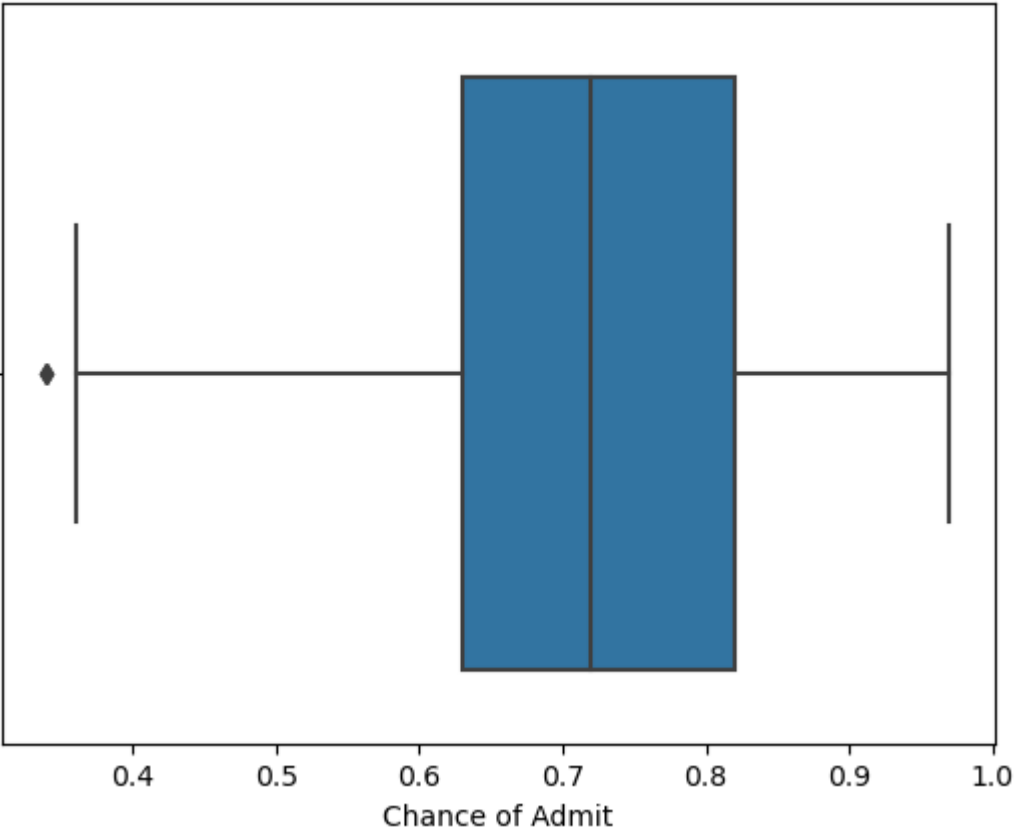
```
10% quantile : 2.0
7.5% quantile : 2.0
5% quantile : 2.0
2.5% quantile : 2.0
1% quantile : 1.5
0.5% quantile : 1.5
0.1% quantile : 1.2495
```

```
In [21]: 1 df['LOR']=winsorize(df['LOR'], limits=(0.005,0))
```

```
In [22]: 1 sns.boxplot(data=df,x=df['LOR']);
```



```
In [23]: 1 sns.boxplot(data=df,x=df['Chance of Admit']);
```



```
In [24]: 1 Q1=df['Chance of Admit'].quantile(0.25)
2 Q3=df['Chance of Admit'].quantile(0.75)
3 IQR=Q3-Q1
4 print(Q1)
5 print(Q3)
6 print(IQR)
7 Lower_Whisker = Q1-(1.5*IQR)
8 Upper_Whisker = Q3+(1.5*IQR)
9 print(Lower_Whisker, Upper_Whisker)

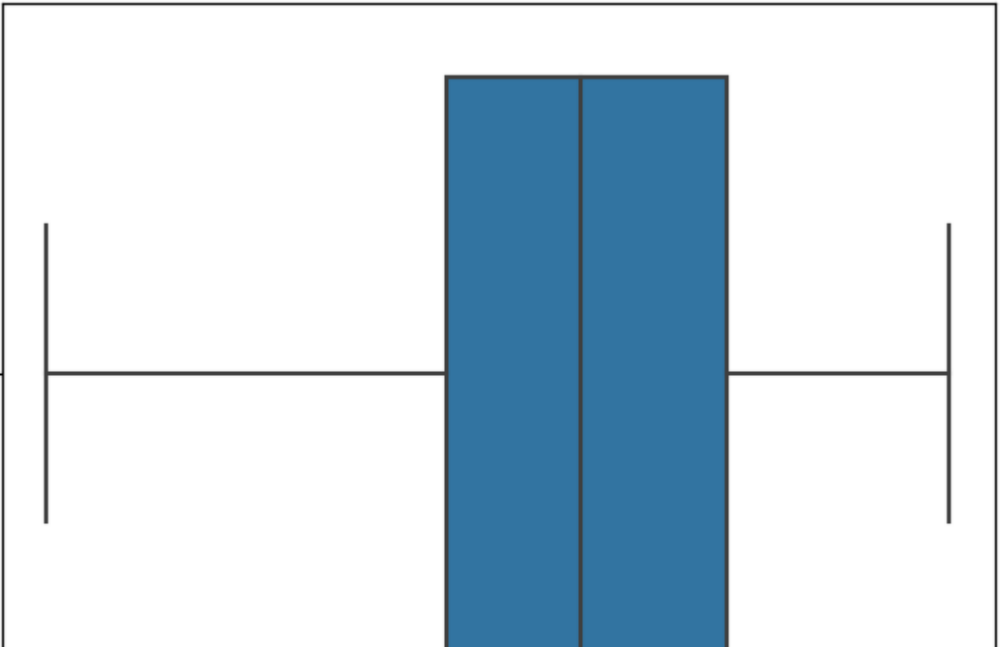
0.63
0.82
0.18999999999999995
0.34500000000000001 1.105
```

```
In [25]: 1 #Explore different quantiles at the Lower end
2 print('10% quantile : ', df['Chance of Admit'].quantile(0.10))
3 print('7.5% quantile : ', df['Chance of Admit'].quantile(0.075))
4 print('5% quantile : ', df['Chance of Admit'].quantile(0.05))
5 print('2.5% quantile : ', df['Chance of Admit'].quantile(0.025))
6 print('1% quantile : ', df['Chance of Admit'].quantile(0.01))
7 print('0.5% quantile : ', df['Chance of Admit'].quantile(0.005))
8 print('0.1% quantile : ', df['Chance of Admit'].quantile(0.001))

10% quantile : 0.53
7.5% quantile : 0.5
5% quantile : 0.47
2.5% quantile : 0.43475
1% quantile : 0.3799
0.5% quantile : 0.36
0.1% quantile : 0.34
```

```
In [26]: 1 df['Chance of Admit']=winsorize(df['Chance of Admit'], limits=(0.005,0))
```

```
In [27]: 1 sns.boxplot(data=df,x=df['Chance of Admit']);
```



```
In [28]: 1 with pd.option_context('display.max_rows', 500):
2 display(df)
```

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
Serial No.								
1	337	118	4	4.5	4.5	9.65	1	0.92
2	324	107	4	4.0	4.5	8.87	1	0.76
3	316	104	3	3.0	3.5	8.00	1	0.72
4	322	110	3	3.5	2.5	8.67	1	0.80
5	314	103	2	2.0	3.0	8.21	0	0.65
6	330	115	5	4.5	3.0	9.34	1	0.90
7	321	109	3	3.0	4.0	8.20	1	0.75
8	308	101	2	3.0	4.0	7.90	0	0.68
9	302	102	1	2.0	1.5	8.00	0	0.50
10	323	108	3	3.5	3.0	8.60	0	0.45

```
In [29]: 1 df.shape
```

Out[29]: (500, 8)

Now, No Outliers are Present

Describe the Dataset

```
In [30]: 1 df.describe().transpose()
```

Out[30]:

	count	mean	std	min	25%	50%	75%	max
GRE Score	500.0	316.47200	11.295148	290.00	308.0000	317.00	325.00	340.00
TOEFL Score	500.0	107.19200	6.081868	92.00	103.0000	107.00	112.00	120.00
University Rating	500.0	3.11400	1.143512	1.00	2.0000	3.00	4.00	5.00
SOP	500.0	3.37400	0.991004	1.00	2.5000	3.50	4.00	5.00
LOR	500.0	3.48500	0.923027	1.50	3.0000	3.50	4.00	5.00
CGPA	500.0	8.57644	0.604813	6.80	8.1275	8.56	9.04	9.92
Research	500.0	0.56000	0.496884	0.00	0.0000	1.00	1.00	1.00
Chance of Admit	500.0	0.72182	0.140929	0.36	0.6300	0.72	0.82	0.97

```
In [31]: 1 df.corr()
```

Out[31]:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
GRE Score	1.000000	0.827200	0.635376	0.613498	0.524377	0.825878	0.563398	0.810610
TOEFL Score	0.827200	1.000000	0.649799	0.644410	0.540630	0.810574	0.467012	0.792462
University Rating	0.635376	0.649799	1.000000	0.728024	0.608241	0.705254	0.427047	0.690613
SOP	0.613498	0.644410	0.728024	1.000000	0.662848	0.712154	0.408116	0.685091
LOR	0.524377	0.540630	0.608241	0.662848	1.000000	0.636923	0.372280	0.645097
CGPA	0.825878	0.810574	0.705254	0.712154	0.636923	1.000000	0.501311	0.882940
Research	0.563398	0.467012	0.427047	0.408116	0.372280	0.501311	1.000000	0.546048
Chance of Admit	0.810610	0.792462	0.690613	0.685091	0.645097	0.882940	0.546048	1.000000

Exploratory Analysis and Visualization

Extracting Data insights as well as visualization methods

```
In [32]: 1 df.sample(10)
```

Out[32]:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
Serial No.								
263	308	103	2	2.5	4.0	8.36	1	0.70
69	318	109	3	3.5	4.0	9.22	1	0.68
138	316	100	2	1.5	3.0	8.16	1	0.71
432	320	112	2	3.5	3.5	8.78	1	0.73
487	319	102	3	2.5	2.5	8.37	0	0.68
125	301	106	4	2.5	3.0	8.47	0	0.57
148	326	114	3	3.0	3.0	9.11	1	0.83
95	303	99	3	2.0	2.5	7.66	0	0.36
250	321	111	3	3.5	4.0	8.83	1	0.77
37	299	106	2	4.0	4.0	8.40	0	0.64

```
In [33]: 1 sns.set_style('darkgrid')
2 matplotlib.rcParams['font.size'] = 14
3 matplotlib.rcParams['figure.figsize'] = (9, 5)
4 matplotlib.rcParams['figure.facecolor'] = '#00000000'
```

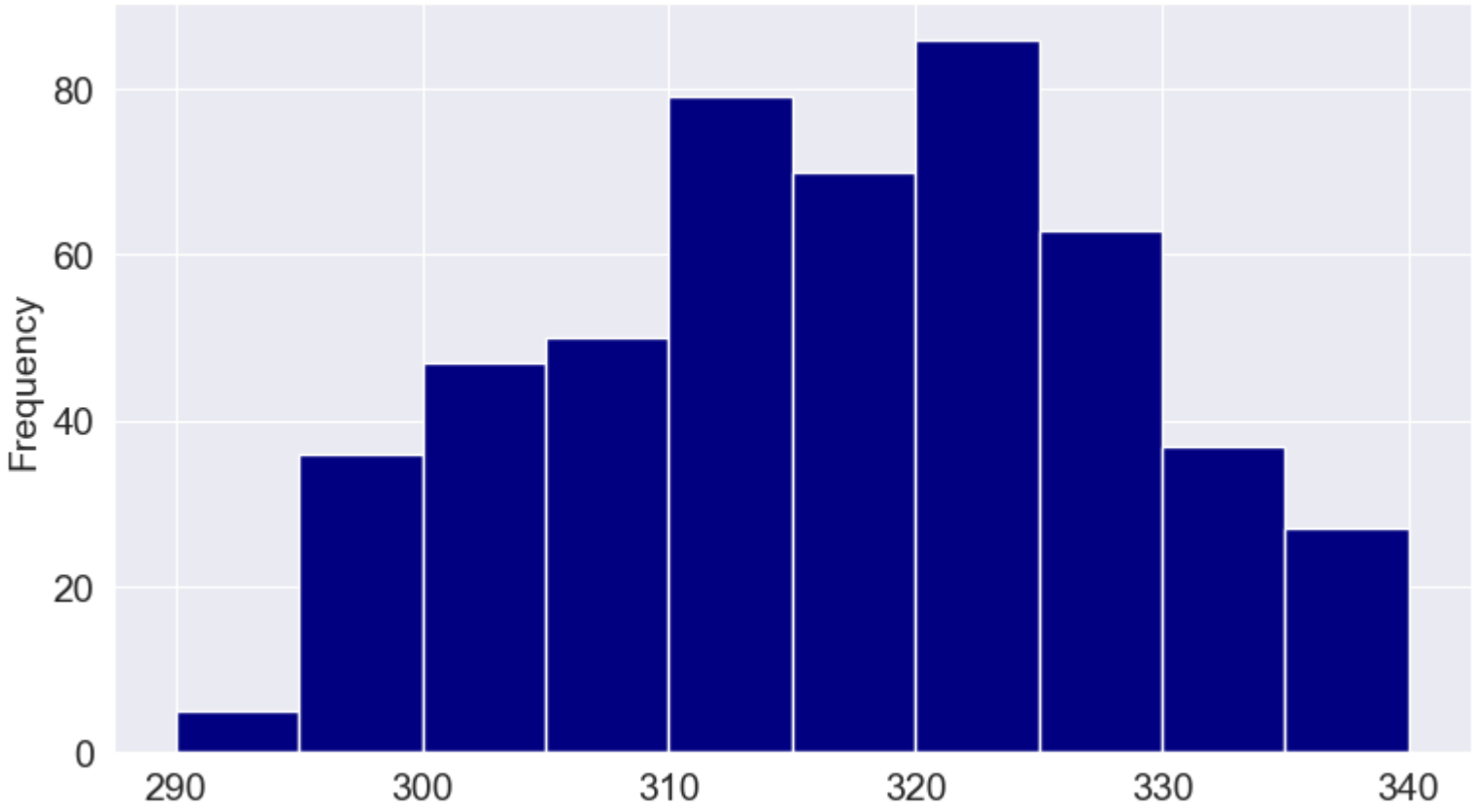
```
In [34]: 1 df['Chance of Admit'].plot(kind='hist', color='salmon');
```



