Business Case: Jamboree Education - Linear Regression

About Jamboree Education

Jamboree has helped thousands of students like you 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.

https://drive.google.com/drive/folders/1xg-7LF6N36gb97w-7RjcQsBxos98ztPW?usp=sharing

Overview of the Notebook - Jamboree Education

EDA

- **Loading and inspecting the Dataset**
  - Checking Shape of the Dateset , Meaningful Column names
  - Validating Duplicate Records, Checking Missing values
  - Unique values (counts & names) for each Feature
  - Data & Datatype validation
- **Univariante & Bivariante Analysis**
  - Numerical Variables
  - Categorial variables
  - Correlation Analysis
  - Handling Multicollinearity
- **Model Building**
  - Handling Categorical variables using dummies
  - Test & Train Split

    - Rescaling features
    - Train Model
- **Validate Linear Regression Assumptions**
    - Multicolillinearity check
    - Mean of residuals
    - Linearity of variables
    - Test for Homoscedasticity
    - Normality of residuals
- **Model Performance Evaluation**
    - Metrics checked - MAE,RMSE,R2,Adj R2
    - Train and Test performances are checked
    - Comments on performance measures
- **Summary of final recommendations**

In [1]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error,mean_absolute_percentage_error
from statsmodels.stats.outliers_influence import variance_inflation_factor
import statsmodels.api as sm
from sklearn.preprocessing import StandardScaler
```

In [2]:

```
from IPython.core.display import display, HTML
display(HTML("<style>.container { width:100% !important; }</style>"))
pd.set_option("display.max_rows",50)
pd.set_option("display.max_columns",50)
```

```
C:\Users\hp\AppData\Local\Temp\ipykernel_13940\2873301260.py:1: DeprecationWarning: Importing display from IPython.core.display is deprecated since IPython 7.14, please import from IPython display
  from IPython.core.display import display, HTML
```

In [3]:
```
df= pd.read_csv("jamboree_admission.csv")
df
```

Out[3]:

	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

Shape and Structure and Column name of Dataset

In [4]:
```
df.shape
```

Out[4]:
```
(500, 9)
```

In [5]:
```
print(f"Number of rows: {df.shape[0]}\nNumber of columns: {df.shape[1]}")
```

```
Number of rows: 500
Number of columns: 9
```

In [6]:
```
df.columns
```

Out[6]:
```
Index(['Serial No.', 'GRE Score', 'TOEFL Score', 'University Rating', 'SOP',
       'LOR ', 'CGPA', 'Research', 'Chance of Admit '],
      dtype='object')
```

Missing Values Detection

In [7]:
```
df.isnull().sum()
```

Out[7]:
```
Serial No.           0
GRE Score            0
TOEFL Score          0
University Rating    0
SOP                  0
LOR                  0
CGPA                 0
Research             0
Chance of Admit      0
dtype: int64
```

In dataset there is no missing or null values

Removing unwanted column from the dataset

In [8]:
```
df.drop(columns=['Serial No.'],inplace=True)
```

In [9]:
```
df
```

Out[9]:

	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
...	...	...	...	...	...	...	...	...
495	332	108	5	4.5	4.0	9.02	1	0.87
496	337	117	5	5.0	5.0	9.87	1	0.96
497	330	120	5	4.5	5.0	9.56	1	0.93
498	312	103	4	4.0	5.0	8.43	0	0.73
499	327	113	4	4.5	4.5	9.04	0	0.84

500 rows × 8 columns

Validating Duplicate Records

In [10]:
```
df.duplicated().sum()
```

Out[10]:
```
0
```

Unique values are checked

In [11]:
```
df.nunique()
```

Out[11]:

```
GRE Score            49
TOEFL Score          29
University Rating     5
SOP                   9
LOR                   9
CGPA                184
Research              2
Chance of Admit      61
dtype: int64
```

Research and University rating are categorical variables

Dtype of each column

In [12]:

```
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
```

In [13]:

```
df.describe()
```

Out[13]:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
count	500.000000	500.000000	500.000000	500.000000	500.00000	500.000000	500.000000	500.00000
mean	316.472000	107.192000	3.114000	3.374000	3.48400	8.576440	0.560000	0.72174
std	11.295148	6.081868	1.143512	0.991004	0.92545	0.604813	0.496884	0.14114
min	290.000000	92.000000	1.000000	1.000000	1.00000	6.800000	0.000000	0.34000
25%	308.000000	103.000000	2.000000	2.500000	3.00000	8.127500	0.000000	0.63000
50%	317.000000	107.000000	3.000000	3.500000	3.50000	8.560000	1.000000	0.72000
75%	325.000000	112.000000	4.000000	4.000000	4.00000	9.040000	1.000000	0.82000
max	340.000000	120.000000	5.000000	5.000000	5.00000	9.920000	1.000000	0.97000

Exploratory Data Analysis

Exam scores (GRE, TOEFL and CGPA) have a high positive correlation with chance of admit

While university ranking, rating of SOP and LOR also have an impact on chances of admit, research is the only variable which doesn't have much of an impact

We can see from the scatterplot that the values of university ranking, SOP, LOR and research are not continuous. We can convert these columns to categorical variables

In [14]:

```
df.rename(columns={'LOR ':'LOR', 'Chance of Admit ':'Chance of Admit'}, inplace=True)
```

In [15]:

```
df[['University Rating', 'SOP', 'LOR','Research']] = df[['University Rating', 'SOP', 'LOR','Research']].astype("category")
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    category
 3   SOP                500 non-null    category
 4   LOR                500 non-null    category
 5   CGPA               500 non-null    float64
 6   Research           500 non-null    category
 7   Chance of Admit    500 non-null    float64
dtypes: category(4), float64(2), int64(2)
memory usage: 18.8 KB
```

Bivariate Analysis

Numerical variables

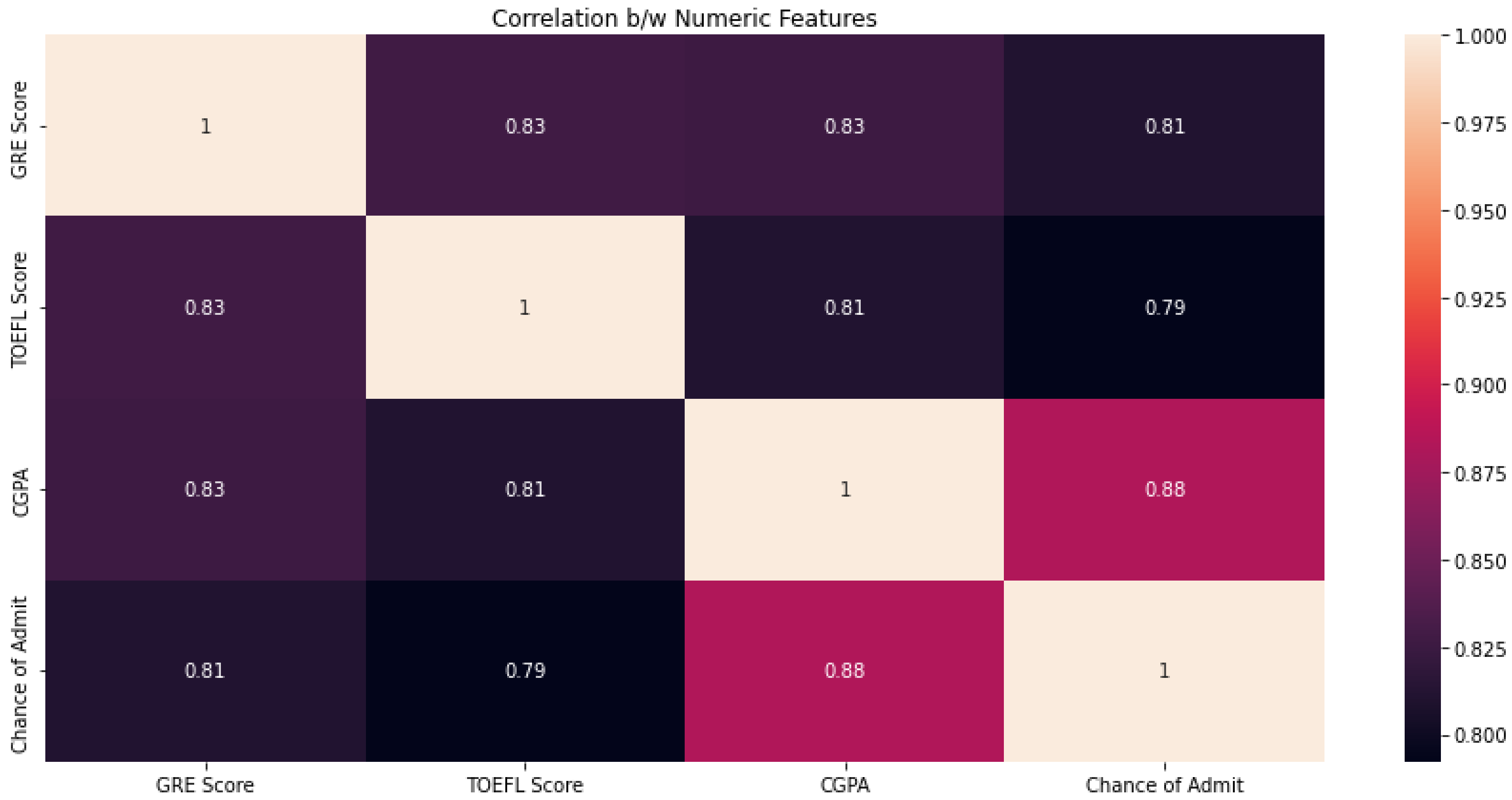
- 'GRE Score' vs 'Chance of Admit'
- 'TOEFL Score' vs 'Chance of Admit'
- 'CGPA' vs 'Chance of Admit'

Categorical variables

- 'Research' vs 'Chance of Admit'
- 'Univarsity rating' vs 'Chance of Admit'
- 'LOR' vs 'Chance of Admit'
- 'SOP' vs 'Chance of Admit'

In [16]:

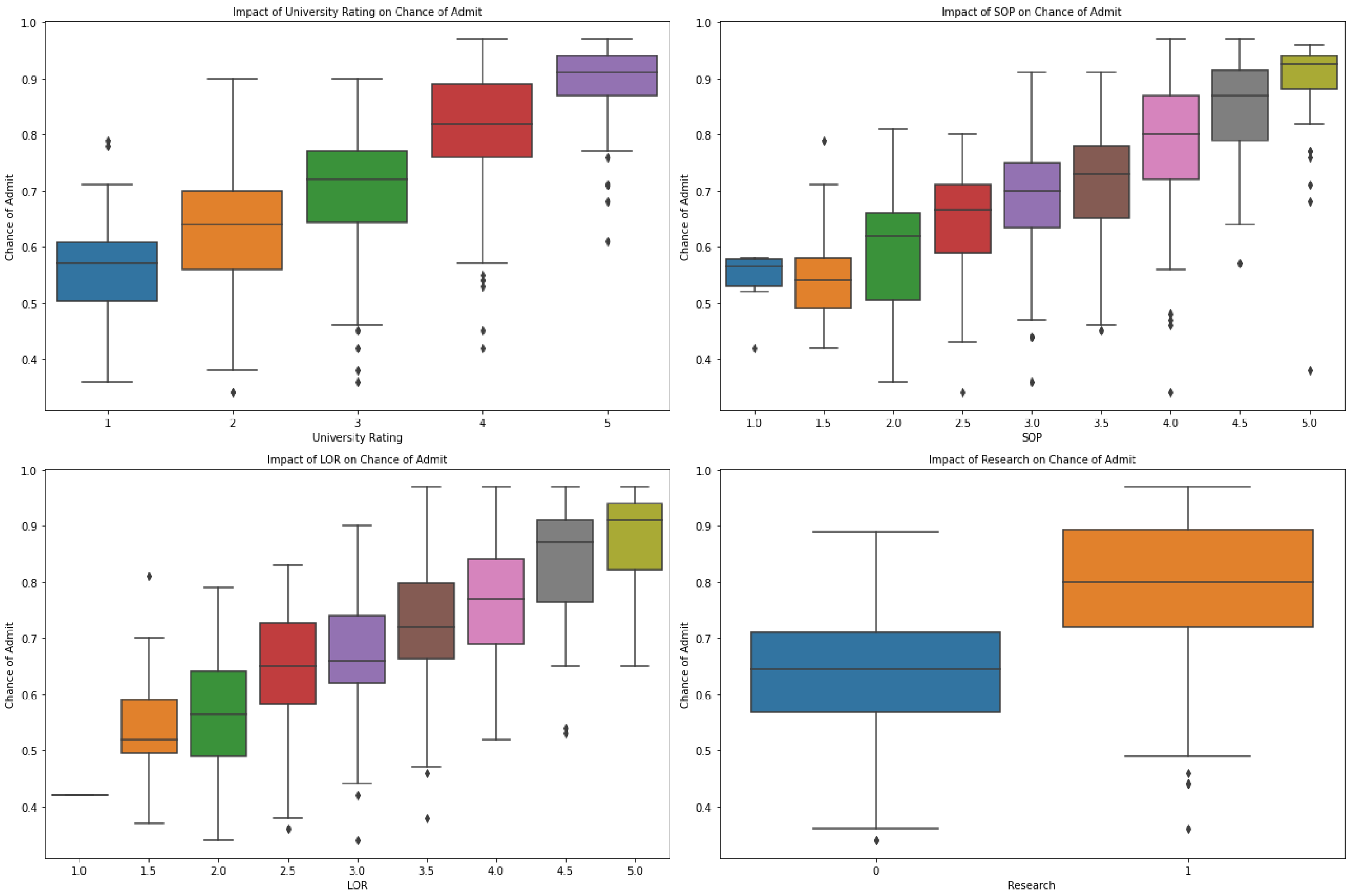
```
# Heatmap to analyse the correlation between numerical features and Chance of Admit
plt.figure(figsize=[15,7])
sns.heatmap(df.corr(),annot=True)
plt.title('Correlation b/w Numeric Features')
plt.show()
```



- Conrming the inferences from pairplot, the correlation matrix also shows that **exam scores (CGPA/GRE/TOEFL)** have a strong positive correlation with chance of admit
- Infact, they are also highly correlated amongst themselves

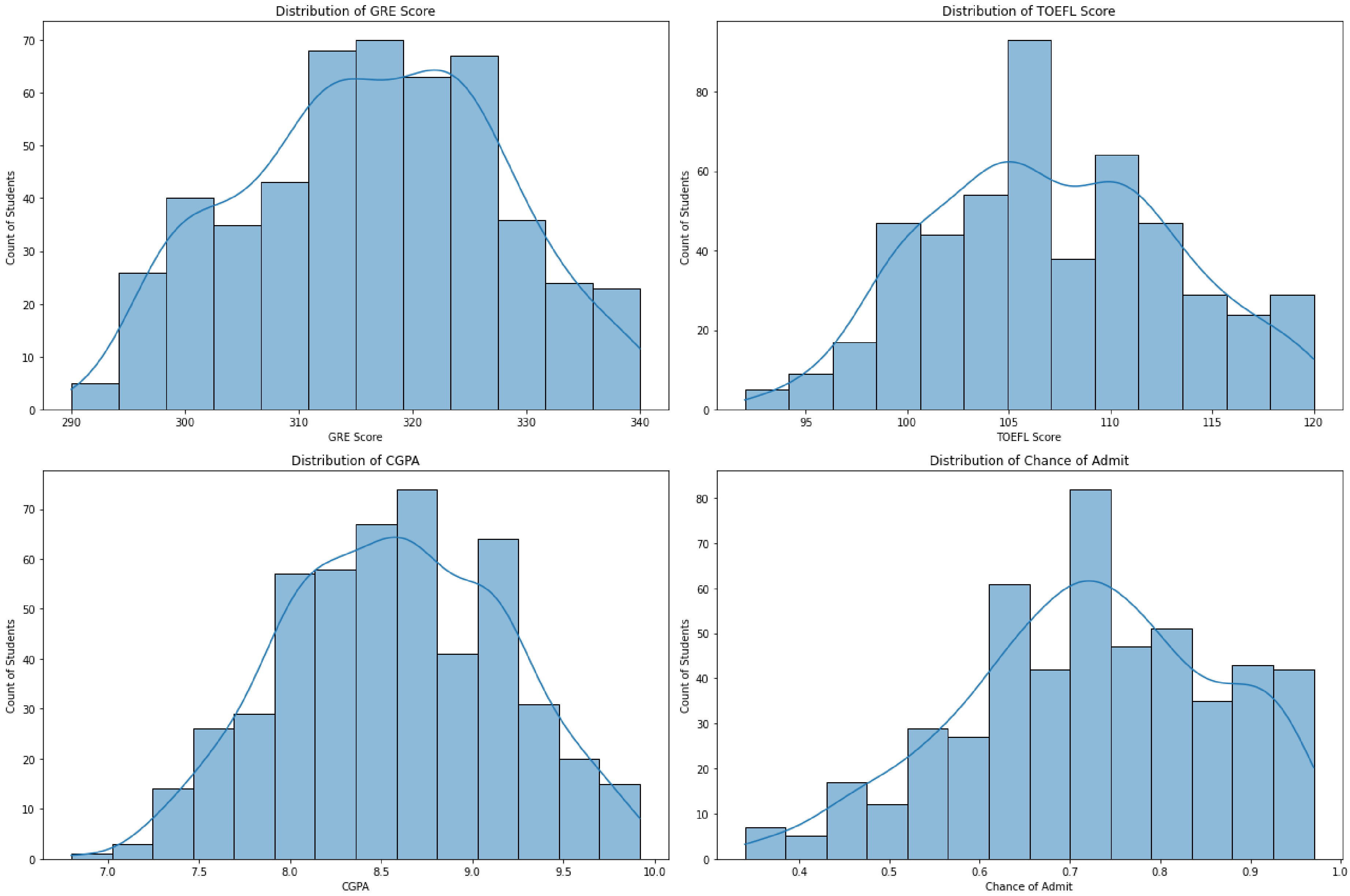
In [17]:
```
# Boxplots to analyse the relationship between categorical variables and Chance of Admi
cat_cols = df.select_dtypes(include=['bool','category']).columns.tolist()
plt.figure(figsize=(18,12))
i=1
for col in cat_cols:
    ax = plt.subplot(2,2,i)
    sns.boxplot(data = df, x=col, y='Chance of Admit')
    plt.title(f"Impact of {col} on Chance of Admit", fontsize=10)
    plt.xlabel(col)
    plt.ylabel('Chance of Admit')
```

