Graduate Admission - Linear Regression

Business Problem:

- To **understand about the factors** which are important in graduate admissions and how these factors are **interrelated** among themselves which will help Educational Institutions **to predict one's chances of admission** given the rest of the variables.

Column Profiling:

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

Overview of the notebook:

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

Exploratory data analysis:

Importing required packages:

In [7]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
sns.set(style='whitegrid')
from numpy import NaN, nan
from scipy import stats
import statsmodels.api as  sm
import warnings
warnings.filterwarnings("ignore")

# Train & Test data split
from sklearn.model_selection import train_test_split

# Feature scaling
from sklearn.preprocessing import StandardScaler

# Check for the VIF values of the feature variables.
from statsmodels.stats.outliers_influence import variance_inflation_factor

# Importing RFE and LinearRegression
from sklearn.feature_selection import RFE
from sklearn.linear_model import LinearRegression

from sklearn.metrics import mean_absolute_error, r2_score, mean_squared_error
from sklearn.metrics import mean_absolute_percentage_error
```

Loading data into Dataframe:

In [8]:

```
grad_adm_data=pd.read_csv('Jamboree_Admission.txt')
grad_adm_data.head()
```

Out[8]:

	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

Dropping the unique row Identifier - which is Serial No.

In [9]:

```
grad_adm_data=grad_adm_data.drop('Serial No.',axis =1)
grad_adm_data.head()
```

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

Identification of variables and data types:

In [10]:

```
grad_adm_data.shape
```

Out[10]:

```
(500, 8)
```

In [11]:

```
grad_adm_data.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
```

Analysing the basic metrics:

In [12]:

```
grad_adm_data.describe()
```

Out[12]:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	C of
count	500.000000	500.000000	500.000000	500.000000	500.00000	500.000000	500.000000	500.
mean	316.472000	107.192000	3.114000	3.374000	3.48400	8.576440	0.560000	0.
std	11.295148	6.081868	1.143512	0.991004	0.92545	0.604813	0.496884	0
min	290.000000	92.000000	1.000000	1.000000	1.00000	6.800000	0.000000	0.
25%	308.000000	103.000000	2.000000	2.500000	3.00000	8.127500	0.000000	0.
50%	317.000000	107.000000	3.000000	3.500000	3.50000	8.560000	1.000000	0.
75%	325.000000	112.000000	4.000000	4.000000	4.00000	9.040000	1.000000	0.
max	340.000000	120.000000	5.000000	5.000000	5.00000	9.920000	1.000000	0.

In [13]:

```
def missingValue(df):
  #Identifying Missing data.
    total_null = df.isnull().sum().sort_values(ascending=False)
    percent=((df.isnull().sum()/len(df))*100).sort_values(ascending=False)
    print(f"Total records in our data = {df.shape[0]} where missing values are as follows:"
    missing_data=pd.concat([total_null,percent.round(2)],axis=1,keys=['Total Missing','In P
    return missing_data
```

In [14]:

```
missingValue(grad_adm_data)
```

```
Total records in our data = 500 where missing values are as follows:
```

Out[14]:

	Total Missing	In Percent
GRE Score	0	0.0
TOEFL Score	0	0.0
University Rating	0	0.0
SOP	0	0.0
LOR	0	0.0
CGPA	0	0.0
Research	0	0.0
Chance of Admit	0	0.0

Summary:

- No missing values present in the dataset

In [15]:

```
numerical_cols = ['GRE Score', 'TOEFL Score', 'University Rating', 'SOP', 'LOR ', 'CGPA', '
for i in numerical_cols:

    print(f" Unique value count in {i} is {grad_adm_data[i].nunique()}")
```

```
 Unique value count in GRE Score is 49
 Unique value count in TOEFL Score is 29
 Unique value count in University Rating is 5
 Unique value count in SOP is 9
 Unique value count in LOR  is 9
 Unique value count in CGPA is 184
 Unique value count in Research is 2
 Unique value count in Chance of Admit  is 61
```

In [16]:

```
characteristics_catg = ['University Rating', 'SOP', 'LOR ','Research']
for i in characteristics_catg:
    print(f" Unique values in {i} are {grad_adm_data[i].unique()}")
```

```
 Unique values in University Rating are [4 3 2 5 1]
 Unique values in SOP are [4.5 4.  3.  3.5 2.  5.  1.5 1.  2.5]
 Unique values in LOR  are [4.5 3.5 2.5 3.  4.  1.5 2.  5.  1. ]
 Unique values in Research are [1 0]
```

In [17]:

```
for i in characteristics_catg:
    grad_adm_data[i] = grad_adm_data[i].astype("category")
grad_adm_data.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
```

In [18]:

```
grad_adm_data.select_dtypes('category').columns
```

Out[18]:

```
Index(['University Rating', 'SOP', 'LOR ', 'Research'], dtype='object')
```

In [19]:

```
list(grad_adm_data.select_dtypes('category').columns)
```

Out[19]:

```
['University Rating', 'SOP', 'LOR ', 'Research']
```

In [20]:

```
print(f"Columns with category datatypes (Categorical Features) are : \
{list(grad_adm_data.select_dtypes('category').columns)}")
print(f"Columns with integer and float datatypes (Numerical Features) are: \
{list(grad_adm_data.select_dtypes(['int64','float64']).columns)}")
```

```
Columns with category datatypes (Categorical Features) are : ['University Ra
ting', 'SOP', 'LOR ', 'Research']
Columns with integer and float datatypes (Numerical Features) are: ['GRE Sco
re', 'TOEFL Score', 'CGPA', 'Chance of Admit ']
```

Univariate Analysis:

In [21]:

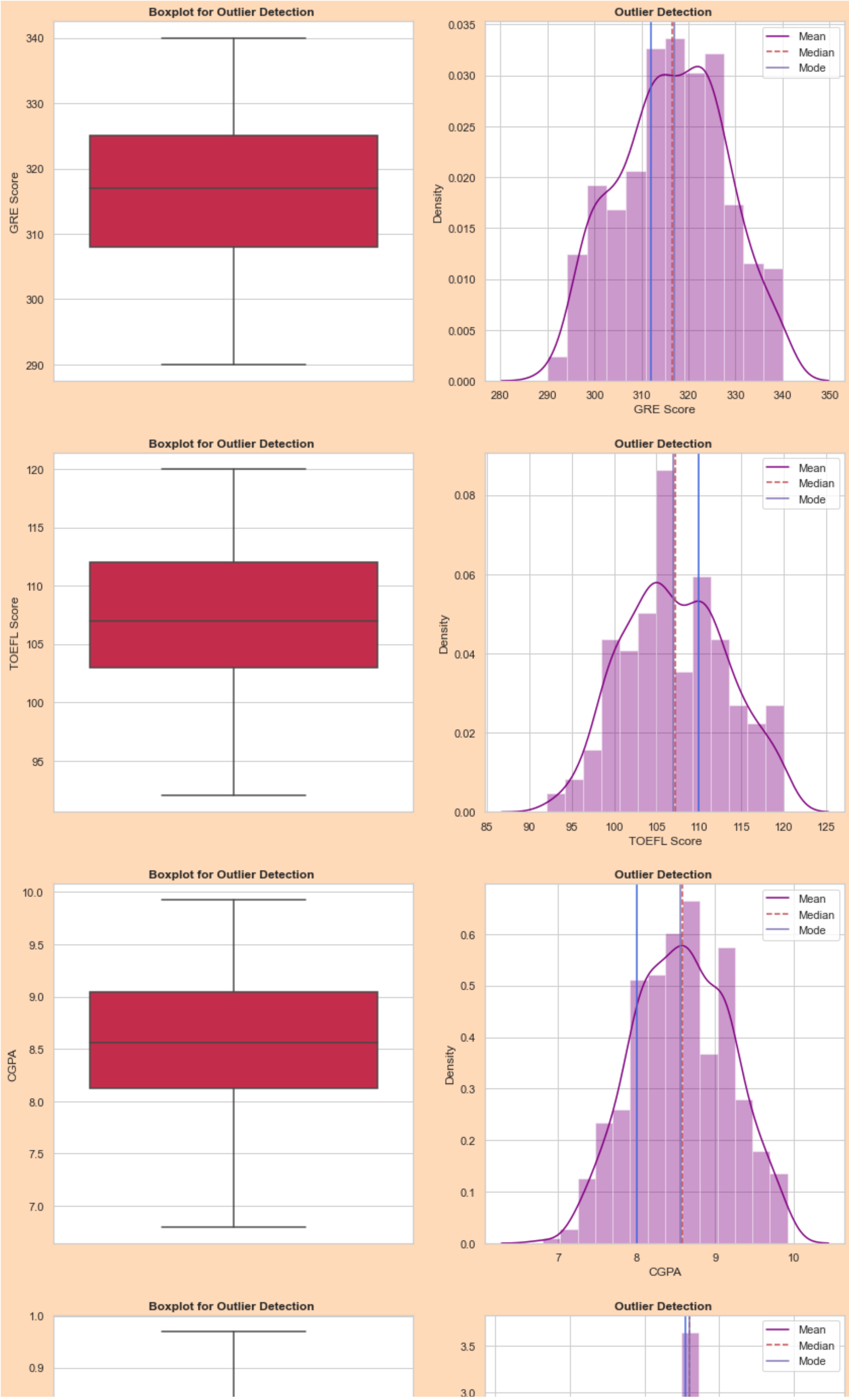
```
def outlier_detect(df,colname,nrows=2,mcols=2,width=20,height=15):
    fig,ax=plt.subplots(nrows,mcols,figsize=(width,height))
    fig.set_facecolor("peachpuff")
    rows=0
    for var in colname:
        ax[rows][0].set_title("Boxplot for Outlier Detection ", fontweight="bold")
        plt.ylabel(var,fontsize=12)
        sns.boxplot(y=df[var],color='crimson',ax=ax[rows][0])

        #plt.subplot(nrows,mcols,pltcounter+1)
        sns.distplot(df[var],color='purple',ax=ax[rows][1])
        ax[rows][1].axvline(df[var].mean(),color='r',linestyle='--',label="Mean")
        ax[rows][1].axvline(df[var].median(),color='m',linestyle='-',label="Median")
        ax[rows][1].axvline(df[var].mode()[0],color='royalblue',linestyle='-',label="Mode")
        ax[rows][1].set_title("Outlier Detection ",fontweight="bold")
        ax[rows][1].legend({'Mean':df[var].mean(),'Median':df[var].median(),'Mode':df[var].
        rows+=1
    plt.show()
```

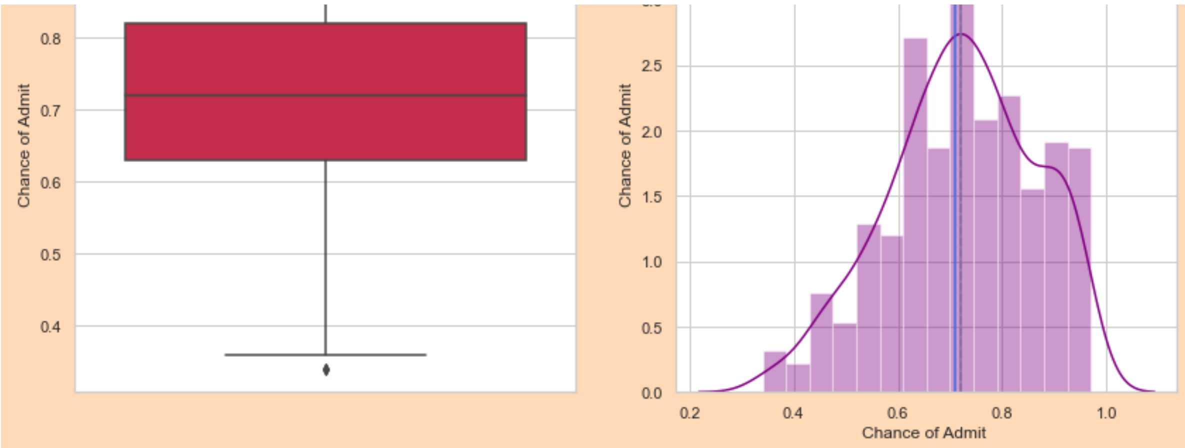
In [22]:

```
numerical_cols = ['GRE Score', 'TOEFL Score', 'CGPA', 'Chance of Admit ']
```

In [23]:

```
outlier_detect(grad_adm_data,numerical_cols,len(numerical_cols),2,14,30)
```





- The data for 'GRE Score', 'TOEFL Score', 'CGPA' is normally distibuted with no outliers present.
- The data for 'Chance of Admit ' has a little skewness towards left, with a very negligible no. of outliers

In [24]:

```
# Frequency of each feature in percentage.
def cat_analysis(df, colnames, nrows=2,mcols=2,width=20,height=30,sortbyindex=False):
    fig,ax=plt.subplots(nrows,mcols,figsize=(width,height))
    fig.set_facecolor(color='peachpuff')
    string="Frequency of "
    rows=0
    for colname in colnames:
        count=(df[colname].value_counts(normalize=True)*100)
        string+=colname + ' in (%)'
        if sortbyindex:
            count = count.sort_index()
        count.plot.bar(color=sns.color_palette("flare"),ax=ax[rows][0])
        ax[rows][0].set_ylabel(string,fontsize=14)
        ax[rows][0].set_xlabel(colname,fontsize=14)

        count.plot.pie(colors=sns.color_palette("flare"),autopct='%0.0f%%',textprops={'font
        #explode=[0.2 if colname{i}==min(colname) else 0]
        ax[rows][0].set_title("Frequency wise " + colname, fontweight="bold")
        string ="Frequency of "
        rows+=1
```

In [25]:

```
categorical_cols = ['University Rating', 'SOP', 'LOR ', 'Research']
```

In [26]:

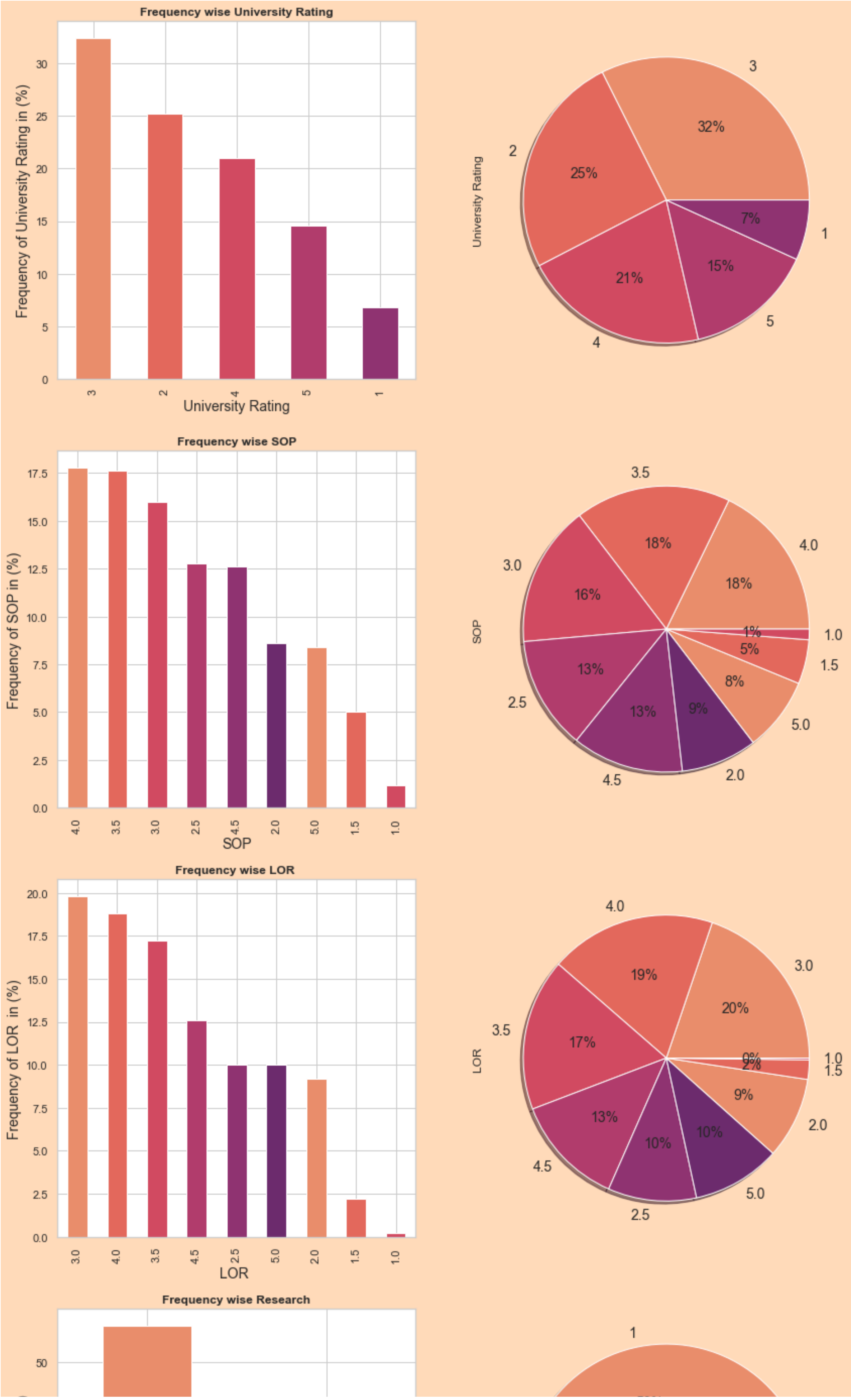
```
(grad_adm_data['University Rating'].value_counts(normalize=True))
```

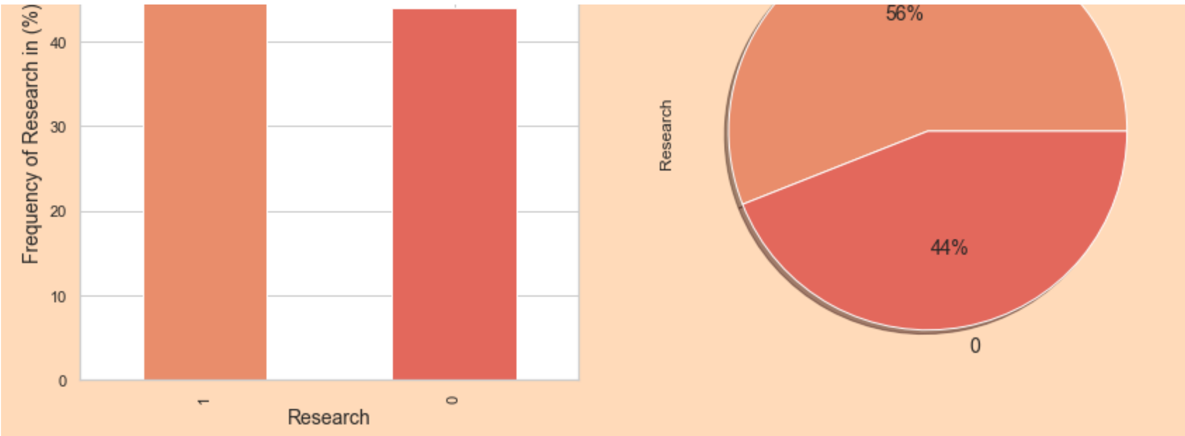
Out[26]:

```
3    0.324
2    0.252
4    0.210
5    0.146
1    0.068
Name: University Rating, dtype: float64
```

In [27]:

```
cat_analysis(grad_adm_data,categorical_cols,len(categorical_cols),2,14,30)
```





Data Preparation

In [28]:

```
grad_adm_data.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
```

In [29]:

```
grad_adm_data['GRE Score'].sort_values().head()
```

Out[29]:

```
377    290
117    290
168    293
79     294
272    294
Name: GRE Score, dtype: int64
```

Backup of orginial dataset

In [30]:

```
grad_adm_data_new = grad_adm_data.copy()
```

In [31]:

```
grad_adm_data_new['GRE Score'].sort_values()
```

Out[31]:

```
377    290
117    290
168    293
79     294
272    294
      ...
81     340
84     340
143    340
384    340
429    340
Name: GRE Score, Length: 500, dtype: int64
```

In [32]:

```
bins = [290,300,310,320,330,340]
labels =["290-300","300-310","310-320","320-330","330-340"]
grad_adm_data_new['GRE Score bins'] = pd.cut(grad_adm_data_new['GRE Score'], bins, labels=l
```

In [33]:

```
grad_adm_data_new['TOEFL Score'].sort_values()
```

Out[33]:

```
368     92
28      93
79      93
411     94
347     94
      ...
81     120
97     120
297    120
143    120
497    120
Name: TOEFL Score, Length: 500, dtype: int64
```

In [34]:

```
bins = [90,100,110,120]
labels =['90-100','100-110','110-120']
grad_adm_data_new['TOEFL Score bins'] = pd.cut(grad_adm_data_new['TOEFL Score'], bins,label
```

In [35]:

```
grad_adm_data_new['CGPA'].sort_values()
```

Out[35]:

```
58     6.80
28     7.20
464    7.21
436    7.23
348    7.25
       ...
425    9.86
203    9.87
496    9.87
202    9.91
143    9.92
Name: CGPA, Length: 500, dtype: float64
```

In [36]:

```
bins = [6.5,7.0,7.5,8.0,8.5,9.0,9.5,10.0]
labels =['6.5-7.0','7.0-7.5','7.5-8.0','8.0-8.5','8.5-9.0','9.0-9.5','Above 9.5']
grad_adm_data_new['CGPA bins'] = pd.cut(grad_adm_data_new['CGPA'], bins,labels=labels)
```

In [37]:

```
grad_adm_data_new
```

Out[37]:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit	GRE Score bins	TOEFL Score bins	CGPA bins
0	337	118	4	4.5	4.5	9.65	1	0.92	330-340	110-120	Above 9.5
1	324	107	4	4.0	4.5	8.87	1	0.76	320-330	100-110	8.5-9.0
2	316	104	3	3.0	3.5	8.00	1	0.72	310-320	100-110	7.5-8.0
3	322	110	3	3.5	2.5	8.67	1	0.80	320-330	100-110	8.5-9.0
4	314	103	2	2.0	3.0	8.21	0	0.65	310-320	100-110	8.0-8.5
...	...	...	...	...	...	...	...	...	...	...	...
495	332	108	5	4.5	4.0	9.02	1	0.87	330-340	100-110	9.0-9.5
496	337	117	5	5.0	5.0	9.87	1	0.96	330-340	110-120	Above 9.5
497	330	120	5	4.5	5.0	9.56	1	0.93	320-330	110-120	Above 9.5
498	312	103	4	4.0	5.0	8.43	0	0.73	310-320	100-110	8.0-8.5
499	327	113	4	4.5	4.5	9.04	0	0.84	320-330	110-120	9.0-9.5

500 rows × 11 columns

In [38]:

```
grad_adm_data_new.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 11 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 
 8   GRE Score bins     498 non-null    category
 9   TOEFL Score bins   500 non-null    category
 10  CGPA bins          500 non-null    category
dtypes: category(7), float64(2), int64(2)
memory usage: 20.9 KB
```

In [39]:

```
#sns.lineplot(x='GRE Score bins',hue='University Rating',data=grad_adm_data_new,palette="ro
```

In [40]:

```
characteristics_catg = ['University Rating', 'SOP', 'LOR ','Research','GRE Score bins','CGP
```

Bi-Variate Analysis with Research

Categorical variables

In [41]:

```
def cat_bi_analysis(df,colname,depend_var,nrows=2,mcols=2,width=20,height=15):
    fig,ax=plt.subplots(nrows,mcols,figsize=(width,height))
    sns.set(style='white')
    fig.set_facecolor("peachpuff")
    rows=0
    string=" based Distribution"
    for var in colname:
        string= var + string
        sns.countplot(data=df,x=depend_var, hue=var, palette="hls",ax=ax[rows][0])
        sns.countplot(data=df, x=var, hue=depend_var, palette="husl",ax=ax[rows][1])
        ax[rows][0].set_title(string, fontweight="bold",fontsize=14)
        ax[rows][1].set_title(string, fontweight="bold",fontsize=14)
        ax[rows][0].set_ylabel('count', fontweight="bold",fontsize=14)
        ax[rows][0].set_xlabel(var, fontweight="bold",fontsize=14)
        ax[rows][1].set_ylabel('count', fontweight="bold",fontsize=14)
        ax[rows][1].set_xlabel(var, fontweight="bold",fontsize=14)
        rows+=1
        string = " based Distribution"
    plt.show()
```

In [42]:

```
col_names = ['University Rating', 'SOP', 'LOR ','GRE Score bins','TOEFL Score bins','CGPA b
cat_bi_analysis(grad_adm_data_new,col_names,'Research',6,2,20,36)
```

Research criteria is predominantly useful because of following reasons:

- Students to Research papers have more chances of getting into Univeristies with top class ratings (4 & 5).
- Students with higher ratings in LOR and SOP are the students with most number of research paper publications.
- It shouldn't be surprising that the students with higher scores in academics (GRE, TOEFL and CGPA) are the one's who are actively publishing or had published Research papers in the past.

Multi-Variant Analysis:

Categorical variables and Numerical variables

In [43]:

```
def num_bi_analysis(df,colname,category,groupby,nrows=1,mcols=2,width=20,height=8):
    fig,ax=plt.subplots(nrows,mcols,figsize=(width,height),squeeze=False)
    fig.set_facecolor("peachpuff")
    rows=0
    for var in colname:
        sns.boxplot(x=category,y=var,data=df,ax=ax[rows][0])
        sns.lineplot(x=df[category],y=df[var],ax=ax[rows][1],hue=df[groupby])
        ax[rows][0].set_ylabel(var,fontweight="bold",fontsize=14)
        ax[rows][0].set_xlabel(category,fontweight="bold",fontsize=14)
        ax[rows][1].set_ylabel(var,fontweight="bold",fontsize=14)
        ax[rows][1].set_xlabel(category,fontweight="bold",fontsize=14)
    plt.show()
```

In [44]:

```
col_names = ['University Rating', 'SOP', 'LOR ','GRE Score bins','TOEFL Score bins','CGPA b
```

In [45]:

```
grad_adm_data_new.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 11 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 
 8   GRE Score bins     498 non-null    category
 9   TOEFL Score bins   500 non-null    category
 10  CGPA bins          500 non-null    category
dtypes: category(7), float64(2), int64(2)
memory usage: 20.9 KB
```

Column Cleaning

In [46]:

```
grad_adm_data_new.columns
```

Out[46]:

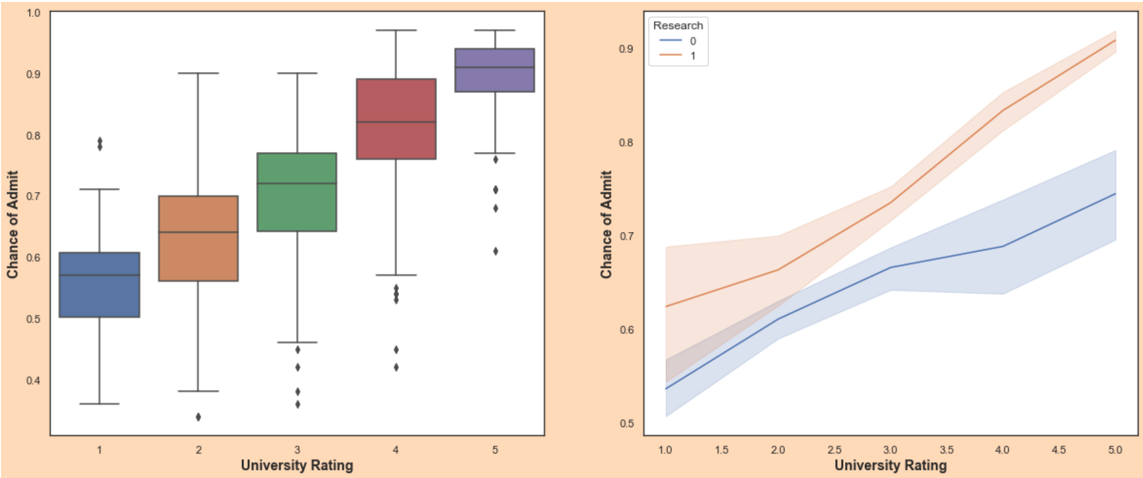
```
Index(['GRE Score', 'TOEFL Score', 'University Rating', 'SOP', 'LOR ', 'CGP
A',
       'Research', 'Chance of Admit ', 'GRE Score bins', 'TOEFL Score bins',
       'CGPA bins'],
      dtype='object')
```

In [47]:

```
grad_adm_data['LOR'] = grad_adm_data['LOR ']
grad_adm_data['Chance of Admit'] = grad_adm_data['Chance of Admit ']

grad_adm_data_new['LOR'] = grad_adm_data_new['LOR ']
grad_adm_data_new['Chance of Admit'] = grad_adm_data_new['Chance of Admit ']
```

In [48]:

```
col_num = [ 'Chance of Admit']
num_bi_analysis(grad_adm_data_new,col_num,"University Rating",'Research')

col_num = [ 'Chance of Admit']
num_bi_analysis(grad_adm_data_new,col_num,"SOP",'CGPA bins')

col_num = [ 'Chance of Admit']
num_bi_analysis(grad_adm_data_new,col_num,"LOR",'GRE Score bins')

col_num = [ 'Chance of Admit']
num_bi_analysis(grad_adm_data_new,col_num,"LOR",'TOEFL Score bins')

col_num = [ 'Chance of Admit']
num_bi_analysis(grad_adm_data_new,col_num,'Research',"CGPA bins")
```



In [49]:

```
grad_adm_data.columns
```

Out[49]:

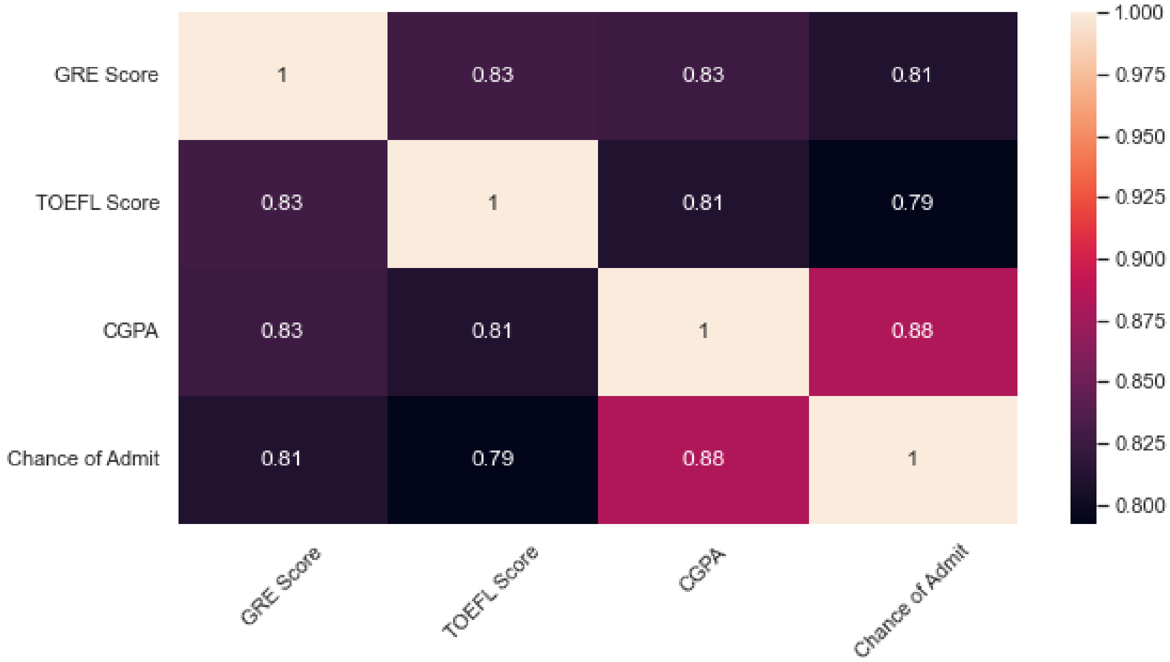
```
Index(['GRE Score', 'TOEFL Score', 'University Rating', 'SOP', 'LOR ', 'CGP
A',
       'Research', 'Chance of Admit ', 'LOR', 'Chance of Admit'],
      dtype='object')
```

In [50]:

```
grad_adm_data = grad_adm_data.drop('Chance of Admit ', axis = 1)
```

In [51]:

```
# Correlation between numerical variables

plt.figure(figsize=(10,5))
sns.heatmap(grad_adm_data.corr(method="pearson"),annot=True)
plt.yticks(rotation=360)
plt.xticks(rotation=45)
plt.show()
```



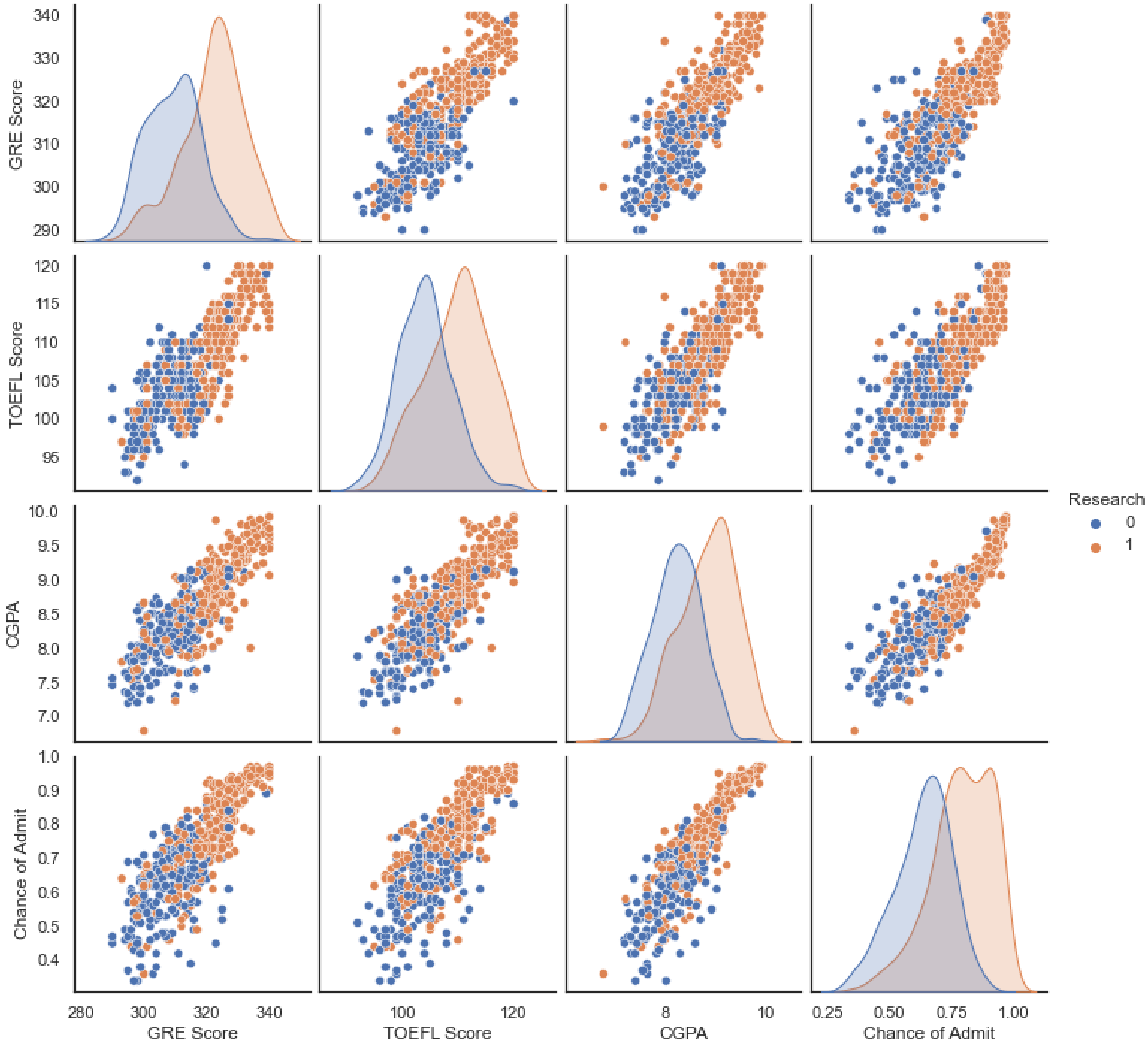
- As We can See Chance of Admit is highly Correlated with GRE Score,Toefl Score and CGPA

In [52]:

```
sns.pairplot(grad_adm_data,hue="Research")
```

Out[52]:

```
<seaborn.axisgrid.PairGrid at 0x1f38ad0d970>
```



In [53]:

```
grad_adm_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 9 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   LOR                500 non-null    category
 8   Chance of Admit    500 non-null    float64 
dtypes: category(5), float64(2), int64(2)
memory usage: 19.6 KB
```

In [54]:

```
categorical_cols_int = ['University Rating','Research']
categorical_cols_float = ['SOP', 'LOR']
for i in categorical_cols_int:
    grad_adm_data[i] = grad_adm_data[i].astype("int64")
for i in categorical_cols_float:
    grad_adm_data[i] = grad_adm_data[i].astype("float64")
grad_adm_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 9 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    category
 5   CGPA               500 non-null    float64 
 6   Research           500 non-null    int64   
 7   LOR                500 non-null    float64 
 8   Chance of Admit    500 non-null    float64 
dtypes: category(1), float64(4), int64(4)
memory usage: 32.2 KB
```

In [55]:

```
grad_adm_data = grad_adm_data.drop('LOR ', axis = 1)
```

In [56]:

```
grad_adm_data.info()
```

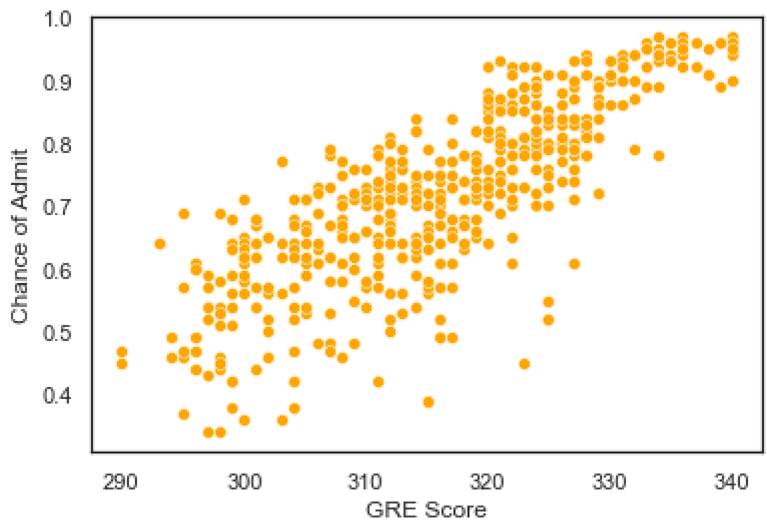
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 8 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   GRE Score          500 non-null    int64  
 1   TOEFL Score        500 non-null    int64  
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

In [57]:

```
sns.scatterplot(x="GRE Score",y="Chance of Admit",data=grad_adm_data,color='orange')
```

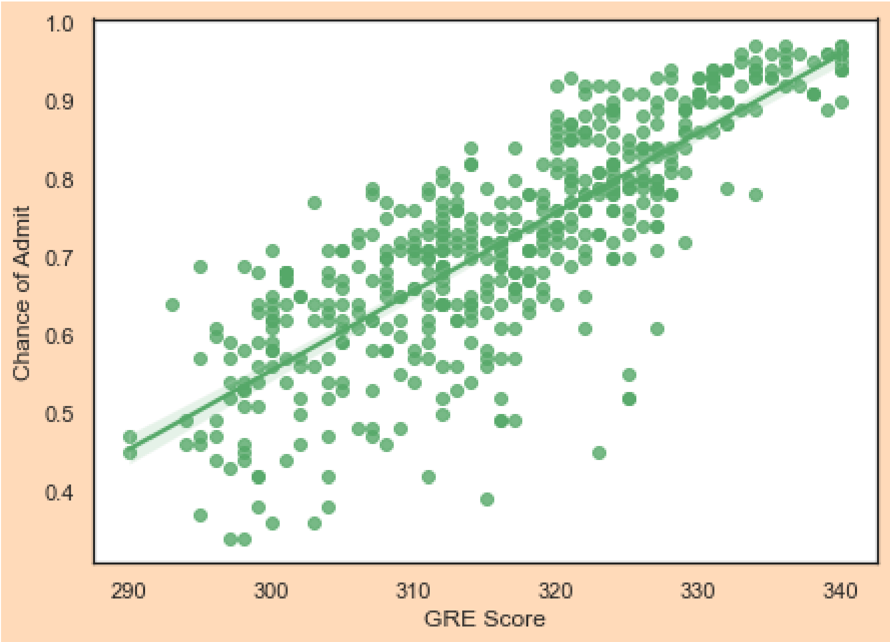
Out[57]:

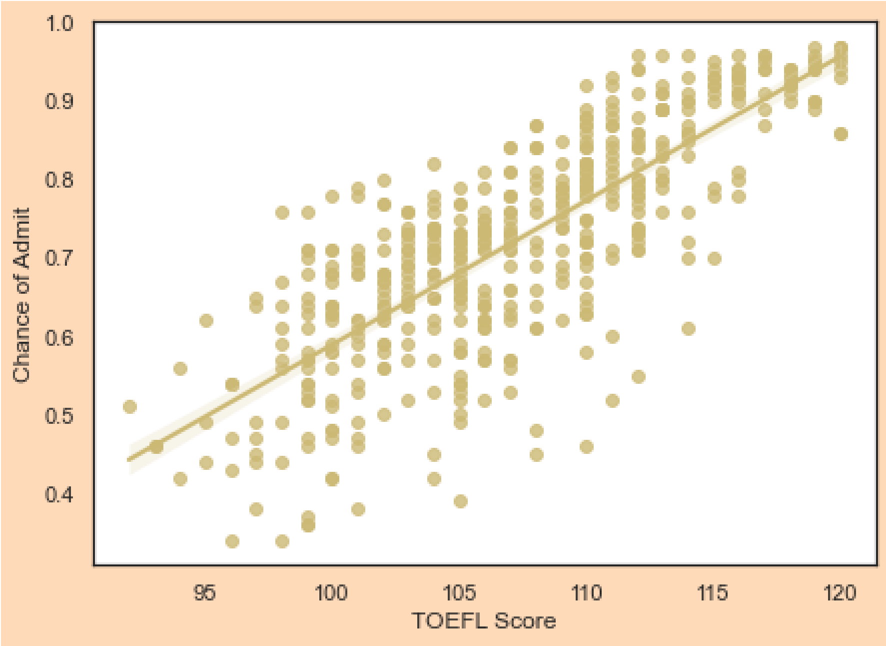
```
<AxesSubplot:xlabel='GRE Score', ylabel='Chance of Admit'>
```



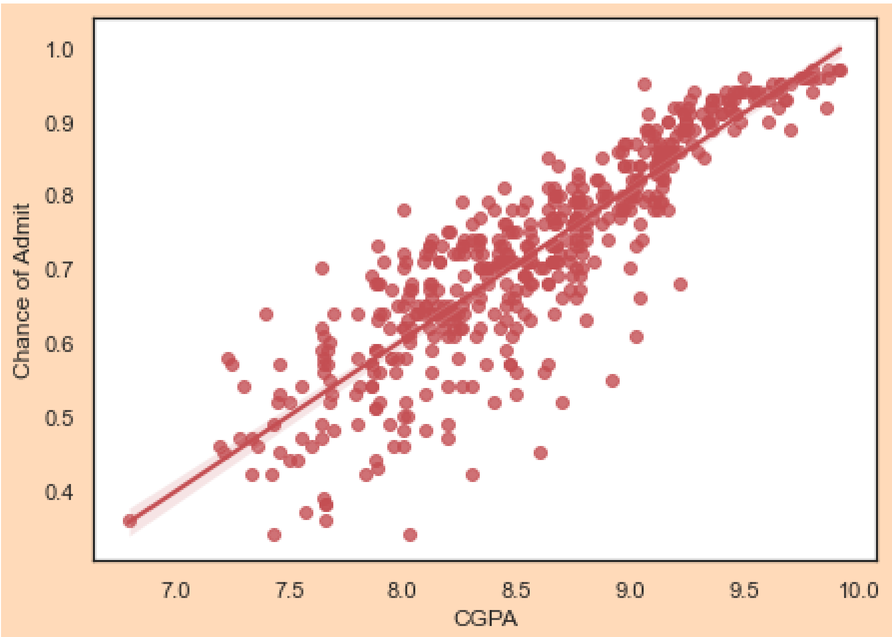
In [58]:

```
fig=plt.figure(figsize=(7,5))
fig.set_facecolor(color='peachpuff')
sns.regplot(x='GRE Score',y='Chance of Admit',color="g",data=grad_adm_data);

fig=plt.figure(figsize=(7,5))
fig.set_facecolor(color='peachpuff')
sns.regplot(x='TOEFL Score',y='Chance of Admit',color="y",data=grad_adm_data);

fig=plt.figure(figsize=(7,5))
fig.set_facecolor(color='peachpuff')
sns.regplot(x='CGPA',y='Chance of Admit',color="r",data=grad_adm_data);

fig=plt.figure(figsize=(7,5))
fig.set_facecolor(color='peachpuff')
sns.regplot(x='University Rating',y='Chance of Admit',color="g",data=grad_adm_data);

fig=plt.figure(figsize=(7,5))
fig.set_facecolor(color='peachpuff')
sns.regplot(x='Research',y='Chance of Admit',color="g",data=grad_adm_data);
```

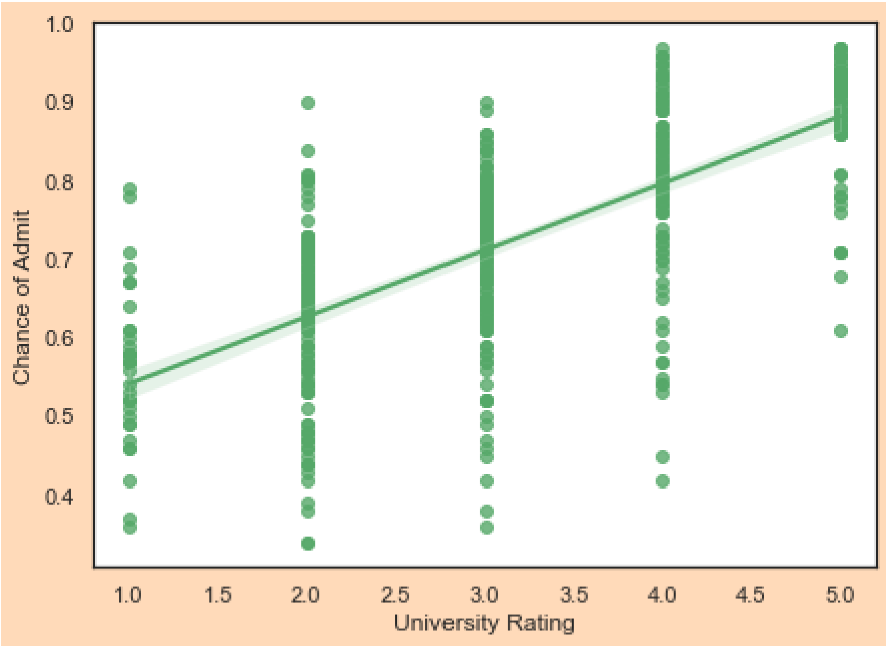


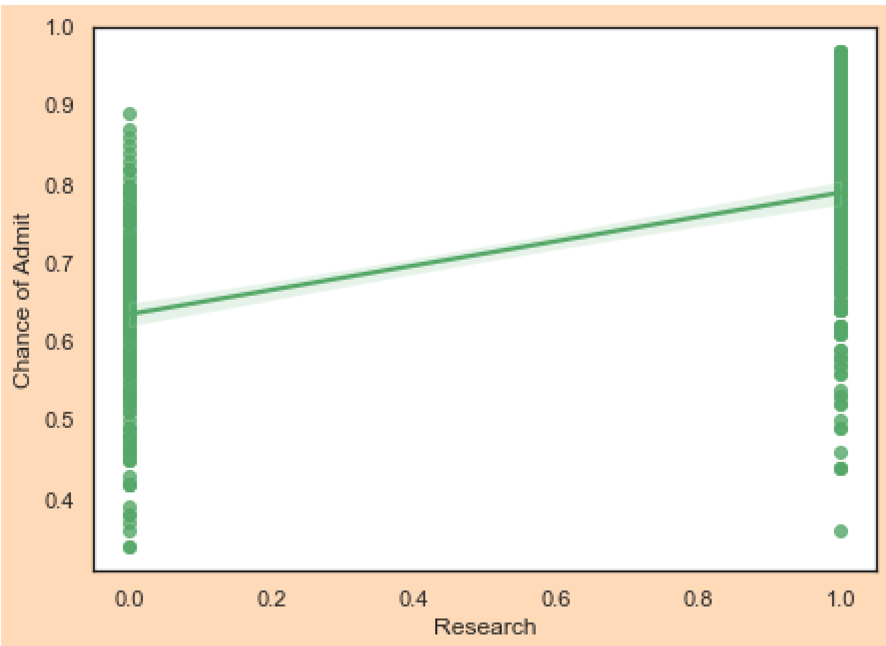


1.0
0.9
0.8
0.7
0.6
0.5
0.4
Chance of Admit
95
100
105
110
115
120
TOEFL Score



1.0
0.9
0.8
0.7
0.6
0.5
0.4
Chance of Admit
7.0
7.5
8.0
8.5
9.0
9.5
10.0
CGPA


1.0
0.9
0.8
0.7
0.6
0.5
0.4
Chance of Admit
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
University Rating


1.0
0.9
0.8
0.7
0.6
0.5
0.4
Chance of Admit
0.0
0.2
0.4
0.6
0.8
1.0
Research

EDA specific Observations and Inferences :

- By analyzing the distribution of ChanceOfAdmit, we can say that highest percentage of the getting admission at the university is between "0.6" & "1.0"
- By analyzing the distribution of Research, we can say that highest number of the students Research is "1".
- By analyzing the distribution of LOR, we can say that highest number of the Letter of recommendation (LOR) is between "2.5" & "4.5".
- By analyzing the distribution of SOP, we can say that highest number of the Statement of purpose is between "2.5" & "4.5".
- By analyzing the distribution of University Rating, we can say that highest number of the University rating is "2" & "3".
- By analyzing the distribution of TOEFLScore, we can say that highest number of the students TOEFLscore is "110" & "105". Highest TOEFLScore of students is between "99" & "115".
- By analyzing the distribution of GREScore, we can say that highest number of the students GREscore is "312" & "324".Highest GREScore of students is between "304" & "330".
- There is a strong positive relationship between GREScore and Chance Of Admit.
- There is a strong positive relationship between TOEFLScore and Chance Of Admit.
- There is a strong positive relationship between TOEFLScore and Chance Of Admit.
- We cant see any relationship between SOP and Chance Of Admit.
- We cant see any relationship between LOR and Chance Of Admit.
- We can see that the students with Research expericence has higher chance of getting an admit
- There is a strong relationship between UniversityRating and ChanceOfAdmit, but the university with higher rating tends to have a high chance of admit for students

Building Model with Linear Regression:

Assumptions made for Simple Linear Regression:

- **Linearity of residuals:** There needs to be a linear relationship between the dependent variable and independent variable(s).
- **Independence of residuals:** The error terms should not be dependent on one another (like in time-series data wherein the next value is dependent on the previous one). There should be no correlation between the residual terms. The absence of this phenomenon is known as Autocorrelation.There should not be any visible patterns in the error terms.

- **Normal distribution of residuals:** The mean of residuals should follow a normal distribution with a mean equal to zero or close to zero. This is done in order to check whether the selected line is actually the line of best fit or not.If the error terms are non-normally distributed, suggests that there are a few unusual data points that must be studied closely to make a better model.
- **The equal variance of residuals:** The error terms must have constant variance. This phenomenon is known as Homoscedasticity.The presence of non-constant variance in the error terms is referred to as Heteroscedasticity. Generally, non-constant variance arises in the presence of outliers or extreme leverage values.

Considerations of Multiple Linear Regression:

- All the four assumptions made for Simple Linear Regression still hold true for Multiple Linear Regression along with a few new additional assumptions.
- **Linear Relationship** should be present between input variables and target variables
  - We have already checked this in EDA
- **Multicollinearity:** It is the phenomenon where a model with several independent variables, may have some variables interrelated.
  - **No Multicollinearity** should be present among input variables. As Chance of Admit is highly Correlated with GRE Score,Toefl Score and CGPA, we will cross check which one to check after VIF.
- **Normal Distribution** of target varaibles.
  - Checked this in EDA.
- **Overfitting:** When more and more variables are added to a model, the model may become far too complex and usually ends up memorizing all the data points in the training set. This phenomenon is known as the overfitting of a model. This usually leads to high training accuracy and very low test accuracy.
- **Feature Selection:** With more variables present, selecting the optimal set of predictors from the pool of given features (many of which might be redundant) becomes an important task for building a relevant and better model.

Hypothesis in Linear Regression

Once you have fitted a straight line on the data, you need to ask, “Is this straight line a significant fit for the data?” Or “Is the beta coefficient explain the variance in the data plotted?” And here comes the idea of hypothesis testing on the beta coefficient. The Null and Alternate hypotheses in this case are: H0: B1 = 0

HA: B1 ≠ 0

Assessing the model fit

Some other parameters to assess a model are: t statistic: It is used to determine the p-value and hence, helps in determining whether the coefficient is significant or not F statistic: It is used to assess whether the overall model fit is significant or not. Generally, the higher the value of the F-statistic, the more significant a model turns out to be.

In [59]:

```
grad_adm_data.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   CGPA               500 non-null    float64
 5   Research           500 non-null    int64  
 6   LOR                500 non-null    float64
 7   Chance of Admit    500 non-null    float64
dtypes: float64(4), int64(4)
memory usage: 31.4 KB
```

Model 1

In [60]:

```
df_1 = grad_adm_data.copy()
```

In [61]:

```
df_1.head()
```

Out[61]:

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

In [62]:

```
df_1.columns
```

Out[62]:

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

Performing Linear Regression

- Assigning the featurs as X and trarget as Y

In [63]:

```
Y= df_1["Chance of Admit"]
```

In [64]:

```
Y
```

Out[64]:

```
0      0.92
1      0.76
2      0.72
3      0.80
4      0.65
       ...
495    0.87
496    0.96
497    0.93
498    0.73
499    0.84
Name: Chance of Admit, Length: 500, dtype: float64
```

In [65]:

```
X= df_1.drop(["Chance of Admit"],axis =1)
```

In [66]:

```
X
```

Out[66]:

	GRE Score	TOEFL Score	University Rating	SOP	CGPA	Research	LOR
0	337	118	4	4.5	9.65	1	4.5
1	324	107	4	4.0	8.87	1	4.5
2	316	104	3	3.0	8.00	1	3.5
3	322	110	3	3.5	8.67	1	2.5
4	314	103	2	2.0	8.21	0	3.0
...	...	...	...	...	...	...	...
495	332	108	5	4.5	9.02	1	4.0
496	337	117	5	5.0	9.87	1	5.0
497	330	120	5	4.5	9.56	1	5.0
498	312	103	4	4.0	8.43	0	5.0
499	327	113	4	4.5	9.04	0	4.5

500 rows × 7 columns

In [141]:

```
X_train_org, X_test_org, y_train_org, y_test_org = train_test_split(X, Y,test_size=0.20, ra
```

In [143]:

```
X_train_org.shape, X_test_org.shape, y_train_org.shape, y_test_org.shape
```

Out[143]:

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

In [144]:

```
print(X.shape)
print(Y.shape)
X.head()
```

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

Out[144]:

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

In [145]:

```
import statsmodels.api as sm
```

In [146]:

```
# Adding a constant to get an intercept
X_train_sm = sm.add_constant(X_train_org)

# Fitting the regression line using 'OLS'
lr = sm.OLS(y_train_org, X_train_sm).fit() #statsmodels.regression.linear_model
```

In [147]:

```
lr.summary()
```

Out[147]:

OLS Regression Results

Dep. Variable:	Chance of Admit	**R-squared:**	0.817
Model:	OLS	**Adj. R-squared:**	0.814
Method:	Least Squares	**F-statistic:**	250.3
Date:	Wed, 10 Aug 2022	**Prob (F-statistic):**	2.27e-140
Time:	20:18:48	**Log-Likelihood:**	556.28
No. Observations:	400	**AIC:**	-1097.
Df Residuals:	392	**BIC:**	-1065.
Df Model:	7		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	-1.2511	0.119	-10.551	0.000	-1.484	-1.018
GRE Score	0.0015	0.001	2.626	0.009	0.000	0.003
TOEFL Score	0.0031	0.001	3.148	0.002	0.001	0.005
University Rating	0.0050	0.004	1.164	0.245	-0.003	0.013
SOP	-0.0010	0.005	-0.195	0.845	-0.011	0.009
CGPA	0.1234	0.011	10.993	0.000	0.101	0.145
Research	0.0268	0.007	3.587	0.000	0.012	0.042
LOR	0.0193	0.005	4.081	0.000	0.010	0.029

Omnibus:	89.475	**Durbin-Watson:**	2.105
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	200.788
Skew:	-1.139	**Prob(JB):**	2.51e-44
Kurtosis:	5.618	**Cond. No.**	1.30e+04

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.3e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

Notes:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 1.3e+04. This might indicate that there are strong multicollinearity or other numerical problems.

In [148]:

```
# skLearn.Linear_model  -- just another way of getting r2 value

final_model = LinearRegression()
final_model.fit(X_train_org,y_train_org)
final_model.score(X_train_org,y_train_org)
```

Out[148]:

```
0.8171827660479396
```

Performing predictions on the test set

In [149]:

```
# Add a constant to X_test
X_test_sm = sm.add_constant(X_test_org)

# Predict the y values corresponding to X_test_sm using stats model mased approach
y_pred = lr.predict(X_test_sm)
```

In [150]:

```
type(lr), type(final_model)
```

Out[150]:

```
(statsmodels.regression.linear_model.RegressionResultsWrapper,
 sklearn.linear_model._base.LinearRegression)
```

Observations:

- Adding constant to X_test then predicting y_pred using final_model (sklearn) is giving an error as size 7 (orginal) is different from 8 (after adding constant) and hence we will use lr (stats model) to predict y_pred.
- Also, the reason to use stats model is that we don't have to check the normality of input varaiables.

Testing the assumptions of the linear regression model:

1. Multicollinearity check by VIF score :

In [153]:

```
# Check for the VIF values of the feature variables.
from statsmodels.stats.outliers_influence import variance_inflation_factor

# 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 [154]:

```
getVIF(X_train_sm)
```

Out[154]:

	Features	VIF
0	const	1519.68
5	CGPA	4.81
1	GRE Score	4.77
2	TOEFL Score	3.89
4	SOP	2.77
3	University Rating	2.56
7	LOR	2.02
6	Research	1.50

Observations from Multicollinearity check:

- All features have VIF < 5
- The problem is we have not considered the some numerical varaiables disguised as categorical varaibles-- We will deal with this in next model

Residuals Analysis

In [155]:

```
from sklearn.metrics import mean_absolute_error,r2_score,mean_squared_error,mean_absolute_p
#R-squared value
print("R2 score of the model is ",r2_score(y_test_org,y_pred))

#MAE value
print("mean_absolute_error  of the model is ",mean_absolute_error(y_test_org,y_pred))

#RMSE value
print( "Root mean squared error of the model is ",np.sqrt( mean_squared_error( y_test_org,

#MAPE value
print("Mean absolute percentage error of the model is ", mean_absolute_percentage_error(y_t
```

```
R2 score of the model is  0.83052087343053358
mean_absolute_error  of the model is  0.04414761591573461
Root mean squared error of the model is  0.05731490780917765 4
Mean absolute percentage error of the model is  0.06666612045380146
```

Final Predictions using orignal test data and calculating residuals

In [81]:

```
y_preds = lr.predict(X_test_sm)
errors = y_test_org - y_preds
```

2. The mean of residuals is nearly zero

In [82]:

```
np.mean(errors)
```

Out[82]:

```
0.014724738335377853
```

3. Linearity of variables

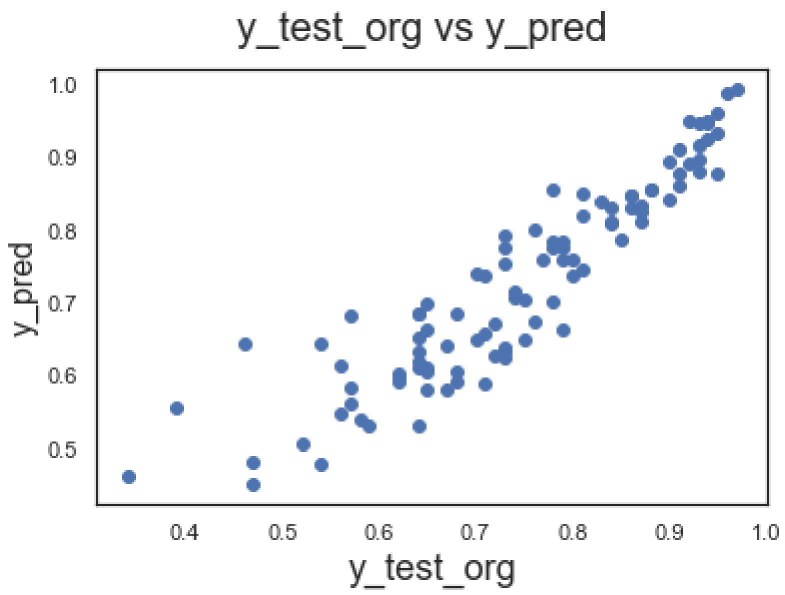
- No pattern in the residual plot

In [83]:

```
# Plotting y_test and y_pred to understand the spread.
fig = plt.figure()
plt.scatter(y_test_org,y_pred)
fig.suptitle('y_test_org vs y_pred', fontsize=20)              # Plot heading
plt.xlabel('y_test_org', fontsize=18)                          # X-label
plt.ylabel('y_pred', fontsize=16)
```

Out[83]:

```
Text(0, 0.5, 'y_pred')
```

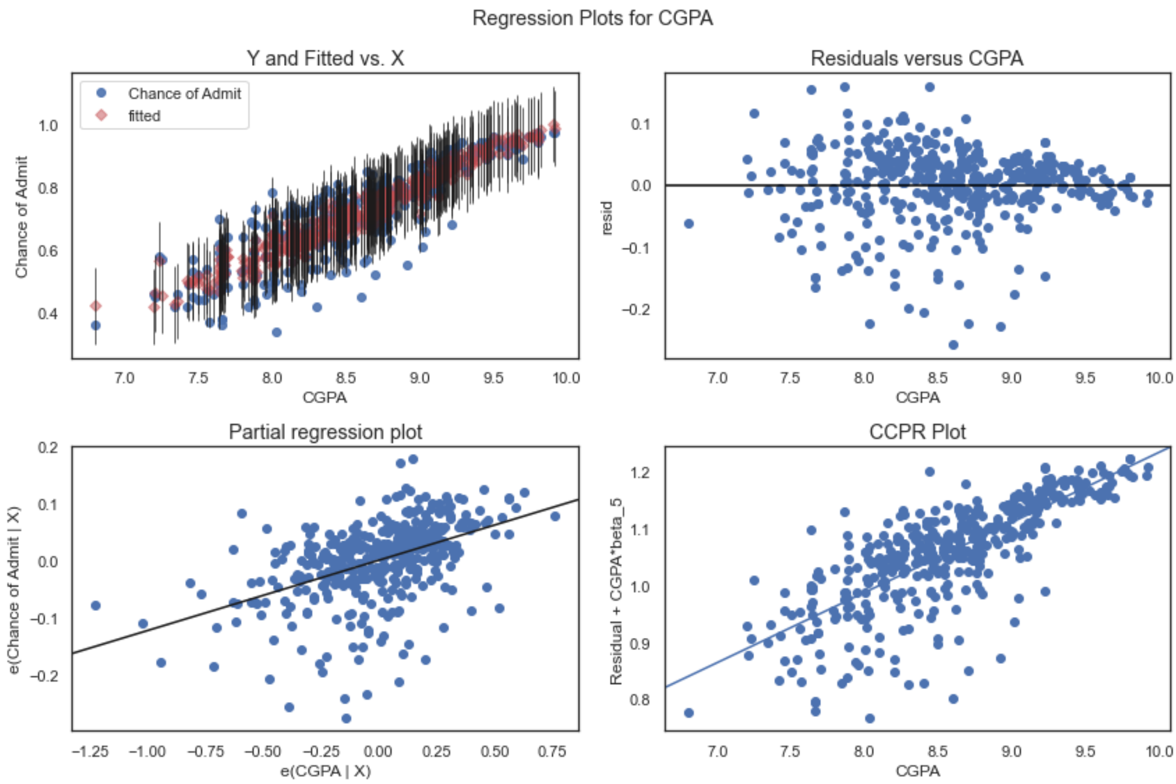


4. Test for Homoscedasticity

In [84]:

```
fig = plt.figure(figsize=(12,8))
fig = sm.graphics.plot_regress_exog(lr, 'CGPA', fig=fig)
```

```
eval_env: 1
```

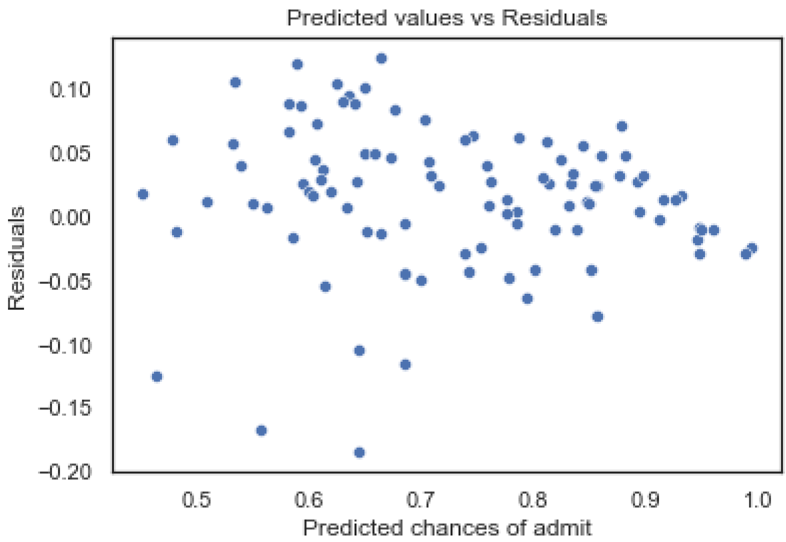


In [85]:

```
sns.scatterplot(y_preds,errors)
plt.xlabel("Predicted chances of admit")
plt.ylabel("Residuals")
plt.title("Predicted values vs Residuals")
```