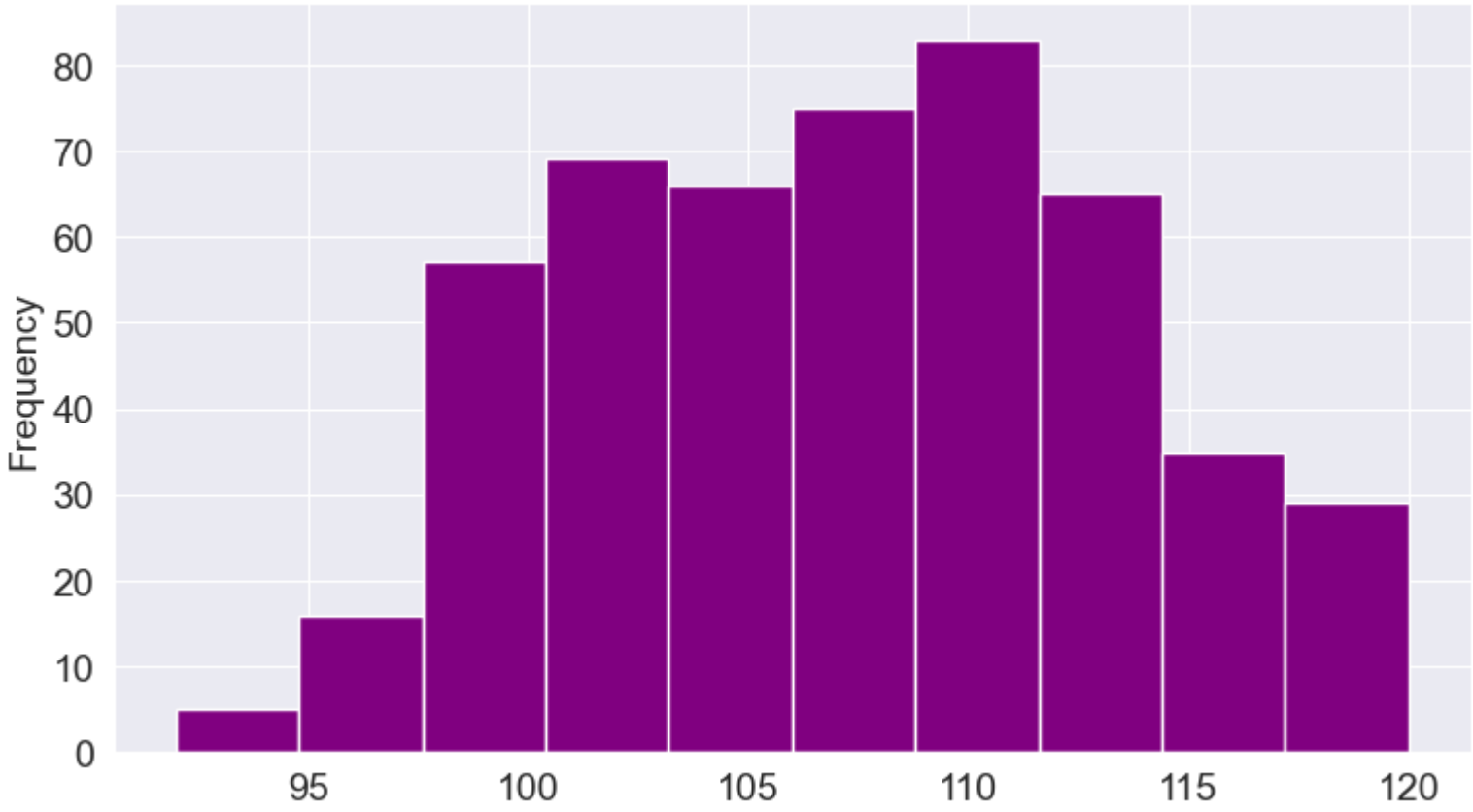
```
In [35]: 1 df['CGPA'].plot(kind='hist', color='cyan');
```



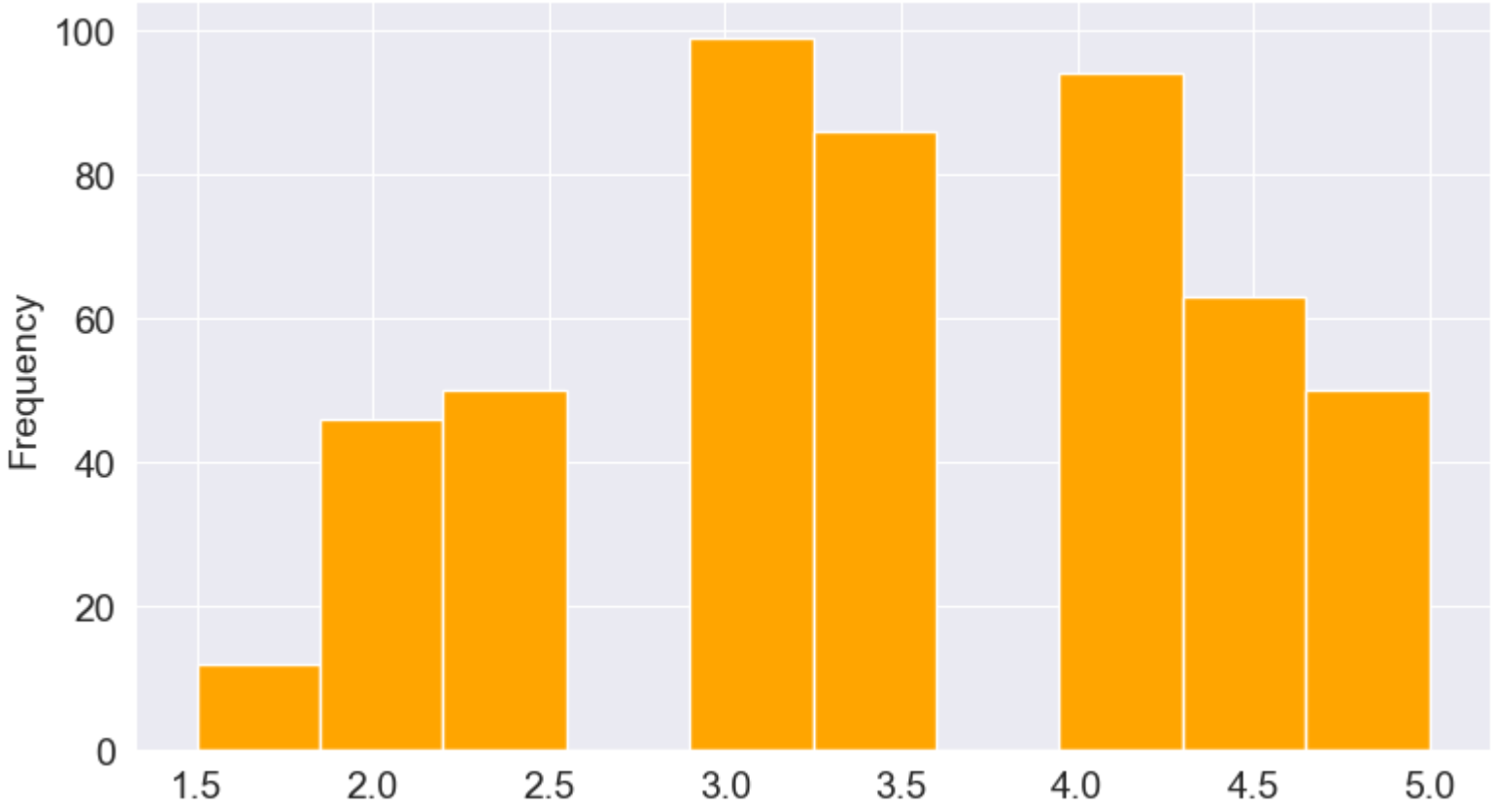
```
In [36]: 1 df['GRE Score'].plot(kind='hist', color='navy');
```



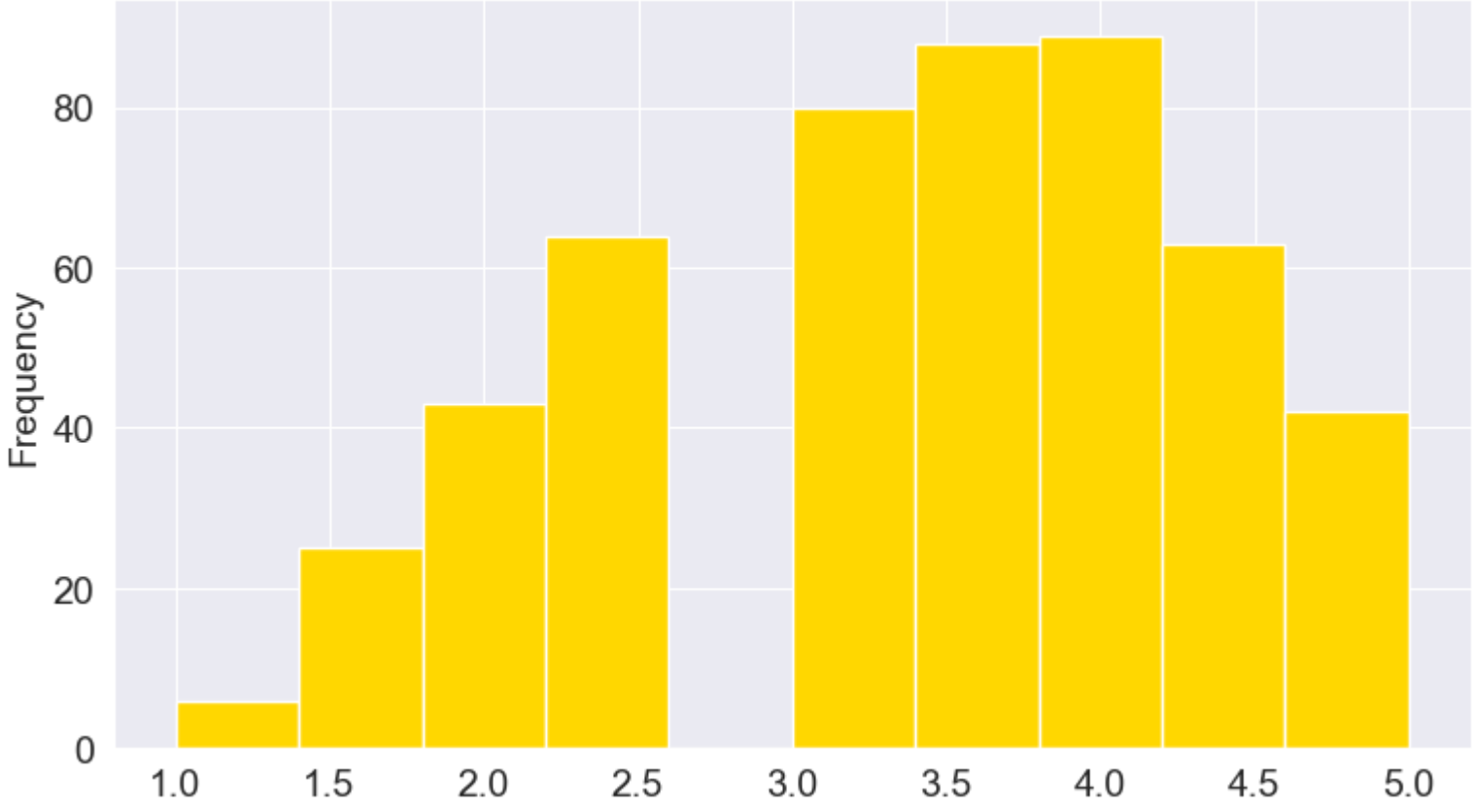
```
In [37]: 1 df['TOEFL Score'].plot(kind='hist', color='purple');
```



```
In [38]: 1 df['LOR'].plot(kind='hist', color='orange');
```

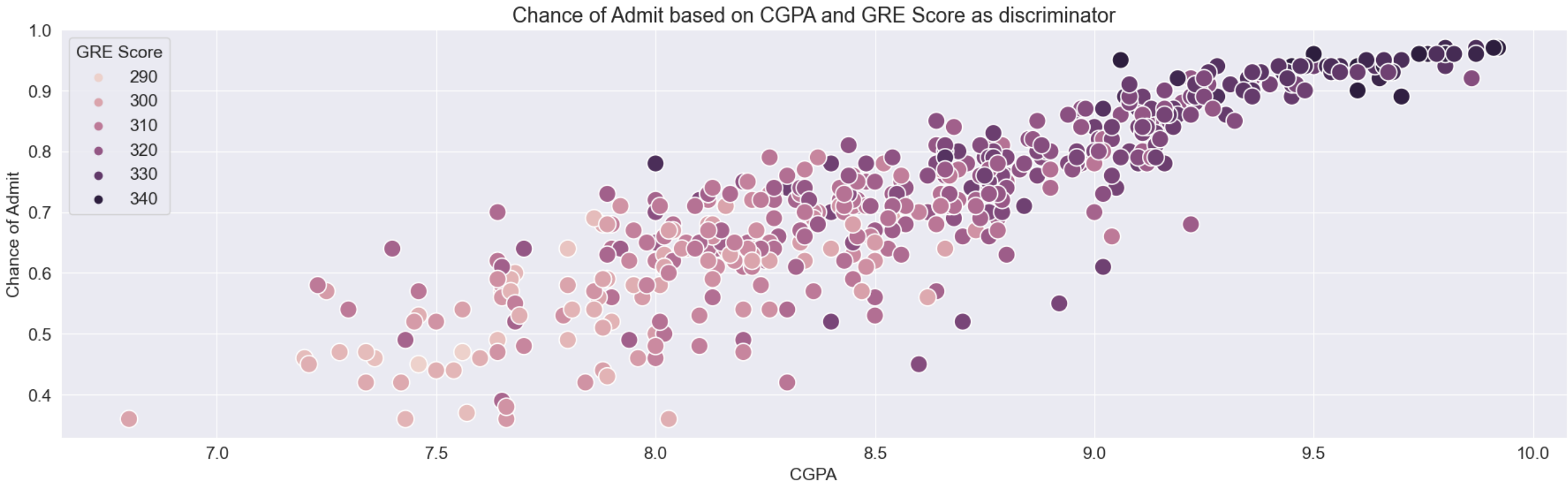


```
In [39]: 1 df['SOP'].plot(kind='hist', color='gold');
```