```
    i+=1
plt.tight_layout()
plt.show()
```



As seen in the pairplot earlier, the categorical variables such as university ranking, research, quality of SOP and LOR also increase the chances of admit.

In [18]:
```
numeric_cols = df.select_dtypes(include=['float','int']).columns.tolist()
# Boxplots to analyse the relationship between categorical variables and Chance of Admi
cat_cols = df.select_dtypes(include=['bool','category']).columns.tolist()
plt.figure(figsize=(18,12))
i=1
for col in numeric_cols:
    ax=plt.subplot(2,2,i)
    sns.histplot(data=df[col], kde=True)
    plt.title(f'Distribution of {col}')
    plt.xlabel(col)
    plt.ylabel('Count of Students')
    i += 1
plt.tight_layout()
plt.show();
```

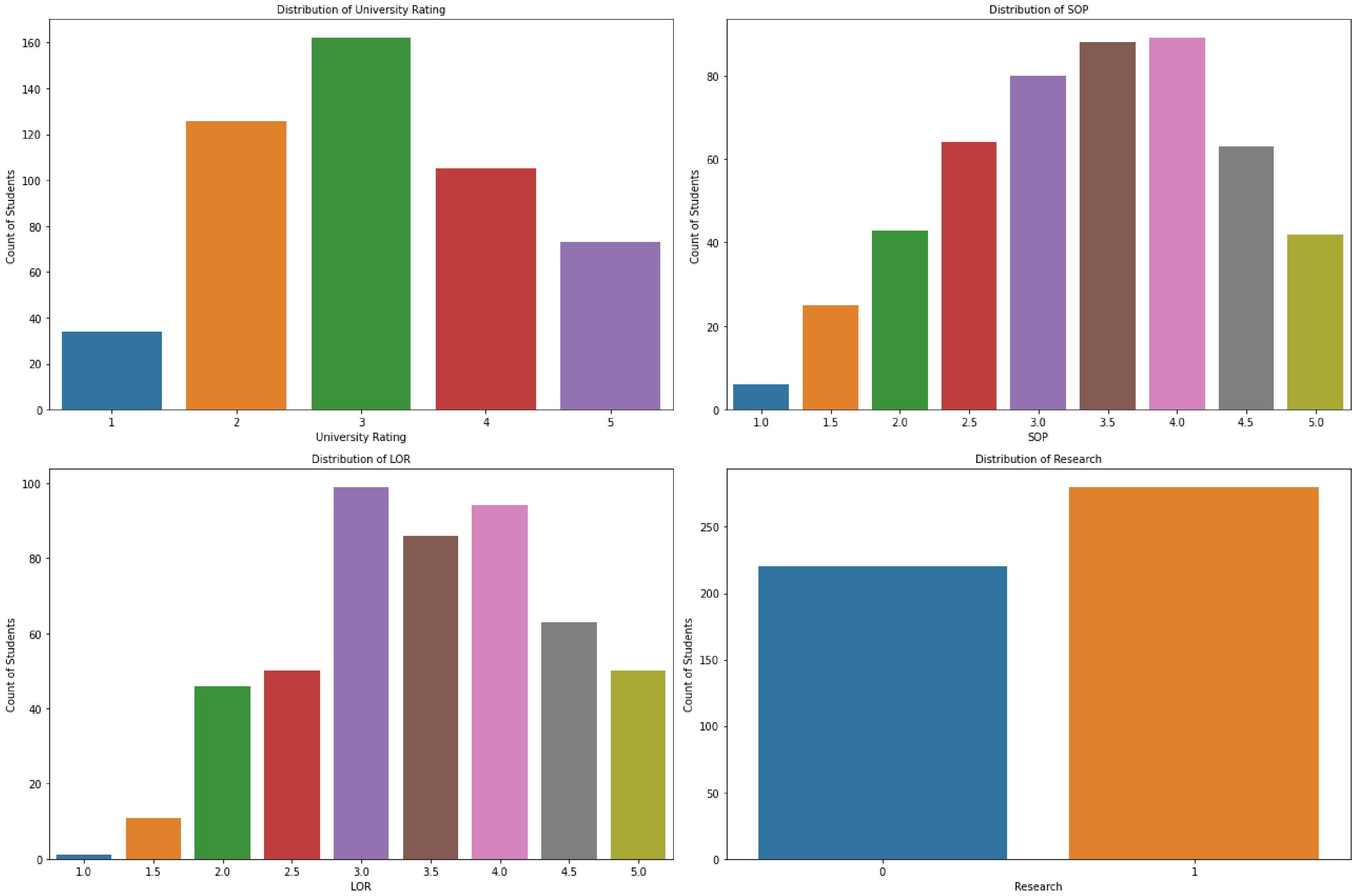


We can see the range of all the numerical attributes:

- GRE scores are between 290 and 340, with maximum students scoring in the range 310-330
- TOEFL scores are between 90 and 120, with maximum students scoring around 105

- CGPA ranges between 7 and 10, with maximum students scoring around 8.5
- Chance of Admit is a probability percentage between 0 and 1, with maximum students scoring around 70%-75%

In [19]:
```
# Distribution of categorical variables
plt.figure(figsize=(18,12))
i=1
for col in cat_cols:
    ax = plt.subplot(2,2,i)
    sns.countplot(x=df[col])
    plt.title(f'Distribution of {col}', fontsize=10)
    plt.xlabel(col)
    plt.ylabel('Count of Students')
    i+=1
plt.tight_layout()
plt.show();
```



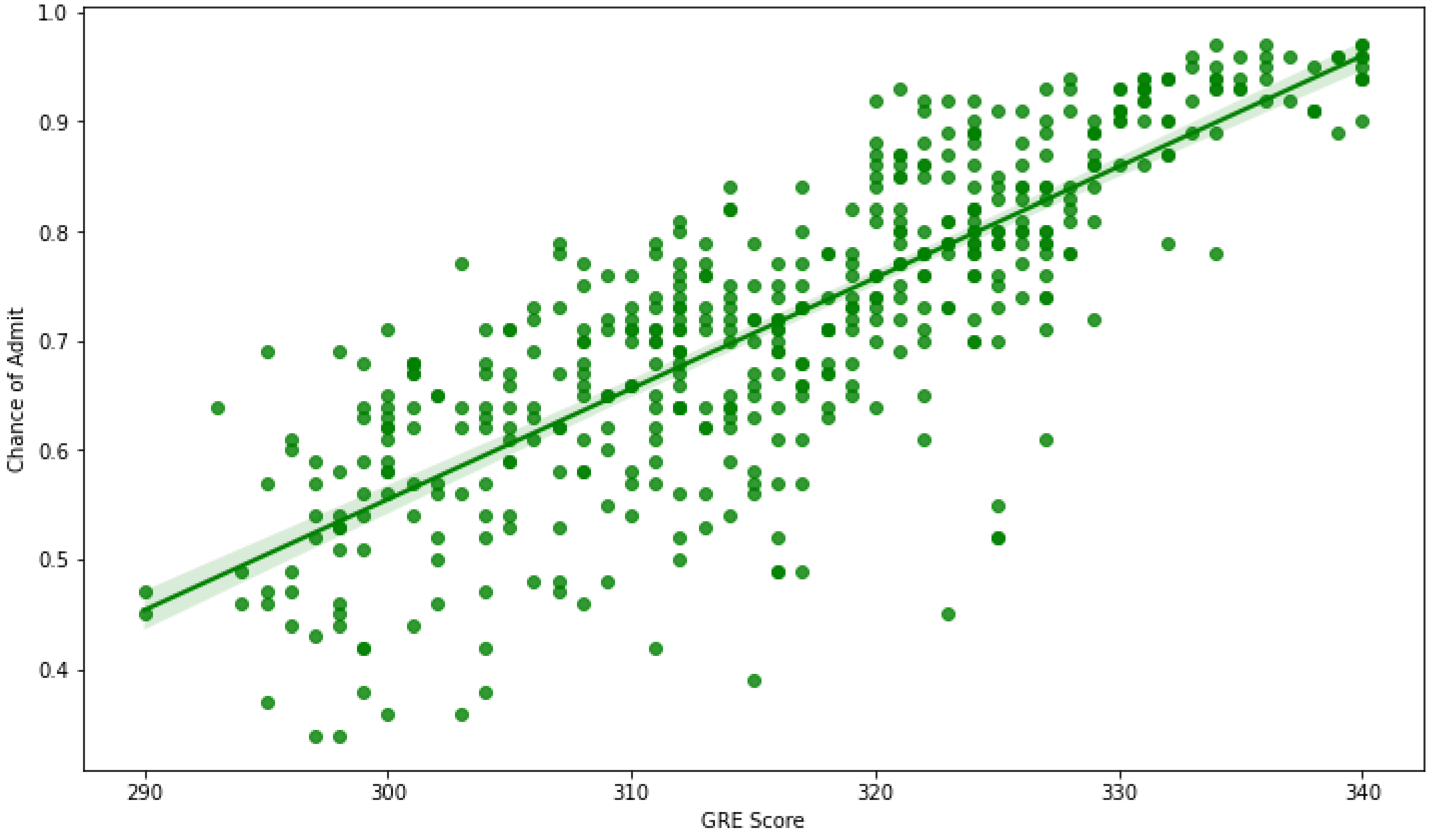
It can be observed that the most frequent value of categorical features is as following:

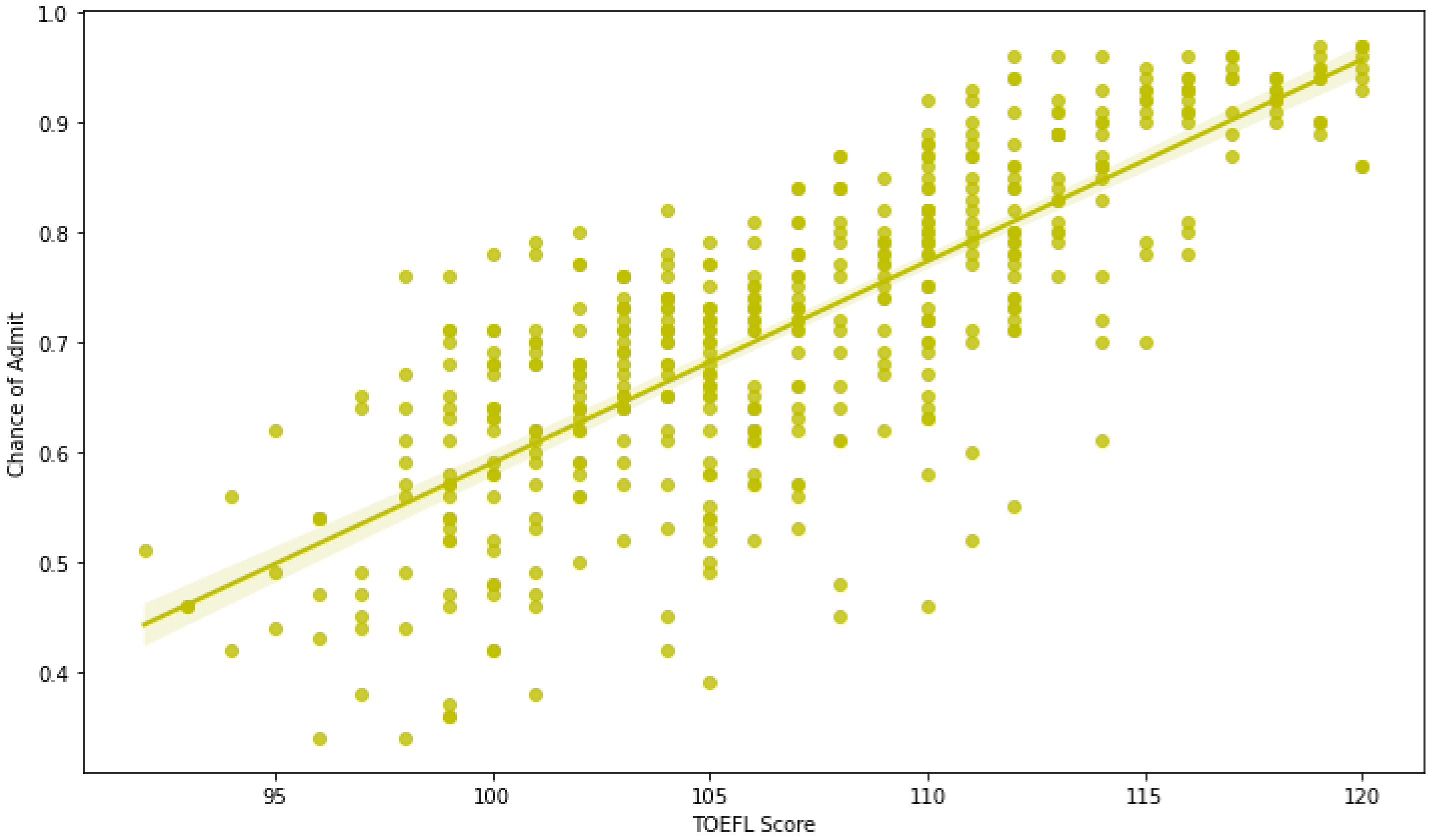
- University Rating: 3
- SOP: 3.5 & 4

- LOR: 3
- Research: True

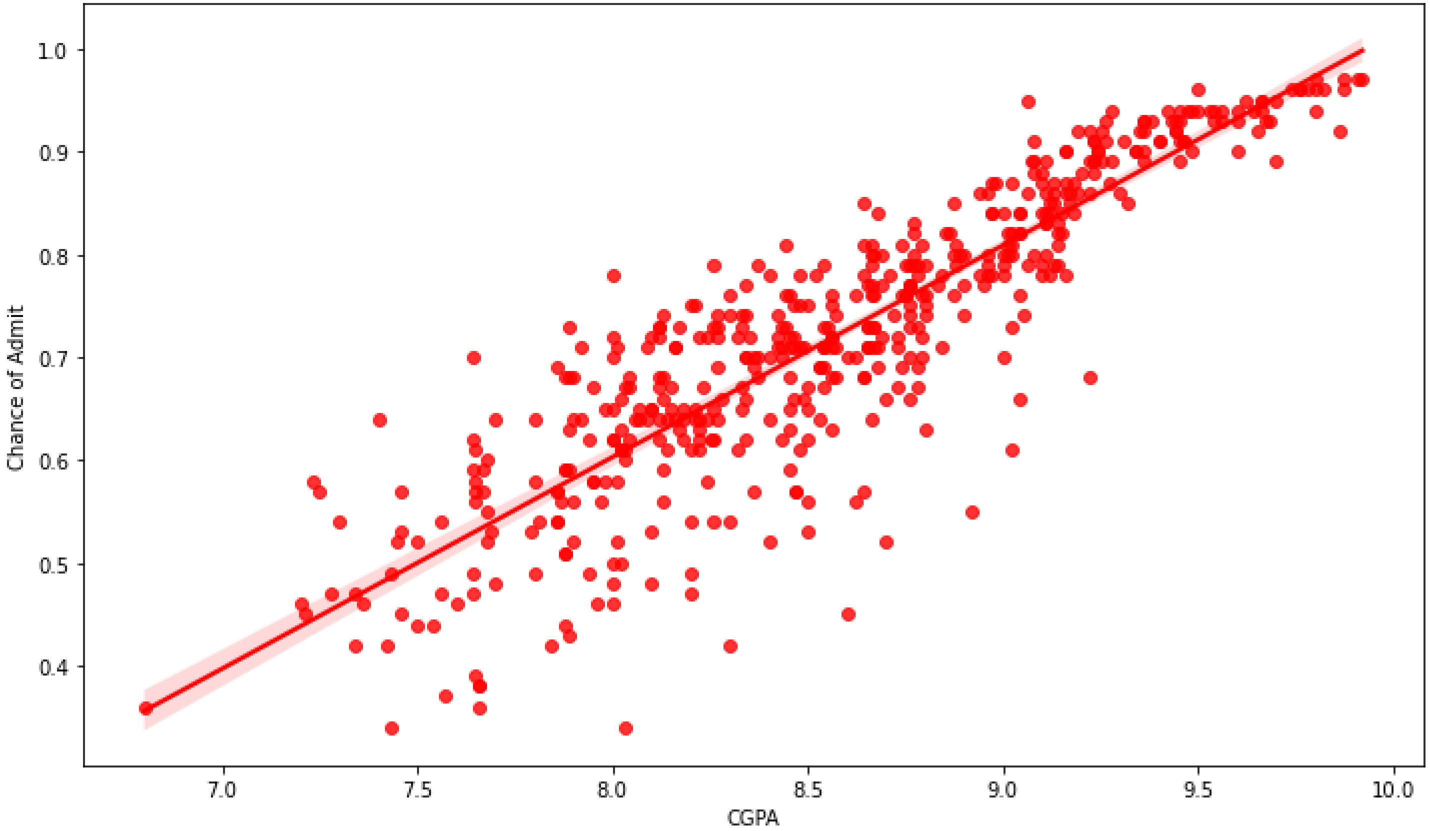
In [20]:

```
fig = plt.figure(figsize=(12, 7))
sns.regplot(x='GRE Score',y='Chance of Admit',color="g",data=df);

fig = plt.figure(figsize=(12, 7))
sns.regplot(x='TOEFL Score',y='Chance of Admit',color="y",data=df);

fig = plt.figure(figsize=(12, 7))
sns.regplot(x='CGPA',y='Chance of Admit',color="r",data=df);
```





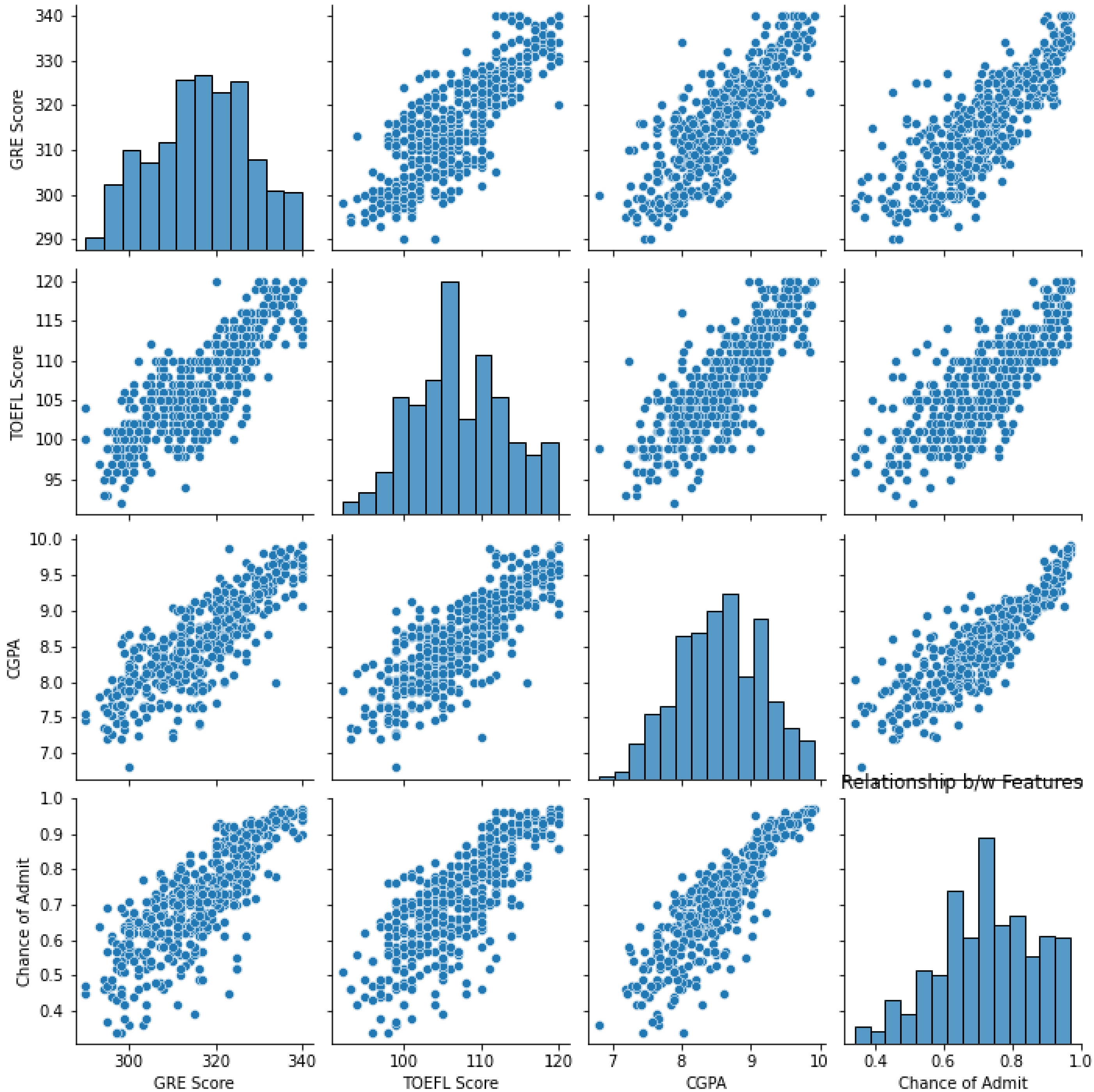
1.0
0.9
0.8
0.7
0.6
0.5
0.4
Chance of Admit
95
100
105
110
115
120
TOEFL Score



- A strong positive relationship exists between Chance of admit and numerical variables (GRE & TOEFL score and CGPA).

Correlation Analysis

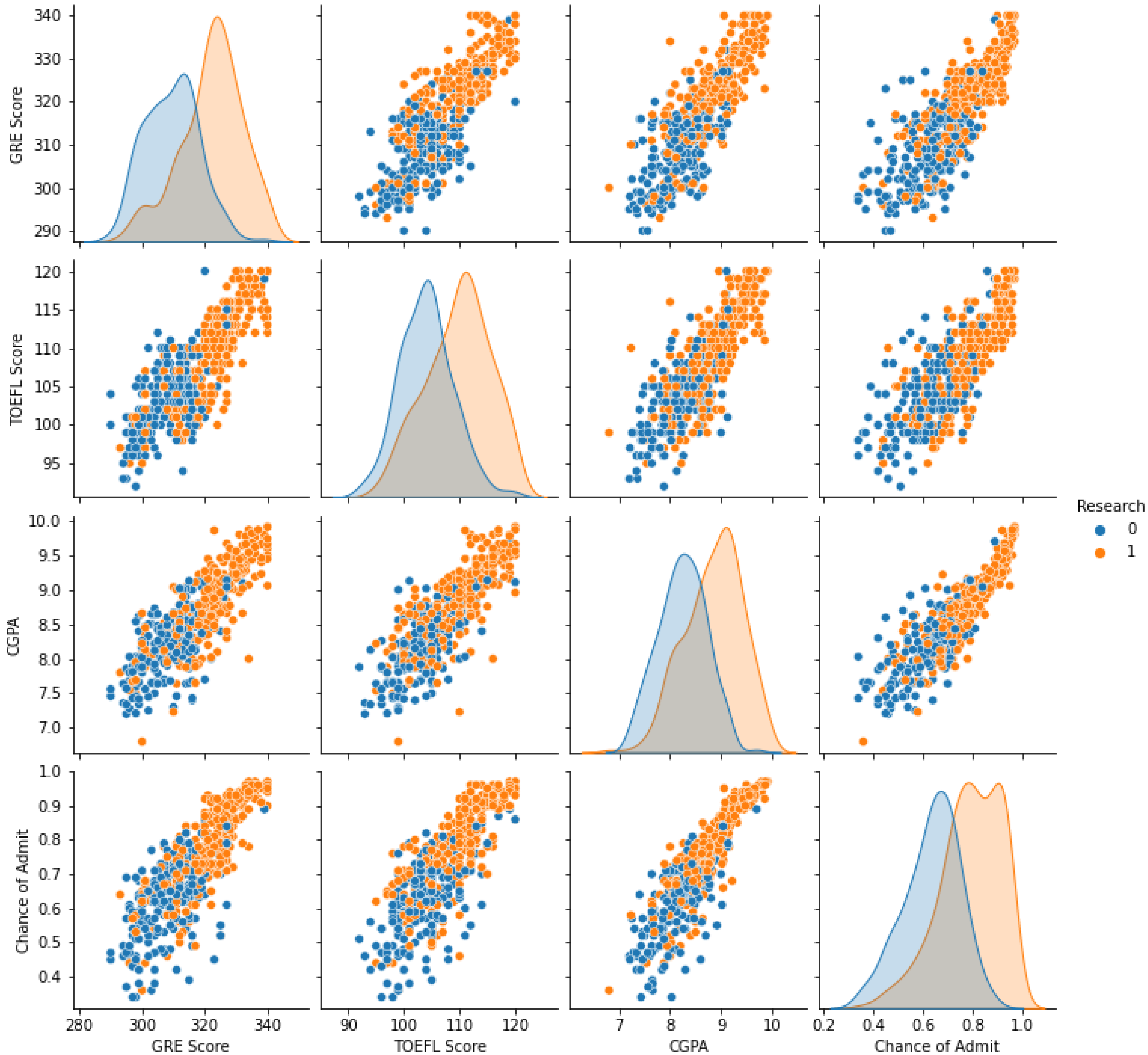
In [21]:
```
sns.pairplot(df)
plt.title('Relationship b/w Features')
plt.show()
```



Relationship b/w Features
GRE Score
TOEFL Score
CGPA
Chance of Admit

In [22]:

```
sns.pairplot(df,hue='Research')
plt.show()
```



GRE Score
TOEFL Score
CGPA
Chance of Admit
Research
0
1

Data Preprocessing

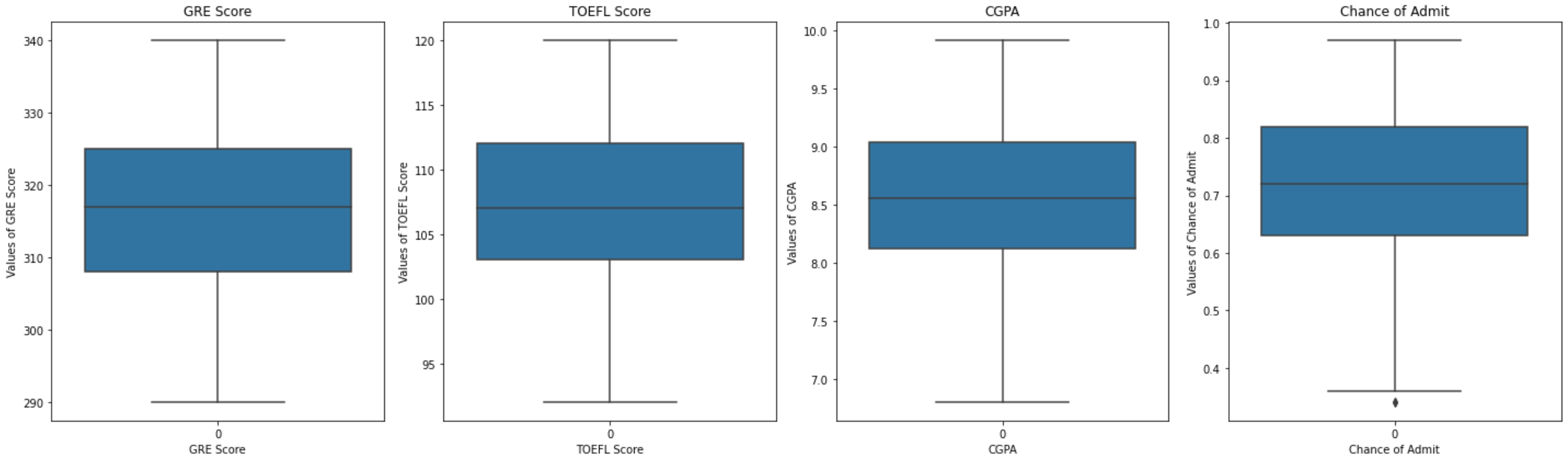
Missing Values/Outliers/Duplicates Check

In [23]:
```
#Check for missing values in all columns
df.isna().sum()
```

Out[23]:
```
GRE Score            0
TOEFL Score          0
University Rating    0
SOP                  0
LOR                  0
CGPA                 0
Research             0
Chance of Admit      0
dtype: int64
```

- There are no missing values in the dataset

In [24]:
```
plt.figure(figsize=(20,6))
i=1
for col in numeric_cols:
    ax = plt.subplot(1,4,i)
    sns.boxplot(orient="v",data=df[col])
    plt.title(col)
    plt.xlabel(col)
    plt.ylabel(f'Values of {col}')
    i+=1
plt.tight_layout()
plt.show()
```



It can be observed that there are no outliers in the numeric columns (all the observations are within the whiskers which represent the mimimum and maximum of the range of values)

In [25]:
```
# Check for Duplicate rows
df[df.duplicated()].shape
```

Out[25]:
```
(0, 8)
```

There are no duplicate rows in the dataset

Handling Categorical variable for Linear Regression

- Used pandas Dummies to covert categorical variables to Numerical variables

Considered only Significant variables

- When multiple features are highly correlated (above 0.80), only one feature is considered

In [26]:
```
# Creating the new dataframe with only significant variables.
significant_colname = ['GRE Score', 'University Rating', 'SOP', 'LOR', 'Research', 'Chance of Admit']
```

```
sig_edu_data = df[significant_colname]
sig_edu_data.shape
```

Out[26]: (500, 6)

In [27]:
```
significant_cat_colname = ['University Rating','SOP','LOR']

# Creating dummy variables for 'Cars_Category','enginetype','carbody','cylindernumber', 'drivewheel'
dummyVar = pd.get_dummies(sig_edu_data[significant_cat_colname],drop_first=True)
dummyVar.shape
```

Out[27]: (500, 20)

In [28]:
```
dummyVar.head()
```

Out[28]:

	University Rating_2	University Rating_3	University Rating_4	University Rating_5	SOP_1.5	SOP_2.0	SOP_2.5	SOP_3.0	SOP_3.5	SOP_4.0	SOP_4.5	SOP_5.0	LOR_1.5	LOR_2.0	LOR_2.5
0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0
1	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0
2	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0
3	0	1	0	0	0	0	0	0	1	0	0	0	0	0	1
4	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0

In [29]:
```
# Merging the dummy variable to significant variable dataframe.
sig_edu_data = pd.concat([sig_edu_data,dummyVar],axis=1)
sig_edu_data.shape
```

Out[29]: (500, 26)

In [30]:
```
# Dropping origincal Categorical variables as no need. Already added them as numerical.
sig_edu_data.drop(significant_cat_colname,axis=1,inplace=True)
sig_edu_data.shape
```

Out[30]: (500, 23)

Splitting the Data into Training and Testing Sets

In [31]:
```
# Splitting the avilable data into training and testing set with 70:30 ratio (train:test)
df_train, df_test = train_test_split(sig_edu_data, train_size = 0.7, random_state = 100)
print(df_train.shape)
print(df_test.shape)
```

```
(350, 23)
(150, 23)
```

In [32]:
```
sig_edu_data.head()
```

Out[32]:

	GRE Score	Research	Chance of Admit	University Rating_2	University Rating_3	University Rating_4	University Rating_5	SOP_1.5	SOP_2.0	SOP_2.5	SOP_3.0	SOP_3.5	SOP_4.0	SOP_4.5	SOP_5.0	LO
0	337	1	0.92	0	0	1	0	0	0	0	0	0	0	1	0	
1	324	1	0.76	0	0	1	0	0	0	0	0	0	1	0	0	
2	316	1	0.72	0	1	0	0	0	0	0	1	0	0	0	0	
3	322	1	0.80	0	1	0	0	0	0	0	0	1	0	0	0	
4	314	0	0.65	1	0	0	0	0	1	0	0	0	0	0	0	

In [33]:
```
df_train.columns
```

Out[33]:
```
Index(['GRE Score', 'Research', 'Chance of Admit', 'University Rating_2',
       'University Rating_3', 'University Rating_4', 'University Rating_5',
       'SOP_1.5', 'SOP_2.0', 'SOP_2.5', 'SOP_3.0', 'SOP_3.5', 'SOP_4.0',
       'SOP_4.5', 'SOP_5.0', 'LOR_1.5', 'LOR_2.0', 'LOR_2.5', 'LOR_3.0',
       'LOR_3.5', 'LOR_4.0', 'LOR_4.5', 'LOR_5.0'],
      dtype='object')
```

Rescaling the Features

As per above table, features are varying in different ranges. This will be problem. It is important that we rescale the feature such that thay have a comparable scales. This can lead us time consuming during model evaluation.

So it is advices to Standardization and normalization so that units of coefficients obtained are in same scale. Two common ways of rescaling are

1. Standardization (mean-0, sigma-1)
2. Min-Max scaling (Normization)

- We will be using standardization scaling

In [34]:
```
# Using MinMaxScaler to scale all the numeric variables in the same scale between 0 and 1.
scaler = StandardScaler()

# Apply scaler() to all numerical columns
num_col = ['GRE Score', 'Chance of Admit']

df_train[num_col] = scaler.fit_transform(df_train[num_col])
df_train.head()
```

Out[34]:

	GRE Score	Research	Chance of Admit	University Rating_2	University Rating_3	University Rating_4	University Rating_5	SOP_1.5	SOP_2.0	SOP_2.5	SOP_3.0	SOP_3.5	SOP_4.0	SOP_4.5	SOI
153	0.664269	0	0.483718	0	1	0	0	0	0	0	1	0	0	0	
84	2.084080	1	1.557510	0	0	0	1	0	0	0	0	0	0	1	
310	0.309316	1	0.268959	0	1	0	0	0	0	0	1	0	0	0	
494	-1.376710	1	-0.303730	0	1	0	0	0	0	1	0	0	0	0	
126	0.575531	1	0.913235	0	1	0	0	0	0	0	0	0	1	0	

In [35]:
```
df_train.describe().T
```

Out[35]:

	count	mean	std	min	25%	50%	75%	max
GRE Score	350.0	-1.711647e-15	1.001432	-2.352830	-0.755543	-0.045637	0.664269	2.084080
Chance of Admit	350.0	-7.448010e-16	1.001432	-2.737658	-0.661660	-0.017385	0.698476	1.772268
University Rating_2	350.0	2.542857e-01	0.436082	0.000000	0.000000	0.000000	1.000000	1.000000
University Rating_3	350.0	3.142857e-01	0.464895	0.000000	0.000000	0.000000	1.000000	1.000000
University Rating_4	350.0	2.285714e-01	0.420514	0.000000	0.000000	0.000000	0.000000	1.000000
University Rating_5	350.0	1.342857e-01	0.341447	0.000000	0.000000	0.000000	0.000000	1.000000
SOP_1.5	350.0	4.857143e-02	0.215278	0.000000	0.000000	0.000000	0.000000	1.000000
SOP_2.0	350.0	7.714286e-02	0.267200	0.000000	0.000000	0.000000	0.000000	1.000000
SOP_2.5	350.0	1.285714e-01	0.335204	0.000000	0.000000	0.000000	0.000000	1.000000
SOP_3.0	350.0	1.742857e-01	0.379898	0.000000	0.000000	0.000000	0.000000	1.000000
SOP_3.5	350.0	1.742857e-01	0.379898	0.000000	0.000000	0.000000	0.000000	1.000000
SOP_4.0	350.0	1.685714e-01	0.374909	0.000000	0.000000	0.000000	0.000000	1.000000
SOP_4.5	350.0	1.485714e-01	0.356175	0.000000	0.000000	0.000000	0.000000	1.000000
SOP_5.0	350.0	7.142857e-02	0.257908	0.000000	0.000000	0.000000	0.000000	1.000000
LOR_1.5	350.0	2.000000e-02	0.140200	0.000000	0.000000	0.000000	0.000000	1.000000
LOR_2.0	350.0	8.000000e-02	0.271682	0.000000	0.000000	0.000000	0.000000	1.000000
LOR_2.5	350.0	1.000000e-01	0.300429	0.000000	0.000000	0.000000	0.000000	1.000000
LOR_3.0	350.0	1.914286e-01	0.393989	0.000000	0.000000	0.000000	0.000000	1.000000
LOR_3.5	350.0	1.885714e-01	0.391728	0.000000	0.000000	0.000000	0.000000	1.000000
LOR_4.0	350.0	1.885714e-01	0.391728	0.000000	0.000000	0.000000	0.000000	1.000000
LOR_4.5	350.0	1.400000e-01	0.347484	0.000000	0.000000	0.000000	0.000000	1.000000
LOR_5.0	350.0	8.857143e-02	0.284531	0.000000	0.000000	0.000000	0.000000	1.000000

In [36]:

```
df_train.columns
```

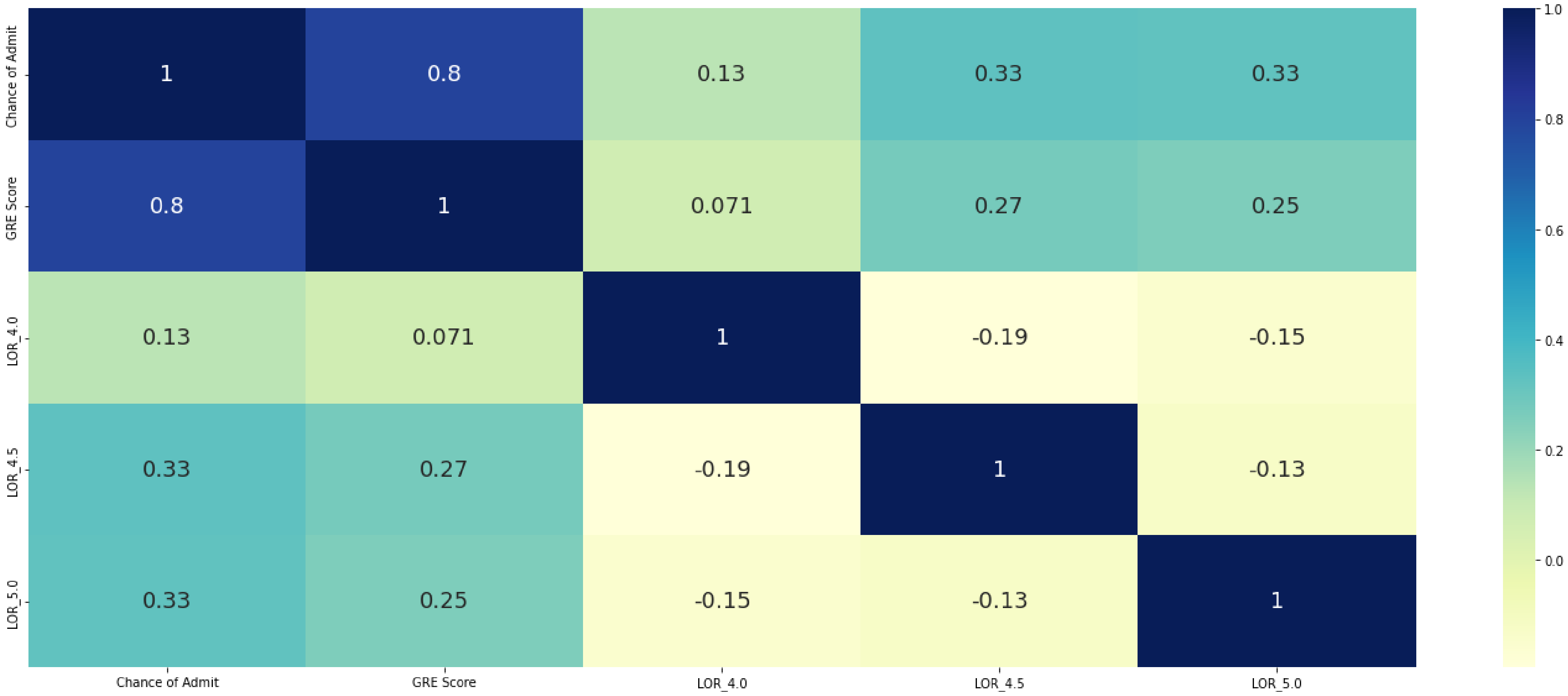
Out[36]:
```
Index(['GRE Score', 'Research', 'Chance of Admit', 'University Rating_2',
       'University Rating_3', 'University Rating_4', 'University Rating_5',
       'SOP_1.5', 'SOP_2.0', 'SOP_2.5', 'SOP_3.0', 'SOP_3.5', 'SOP_4.0',
       'SOP_4.5', 'SOP_5.0', 'LOR_1.5', 'LOR_2.0', 'LOR_2.5', 'LOR_3.0',
       'LOR_3.5', 'LOR_4.0', 'LOR_4.5', 'LOR_5.0'],
      dtype='object')
```

Checking the correlation coefficients to see which variables are highly correlated

In [37]:
```
plt.figure(figsize = (20, 8))
data_set1 = df_train[['Chance of Admit', 'University Rating_2',
       'University Rating_3', 'University Rating_4', 'University Rating_5']]
sns.heatmap(data_set1.corr(),annot=True,cmap="YlGnBu",annot_kws={"size": 18})
plt.tight_layout()
plt.show()
```

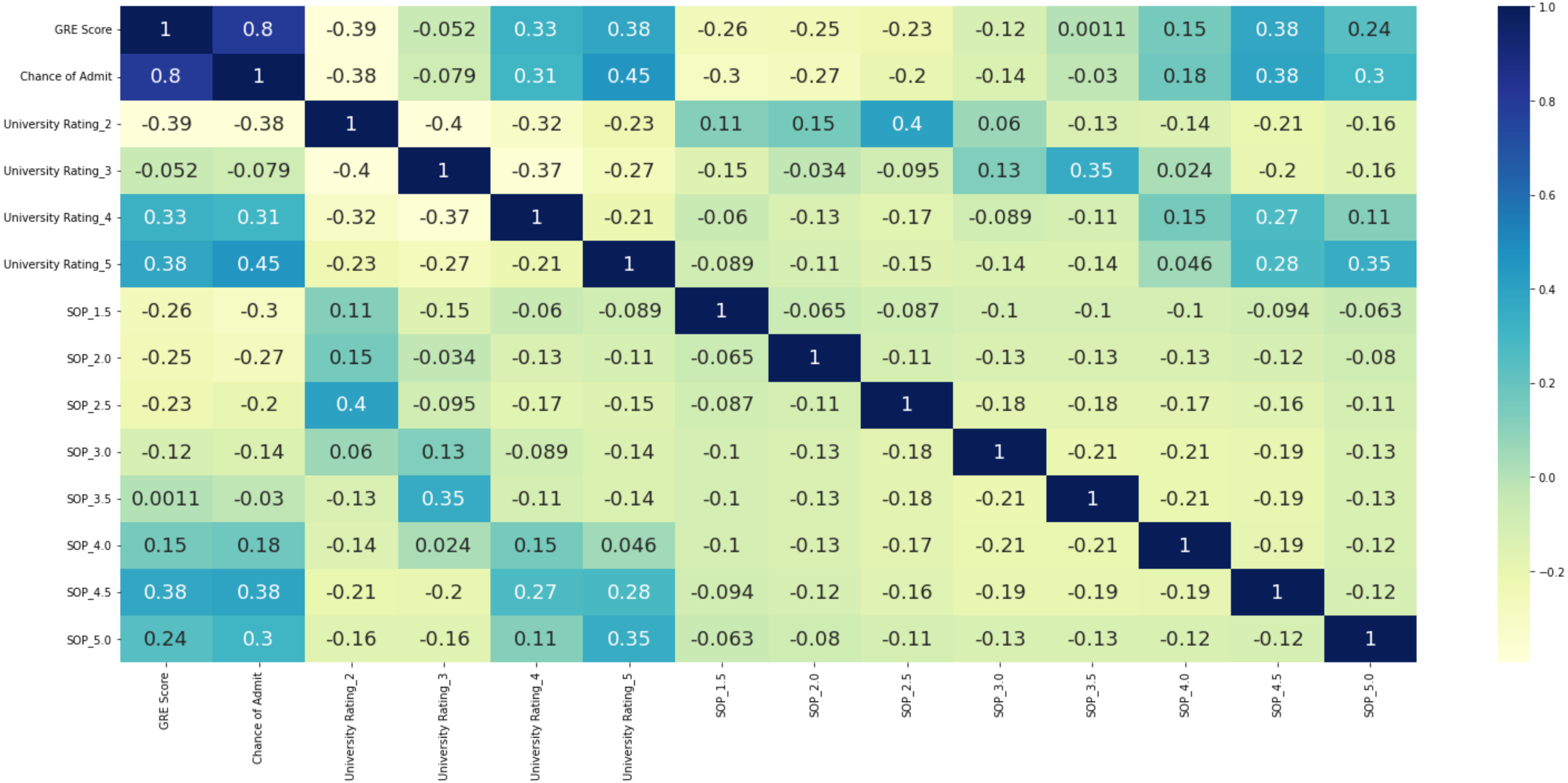
In [38]:

```
plt.figure(figsize = (20, 8))
data_set1 = df_train[['Chance of Admit','GRE Score', 'LOR_4.0', 'LOR_4.5', 'LOR_5.0']]
sns.heatmap(data_set1.corr(),annot=True,cmap="YlGnBu",annot_kws={"size": 18})
plt.tight_layout()
plt.show()
```



In [39]:

```
plt.figure(figsize = (22, 10))
data_set1 = df_train[['GRE Score', 'Research', 'Chance of Admit', 'University Rating_2',
       'University Rating_3', 'University Rating_4', 'University Rating_5',
       'SOP_1.5', 'SOP_2.0', 'SOP_2.5', 'SOP_3.0', 'SOP_3.5', 'SOP_4.0',
       'SOP_4.5', 'SOP_5.0']]
sns.heatmap(data_set1.corr(),annot=True,cmap="YlGnBu",annot_kws={"size": 18})
plt.tight_layout()
plt.show()
```



Inferences

- No new features are highly correlated after creating new features using dummies.

Training the Model

- Used Backward Elimination for Feature Selection

In [40]:
```
y_train = df_train.pop('Chance of Admit')
X_train = df_train
```

In [41]:
```
print(X_train.shape)
print(y_train.shape)
```

```
(350, 22)
(350,)
```

In [42]:
```
X_train_1 = X_train[['GRE Score', 'Research', 'University Rating_2',
       'University Rating_3', 'University Rating_4', 'University Rating_5',
       'SOP_1.5', 'SOP_2.0', 'SOP_2.5', 'SOP_3.0', 'SOP_3.5', 'SOP_4.0',
       'SOP_4.5', 'SOP_5.0', 'LOR_1.5', 'LOR_2.0', 'LOR_2.5', 'LOR_3.0',
       'LOR_3.5', 'LOR_4.0', 'LOR_4.5', 'LOR_5.0']]
X_train_1 = sm.add_constant(X_train_1)
lr_1 = sm.OLS(y_train, X_train_1).fit()

lr_1.summary()
```

Out[42]:

OLS Regression Results

Dep. Variable:	Chance of Admit	**R-squared:**	0.739
Model:	OLS	**Adj. R-squared:**	0.721
Method:	Least Squares	**F-statistic:**	42.08
Date:	Mon, 18 Dec 2023	**Prob (F-statistic):**	1.11e-81
Time:	20:21:11	**Log-Likelihood:**	-261.59
No. Observations:	350	**AIC:**	569.2
Df Residuals:	327	**BIC:**	657.9
Df Model:	22		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-1.3717	0.533	-2.575	0.010	-2.420	-0.324
GRE Score	0.5104	0.043	11.995	0.000	0.427	0.594
Research	0.1533	0.071	2.172	0.031	0.014	0.292
University Rating_2	0.0750	0.138	0.544	0.587	-0.196	0.346
University Rating_3	0.1298	0.146	0.892	0.373	-0.157	0.416
University Rating_4	0.1781	0.163	1.092	0.275	-0.143	0.499
University Rating_5	0.4388	0.181	2.428	0.016	0.083	0.794
SOP_1.5	-0.0281	0.420	-0.067	0.947	-0.855	0.799
SOP_2.0	0.0947	0.410	0.231	0.818	-0.713	0.902
SOP_2.5	0.3224	0.416	0.775	0.439	-0.496	1.141
SOP_3.0	0.2526	0.413	0.612	0.541	-0.560	1.065
SOP_3.5	0.2819	0.418	0.674	0.501	-0.541	1.104
SOP_4.0	0.3772	0.421	0.895	0.371	-0.452	1.206
SOP_4.5	0.4731	0.427	1.107	0.269	-0.368	1.314

SOP_5.0	0.4953	0.437	1.133	0.258	-0.364	1.355
LOR_1.5	0.4028	0.658	0.612	0.541	-0.892	1.698
LOR_2.0	0.4516	0.667	0.677	0.499	-0.861	1.764
LOR_2.5	0.6710	0.658	1.019	0.309	-0.624	1.966
LOR_3.0	0.6789	0.663	1.024	0.307	-0.625	1.983
LOR_3.5	0.7725	0.663	1.165	0.245	-0.532	2.077
LOR_4.0	0.9193	0.664	1.384	0.167	-0.387	2.226
LOR_4.5	1.0768	0.667	1.614	0.108	-0.236	2.389
LOR_5.0	1.1767	0.671	1.754	0.080	-0.143	2.496

Omnibus:	56.599	**Durbin-Watson:**	2.094
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	93.858
Skew:	-0.949	**Prob(JB):**	4.16e-21
Kurtosis:	4.683	**Cond. No.**	100.

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

Inferences

- R-Square value is - 0.739
- Adj. R-squared - 0.721
- Based on the P-values, the following features were removed
    - University rating 2 - 0.587
    - SOP 1.5 - 0.947
    - LOR 1.5 - 0.541

In [43]:

```
X_train_2 = X_train[['GRE Score', 'Research',
       'University Rating_3', 'University Rating_4', 'University Rating_5',
       'SOP_2.0', 'SOP_2.5', 'SOP_3.0', 'SOP_3.5', 'SOP_4.0',
       'SOP_4.5', 'SOP_5.0', 'LOR_2.0', 'LOR_2.5', 'LOR_3.0',
       'LOR_3.5', 'LOR_4.0', 'LOR_4.5', 'LOR_5.0']]
X_train_2 = sm.add_constant(X_train_2)
lr_2 = sm.OLS(y_train, X_train_2).fit()

lr_2.summary()
```

Out[43]:

OLS Regression Results

Dep. Variable:	Chance of Admit	**R-squared:**	0.738
Model:	OLS	**Adj. R-squared:**	0.723
Method:	Least Squares	**F-statistic:**	49.01
Date:	Mon, 18 Dec 2023	**Prob (F-statistic):**	4.93e-84
Time:	20:21:12	**Log-Likelihood:**	-262.01
No. Observations:	350	**AIC:**	564.0
Df Residuals:	330	**BIC:**	641.2
Df Model:	19		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	-1.0296	0.220	-4.686	0.000	-1.462	-0.597
GRE Score	0.5123	0.042	12.105	0.000	0.429	0.596
Research	0.1514	0.070	2.160	0.031	0.014	0.289
University Rating_3	0.0632	0.085	0.745	0.457	-0.104	0.230
University Rating_4	0.1113	0.110	1.009	0.314	-0.106	0.328
University Rating_5	0.3712	0.134	2.765	0.006	0.107	0.635
SOP_2.0	0.1547	0.160	0.969	0.333	-0.159	0.469
SOP_2.5	0.3956	0.147	2.688	0.008	0.106	0.685
SOP_3.0	0.3199	0.151	2.122	0.035	0.023	0.616
SOP_3.5	0.3478	0.161	2.165	0.031	0.032	0.664
SOP_4.0	0.4451	0.165	2.697	0.007	0.120	0.770
SOP_4.5	0.5399	0.179	3.011	0.003	0.187	0.893
SOP_5.0	0.5624	0.201	2.791	0.006	0.166	0.959
LOR_2.0	0.1090	0.213	0.511	0.609	-0.310	0.528

LOR_2.5	0.3347	0.211	1.587	0.114	-0.080	0.750
LOR_3.0	0.3375	0.203	1.664	0.097	-0.062	0.737
LOR_3.5	0.4310	0.205	2.099	0.037	0.027	0.835
LOR_4.0	0.5777	0.209	2.766	0.006	0.167	0.989
LOR_4.5	0.7351	0.219	3.358	0.001	0.304	1.166
LOR_5.0	0.8345	0.230	3.631	0.000	0.382	1.287

Omnibus:	55.485	**Durbin-Watson:**	2.096
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	91.991
Skew:	-0.932	**Prob(JB):**	1.06e-20
Kurtosis:	4.683	**Cond. No.**	27.0

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

Inferences

- No much changes in R-square value after removing 3 - varaibles. (R-square reduced by 0.001)
- Based on the P-values, the following features were removed
  - University rating 3 - 0.457
  - SOP 2.0 - 0.333
  - LOR 2.0 - 0.609

In [44]:
```
X_train_3 = X_train[['GRE Score', 'Research','University Rating_4', 'University Rating_5',
       'SOP_2.5', 'SOP_3.0', 'SOP_3.5', 'SOP_4.0','SOP_4.5', 'SOP_5.0', 'LOR_2.5', 'LOR_3.0',
       'LOR_3.5', 'LOR_4.0', 'LOR_4.5', 'LOR_5.0']]
X_train_3 = sm.add_constant(X_train_3)
lr_3 = sm.OLS(y_train, X_train_3).fit()