Out[85]:

```
Text(0.5, 1.0, 'Predicted values vs Residuals')
```



5. Normality of residuals

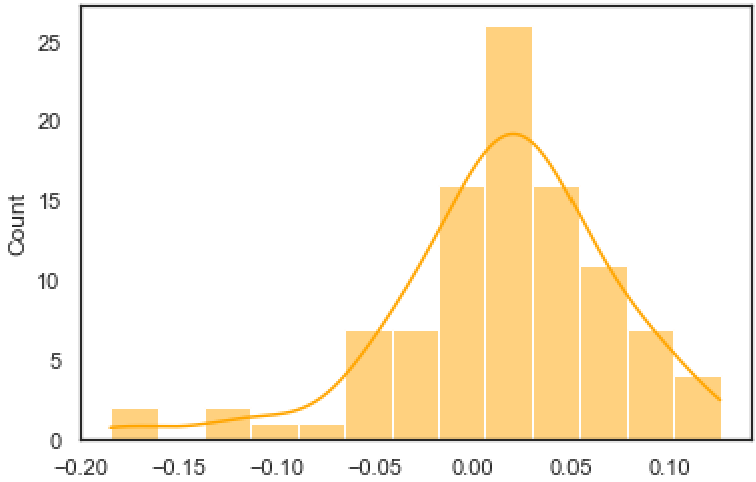
- Left skewed distribution

In [86]:

```
sns.histplot(errors, kde = True, color = 'orange')
```

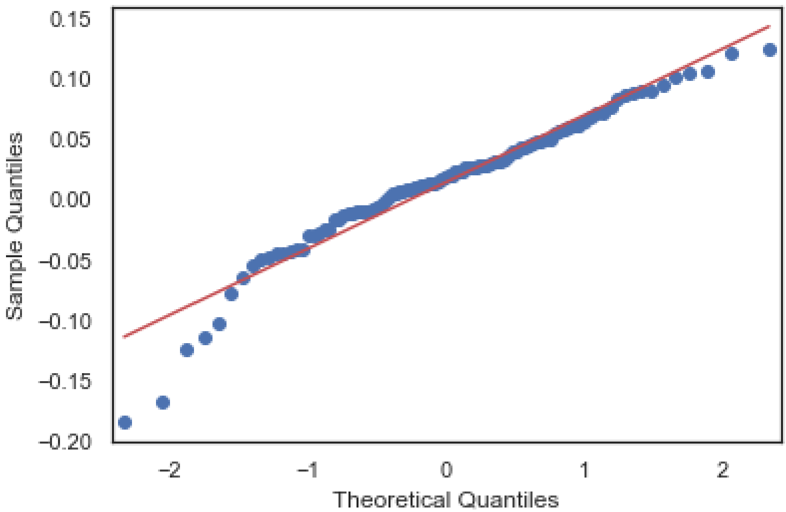
Out[86]:

```
<AxesSubplot:ylabel='Count'>
```



In [87]:

```
sm.qqplot(errors, line = 's')
plt.show()
```



Observations for Model 1:

Here are some key statistics from the summary:

- The coefficient for TOEFL Score is 0.0032, with a very low p-value (0.002). The coefficient is statistically significant. So the association is not purely by chance. Along with TOEFL Score, other scores are GRE Score, Research and CGPA.
- R – squared is 0.83 Meaning that 83.0% of the variance in chance for admit is explained by all the input variables ('GRE Score', 'TOEFL Score', 'University Rating', 'SOP', 'CGPA','Research', 'LOR'). This is a decent R-squared value but the problem here is we have included all features (both numerical and categorical) which is not good for an ideal model. We will deal with this in further models.

- As we have not normalize the data, we have used stats model based approach to predit chance of admit and to calculate errors.In further models, we will use sklearn based approach where we will normalize the data.
- F-statistics has a very low p-value(2.27e-140 -practically low). Meaning that the model fit is statistically significant, and the explained variance isn’t purely by chance.
- Strong multicollinearity or other numerical problems present.So we will be using VIF to detect and solve this problem.
- **Observations from Multicollinearity check:**
  - All features have VIF < 5
  - The problem is we have not considered the some numerical varaiables disguised as categorical varaibles--We will deal with this in next model
- **Observations from Residual mean check:**
  - The mean of residuals is nearly zero (0.01)
- **Observations from Linearity of variables check:**
  - As there's a clear linear relationship between predicted values and given values for chance of admit, we can say that the variance of both the values is similar
- **Observations from test for Homoscedasticity check:**
  - No pattern in the residual plot
- **Observations from Normality of residuals check:**
  - A little Left skewed distribution.

Model 2

Assumptions for Linear Regression:

All the four assumptions made for Simple Linear Regression still hold true for Multiple Linear Regression along with a few new additional assumptions.

- **Linear Relationship** should be present between input variables and target variables
  - We have already checked this in EDA
- **Multicollinearity:** It is the phenomenon where a model with several independent variables, may have some variables interrelated. -**No Multicollinearity** should be present among input variables. As Chance of Admit is highly Correlated with GRE Score,Toefl Score and CGPA, we will cross check which one to check after VIF.
- **Normal Distribution** of target varaibles.
  - Checked this in EDA.
- **Overfitting:** When more and more variables are added to a model, the model may become far too complex and usually ends up memorizing all the data points in the training set. This phenomenon is known as the overfitting of a model. This usually leads to high training accuracy and very low test accuracy.
- **Feature Selection:** With more variables present, selecting the optimal set of predictors from the pool of given features (many of which might be redundant) becomes an important task for building a relevant and better model.

In [88]:

```
# One hot encoding to convert categorical features to numerical features.

df_2 = pd.get_dummies(grad_adm_data, columns = ['SOP', 'LOR', 'University Rating', 'Researc
```

In [89]:

```
df_2.columns
```

Out[89]:

```
Index(['GRE Score', 'TOEFL Score', 'CGPA', 'Chance of Admit', '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', 'University Rating_2',
       'University Rating_3', 'University Rating_4', 'University Rating_5',
       'Research_1'],
      dtype='object')
```

In [90]:

```
df_train, df_test = train_test_split(df_2, train_size = 0.8, random_state = 100)
```

In [91]:

```
df_train.shape, df_test.shape
```

Out[91]:

```
((400, 25), (100, 25))
```

OBS : We have converted all the unique values in categorical columns to one hot encoded values.

Performing Linear Regression

Model Corrections - 2.1

In [92]:

```
X_train = df_train
y_train = df_train.pop('Chance of Admit')
```

In [93]:

```
X_test = df_test
y_test = df_test.pop('Chance of Admit')
```

In [94]:

```
print( X_train.shape )
print( X_test.shape )
print( y_train.shape )
print( y_test.shape )
```

```
(400, 24)
(100, 24)
(400,)
(100,)
```

In [95]:

```
import statsmodels.api as sm
# Adding a constant to get an intercept
X_train_sm = sm.add_constant(X_train)

# Fitting the regression line using 'OLS'
lr = sm.OLS(y_train, X_train_sm).fit() #statsmodels.regression.linear_model

# Printing the parameters,i.e. intercept and slope of the regression line obtained
lr.params
```

Out[95]:

```
const                  -1.223134
GRE Score               0.001439
TOEFL Score             0.003206
CGPA                    0.124173
SOP_1.5                 0.000809
SOP_2.0                 0.006515
SOP_2.5                 0.028547
SOP_3.0                 0.017773
SOP_3.5                 0.011582
SOP_4.0                 0.012419
SOP_4.5                 0.019126
SOP_5.0                 0.014784
LOR_1.5                 0.007156
LOR_2.0                 0.031433
LOR_2.5                 0.055998
LOR_3.0                 0.043623
LOR_3.5                 0.056081
LOR_4.0                 0.067965
LOR_4.5                 0.074233
LOR_5.0                 0.093998
University Rating_2    -0.018473
University Rating_3    -0.013666
University Rating_4    -0.011481
University Rating_5     0.004601
Research_1              0.027252
dtype: float64
```

In [96]:

```
#Performing a summary operation lists out all different parameters of the regression line f
print(lr.summary())
```

```
                            OLS Regression Results
============================================================================
==
Dep. Variable:          Chance of Admit   R-squared:                       0.8
22
Model:                              OLS   Adj. R-squared:                  0.8
11
Method:                   Least Squares   F-statistic:                     72.
26
Date:                  Wed, 10 Aug 2022   Prob (F-statistic):          9.47e-1
25
Time:                          18:30:58   Log-Likelihood:                 561.
87
No. Observations:                   400   AIC:                            -107
4.
Df Residuals:                       375   BIC:                            -97
4.0
Df Model:                            24
Covariance Type:              nonrobust
============================================================================
===========
                     coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------------
-----------
const             -1.2231      0.138     -8.837      0.000      -1.495
-0.951
GRE Score          0.0014      0.001      2.416      0.016       0.000
0.003
TOEFL Score        0.0032      0.001      3.174      0.002       0.001
0.005
CGPA               0.1242      0.012     10.775      0.000       0.102
0.147
SOP_1.5            0.0008      0.040      0.020      0.984      -0.078
0.080
SOP_2.0            0.0065      0.039      0.168      0.867      -0.070
0.083
SOP_2.5            0.0285      0.040      0.715      0.475      -0.050
0.107
SOP_3.0            0.0178      0.040      0.448      0.655      -0.060
0.096
SOP_3.5            0.0116      0.040      0.288      0.774      -0.068
0.091
SOP_4.0            0.0124      0.041      0.306      0.760      -0.067
0.092
SOP_4.5            0.0191      0.042      0.461      0.645      -0.063
0.101
SOP_5.0            0.0148      0.043      0.345      0.730      -0.069
0.099
LOR_1.5            0.0072      0.073      0.099      0.921      -0.135
0.150
LOR_2.0            0.0314      0.072      0.434      0.664      -0.111
0.174
LOR_2.5            0.0560      0.071      0.785      0.433      -0.084
0.196
LOR_3.0            0.0436      0.072      0.605      0.546      -0.098
```

```
0.185
LOR_3.5                 0.0561      0.072      0.776      0.438      -0.086
0.198
LOR_4.0                 0.0680      0.072      0.940      0.348      -0.074
0.210
LOR_4.5                 0.0742      0.073      1.021      0.308      -0.069
0.217
LOR_5.0                 0.0940      0.073      1.284      0.200      -0.050
0.238
University Rating_2    -0.0185      0.015     -1.225      0.221      -0.048
0.011
University Rating_3    -0.0137      0.016     -0.853      0.394      -0.045
0.018
University Rating_4    -0.0115      0.018     -0.639      0.523      -0.047
0.024
University Rating_5     0.0046      0.020      0.226      0.821      -0.035
0.045
Research_1              0.0273      0.008      3.567      0.000       0.012
0.042
============================================================================
==
Omnibus:                       83.034   Durbin-Watson:                   2.1
43
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              182.6
75
Skew:                          -1.068   Prob(JB):                     2.15e-
40
Kurtosis:                       5.529   Cond. No.                     2.37e+
04
============================================================================
==

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is corre
ctly specified.
[2] The condition number is large, 2.37e+04. This might indicate that there
are
strong multicollinearity or other numerical problems.
```

Performing predictions on the test set

In [97]:

```
# Adding a constant to X_test
X_test_sm = sm.add_constant(X_test)

# Predicting the y values corresponding to X_test_sm
y_pred = lr.predict(X_test_sm)

y_pred.head()
```

Out[97]:

```
69     0.857917
29     0.460663
471    0.620067
344    0.434422
54     0.646538
dtype: float64
```

Multicollinearity check by VIF score :

In [98]:

```
# Check for the VIF values of the feature variables.
from statsmodels.stats.outliers_influence import variance_inflation_factor

# 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 [99]:

```
getVIF(X_train_sm)
```

Out[99]:

	Features	VIF
0	const	2036.62
15	LOR_3.0	87.66
17	LOR_4.0	82.94
16	LOR_3.5	81.89
18	LOR_4.5	65.67
14	LOR_2.5	50.90
13	LOR_2.0	44.44
19	LOR_5.0	44.29
9	SOP_4.0	25.60
8	SOP_3.5	24.32
7	SOP_3.0	23.63
10	SOP_4.5	21.06
6	SOP_2.5	19.18
5	SOP_2.0	13.80
12	LOR_1.5	13.63
11	SOP_5.0	12.27
4	SOP_1.5	7.76
22	University Rating_4	5.90
21	University Rating_3	5.89
23	University Rating_5	5.07
3	CGPA	4.99
1	GRE Score	4.90
20	University Rating_2	4.65
2	TOEFL Score	4.00
24	Research_1	1.54

Observations for Model 2.1:

As we can see, this code gives you a brief summary of the linear regression. Here are some key statistics from the summary:

- R – squared is 0.822 Meaning that 82.2% of the variance in chance for admit is explained by all the input variables. This is a decent R-squared value.
- F-statistics has a very low p-value(practically low). Meaning that the model fit is statistically significant, and the explained variance isn't purely by chance.

- No significant drop in adjusted R squared as compared to previous model.
- Strong multicollinearity exists
- features with p-value > 0.05 and VIF > 5 are :
  - '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','University Rating_3', 'University Rating_4', 'University Rating_5'.
- Multicollinearity has been checked by VIF score and variables are dropped one-by-one till none has VIF>5 for above.

Model Corrections - 2.2

In [100]:

```
df_2.columns
```

Out[100]:

```
Index(['GRE Score', 'TOEFL Score', 'CGPA', 'Chance of Admit', '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', 'University Rating_2',
       'University Rating_3', 'University Rating_4', 'University Rating_5',
       'Research_1'],
      dtype='object')
```

In [101]:

```
#Dropping 'GRE Score' as there's a strong corelation between - 'GRE Score', 'TOEFL Score',
# Dropping all features with p-value > 0.05 and VIF > 5
```

In [102]:

```
X_train1 = X_train[['TOEFL Score', 'CGPA', 'Research_1','University Rating_2']]
```

In [103]:

```
import statsmodels.api as sm
# Adding a constant to get an intercept
X_train_sm = sm.add_constant(X_train1)