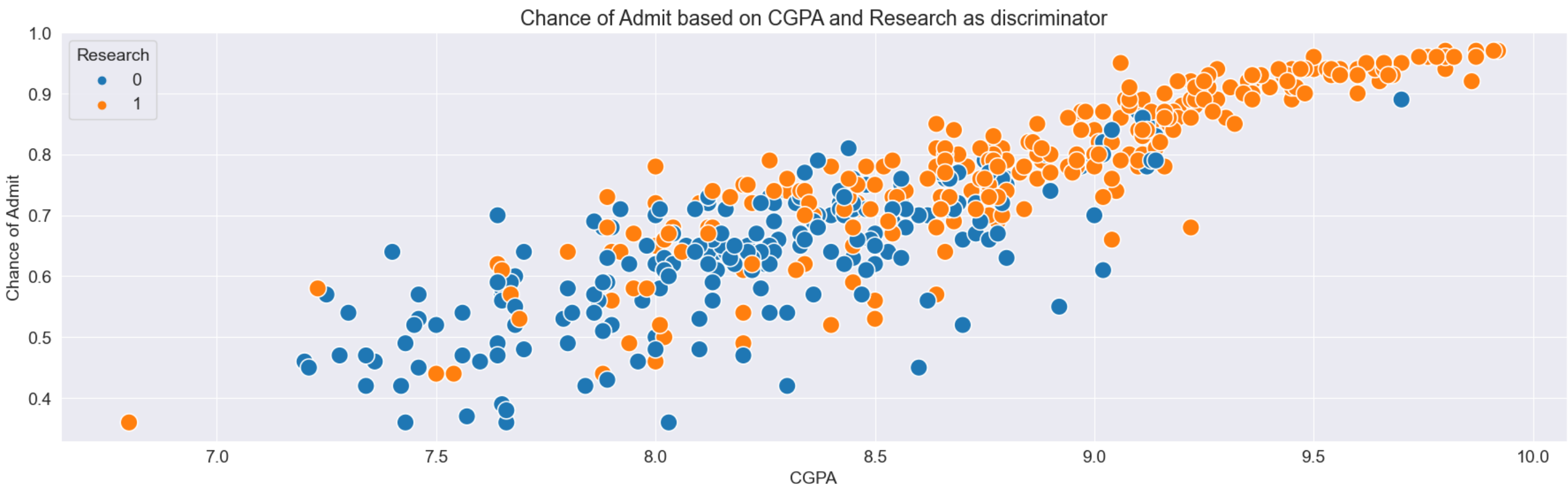
In [40]:

```
1 plt.figure(figsize=(22, 6))
2 plt.title('Chance of Admit based on CGPA and GRE Score as discriminator')
3
4 sns.scatterplot(df['CGPA'], df['Chance of Admit'], hue=df['GRE Score'], s=200);
```



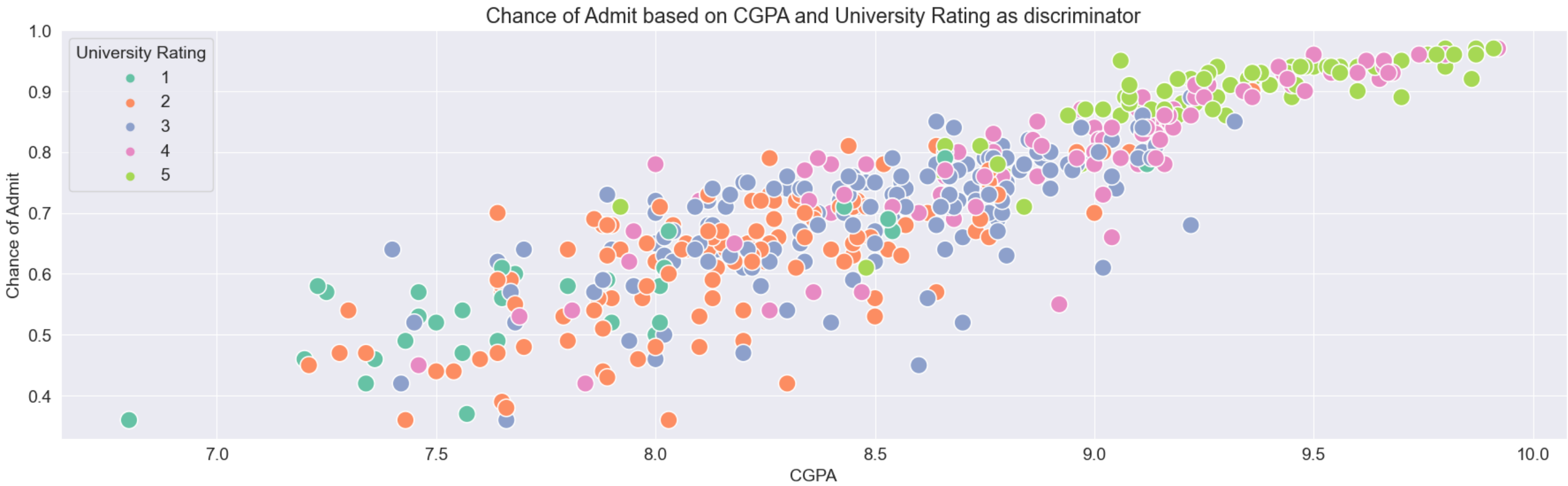
In [41]:

```
1 plt.figure(figsize=(22, 6))
2 plt.title('Chance of Admit based on CGPA and Research as discriminator')
3
4
5 sns.scatterplot(df['CGPA'], df['Chance of Admit'], hue=df['Research'], s=200);
```



In [42]:

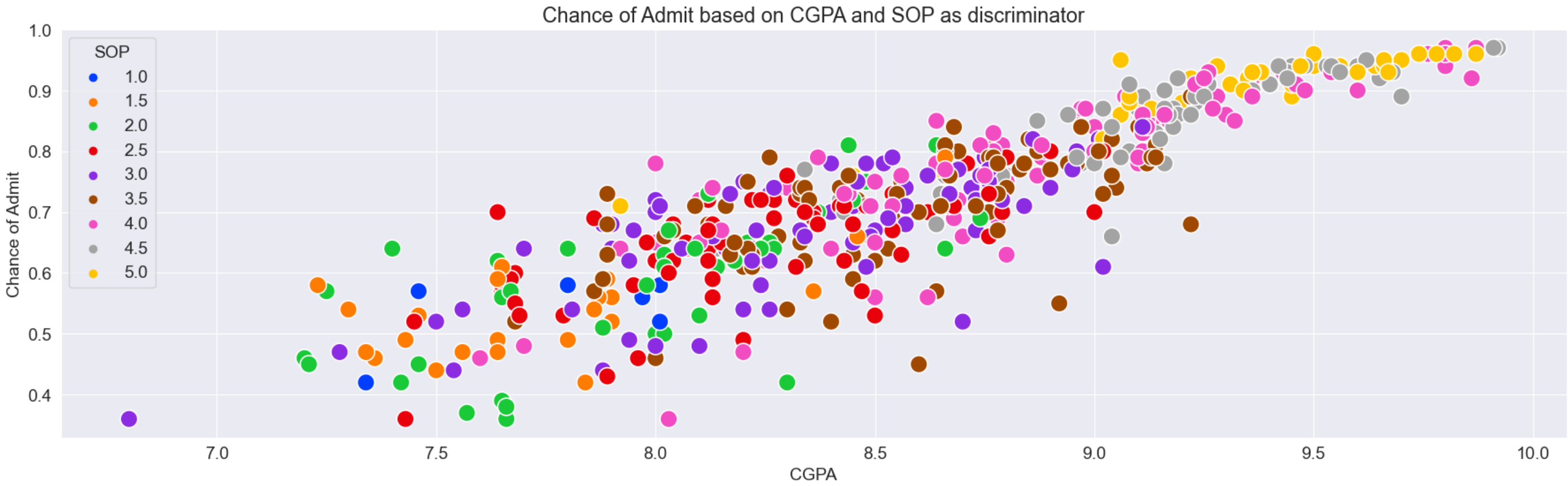
```
1 plt.figure(figsize=(22, 6))
2 plt.title('Chance of Admit based on CGPA and University Rating as discriminator')
3
4 sns.scatterplot(df['CGPA'], df['Chance of Admit'], hue=df['University Rating'], s=200, palette="Set2");
```





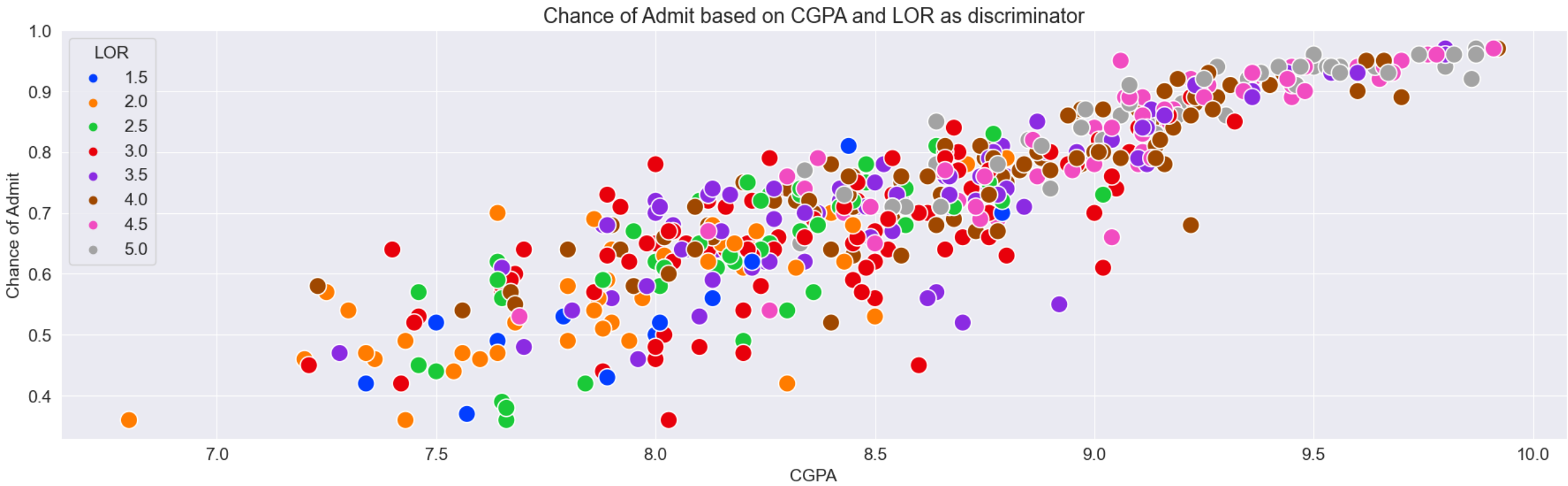
In [43]:

```
1 plt.figure(figsize=(22, 6))
2 plt.title('Chance of Admit based on CGPA and SOP as discriminator')
3
4 sns.scatterplot(df['CGPA'], df['Chance of Admit'], hue=df['SOP'], s=200, palette="bright");
```



In [44]:

```
1 plt.figure(figsize=(22, 6))
2 plt.title('Chance of Admit based on CGPA and LOR as discriminator')
3
4 sns.scatterplot(df['CGPA'], df['Chance of Admit'], hue=df['LOR'], s=200, palette="bright");
```



In [45]:

```
1 cgpa_df = df.groupby('CGPA')[['Chance of Admit', 'GRE Score', 'TOEFL Score']].mean()
2 cgpa_df
```

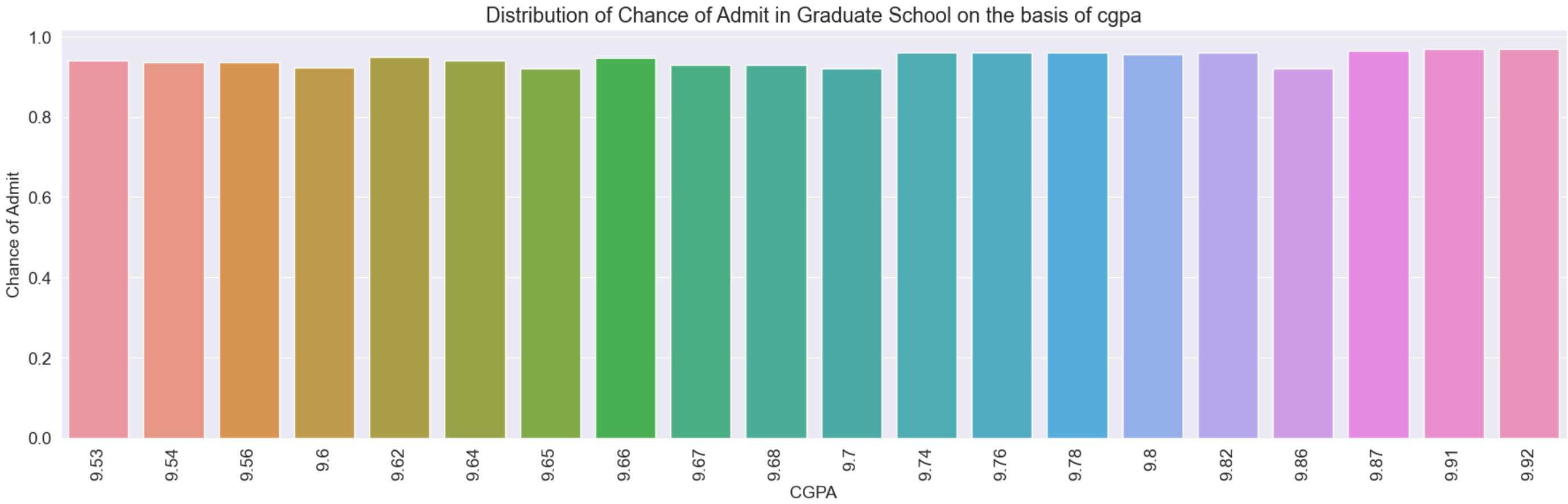
Out[45]:

	Chance of Admit	GRE Score	TOEFL Score
CGPA			
6.80	0.360	300.0	99.0
7.20	0.460	295.0	93.0
7.21	0.450	298.0	97.0
7.23	0.580	310.0	110.0
7.25	0.570	302.0	99.0
...	...	...	...
9.82	0.960	335.0	117.0
9.86	0.920	323.0	111.0
9.87	0.965	335.5	118.5
9.91	0.970	340.0	120.0
9.92	0.970	340.0	120.0

184 rows × 3 columns

In [46]:

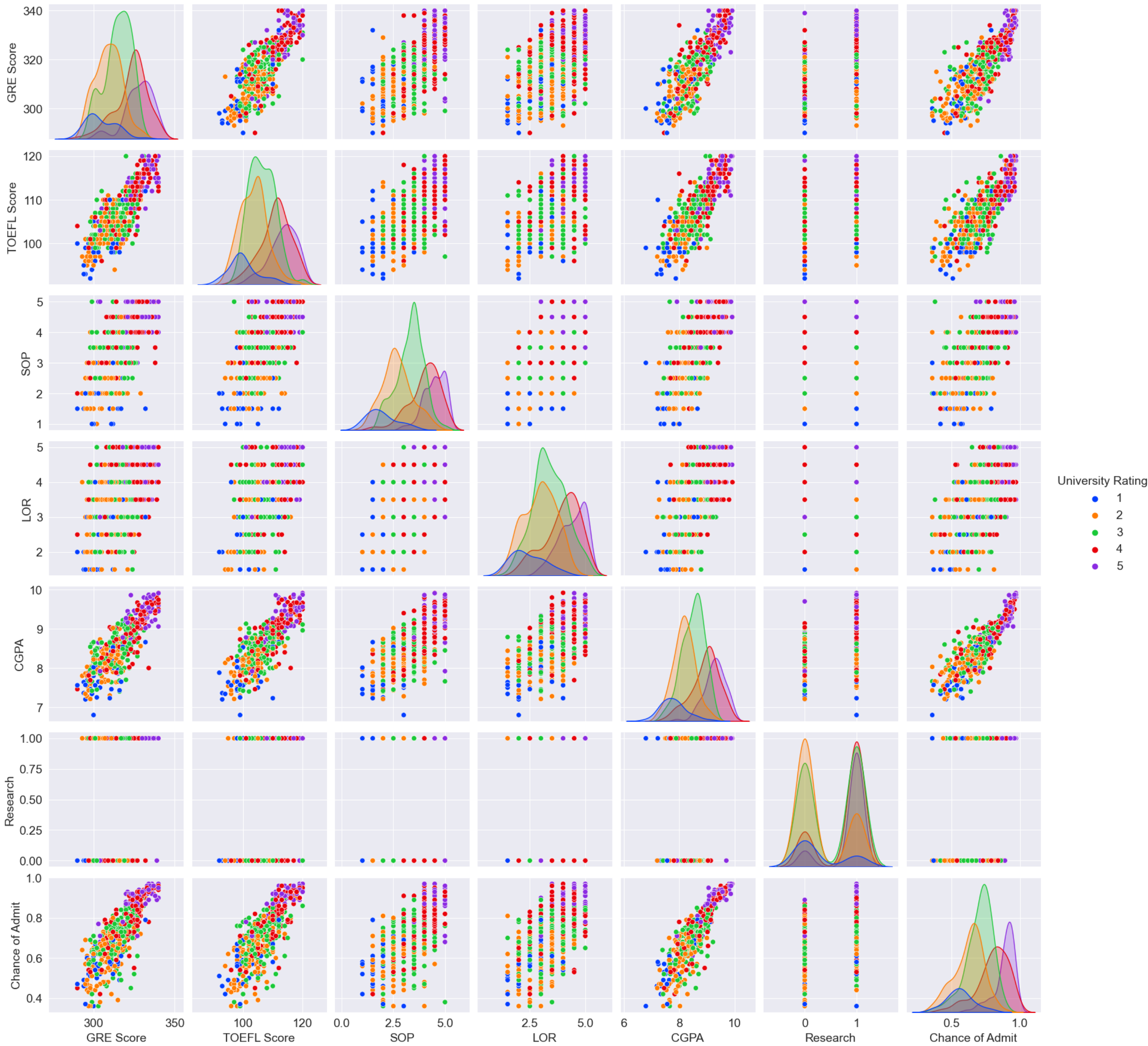
```
1 plt.figure(figsize=(22,6))
2 plt.xticks(rotation=90)
3 plt.title("Distribution of Chance of Admit in Graduate School on the basis of cgpa")
4 sns.barplot(cgpa_df.tail(20).index, cgpa_df['Chance of Admit'].tail(20));
```



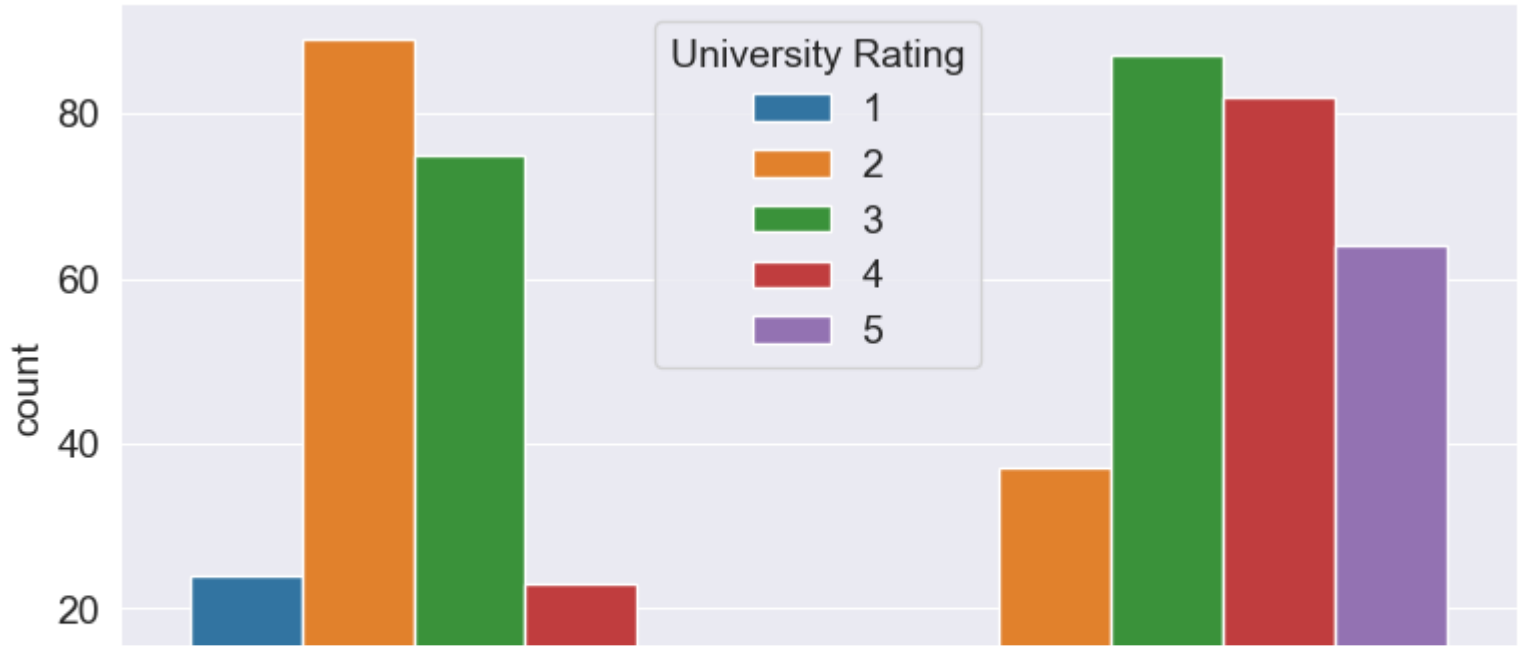
In [47]:

```
1 print("Various types of charts for pairs of features within Graduate Admission dataframe based on University Rating:")
2 sns.pairplot(df, hue='University Rating',palette="bright");
```

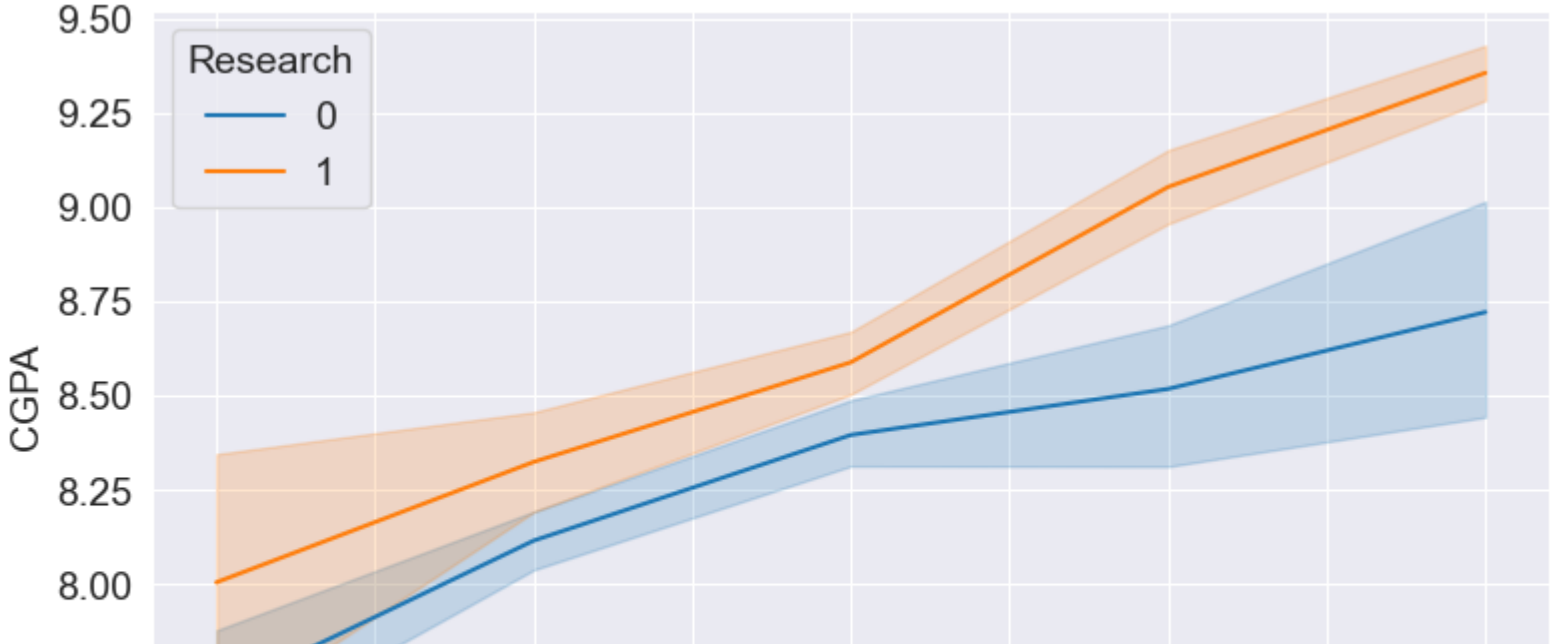
Various types of charts for pairs of features within Graduate Admission dataframe based on University Rating:



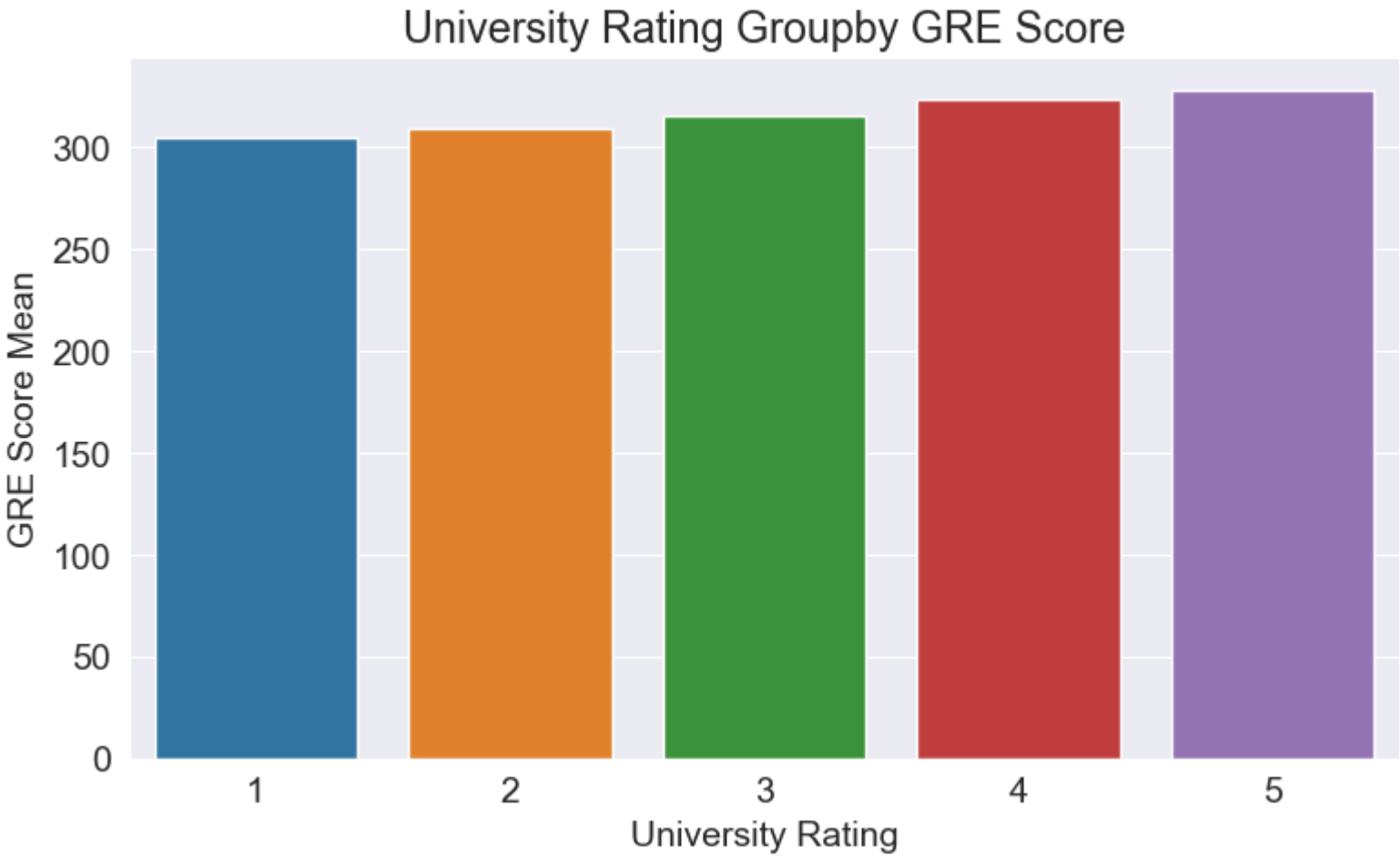
```
In [48]: 1 sns.countplot(x='Research', hue='University Rating', data=df)
2 plt.show()
```