lr_3.summary()
```

Out[44]:

OLS Regression Results

Dep. Variable:	Chance of Admit	**R-squared:**	0.737
Model:	OLS	**Adj. R-squared:**	0.724
Method:	Least Squares	**F-statistic:**	58.26
Date:	Mon, 18 Dec 2023	**Prob (F-statistic):**	3.00e-86
Time:	20:21:12	**Log-Likelihood:**	-263.04
No. Observations:	350	**AIC:**	560.1
Df Residuals:	333	**BIC:**	625.7
Df Model:	16		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.8549	0.119	-7.200	0.000	-1.088	-0.621
GRE Score	0.5190	0.042	12.437	0.000	0.437	0.601
Research	0.1513	0.070	2.169	0.031	0.014	0.288
University Rating_4	0.0600	0.091	0.660	0.510	-0.119	0.239
University Rating_5	0.3181	0.117	2.725	0.007	0.088	0.548
SOP_2.5	0.3085	0.114	2.713	0.007	0.085	0.532
SOP_3.0	0.2471	0.111	2.224	0.027	0.029	0.466
SOP_3.5	0.2882	0.117	2.453	0.015	0.057	0.519
SOP_4.0	0.3793	0.127	2.986	0.003	0.129	0.629
SOP_4.5	0.4709	0.146	3.221	0.001	0.183	0.759
SOP_5.0	0.4935	0.173	2.857	0.005	0.154	0.833
LOR_2.5	0.2815	0.128	2.197	0.029	0.029	0.534
LOR_3.0	0.2719	0.116	2.349	0.019	0.044	0.500
LOR_3.5	0.3678	0.119	3.085	0.002	0.133	0.602

LOR_4.0	0.5151	0.124	4.165	0.000	0.272	0.758
LOR_4.5	0.6777	0.139	4.865	0.000	0.404	0.952
LOR_5.0	0.7765	0.156	4.980	0.000	0.470	1.083

Omnibus:	51.284	**Durbin-Watson:**	2.081
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	82.226
Skew:	-0.885	**Prob(JB):**	1.40e-18
Kurtosis:	4.584	**Cond. No.**	14.3

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

Inferences

- No much changes in R-square value after removing 3 - varaibles. (R-square reduced by 0.001)
- Based on the P-values, the following features were removed
    - University rating 4
    - SOP 3.0
    - LOR 2.5

In [45]:
```
X_train_4 = X_train[['GRE Score', 'Research', 'University Rating_5',
       'SOP_2.5', 'SOP_3.5', 'SOP_4.0','SOP_4.5', 'SOP_5.0','LOR_3.0',
       'LOR_3.5', 'LOR_4.0', 'LOR_4.5', 'LOR_5.0']]
X_train_4 = sm.add_constant(X_train_4)
lr_4 = sm.OLS(y_train, X_train_4).fit()

lr_4.summary()
```

Out[45]:

OLS Regression Results

Dep. Variable:	Chance of Admit	**R-squared:**	0.728
Model:	OLS	**Adj. R-squared:**	0.718
Method:	Least Squares	**F-statistic:**	69.25
Date:	Mon, 18 Dec 2023	**Prob (F-statistic):**	1.06e-86
Time:	20:21:12	**Log-Likelihood:**	-268.65
No. Observations:	350	**AIC:**	565.3
Df Residuals:	336	**BIC:**	619.3
Df Model:	13		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.5747	0.082	-7.002	0.000	-0.736	-0.413
GRE Score	0.5531	0.041	13.647	0.000	0.473	0.633
Research	0.1543	0.070	2.203	0.028	0.017	0.292
University Rating_5	0.2655	0.099	2.683	0.008	0.071	0.460
SOP_2.5	0.1418	0.095	1.497	0.135	-0.044	0.328
SOP_3.5	0.1176	0.091	1.290	0.198	-0.062	0.297
SOP_4.0	0.2139	0.098	2.179	0.030	0.021	0.407
SOP_4.5	0.2943	0.115	2.567	0.011	0.069	0.520
SOP_5.0	0.3222	0.148	2.177	0.030	0.031	0.613
LOR_3.0	0.1683	0.094	1.793	0.074	-0.016	0.353
LOR_3.5	0.2806	0.096	2.920	0.004	0.092	0.470
LOR_4.0	0.4286	0.102	4.187	0.000	0.227	0.630
LOR_4.5	0.5928	0.118	5.011	0.000	0.360	0.825
LOR_5.0	0.6869	0.138	4.965	0.000	0.415	0.959

Omnibus:	45.710	**Durbin-Watson:**	2.048
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	67.468
Skew:	-0.841	**Prob(JB):**	2.24e-15
Kurtosis:	4.342	**Cond. No.**	10.2

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

Inferences

- Based on the P-values, the following features were removed
  - Research
  - SOP 3.5
  - SOP 2.5
  - LOR 3.0

In [46]:
```
X_train_5 = X_train[['GRE Score', 'University Rating_5',
       'SOP_4.0','SOP_4.5', 'SOP_5.0','LOR_3.5', 'LOR_4.0', 'LOR_4.5', 'LOR_5.0']]
X_train_5 = sm.add_constant(X_train_5)
lr_5 = sm.OLS(y_train, X_train_5).fit()

lr_5.summary()
```

Out[46]:

OLS Regression Results

Dep. Variable:	Chance of Admit	**R-squared:**	0.718
Model:	OLS	**Adj. R-squared:**	0.711
Method:	Least Squares	**F-statistic:**	96.19
Date:	Mon, 18 Dec 2023	**Prob (F-statistic):**	6.32e-88
Time:	20:21:12	**Log-Likelihood:**	-275.10
No. Observations:	350	**AIC:**	570.2
Df Residuals:	340	**BIC:**	608.8
Df Model:	9		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	-0.3452	0.050	-6.888	0.000	-0.444	-0.247
GRE Score	0.6120	0.035	17.251	0.000	0.542	0.682
University Rating_5	0.2584	0.100	2.581	0.010	0.061	0.455
SOP_4.0	0.1492	0.088	1.689	0.092	-0.025	0.323
SOP_4.5	0.2111	0.105	2.018	0.044	0.005	0.417
SOP_5.0	0.2490	0.142	1.752	0.081	-0.031	0.529
LOR_3.5	0.2048	0.083	2.471	0.014	0.042	0.368
LOR_4.0	0.3731	0.087	4.291	0.000	0.202	0.544
LOR_4.5	0.5268	0.106	4.970	0.000	0.318	0.735
LOR_5.0	0.6033	0.128	4.699	0.000	0.351	0.856

Omnibus:	44.947	**Durbin-Watson:**	2.083
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	66.353
Skew:	-0.828	**Prob(JB):**	3.91e-15
Kurtosis:	4.344	**Cond. No.**	7.19

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

Inferences

- Based on the P-values, the following features were removed
  - Research
  - SOP 4.0, 4.5 & 5.0
  - University rating 5
  - LOR 3.5

In [47]:
```
X_train_6 = X_train[['GRE Score', 'LOR_4.0', 'LOR_4.5', 'LOR_5.0']]
X_train_6 = sm.add_constant(X_train_6)
lr_6 = sm.OLS(y_train, X_train_6).fit()

lr_6.summary()
```

Out[47]:

OLS Regression Results

Dep. Variable:	Chance of Admit	**R-squared:**	0.696
Model:	OLS	**Adj. R-squared:**	0.693
Method:	Least Squares	**F-statistic:**	197.8
Date:	Mon, 18 Dec 2023	**Prob (F-statistic):**	6.20e-88
Time:	20:21:12	**Log-Likelihood:**	-288.05
No. Observations:	350	**AIC:**	586.1
Df Residuals:	345	**BIC:**	605.4
Df Model:	4		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.2157	0.040	-5.339	0.000	-0.295	-0.136
GRE Score	0.6818	0.033	20.655	0.000	0.617	0.747
LOR_4.0	0.3803	0.080	4.743	0.000	0.223	0.538
LOR_4.5	0.5770	0.094	6.112	0.000	0.391	0.763
LOR_5.0	0.7131	0.113	6.283	0.000	0.490	0.936

Omnibus:	43.870	**Durbin-Watson:**	2.114
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	62.653
Skew:	-0.829	**Prob(JB):**	2.48e-14
Kurtosis:	4.243	**Cond. No.**	4.44

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

Inference

- R-square values is 0.696 (almost 0.7)
- Now that all p-values are 0, we can consider that the model has been built.

Validate Linear Regression Assumptions

- Multicolillinearity check
- Mean of residuals
- Linearity of variables
- Test for Homoscedasticity
- Normality of residuals

Multicolillinearity check using VIF score

Function to calculate the VIF score

In [48]:
```
# Calculate the VIFs for the new model
def getVIF(X_train):
    vif = pd.DataFrame()
    X = X_train
    vif['Features'] = X.columns
    vif['VIF'] = [variance_inflation_factor(X.values, i) for i in range(X.shape[1])]
    vif['VIF'] = round(vif['VIF'], 2)
    vif = vif.sort_values(by = "VIF", ascending = False)
    return(vif)
```

In [49]:
```
getVIF(X_train_6)
```

Out[49]:

	Features	VIF
0	const	1.85
1	GRE Score	1.24
3	LOR_4.5	1.22
4	LOR_5.0	1.18
2	LOR_4.0	1.12

Inferences

- All VIF scores are below 5, indicating no multicollinearity.

In [50]:

```
# Applying the scaling on the test sets
df_test[num_col] = scaler.transform(df_test[num_col])
df_test.head()
```

Out[50]:

	GRE Score	Research	Chance of Admit	University Rating_2	University Rating_3	University Rating_4	University Rating_5	SOP_1.5	SOP_2.0	SOP_2.5	SOP_3.0	SOP_3.5	SOP_4.0	SOP_4.5	SOI
69	1.019222	1	0.412132	0	0	1	0	0	0	0	0	0	0	1	
29	-0.578066	0	-1.305936	1	0	0	0	1	0	0	0	0	0	0	
471	-0.489328	0	-0.590074	0	1	0	0	0	1	0	0	0	0	0	
344	-1.909139	0	-1.807038	1	0	0	0	1	0	0	0	0	0	0	
54	0.486793	0	-0.160557	0	1	0	0	0	0	0	1	0	0	0	

In [51]:

```
df_pred = df_test.copy()
```

In [52]:

```
df_test.shape
```

Out[52]:

```
(150, 23)
```

In [53]:
```
# Dividing test set into X_test and y_test
y_test = df_test.pop('Chance of Admit')
X_test = df_test
X_test = sm.add_constant(X_test)
```

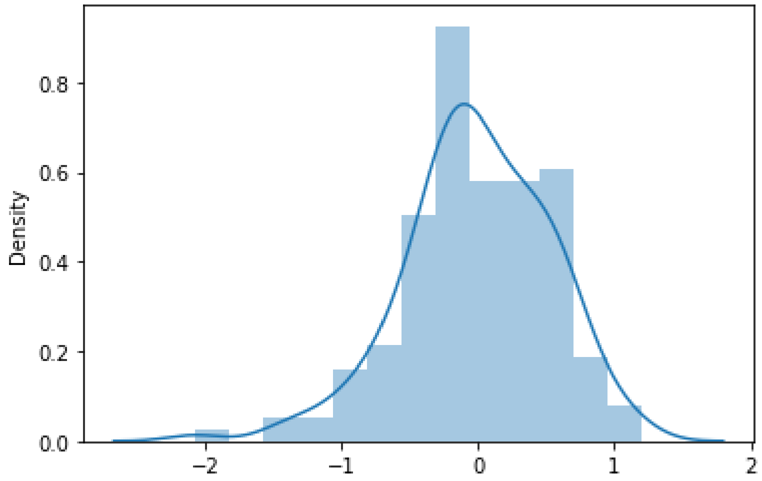
In [54]:
```
X_test_new = X_test[X_train_6.columns]

# Making predictions using the final model
y_pred = lr_6.predict(X_test_new)
```

Mean of residuals

In [55]:
```
residual = y_test - y_pred
sns.distplot(residual)
```

```
C:\Users\hp\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecated function and wi
ll be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibil
ity) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[55]:
```
<AxesSubplot:ylabel='Density'>
```



In [56]:
```
residuals = y_test.values - y_pred
print('Mean of Residuals: ', abs(residuals.mean()))
```

```
Mean of Residuals:  0.007416487467495869
```