# Fitting the regression line using 'OLS'
lr = sm.OLS(y_train, X_train_sm).fit() #statsmodels.regression.linear_model

# Printing the parameters,i.e. intercept and slope of the regression line obtained
lr.params
```

Out[103]:

```
const                 -1.109832
TOEFL Score            0.004614
CGPA                   0.153467
Research_1             0.035551
University Rating_2   -0.009927
dtype: float64
```

In [104]:

```
#Performing a summary operation lists out all different parameters of the regression line f
print(lr.summary())
```

```
                            OLS Regression Results                            
==============================================================================
==
Dep. Variable:        Chance of Admit   R-squared:                       0.8
05
Model:                            OLS   Adj. R-squared:                  0.8
03
Method:                 Least Squares   F-statistic:                     40
6.7
Date:                Wed, 10 Aug 2022   Prob (F-statistic):          1.38e-1
38
Time:                        18:33:41   Log-Likelihood:                 543.
02
No. Observations:                 400   AIC:                            -107
6.
Df Residuals:                     395   BIC:                            -105
6.
Df Model:                           4                                         
Covariance Type:            nonrobust                                         
==============================================================================
===========
                          coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
-----------
const                  -1.1098      0.064    -17.421      0.000      -1.235
-0.985
TOEFL Score             0.0046      0.001      5.198      0.000       0.003
0.006
CGPA                    0.1535      0.009     16.756      0.000       0.135
0.171
Research_1              0.0356      0.007      4.866      0.000       0.021
0.050
University Rating_2    -0.0099      0.008     -1.274      0.203      -0.025
0.005
==============================================================================
==
Omnibus:                       79.874   Durbin-Watson:                   2.0
97
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              156.4
98
Skew:                          -1.081   Prob(JB):                      1.04e-
34
Kurtosis:                       5.172   Cond. No.                      2.19e+
03
==============================================================================
==

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is corre
ctly specified.
[2] The condition number is large, 2.19e+03. This might indicate that there
are
strong multicollinearity or other numerical problems.
```

Performing predictions on the test set

In [105]:

```
X_test.columns
```

Out[105]:

```
Index(['GRE Score', 'TOEFL Score', 'CGPA', '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', 'University Rating_2', 'University Rating_3',
       'University Rating_4', 'University Rating_5', 'Research_1'],
      dtype='object')
```

In [106]:

```
X_train1.shape
```

Out[106]:

```
(400, 4)
```

In [107]:

```
X_test_sm[X_train1.columns]
```

Out[107]:

	TOEFL Score	CGPA	Research_1	University Rating_2
69	115	9.16	1	0
29	99	7.30	0	1
471	103	8.09	0	0
344	96	7.34	0	1
54	110	8.00	0	0
...	...	...	...	...
460	105	8.66	1	0
152	112	9.06	1	0
154	108	8.89	0	0
56	102	7.40	0	0
392	112	9.12	1	0

100 rows × 4 columns

In [108]:

```
# Adding a constant to X_test
X_test_sm = sm.add_constant(X_test)

X_test_new = X_test_sm[X_train_sm.columns]
# Predicting the y values corresponding to X_test_sm
y_pred = lr.predict(X_test_new)

y_pred.head()
```

Out[108]:

```
69     0.862071
29     0.457322
471    0.606944
344    0.449619
54     0.625429
dtype: float64
```

Testing the assumptions of the linear regression model:

1. **Multicollinearity check by VIF score :**

In [109]:

```
# Check for the VIF values of the feature variables.
from statsmodels.stats.outliers_influence import variance_inflation_factor

# 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 [110]:

```
getVIF(X_train_sm)
```

Out[110]:

	Features	VIF
0	const	413.62
2	CGPA	3.02
1	TOEFL Score	2.96
3	Research_1	1.35
4	University Rating_2	1.19

- **Observations from Multicollinearity check:**
  - All features have VIF < 5

- The problem is we have not considered the some numerical varaiables disguised as categorical varaibles--We will deal with this in next model

Residuals Analysis

In [111]:

```
from sklearn.metrics import mean_absolute_error,r2_score,mean_squared_error,mean_absolute_p
#R-squared value
print("R2 score of the model is ",r2_score(y_test,y_pred))

#MAE value
print("mean_absolute_error  of the model is ",mean_absolute_error(y_test,y_pred))

#RMSE value
print( "Root mean squared error of the model is ",np.sqrt( mean_squared_error( y_test, y_pr

#MAPE value
print("Mean absolute percentage error of the model is ", mean_absolute_percentage_error(y_t
```

```
R2 score of the model is  0.811517854949051
mean_absolute_error  of the model is  0.046343636819315526
Root mean squared error of the model is  0.060442803162407O9
Mean absolute percentage error of the model is  0.06959650556889335
```

Final Predictions using orignal test data and calculating residuals

In [112]:

```
y_pred = lr.predict(X_test_new)
errors = y_test - y_pred
```

2.The mean of residuals is nearly zero

In [113]:

```
np.mean(errors)
```

Out[113]:

```
0.016978208743464795
```

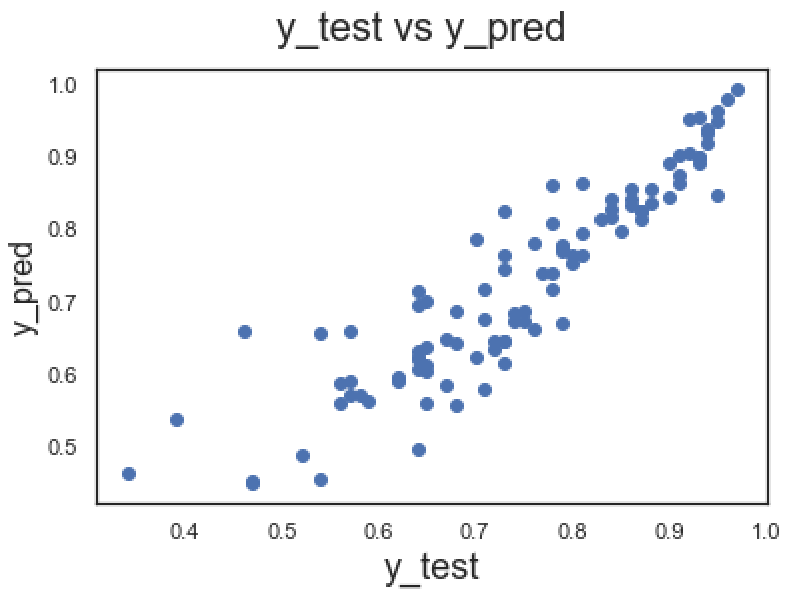
3.Linearity of variables

In [114]:

```
# Plotting y_test and y_pred to understand the spread.
fig = plt.figure()
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)
```

Out[114]:

```
Text(0, 0.5, 'y_pred')
```

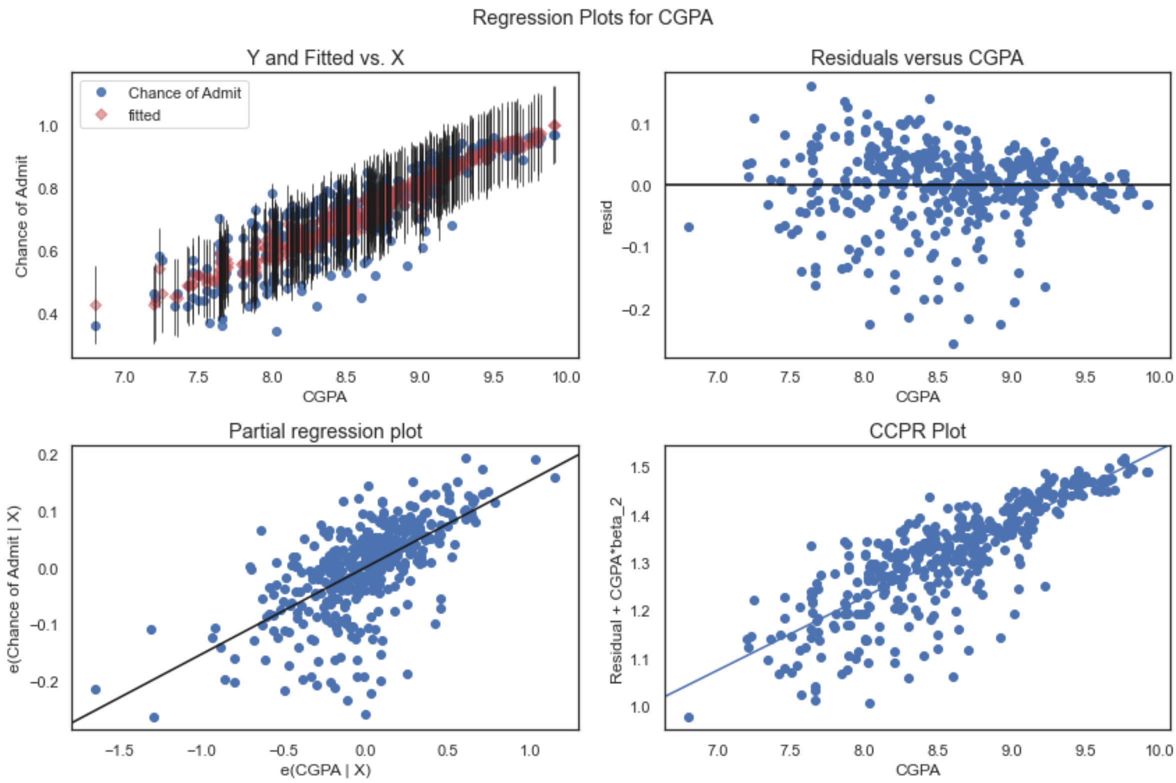


4.Test for Homoscedasticity

In [116]:

```
fig = plt.figure(figsize=(12,8))
fig = sm.graphics.plot_regress_exog(lr, 'CGPA', fig=fig)
```

```
eval_env: 1
```

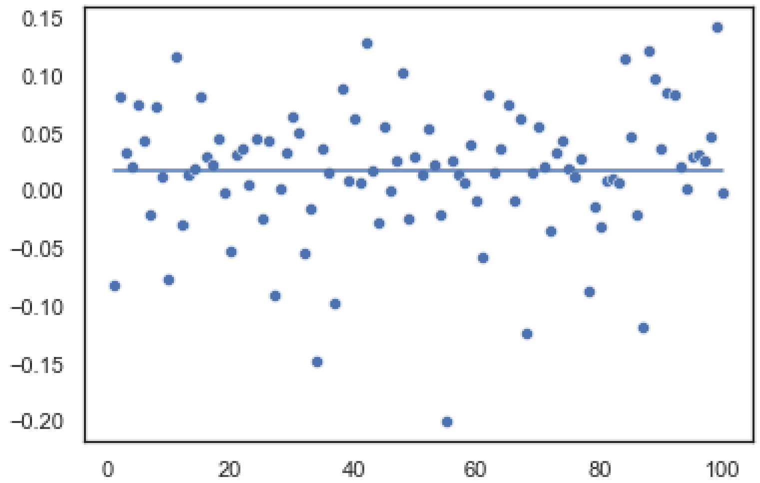


In [117]:

```
sns.scatterplot(np.arange(1,101,1),errors)
sns.lineplot(np.arange(1,101,1),errors.mean())
```

Out[117]:

<AxesSubplot:>

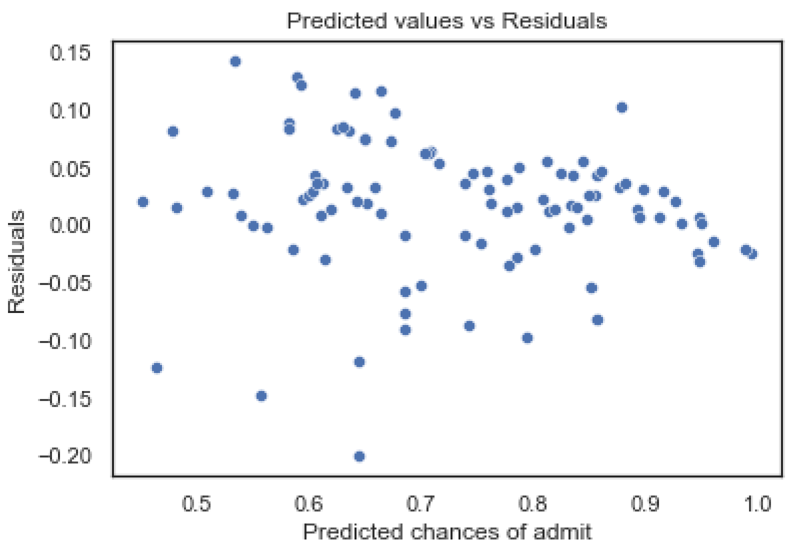


In [118]:

```
sns.scatterplot(y_preds,errors)
plt.xlabel("Predicted chances of admit")
plt.ylabel("Residuals")
plt.title("Predicted values vs Residuals")
```

Out[118]:

Text(0.5, 1.0, 'Predicted values vs Residuals')