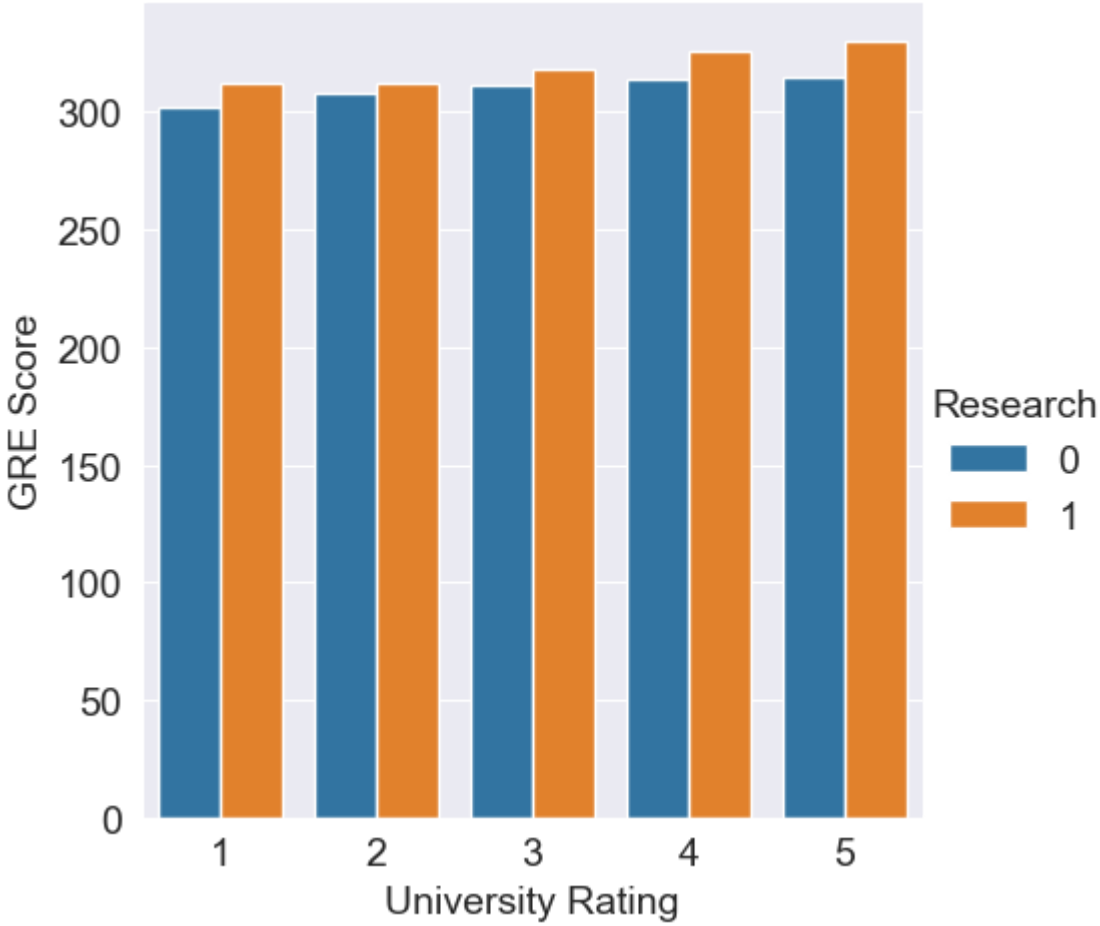
```
In [49]: 1 sns.lineplot(y='CGPA', x='University Rating',
2             hue='Research',data=df)
3 plt.show()
```



```
In [50]: 1 df.groupby('University Rating')['GRE Score'].mean()
2 sns.barplot(x=df.groupby('University Rating')['GRE Score'].mean().index,
3            y=df.groupby('University Rating')['GRE Score'].mean().values)
4 plt.ylabel('GRE Score Mean')
5 plt.title('University Rating Groupby GRE Score')
6 plt.show()
```



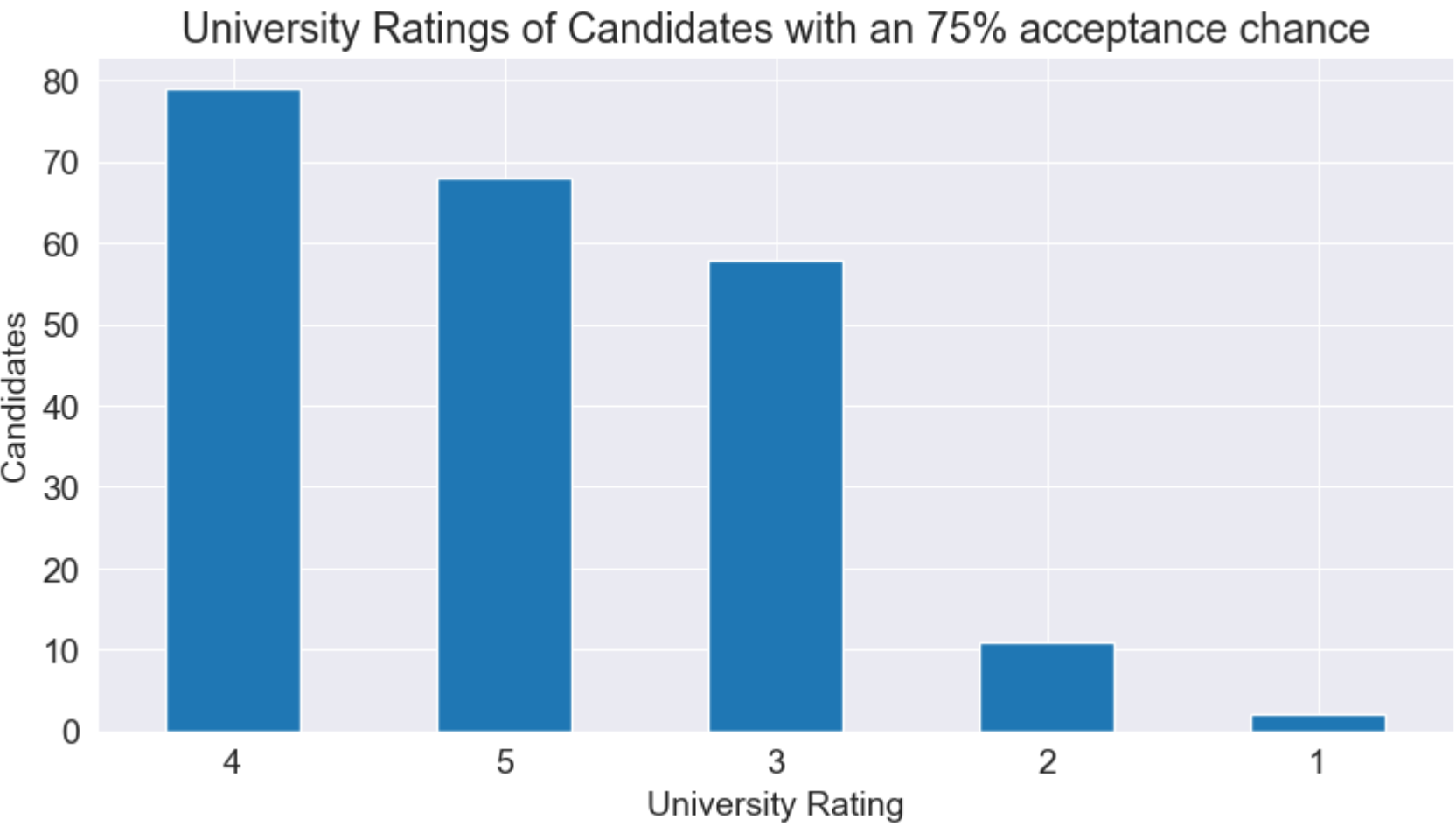
```
In [51]: 1 tt = df.groupby(['University Rating', 'Research']).mean().reset_index()
2 sns.factorplot(x='University Rating', y='GRE Score', hue='Research', data=tt, kind='bar')
3 plt.show()
```





In [52]:

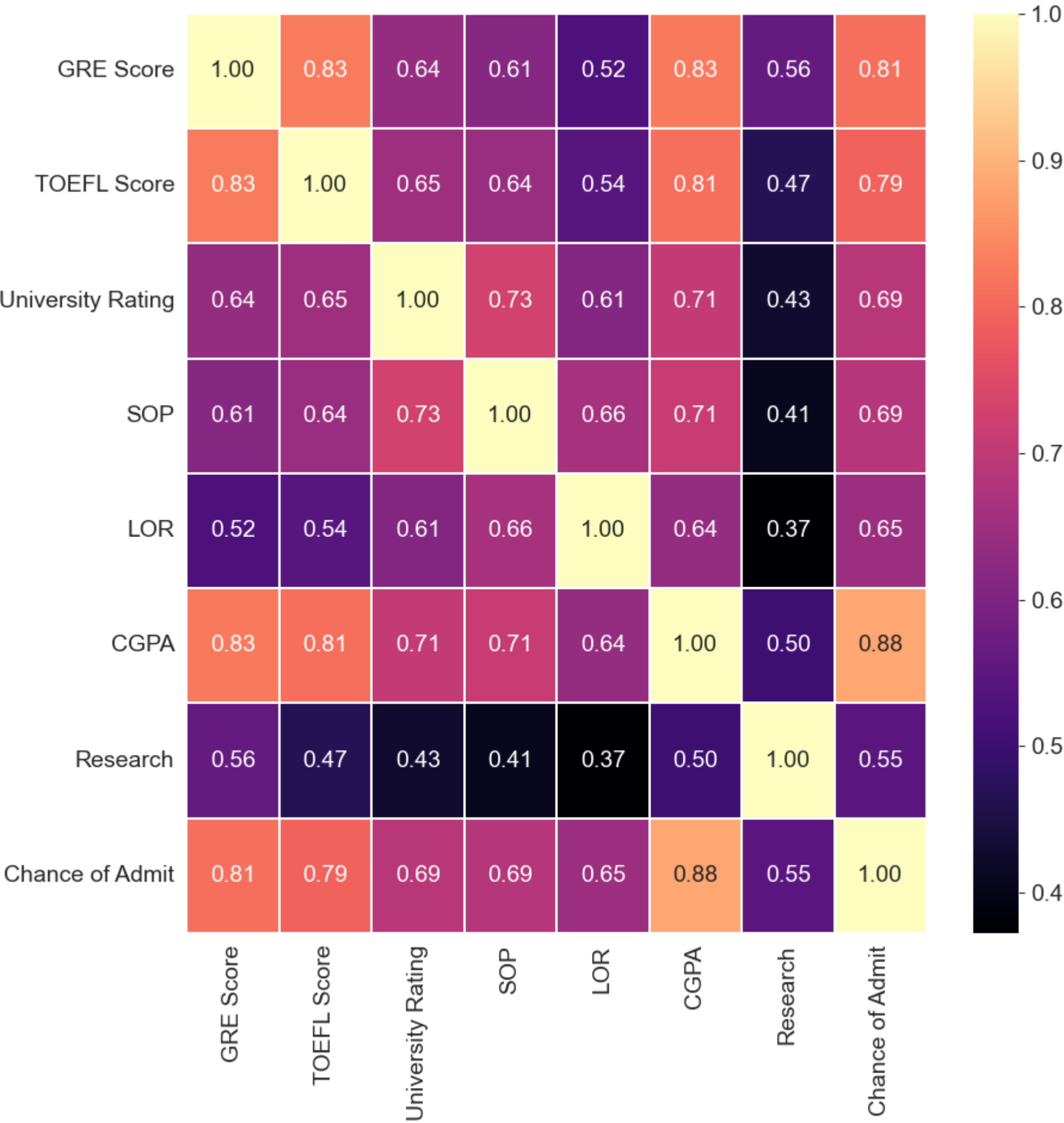
```
1 s = df[df["Chance of Admit"] >= 0.75]["University Rating"].value_counts().head(5)
2 plt.title("University Ratings of Candidates with an 75% acceptance chance")
3 color_list=['red','blue','yellow','orange','black']
4 s.plot(kind='bar',figsize=(10, 5))
5 plt.xlabel("University Rating")
6 plt.ylabel("Candidates")
7 plt.xticks(rotation=360)
8 plt.show()
```



In [53]:

```
1 fig = px.scatter_3d(df, x="CGPA", y="GRE Score", z="TOEFL Score", hover_name="Chance of Admit",)
2 fig.show()
```

```
In [54]: 1 plt.figure(figsize=(10, 10))
2 sns.heatmap(df.corr(), annot=True, linewidths=0.05, fmt= '.2f',cmap="magma")
3 plt.show()
```



Asking Questions and Answering them For Better Insights

Asking several predictive, insightful questions about the graduate admission dataset followed by answering them either by computing the results using Numpy/Pandas or by plotting appropriate graphs using Matplotlib/Seaborn Python libraries

Question 01: Who are the top 20 students with highest chance?



```
In [55]: 1 top_candidates = df.sort_values('Chance of Admit', ascending=False).head(20)
2 top_candidates
```

Out[55]:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
Serial No.								
203	340	120	5	4.5	4.5	9.91	1	0.97
144	340	120	4	4.5	4.0	9.92	1	0.97
25	336	119	5	4.0	3.5	9.80	1	0.97
204	334	120	5	4.0	5.0	9.87	1	0.97
72	336	112	5	5.0	5.0	9.76	1	0.96
214	333	119	5	5.0	4.5	9.78	1	0.96
497	337	117	5	5.0	5.0	9.87	1	0.96
82	340	120	4	5.0	5.0	9.50	1	0.96
131	339	114	5	4.0	4.5	9.76	1	0.96
149	339	116	4	4.0	3.5	9.80	1	0.96
385	340	113	4	5.0	5.0	9.74	1	0.96
386	335	117	5	5.0	5.0	9.82	1	0.96
430	340	115	5	5.0	4.5	9.06	1	0.95
400	333	117	4	5.0	4.0	9.66	1	0.95
213	338	120	4	5.0	5.0	9.66	1	0.95
24	334	119	5	5.0	4.5	9.70	1	0.95
373	336	119	4	4.5	4.0	9.62	1	0.95
215	331	117	4	4.5	5.0	9.42	1	0.94
35	331	112	5	4.0	5.0	9.80	1	0.94
71	332	118	5	5.0	5.0	9.64	1	0.94

Question 02: What is the CGPA for top 20 candidates with highest chance of admission?

```
In [56]: 1 top_candidates = df.sort_values('Chance of Admit', ascending=False).head(20)
2 top_candidates[['CGPA', 'Chance of Admit']]
```

Out[56]:

	CGPA	Chance of Admit
Serial No.		
203	9.91	0.97
144	9.92	0.97
25	9.80	0.97
204	9.87	0.97
72	9.76	0.96
214	9.78	0.96
497	9.87	0.96
82	9.50	0.96
131	9.76	0.96
149	9.80	0.96
385	9.74	0.96
386	9.82	0.96
430	9.06	0.95
400	9.66	0.95
213	9.66	0.95
24	9.70	0.95
373	9.62	0.95
215	9.42	0.94
35	9.80	0.94
71	9.64	0.94

Question 03: How many percent of candidates with 'Chance of Admit'>=75% had Research experience?

```
In [57]: 1 top_OneFourth_df = df[df['Chance of Admit']>=0.75]
2 top_OneFourth_df
3 research_df = top_OneFourth_df.groupby('Research').count()
4 research_df
```

Out[57]:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Chance of Admit
Research							
0	34	34	34	34	34	34	34
1	184	184	184	184	184	184	184