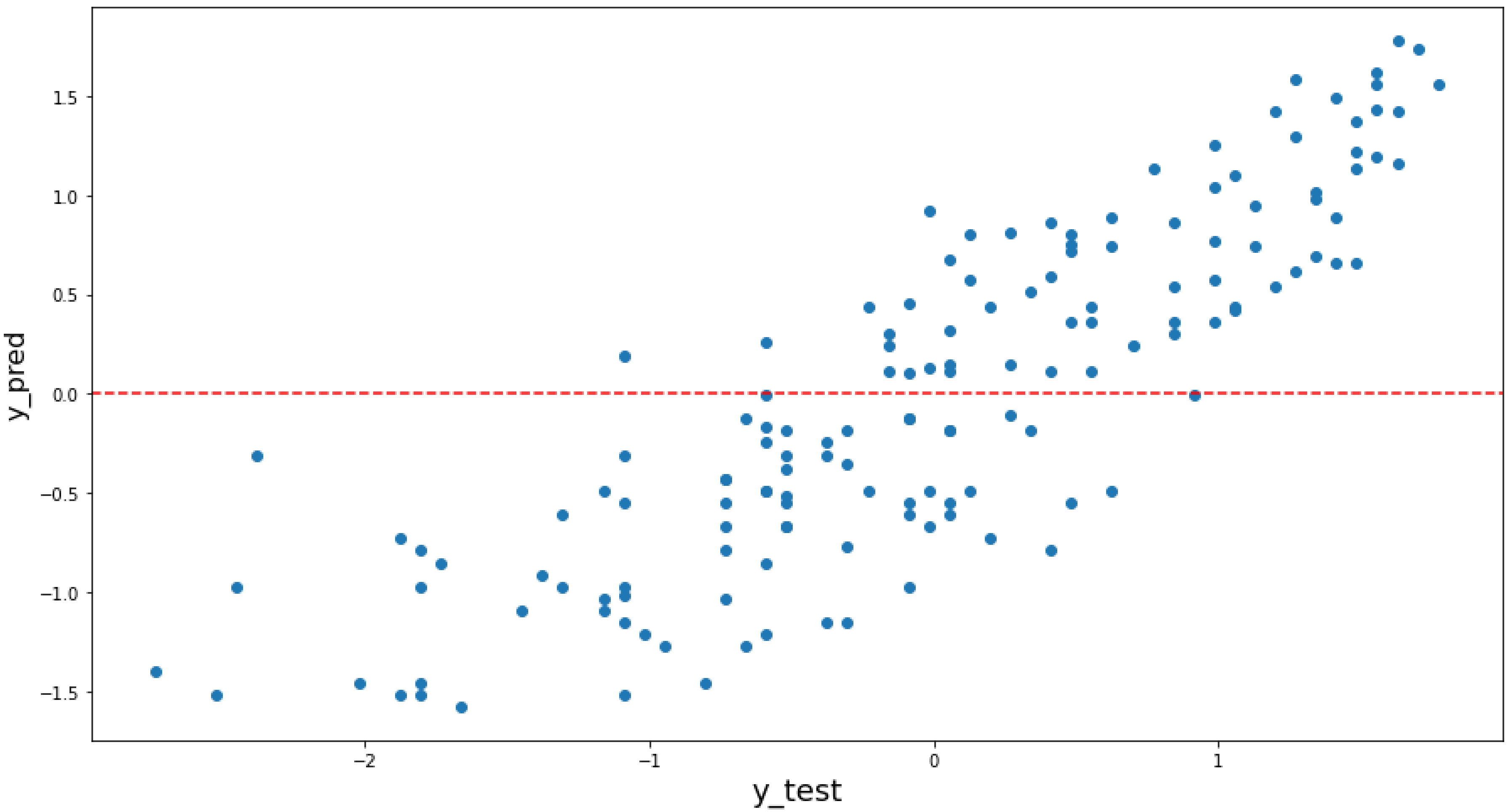
Inferences

- The model's means residuals are 0.0074, which indicates it is a good estimator.
- Since the mean of residuals is very close to 0, we can say that the model is unbiased

Linearity of variables

In [57]:
```
# Plotting y_test and y_pred to understand the spread.
fig = plt.figure(figsize=[15,8])
plt.scatter(y_test,y_pred)
fig.suptitle('y_test vs y_pred', fontsize=20)              # Plot heading
plt.xlabel('y_test', fontsize=18)                          # X-label
plt.ylabel('y_pred', fontsize=16)
plt.axhline(y=0, color="r" , linestyle="--")
plt.show()
```

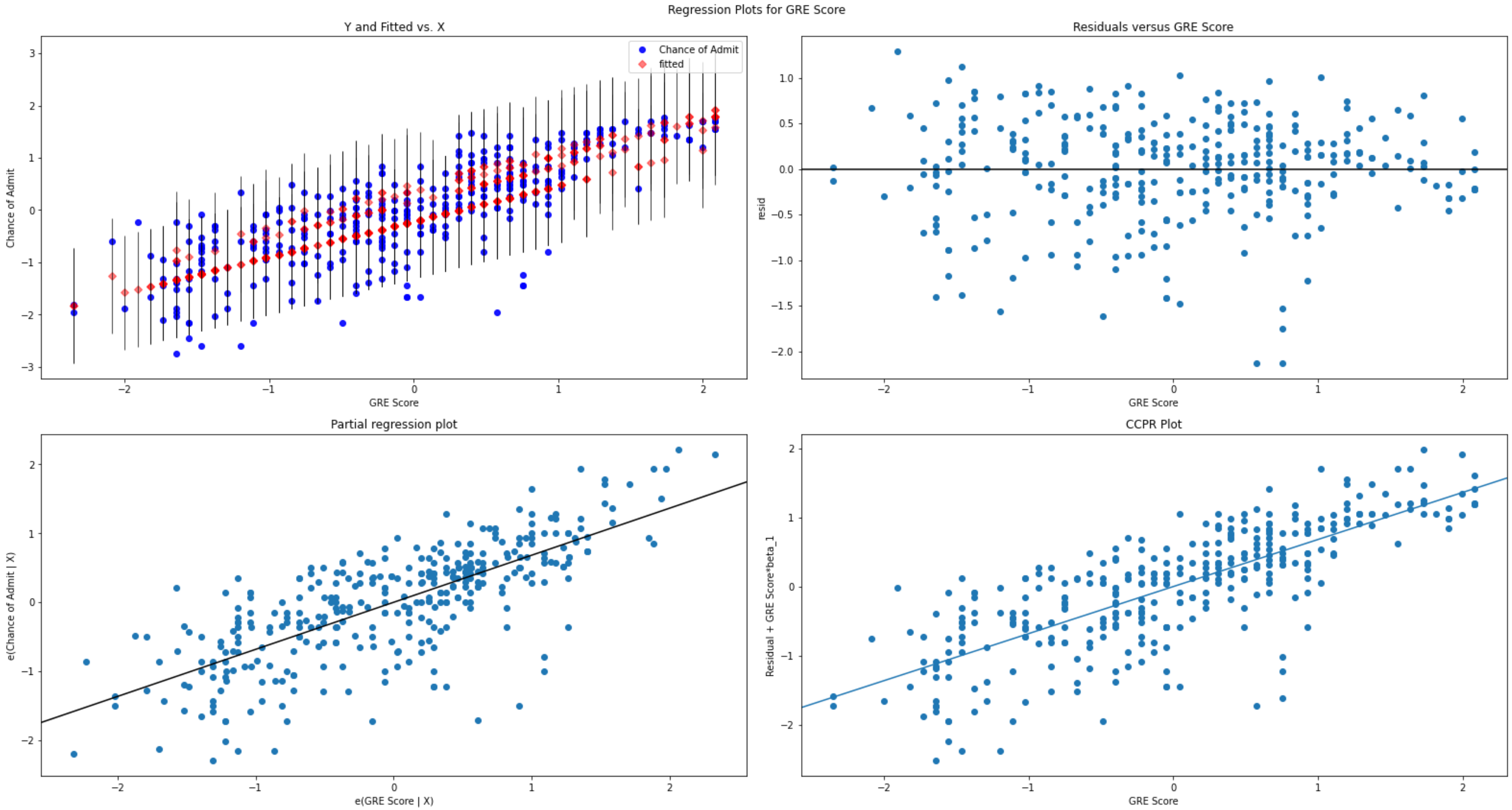
y_test vs y_pred



Test for Homoscedasticity

In [58]:
```
fig = plt.figure(figsize=(22,12))
fig = sm.graphics.plot_regress_exog(lr_6, 'GRE Score', fig=fig)
plt.tight_layout()
plt.show()
```

```
eval_env: 1
```



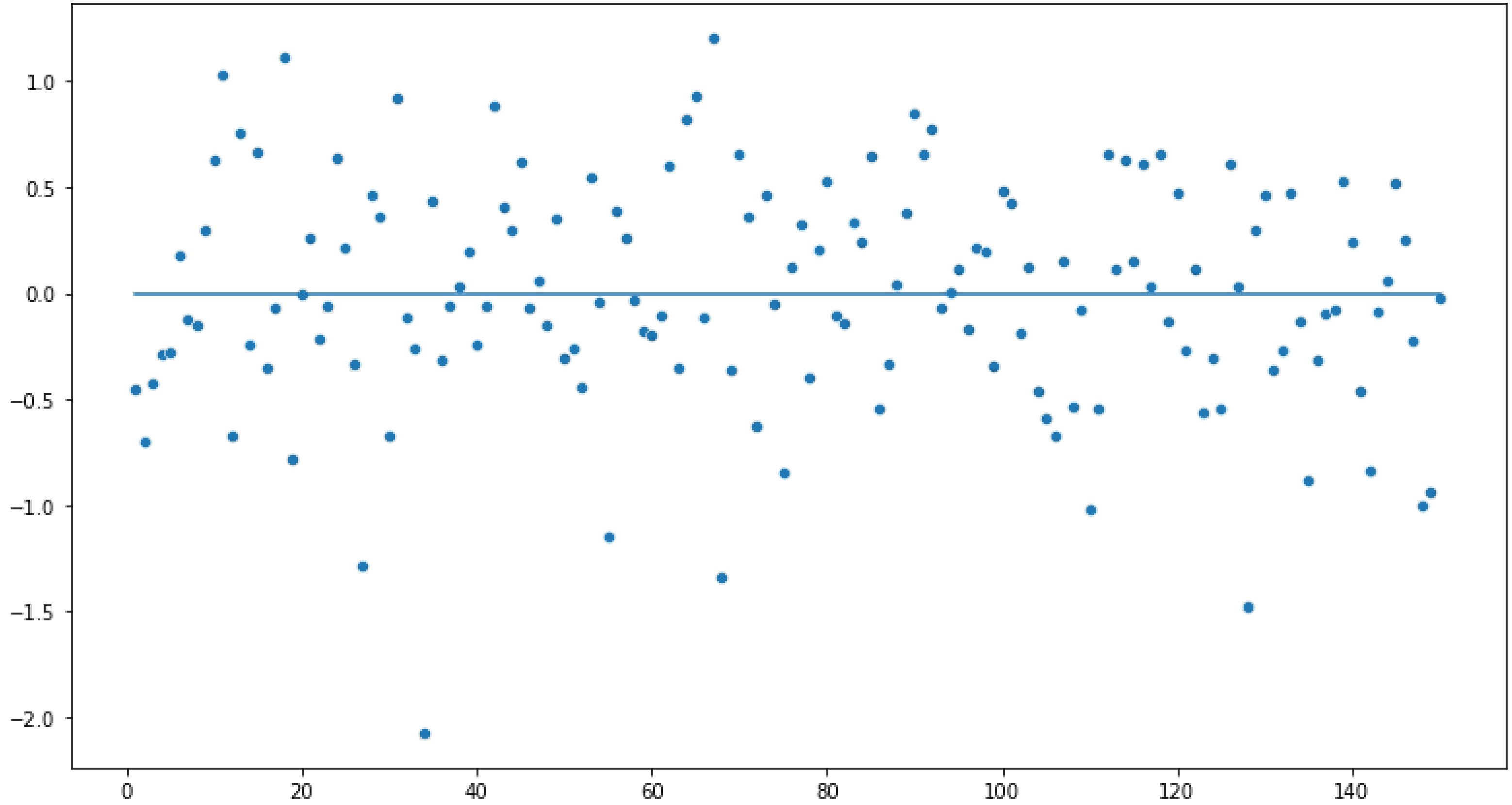
Inferences

- We can see that the points are plotted randomly spread or scattered. points or residuals are scattered around the '0' line, there is no pattern, and points are not based on one side so there's no problem of heteroscedasticity.
- With the predictor variable 'area' there's no heteroscedasticity.