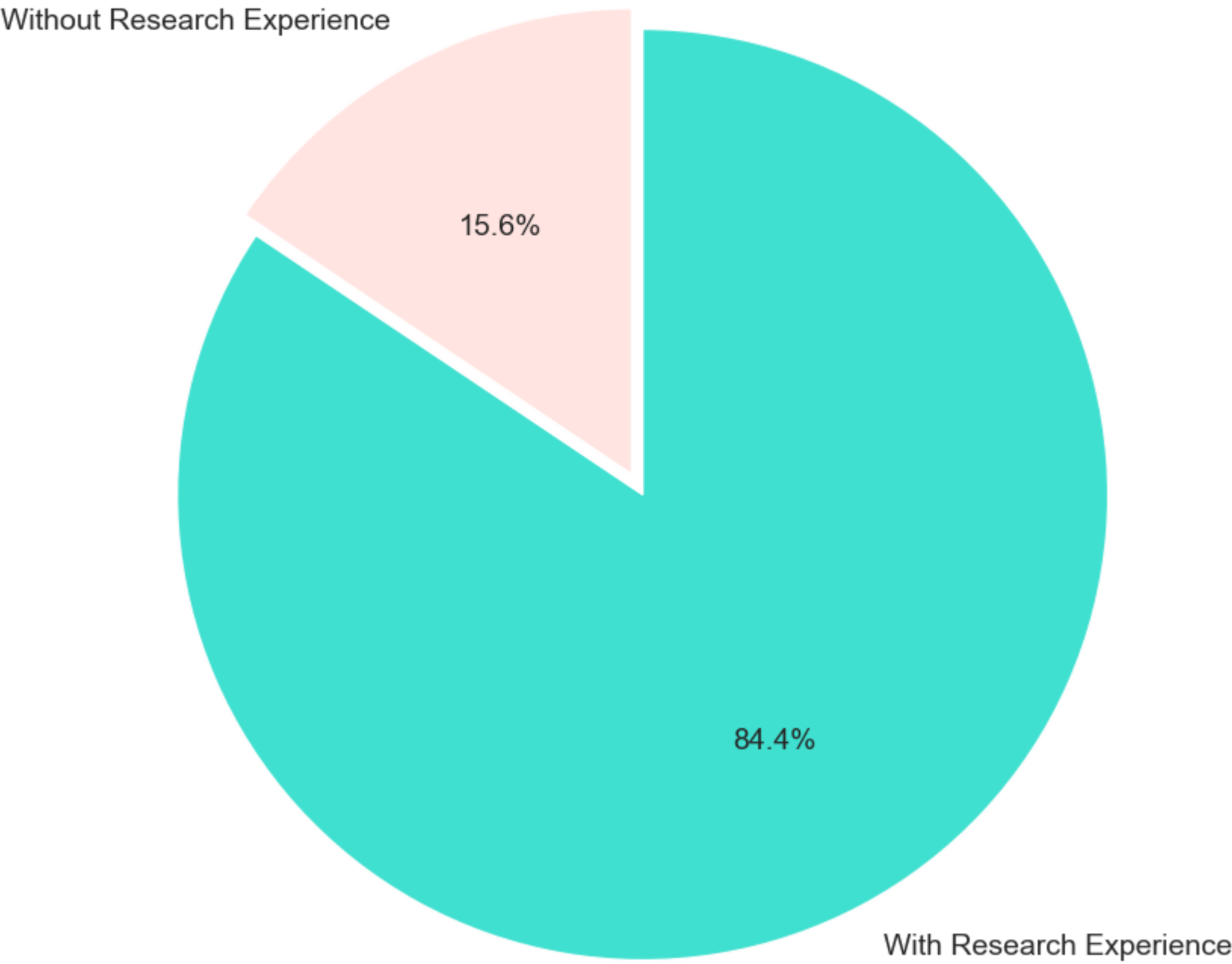
```
In [58]: 1 research_percent_df = ( research_df.at[1, 'Chance of Admit'] / research_df['Chance of Admit'].sum() ) * 100
2 research_percent_df
```

Out[58]: 84.40366972477065

In [59]:

```
1 plt.figure(figsize=(22,10))
2 plt.title("Percentage of candidates with Research Experience and 'Chance of Admit'>75%")
3 colors = ['mistyrose', 'turquoise']
4 explode =(0, 0.05)
5 plt.pie(research_df['Chance of Admit'], labels=['Without Research Experience', 'With Research Experience'],
6         autopct='%1.1f%%', startangle=90, colors=colors, explode = explode);
```

Percentage of candidates with Research Experience and 'Chance of Admit'>75%



Question 04: What is the Average of Chance of Admit for applicants with (SOP && LOR) >= 3.5 ?

In [60]:

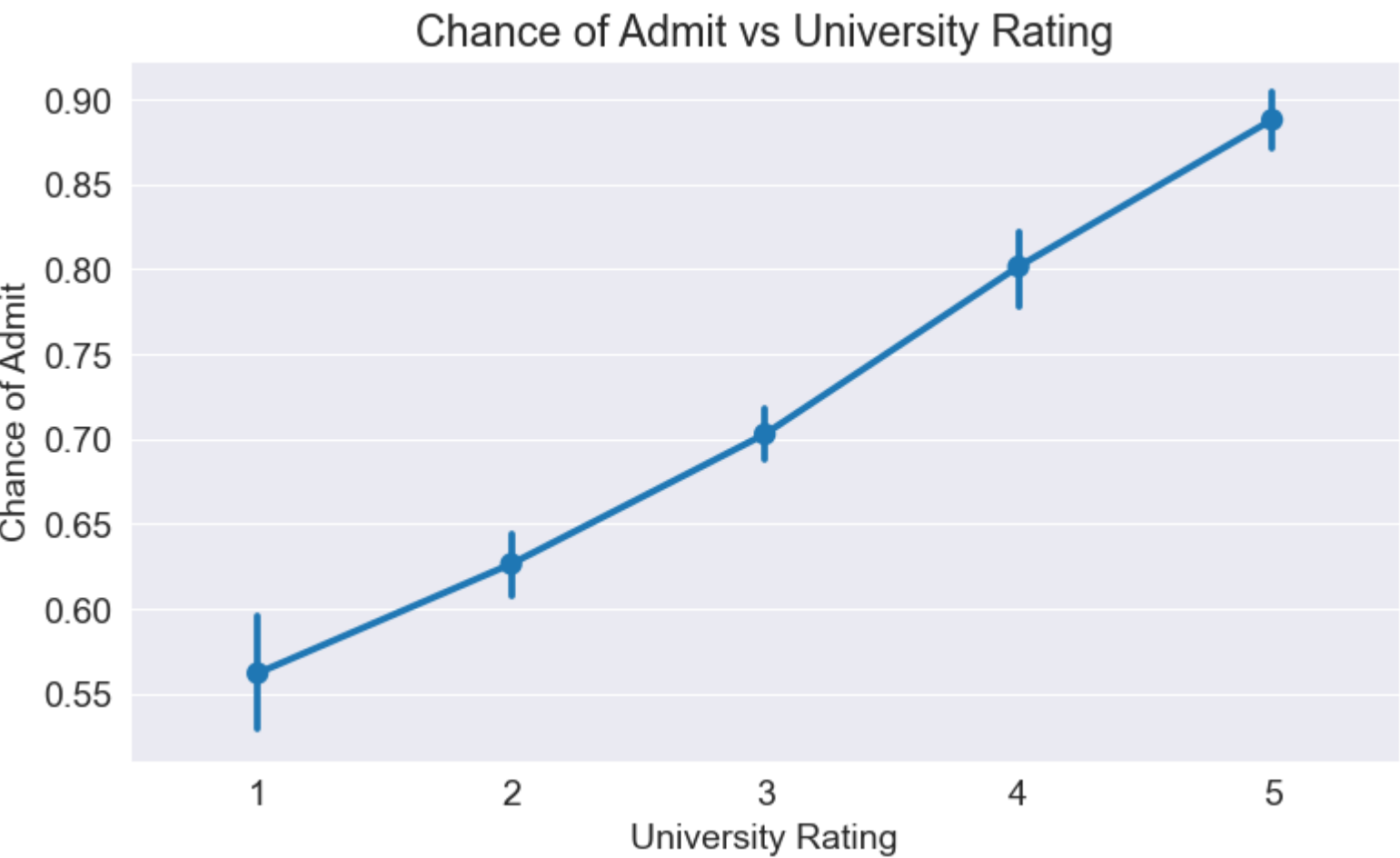
```
1 sop_lor_df = df[(df['SOP']>=3.5) & (df['LOR']>=3.5)]
2 sop_lor_avg = sop_lor_df['Chance of Admit'].mean() * 100
3 print("Average Chance of Admit for applicants with (SOP && LOR) >= 3.5 is: {:.2f} %.".format(sop_lor_avg))
```

Average Chance of Admit for applicants with (SOP && LOR) >= 3.5 is: 81.85 %.

Question 05: How does the University Rating improve the chance of getting admitted ?

In [61]:

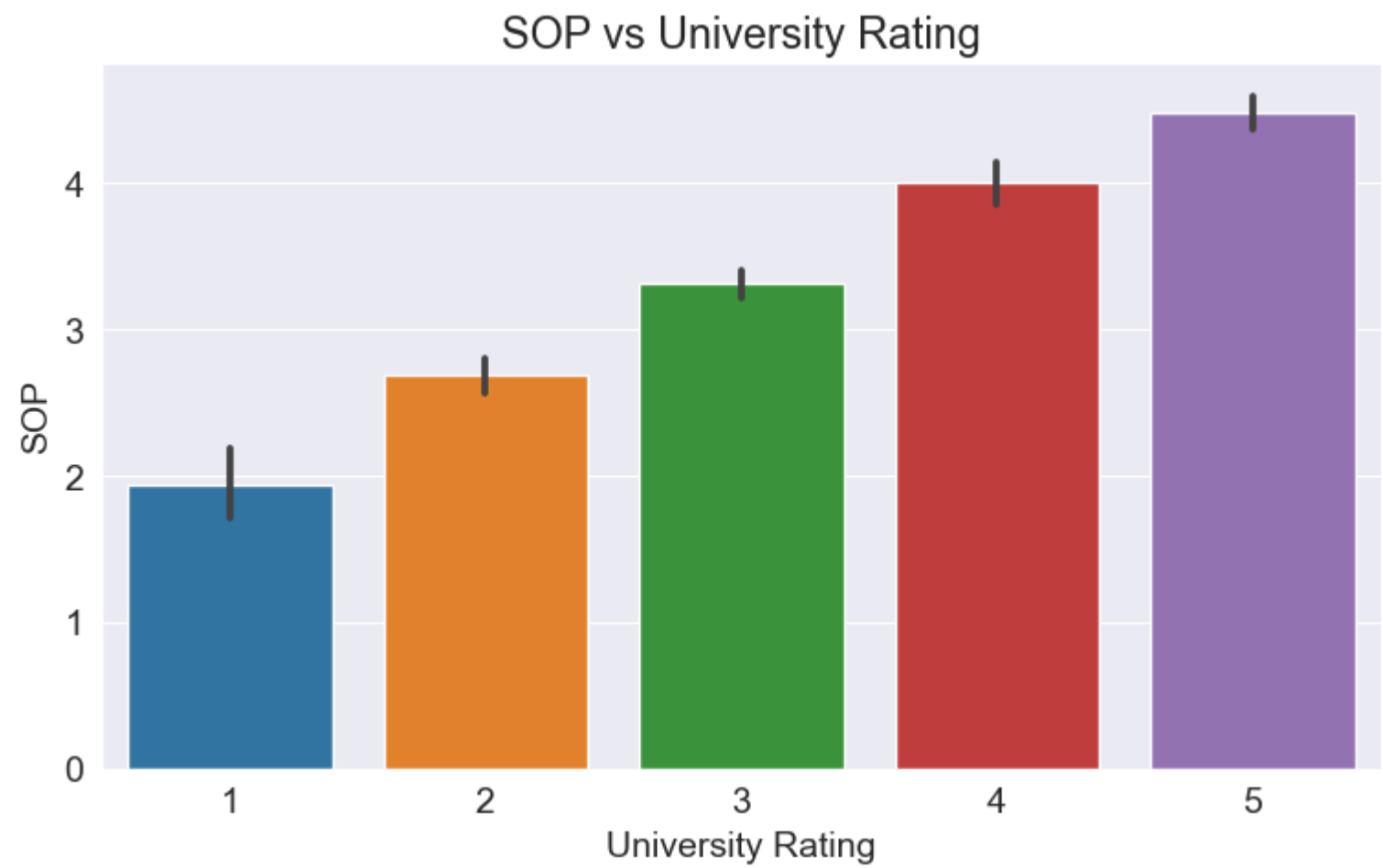
```
1 sns.pointplot(df['University Rating'] , df['Chance of Admit'])
2 plt.title('Chance of Admit vs University Rating')
3 plt.show()
```



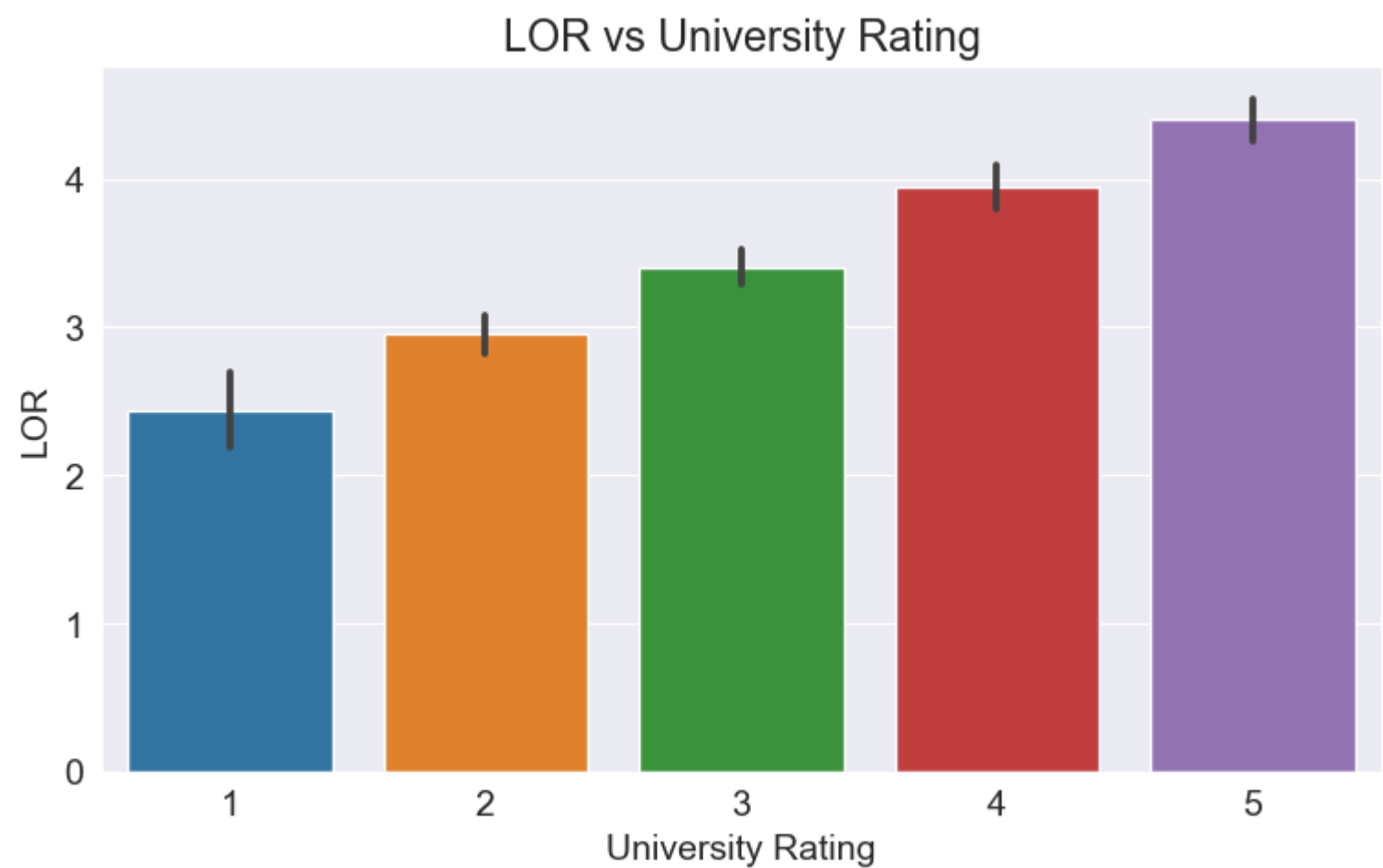
A University Rating of 4 and above have a very good chance of admittance