In [59]:
```
fig = plt.figure(figsize=(11,6))
sns.scatterplot(np.arange(1,151,1),residual)
sns.lineplot(np.arange(1,151,1),residual.mean())
```

```
plt.tight_layout()
plt.show()
```

```
C:\Users\hp\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variables as keyword args:
x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyw
ord will result in an error or misinterpretation.
  warnings.warn(
C:\Users\hp\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variables as keyword args:
x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyw
ord will result in an error or misinterpretation.
  warnings.warn(
```



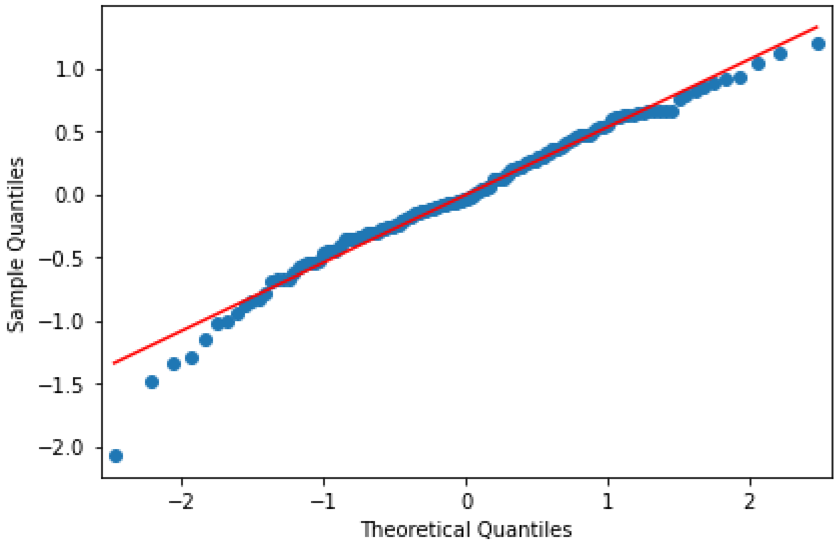
Inferences

- they are pretty symmetrically distributed

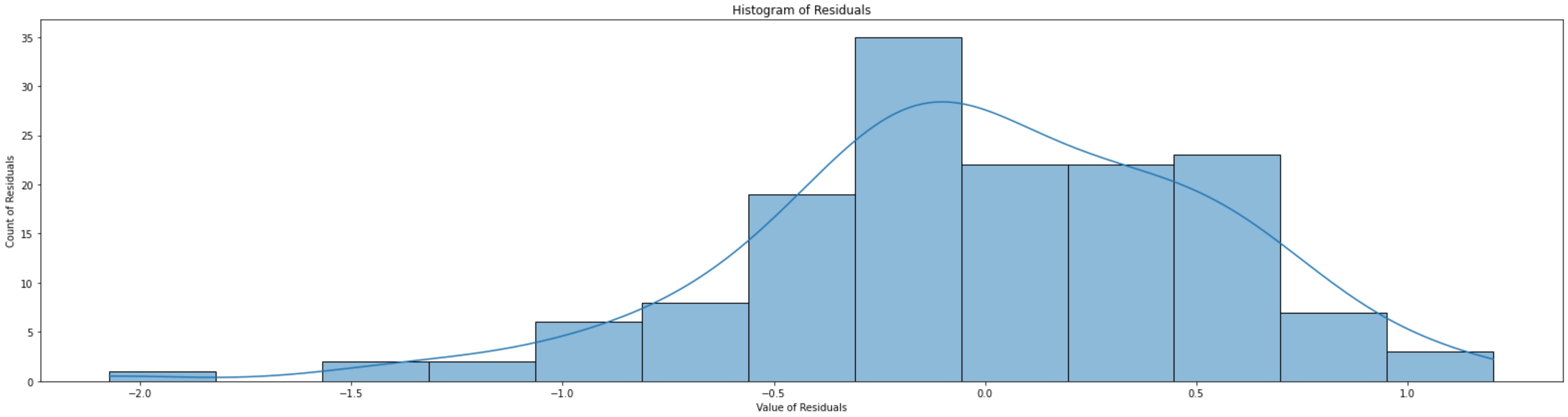
Normality of residuals

In [60]:
```
plt.figure(figsize=(22,6))
sm.qqplot(residual, line = 's')
plt.tight_layout()
plt.show()
```

```
<Figure size 1584x432 with 0 Axes>
```



In [61]:
```
#Histogram of Residuals
plt.figure(figsize=(22,6))
sns.histplot(residual, kde=True)
plt.title('Histogram of Residuals')
plt.xlabel('Value of Residuals')
plt.ylabel('Count of Residuals')
plt.tight_layout()
plt.show()
```



Inferences

- Data that aligns closely to the dotted line indicates a normal distribution.

Model Performance Evaluation

- Metrics checked -
  - MAE
  - RMSE
  - R2
  - Adj R2
- Train and Test performances are checked

In [62]:
```
r2 = r2_score(y_test,y_pred)
mae = mean_absolute_error(y_test,y_pred)
mse = mean_squared_error( y_test, y_pred )
rmse = np.sqrt( mean_squared_error( y_test, y_pred ))
mape = mean_absolute_percentage_error(y_test,y_pred)

# initialise data of lists.
perf_data = [[r2],[mae],[mse],[rmse],[mape]]
# Creates pandas DataFrame.
```

```
eval_ = pd.DataFrame(perf_data,columns= ["Scores"] ,index = ["R-Squared","Mean Absolute Error","Mean Square Error",
                                                              "Root Mean Square Error","Mean Absolute Percentage Error"])
eval_.head()
```

Out[62]:

	Scores
R-Squared	0.727859
Mean Absolute Error	0.418479
Mean Square Error	0.289148
Root Mean Square Error	0.537725
Mean Absolute Percentage Error	2.008603

Inference

Error term

An error term appears in a statistical model, like a regression model, to indicate the uncertainty in the model.

- R-Squared (Accuracy Score) - 0.72
  - This statistic indicates the percentage of the variance in the dependent variable that the independent variables explain collectively.As seen above our residual plot looks good, which means we donot have any bias in our model.
  - R-squared does not indicate if a regression model provides an adequate fit to your data. **A good model can have a low R2 value.** On the other hand, a biased model can have a high R2 value
- Mean Absolute Error - 0.42
  - MAE describes the typical magnitude of the residuals. Small MAE suggests the model is great at prediction, while a large MAE suggests that your model may have trouble in certain areas. There is scope of improvement.
- Root Mean Square Error - 0.54
  - RMSE is defined as the square root of the average squared difference between the predicted and the actual score. The lower the RMSE, the better a model fits a dataset
  - A huge difference between the RMSE and MAE indicates outliers. A smaller difference indicates less outliers in our case.
- Mean Square Error - 0.29
  - MSE equation is most apparent with the presence of outliers in our data.

- While each residual in MAE contributes proportionally to the total error, the error grows quadratically in MSE.This means that outliers in our data will contribute to much higher total error in the MSE than they would the MAE.
- Mean Absolute Percentage Error - 2%
  - MAPE is biased towards predictions that are systematically less than the actual values themselves.MAPE will be lower when the prediction is lower than the actual compared to a prediction that is higher by the same amount

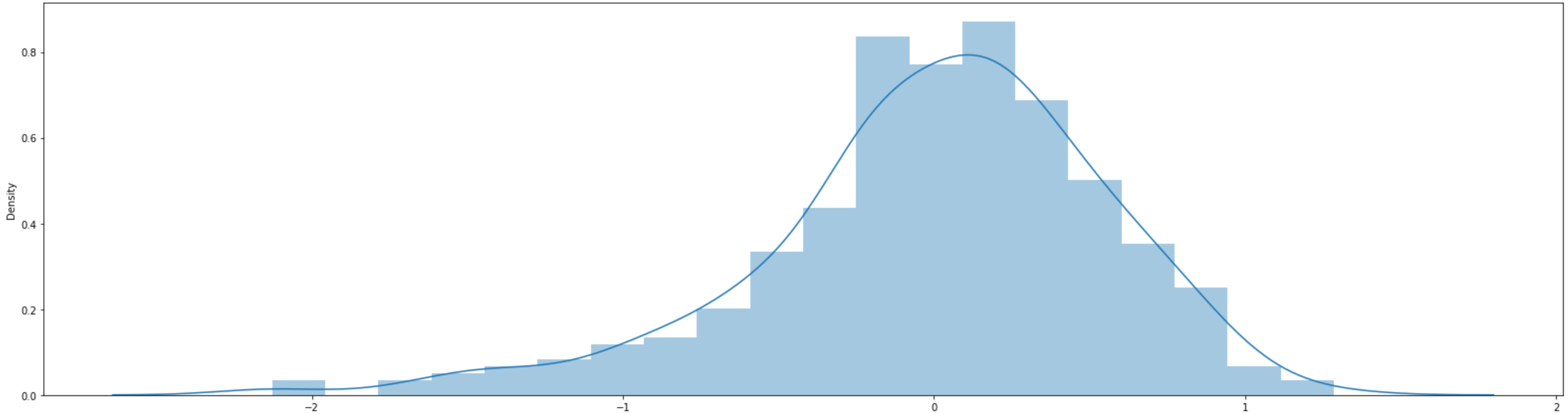
Train & Test performances are checked

Train Performance

In [63]:
```
y_train_pred = lr_6.predict(X_train_6)
```

In [64]:
```
res = y_train - y_train_pred
plt.figure(figsize=(22,6))
sns.distplot(res)
plt.tight_layout()
plt.show()
```

```
C:\Users\hp\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecated function and wi
ll be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibil
ity) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

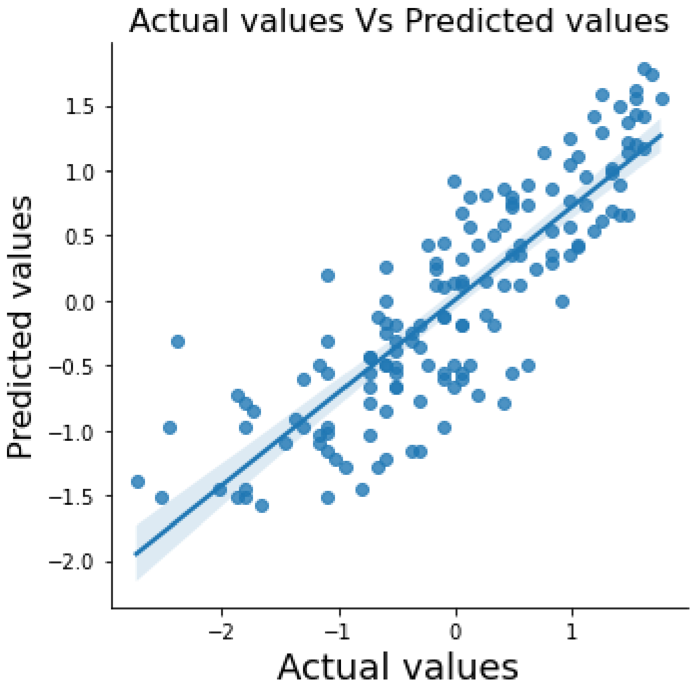


Test Performance

In [65]:
```
df_pred['Preds'] = y_pred
```

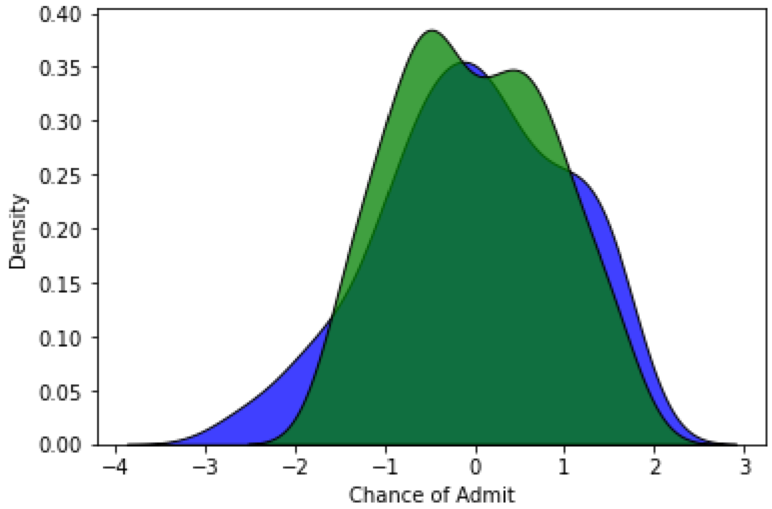
In [66]:
```
# Plotting y_test and y_pred to understand the spread.
fig = plt.figure(figsize=(22,12))
sns.lmplot(x='Chance of Admit', y="Preds", data=df_pred)
plt.xlabel('Actual values', fontsize=18)
plt.ylabel('Predicted values', fontsize=16)
plt.title('Actual values Vs Predicted values', fontsize=16)
plt.tight_layout()
plt.show()
```

```
<Figure size 1584x864 with 0 Axes>
```



In [67]:
```
sns.kdeplot(data=df_pred, x='Chance of Admit', color='b', multiple="stack")
sns.kdeplot(data=df_pred, x='Preds', color='g', multiple="stack")
```

Out[67]:
```
<AxesSubplot:xlabel='Chance of Admit', ylabel='Density'>
```



Inferences

- The above kdeplot shows two graphs - the actual (blue) and predicted (green) values for chance of admission. The graphs shows **Model is a good estimator.**

Conclusions & Recommendations

Inferences based on EDA

- Based on the analysis we donot have outliers for independent features like 'GRE Score', 'TOEFL Score' & 'CGPA'.
- 'Chance of Admit' is slightly left screwed. Since 'Chance of Admit' is a slightly left skewed, we don't have to handle it.
- Among students who have done research vs those who did not, **56 % said Yes and 44 % said No**
- More than **50% of the data has a university rating of 3 or 2**
- A majority of students (56%) have letter of recommendation values between 3.0 and 4.5
- A **strong positive relationship exists between Chance of admit and numerical variables (GRE & TOEFL score and CGPA).**
- **GRE Score** , **TOFEL Score** and **CGPA** are highly correlated **(0.80)**. We should drop two of these.
- Based on the analysis an **upward trend for each categorical variable**. A higher rating or value increases the chance of admission

Inferences based on Model

With a low p-value and low VIF, these variables do describe the **Chance of Admit** to a good extent.

Final predictors which can be proposed are

- GRE Score **(coef : 0.6818, p-value - 0.000, VIF : 1.24)**
- LOR_4.0 **(coef : 0.3803, p-value - 0.000, VIF : 1.22)**
- LOR_4.5 **(coef : 0.5770, p-value - 0.000, VIF : 1.18)**
- LOR_5.0 **(coef : 0.7131, p-value - 0.000, VIF : 1.12)**

We can see that the equation of our best fitted line is:

```
$ Chance of Admit = (0.6818 * GRE Score ) + (0.3803 * LOR_4.0) + (0.5770 * LOR_4.5) - (0.7131 *  LOR_5.0) -
0.2157$
```

Above equation implies how the "Chance of Admit" with a unit change in any of these predictor variable with all other variables held constant.

e.g.

1. The predictor GRE Score suggest that the Chance of Admit increases by a factor of 0.6818 when GRE Score is high.

Overall we have a decent model, still there are area of improvements.

Adj. R-squared	r2_score	Prob (F-statistic)	AIC	BIC	RMSE
0.693	0.696	620e-88	**586**	**605**	**0.54**

Note - We found that TOEFL and CGPA are highly correlated with GRE scores, hence these variables can also be used in exchange for GRE scores.

Possible Model Improvement Areas

We have a couple of options:

1. Add new features GRE_TOEFL_CGPA_Ratio = (GRE & TOEFL Score & CGPA ratio) etc.
2. Removing outliers or handling outlier by minmax distribution.
3. Build a non-linear model

Suggestions

Graduation Admission - Can use the above model to create new feature where students/learners can come to their website and check their probability of getting into the IVY league college.

Key features which influence the chance of Admit are

- GRE Score
- TOEFL Score
- CGPA
- LOR greater or equal to than 4.5

A higher University rating will increases the chance of admission

A higher value of LOR and SPO will also increases the chance of admission for the student.

https://drive.google.com/drive/folders/1xg-7LF6N36gb97w-7RjcQsBxos98ztPW?usp=sharing