Question 06: Does the University Rating influence my SOP and LOR Rating?

```
In [62]: 1 sns.barplot(df['University Rating'] , df['SOP'])
2 plt.title('SOP vs University Rating')
3 plt.show()
```



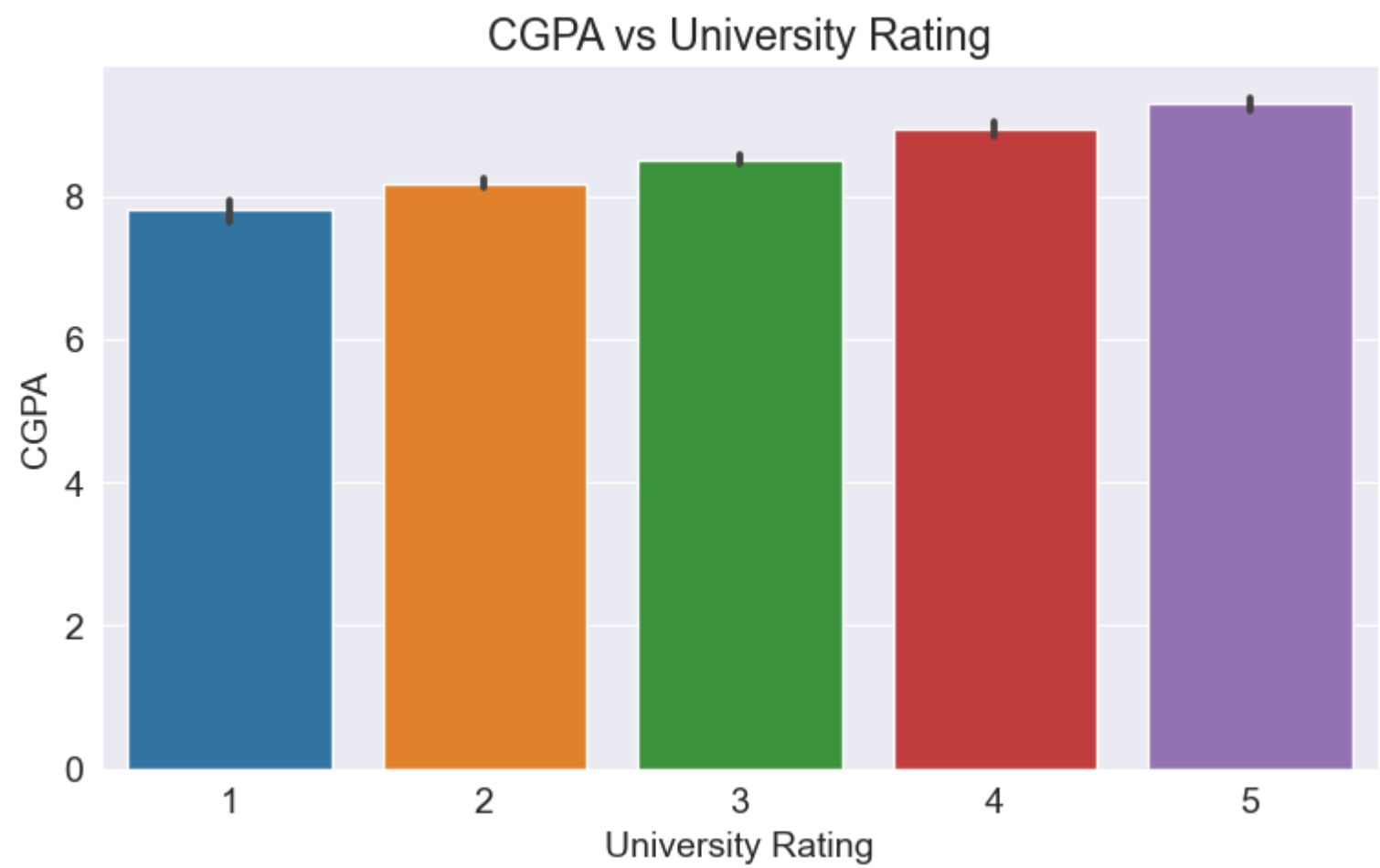
```
In [63]: 1 sns.barplot(df['University Rating'] , df['LOR'])
2 plt.title('LOR vs University Rating')
3 plt.show()
```



The more the university rating you have , the more rating your SOP & LOR will get , this is relatable because SOP and LOR are attested by the university in which you studied and hence the University Rating influences the rating of your SOP & LOR

Question 07: Does CGPA influence my University Rating?

```
In [64]: 1 sns.barplot(df['University Rating'] , df['CGPA'])
2 plt.title('CGPA vs University Rating')
3 plt.show()
```

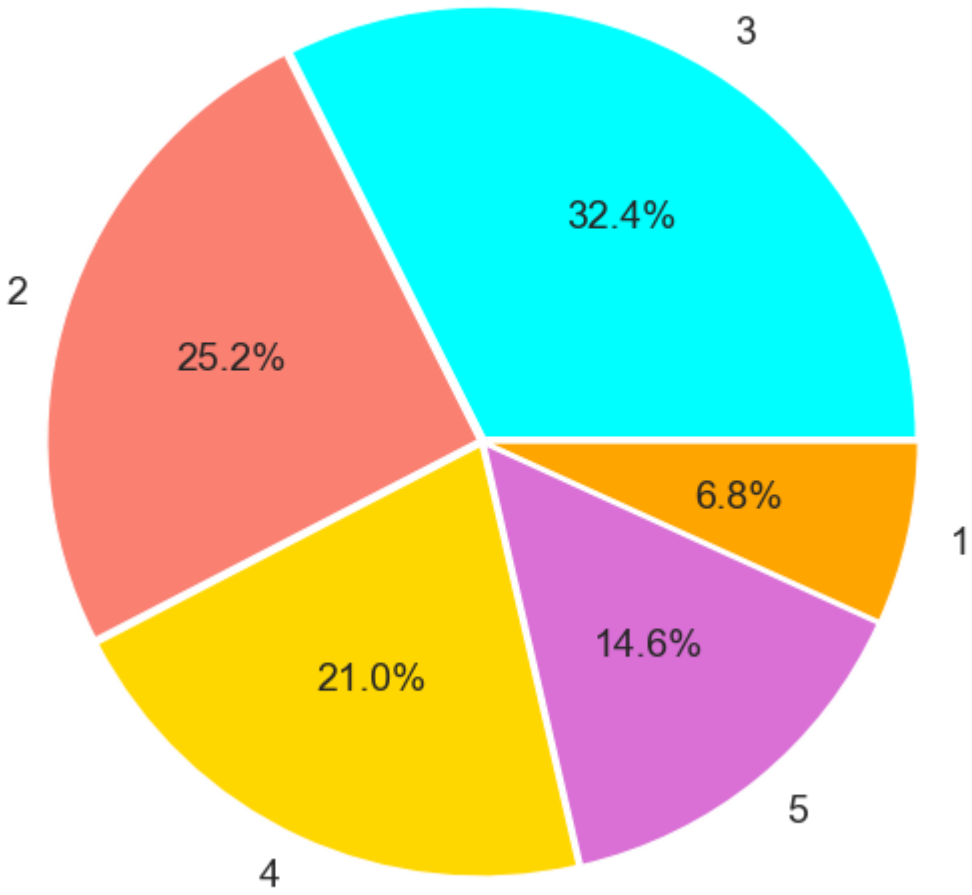


*Students with more that 8.5 CGPA have high University Rating*

Question 08: How much percentage of students are in each university type?

```
In [65]: 1 # df.groupby(['University Rating'])['University Rating'].count().plot.pie(autopct='%f%%')
2 # plt.title('Percentage of students from different rated university')
3 # plt.show()
4
5 #The analysis of the university rating values was made.
6 #A maximum of 3.0 is shown in the extracted results. All of these analysis results are given in pie.
7 colors = ['cyan','salmon','gold','orchid','orange']
8 explode = [0.01,0.01,0.01,0.01,0.01]
9 plt.figure(figsize=(7,7))
10 plt.pie(df['University Rating'].value_counts().values,explode=explode,
11         labels=df['University Rating'].value_counts().index,colors=colors,autopct='%1.1f%%')
12 plt.title('University Rating',color='red',fontsize=25)
13 plt.show()
```

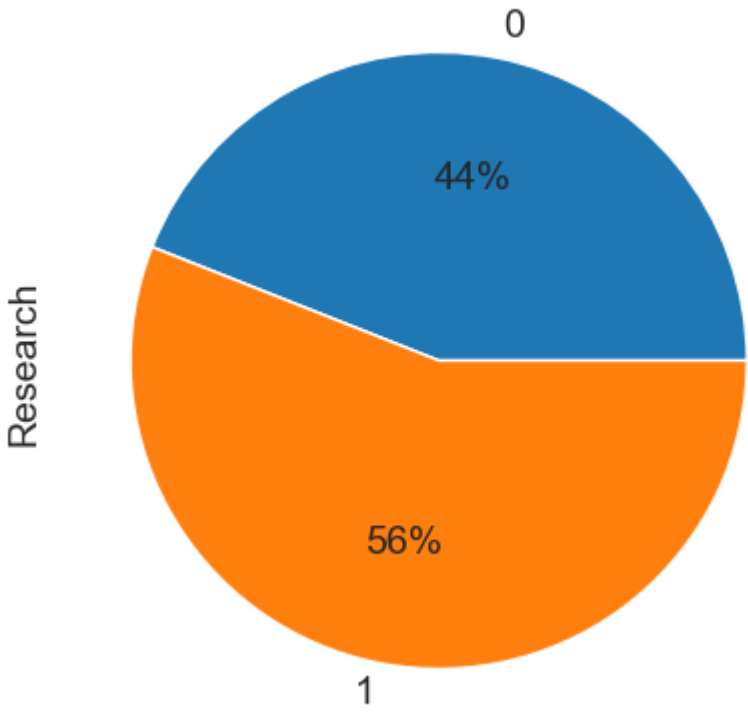
## University Rating



Question 09: How much percentage of students having Research Experience?

```
In [66]: 1 df.groupby(['Research'])['Research'].count().plot.pie(autopct='%f%%')# ,ax=ax[0] ,shadow=True )
2 plt.title('Percentage of students having Research experience')
3 plt.show()
```

## Percentage of students having Research experience



### Some Important Inferences

- A high score in GRE & TOEFL is very important
- GRE : 320+
- TOEFL : 110+
- A CGPA of more than 8.5 is a must
- Having Research experience is not very important , but having it is an added advantage
- University Rating of 4 and above is very important
- University Rating also influences the Rating of SOP & LOR

```
In [67]: 1 df.groupby('University Rating')[['SOP', 'LOR', 'CGPA']].mean()
```

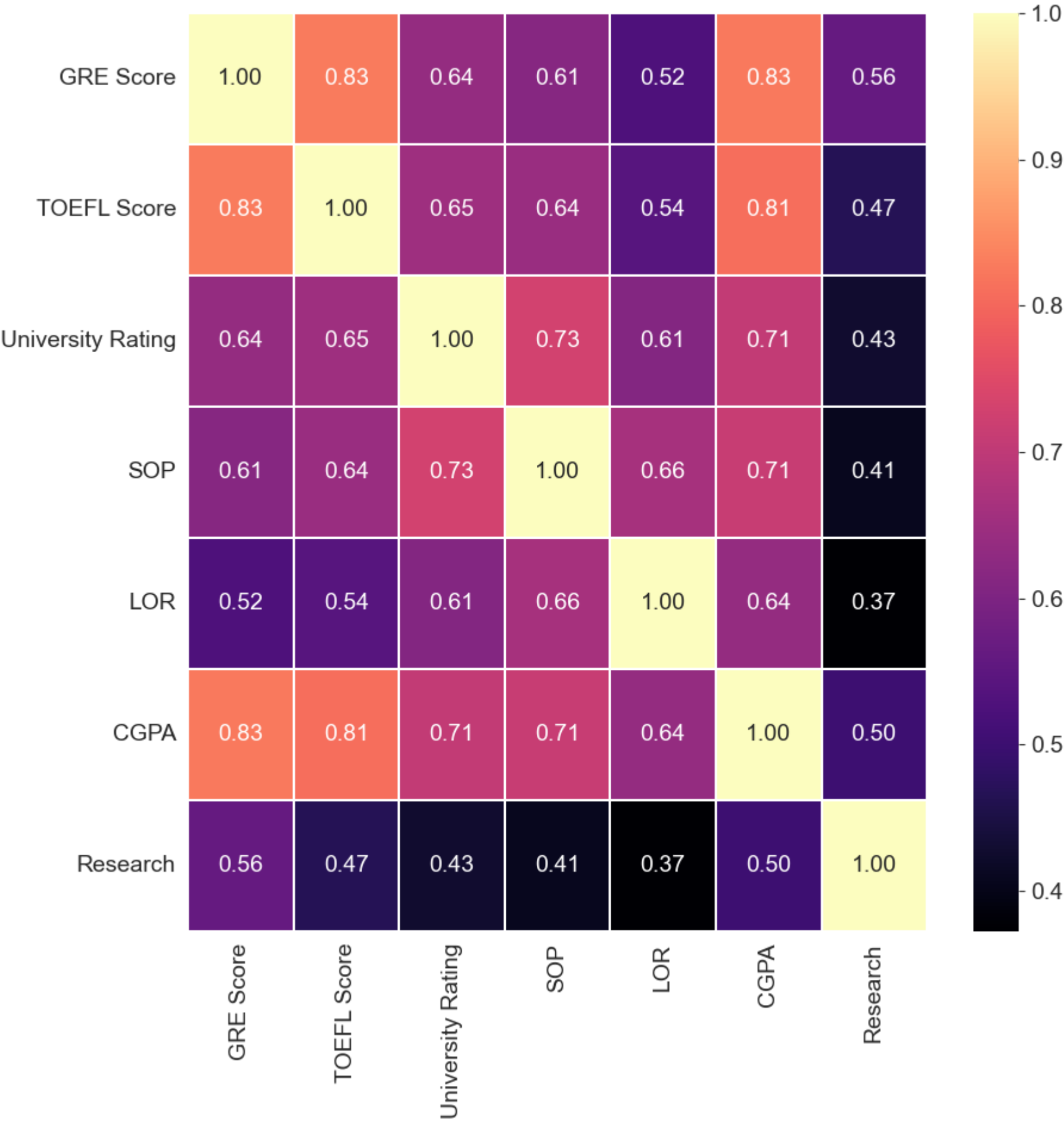
Out[67]:

	SOP	LOR	CGPA
University Rating			
1	1.941176	2.441176	7.798529
2	2.682540	2.956349	8.177778
3	3.308642	3.401235	8.500123
4	4.000000	3.947619	8.936667
5	4.479452	4.404110	9.278082

Heatmap

```
In [68]: 1 df1 = df.iloc[:, 0:7]

In [69]: 1 plt.figure(figsize=(10, 10))
2 sns.heatmap(df1.corr(), annot=True, linewidths=0.05, fmt= '.2f',cmap="magma")
3 plt.show()
```



Checking VIF

```
In [70]: 1 def compute_vif(considered_features):
2
3     X = df[considered_features]
4     # the calculation of variance inflation requires a constant
5     X['intercept'] = 1
6
7     # create dataframe to store vif values
8     vif = pd.DataFrame()
9     vif["Variable"] = X.columns
10    vif["VIF"] = [variance_inflation_factor(X.values, i) for i in range(X.shape[1])]
11    vif = vif[vif['Variable']!='intercept']
12    return vif

In [71]: 1 df1
```

Out[71]:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research
Serial No.							
1	337	118	4	4.5	4.5	9.65	1
2	324	107	4	4.0	4.5	8.87	1
3	316	104	3	3.0	3.5	8.00	1
4	322	110	3	3.5	2.5	8.67	1
5	314	103	2	2.0	3.0	8.21	0
...	...	...	...	...	...	...	...
496	332	108	5	4.5	4.0	9.02	1
497	337	117	5	5.0	5.0	9.87	1
498	330	120	5	4.5	5.0	9.56	1
499	312	103	4	4.0	5.0	8.43	0
500	327	113	4	4.5	4.5	9.04	0

500 rows × 7 columns

```
In [72]: 1 compute_vif(df1.columns).sort_values('VIF', ascending=False)
```

Out[72]:

	Variable	VIF
5	CGPA	4.777833
0	GRE Score	4.463733
1	TOEFL Score	3.904258
3	SOP	2.833239
2	University Rating	2.621300
4	LOR	2.029224
6	Research	1.493982

All VIF values are less than 5



```
In [73]: 1 df.head()
```

Out[73]:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
Serial No.								
1	337	118	4	4.5	4.5	9.65	1	0.92
2	324	107	4	4.0	4.5	8.87	1	0.76
3	316	104	3	3.0	3.5	8.00	1	0.72
4	322	110	3	3.5	2.5	8.67	1	0.80
5	314	103	2	2.0	3.0	8.21	0	0.65

```
In [74]: 1 x = df.iloc[:, :-1]
2 y = df.iloc[:, -1]
```

```
In [75]: 1 x.head()
```

Out[75]:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research
Serial No.							
1	337	118	4	4.5	4.5	9.65	1
2	324	107	4	4.0	4.5	8.87	1
3	316	104	3	3.0	3.5	8.00	1
4	322	110	3	3.5	2.5	8.67	1
5	314	103	2	2.0	3.0	8.21	0

```
In [76]: 1 y.head()
```

Out[76]:

```
Serial No.
1    0.92
2    0.76
3    0.72
4    0.80
5    0.65
Name: Chance of Admit, dtype: float64
```

```
In [77]: 1 # from sklearn.preprocessing import StandardScaler
2 # sc = StandardScaler()
3 # x = sc.fit_transform(x)
```

```
In [78]: 1 xtrain,xtest,ytrain, ytest = train_test_split(x, y, test_size = 0.2, random_state = 42)
```

```
In [79]: 1 xtrain.shape, xtest.shape, ytrain.shape,ytest.shape
```

Out[79]:

```
((400, 7), (100, 7), (400,), (100,))
```

In [80]:

```
1 k = 42
2 models = [LinearRegression(),DecisionTreeRegressor(random_state = k),
3           RandomForestRegressor(random_state = k),Lasso(random_state = k),Ridge(random_state = k),
4           SVR(),AdaBoostRegressor(random_state = k),GradientBoostingRegressor(random_state = k),
5           XGBRegressor(random_state = k)]
6 for i in models:
7     print(20*','=',i,20*'=')
8     model = i
9     model.fit(xtrain,ytrain)
10    ypred = model.predict(xtest)
11    print('Training_Score   : ',model.score(xtrain,ytrain))
12    print('Testing_Score    : ',model.score(xtest,ytest))
13    print('MSE              : ',mean_squared_error(ytest,ypred))
14    print('MAE              : ',mean_absolute_error(ytest,ypred))
15    print('RMSE            : ',np.sqrt(mean_squared_error(ytest,ypred)))
16    print('MAPE            : ',mean_absolute_percentage_error(ytest,ypred))
17    print('R^2_Score       : ', r2_score(ytest,ypred) )
18    print(70*'=')
```

```
===== LinearRegression() =====
Training_Score   :  0.8220935158272195
Testing_Score    :  0.8188835723780066
MSE              :  0.0037038309448697666
MAE              :  0.04276066764019817
RMSE             :  0.0608591073288934
MAPE             :  0.06873872864871644
R^2_Score        :  0.8188835723780066
*****
===== DecisionTreeRegressor(random_state=42) =====
Training_Score   :  1.0
Testing_Score    :  0.5748166259168705
MSE              :  0.008695
MAE              :  0.0651
RMSE             :  0.09324698386543127
MAPE             :  0.1041439388354414
R^2_Score        :  0.5748166259168705
*****
===== RandomForestRegressor(random_state=42) =====
Training_Score   :  0.9684910559531074
Testing_Score    :  0.7868410904645475
MSE              :  0.004359099700000005
MAE              :  0.04415500000000004
RMSE             :  0.06602347839973297
MAPE             :  0.07109224597154623
R^2_Score        :  0.7868410904645475
*****
===== Lasso(random_state=42) =====
Training_Score   :  0.2493920395872561
Testing_Score    :  0.25365072710870284
MSE              :  0.015262842630627028
MAE              :  0.09791809312040024
RMSE             :  0.12354287770093032
MAPE             :  0.1530851719005555
R^2_Score        :  0.25365072710870284
*****
===== Ridge(random_state=42) =====
Training_Score   :  0.8220453813318152
Testing_Score    :  0.818016612172706
MSE              :  0.003721560281068162
MAE              :  0.042917516302701075
RMSE             :  0.061004592294909746
MAPE             :  0.06897860317909855
R^2_Score        :  0.818016612172706
*****
===== SVR() =====
Training_Score   :  0.6828082393392991
Testing_Score    :  0.6488683464303023
MSE              :  0.007180642315500319
MAE              :  0.0656958619266159
RMSE             :  0.08473867072063568
MAPE             :  0.1010695975940182
R^2_Score        :  0.6488683464303023
*****
===== AdaBoostRegressor(random_state=42) =====
Training_Score   :  0.8188963182373812
Testing_Score    :  0.7425724070328582
MSE              :  0.00526439427617805
MAE              :  0.05590712707706519
RMSE             :  0.0725561456816585
MAPE             :  0.08658446128281667
R^2_Score        :  0.7425724070328582
*****
===== GradientBoostingRegressor(random_state=42) =====
Training_Score   :  0.9243656602090589
Testing_Score    :  0.7773537419514935
MSE              :  0.004553115977091958
MAE              :  0.04597086322530619
RMSE             :  0.06747678102200755
MAPE             :  0.07473722154893324
R^2_Score        :  0.7773537419514935
*****
===== XGBRegressor(base_score=None, booster=None, colsample_bylevel=None,
                      colsample_bynode=None, colsample_bytree=None,
                      enable_categorical=False, gamma=None, gpu_id=None,
                      importance_type=None, interaction_constraints=None,
                      learning_rate=None, max_delta_step=None, max_depth=None,
                      min_child_weight=None, missing=nan, monotone_constraints=None,
                      n_estimators=100, n_jobs=None, num_parallel_tree=None,
                      predictor=None, random_state=42, reg_alpha=None, reg_lambda=None,
                      scale_pos_weight=None, subsample=None, tree_method=None,
                      validate_parameters=None, verbosity=None) =====
Training_Score   :  0.9997214418550461
Testing_Score    :  0.7486829721505667
MSE              :  0.005139433219520912
MAE              :  0.05065038965940476
RMSE             :  0.07168984042052899
MAPE             :  0.08086546460869791
R^2_Score        :  0.7486829721505667
*****
```

In [81]:

```
1 best_model = LinearRegression()
```

In [82]:

```
1 best_model.fit(xtrain,ytrain)
```

Out[82]:

▼ LinearRegression

LinearRegression()

In [83]:

```
1 ypred = best_model.predict(xtest)
```

In [84]:

```
1 print('Training_Score : ',best_model.score(xtrain,ytrain))
2 print('Testing_Score : ',best_model.score(xtest,ytest))
3 print('MSE : ',mean_squared_error(ytest,ypred))
4 print('MAE : ',mean_absolute_error(ytest,ypred))
5 print('RMSE : ',np.sqrt(mean_squared_error(ytest,ypred)))
6 print('MAPE : ',mean_absolute_percentage_error(ytest,ypred))
7 print('R^2 Score : ', r2_score(ytest,ypred))
```

Training\_Score : 0.8220935158272195  
Testing\_Score : 0.8188835723780066  
MSE : 0.0037038309448697666  
MAE : 0.04276066764019817  
RMSE : 0.0608591073288934  
MAPE : 0.06873872864871644  
R^2 Score : 0.8188835723780066

In [85]:

```
1 df_Actual_predicted = pd.DataFrame({'Actual_values':ytest,'Predicted_values':ypred})
2 with pd.option_context('display.max_rows', 100):
3     display(df_Actual_predicted)
```

	Actual_values	Predicted_values
Serial No.		
362	0.93	0.914374
74	0.84	0.795483
375	0.39	0.572660
156	0.77	0.707463
105	0.74	0.815830
395	0.89	0.862125
378	0.47	0.474943
125	0.57	0.648636
69	0.68	0.823767
451	0.82	0.807089
10	0.45	0.722068
195	0.77	0.726076
407	0.61	0.656452
85	0.94	0.936521
372	0.89	0.824162
389	0.49	0.510105
496	0.87	0.839395
31	0.65	0.597778
317	0.54	0.533592
409	0.57	0.571595
491	0.67	0.665404
492	0.54	0.553492
281	0.68	0.722839
357	0.79	0.794955
77	0.74	0.780085
462	0.68	0.602818
498	0.93	0.948084
212	0.82	0.847650
102	0.64	0.627865
335	0.73	0.743791
476	0.59	0.555968
337	0.72	0.730090
441	0.53	0.545130
174	0.89	0.861044
3	0.72	0.657211
334	0.71	0.737118
410	0.61	0.554582
71	0.94	0.957030
210	0.68	0.643964
64	0.56	0.710942
385	0.96	0.970262
94	0.44	0.575453
486	0.70	0.670838
186	0.89	0.858283
34	0.90	0.940819
78	0.64	0.578549
1	0.92	0.958127
12	0.84	0.838919
416	0.76	0.795932
23	0.94	0.925642
73	0.93	0.888191
183	0.68	0.564104
132	0.77	0.704202
411	0.54	0.527080
194	0.94	0.953304
56	0.64	0.597646
149	0.96	0.955739
19	0.63	0.739441
205	0.69	0.662935
79	0.44	0.502025
495	0.68	0.629898
263	0.70	0.680322
324	0.62	0.599130
484	0.71	0.592883
80	0.46	0.441329
40	0.48	0.589113
452	0.89	0.866763
47	0.86	0.897532
239	0.70	0.658224
392	0.71	0.706496
353	0.64	0.618025
342	0.79	0.785821
278	0.70	0.691608
291	0.58	0.562877
318	0.58	0.554340
305	0.62	0.651017
269	0.83	0.846238
70	0.78	0.863718

	Actual_values	Predicted_values
Serial No.		
456	0.59	0.537338
466	0.54	0.631701
155	0.80	0.769475
83	0.92	0.848362
478	0.65	0.617399
173	0.86	0.847013
322	0.73	0.734321
91	0.64	0.667111
181	0.71	0.604943
415	0.72	0.738681
313	0.78	0.789300
279	0.66	0.663453
382	0.73	0.742824
473	0.90	0.907779
363	0.91	0.915485
325	0.67	0.650814
432	0.73	0.776935
348	0.42	0.444565
87	0.72	0.687136
76	0.72	0.785365
439	0.67	0.734513
16	0.54	0.649033

Pickling the Best Model

In [86]:

1import pickle

In [87]:

1file = 'regressor.pkl'  
2pickle.dump(best\_model, open('regressor.pkl', 'wb')) #write binary

In [88]:

1pic = pickle.load(open('regressor.pkl', 'rb')) #read binary  
2pic

Out[88]:

▼ LinearRegression

LinearRegression()

In [89]:

1pic.predict([[334,116,4,4.0,3.5,9.54,1]])

Out[89]: array([0.91437431])

In [90]:

1pic.predict([[318,110,1,2.5,3.5,8.54,1]])

Out[90]: array([0.73451297])

In [91]:

1xtest

Out[91]:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research
Serial No.							
362	334	116	4	4.0	3.5	9.54	1
74	314	108	4	4.5	4.0	9.04	1
375	315	105	2	2.0	2.5	7.65	0
156	312	109	3	3.0	3.0	8.69	0
105	326	112	3	3.5	3.0	9.05	1
...	...	...	...	...	...	...	...
348	299	94	1	1.0	1.5	7.34	0
87	315	106	3	4.5	3.5	8.42	0
76	329	114	2	2.0	4.0	8.56	1
439	318	110	1	2.5	3.5	8.54	1
16	314	105	3	3.5	2.5	8.30	0

100 rows × 7 columns

In [92]:

1ytest

Out[92]:

Serial No.  
362 0.93  
74 0.84  
375 0.39  
156 0.77  
105 0.74  
...  
348 0.42  
87 0.72  
76 0.72  
439 0.67  
16 0.54  
Name: Chance of Admit, Length: 100, dtype: float64

End