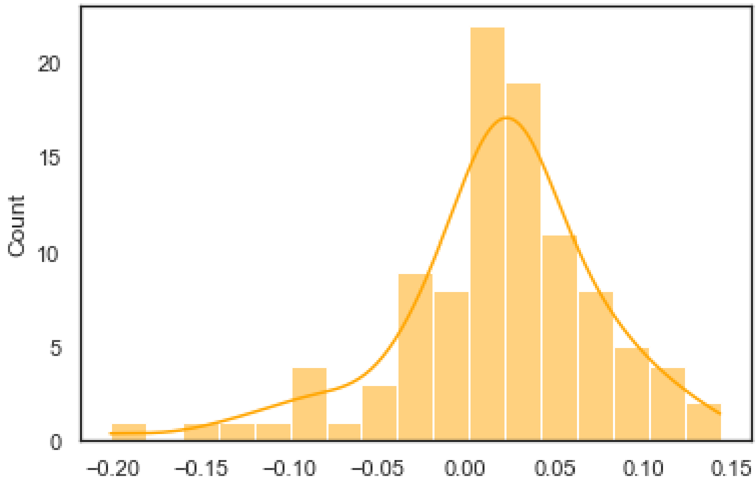
5.Normality of residuals

In [119]:

```
sns.histplot(errors, kde = True, color = 'orange')
```

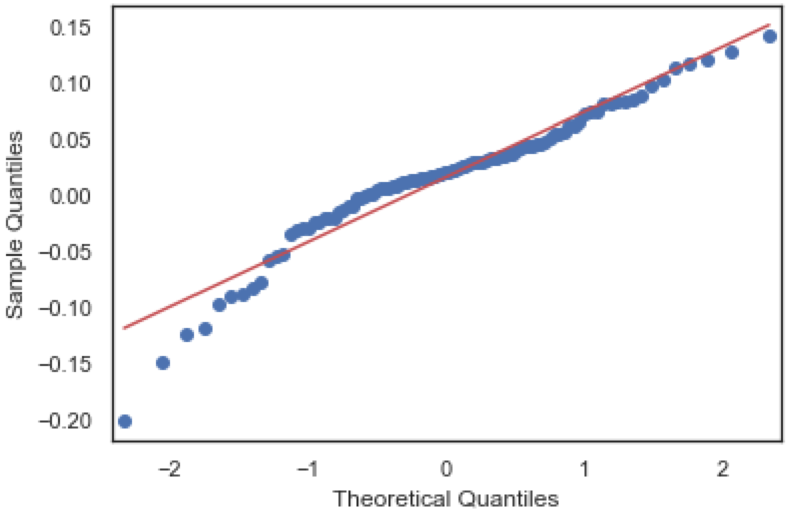
Out[119]:

```
<AxesSubplot:ylabel='Count'>
```



In [120]:

```
sm.qqplot(errors, line = 's')
plt.show()
```



The residuals looks normaly distributed

Observations for Model 2.2:

As we can see, this code gives you a brief summary of the linear regression. Here are some key statistics from the summary:

- R – squared is 0.805 Meaning that 80.5% of the variance in chance for admit is explained by all the input variables. This is a decent R-squared value.
- F-statistics has a very low p-value(practically low). Meaning that the model fit is statistically significant, and the explained variance isn't purely by chance.
- No significant drop in adjusted R squared as compared to previous model.

- Strong multicollinearity still exists
- No features with p-value > 0.05 and VIF > 5
- **Observations from Multicollinearity check:**
    - All features have VIF < 5
- **Observations from Residual mean check:**
    - The mean of residuals is nearly zero (0.01)
- **Observations from Linearity of variables check:**
    - As there's a clear linear relationship between predicted values and given values for chance of admit, we can say that the variance of both the values is similar
- **Observations from test for Homoscedasticity check:**
    - No pattern in the residual plot
- **Observations from Normality of residuals check:**
    - The residuals looks nearly normally distributed

Model Corrections - 2.3

In [121]:

```
X_train2 = X_train[['CGPA','Research_1']]
```

In [122]:

```
import statsmodels.api as sm
# Adding a constant to get an intercept
X_train_sm = sm.add_constant(X_train2)

# Fitting the regression line using 'OLS'
lr = sm.OLS(y_train, X_train_sm).fit() #statsmodels.regression.linear_model

# Printing the parameters,i.e. intercept and slope of the regression line obtained
lr.params
```

Out[122]:

```
const        -0.946642
CGPA          0.191245
Research_1    0.043043
dtype: float64
```

In [123]:

```
#Performing a summary operation lists out all different parameters of the regression line f
print(lr.summary())
```

```
                            OLS Regression Results
==============================================================================
==
Dep. Variable:        Chance of Admit   R-squared:                       0.7
90
Model:                            OLS   Adj. R-squared:                  0.7
89
Method:                 Least Squares   F-statistic:                     74
6.5
Date:                Wed, 10 Aug 2022   Prob (F-statistic):          3.02e-1
35
Time:                        18:37:06   Log-Likelihood:                 528.
51
No. Observations:                 400   AIC:                            -105
1.
Df Residuals:                     397   BIC:                            -103
9.
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
==
                 coef    std err          t      P>|t|      [0.025      0.97
5]
------------------------------------------------------------------------------
--
const         -0.9466      0.051    -18.482      0.000      -1.047      -0.8
46
CGPA           0.1912      0.006     30.992      0.000       0.179       0.2
03
Research_1     0.0430      0.007      5.840      0.000       0.029       0.0
58
==============================================================================
==
Omnibus:                       65.845   Durbin-Watson:                   2.0
59
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              118.2
52
Skew:                          -0.941   Prob(JB):                      2.10e-
26
Kurtosis:                       4.886   Cond. No.                         13
8.
==============================================================================
==

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

In [124]:

```
X_test.columns
```

Out[124]:

```
Index(['GRE Score', 'TOEFL Score', 'CGPA', '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', 'University Rating_2', 'University Rating_3',
       'University Rating_4', 'University Rating_5', 'Research_1'],
      dtype='object')
```

In [125]:

```
# Adding a constant to X_test
X_test_sm = sm.add_constant(X_test)
X_test_new1 = X_test_sm[X_train_sm.columns]
# Predicting the y values corresponding to X_test_sm
y_pred = lr.predict(X_test_new1)

y_pred.head()
```

Out[125]:

```
69     0.848201
29     0.449444
471    0.600527
344    0.457093
54     0.583315
dtype: float64
```

Testing the assumptions of the linear regression model (2.3):

1. **Multicollinearity check by VIF score :**

In [126]:

```
# Check for the VIF values of the feature variables.
from statsmodels.stats.outliers_influence import variance_inflation_factor

# 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 [127]:

```
getVIF(X_train_sm)
```

Out[127]:

	Features	VIF
0	const	249.93
1	CGPA	1.28
2	Research_1	1.28

- **Observations from Multicollinearity check:**
  - All features have VIF < 5

Model performance evaluation and Residuals Analysis

In [128]:

```
from sklearn.metrics import mean_absolute_error,r2_score,mean_squared_error,mean_absolute_p
#R-squared value
print("R2 score of the model is ",r2_score(y_test,y_pred))

#MAE value
print("mean_absolute_error  of the model is ",mean_absolute_error(y_test,y_pred))

#RMSE value
print( "Root mean squared error of the model is ",np.sqrt( mean_squared_error( y_test, y_pr

#MAPE value
print("Mean absolute percentage error of the model is ", mean_absolute_percentage_error(y_t
```

```
R2 score of the model is  0.7924005722145115
mean_absolute_error  of the model is  0.050028583149944475
Root mean squared error of the model is  0.06343406832938923
Mean absolute percentage error of the model is  0.0745103804105193
```

Final Predictions using orignal test data and calculating residuals

In [129]:

```
y_pred=lr.predict(X_test_new1)
errors=y_test-y_pred
```

2.The mean of residuals is nearly zero

In [130]:

```
np.mean(errors)
```

Out[130]:

```
0.020401593595412038
```

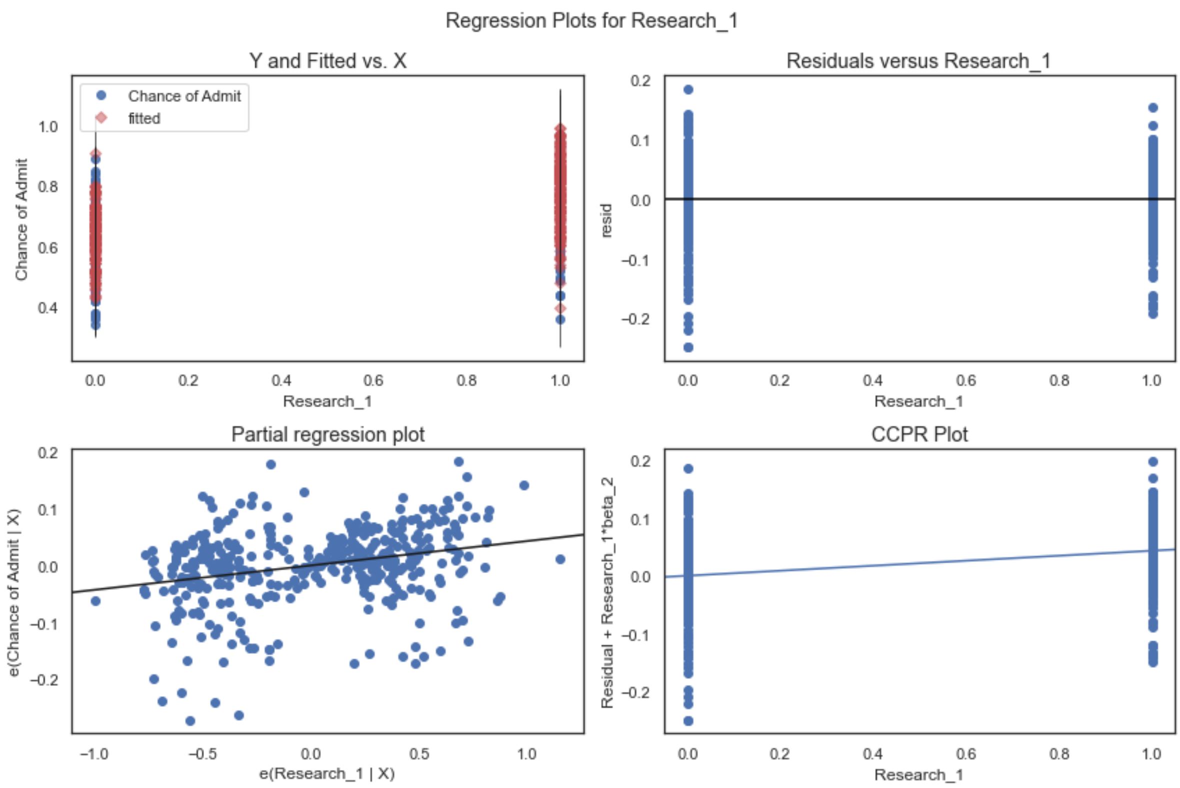
3.Test for Homoscedasticity

```
- No pattern in the residual plot
```

In [131]:

```
fig=plt.figure(figsize=(12,8))
fig=sm.graphics.plot_regress_exog(lr,'Research_1',fig=fig)
```

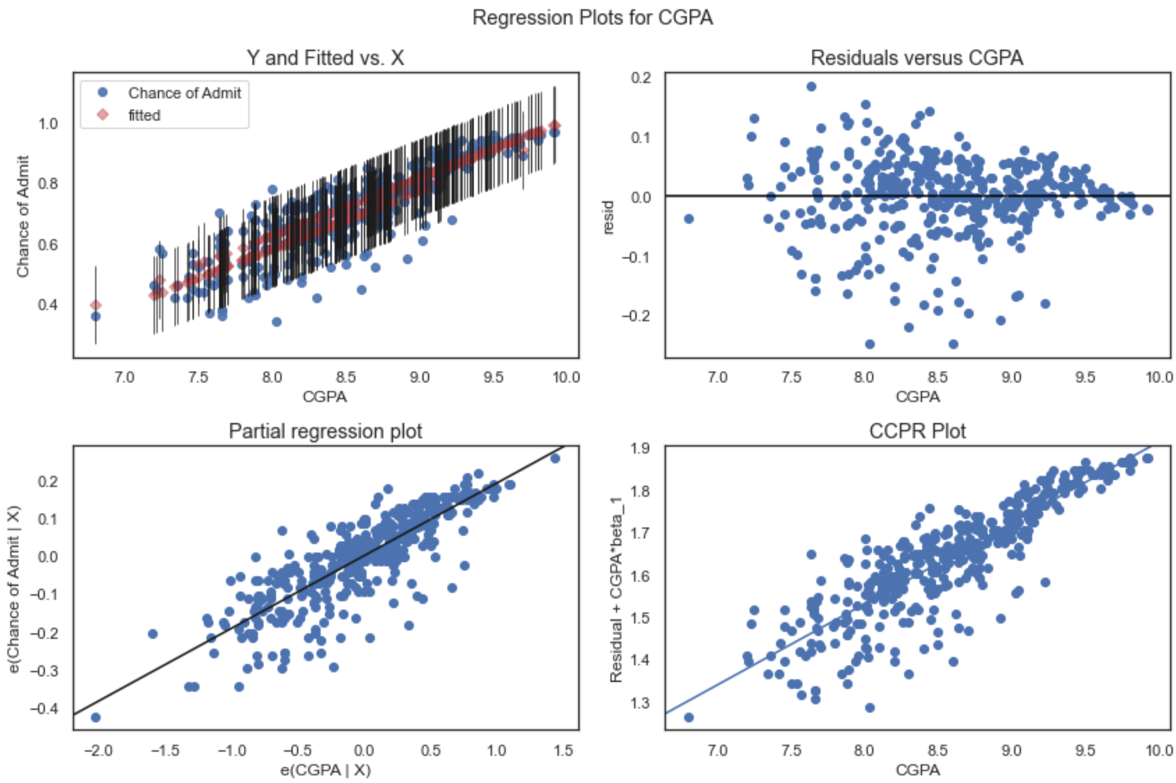
```
eval_env: 1
```



In [132]:

```
fig=plt.figure(figsize=(12,8))
fig=sm.graphics.plot_regress_exog(lr,'CGPA',fig=fig)
```

```
eval_env: 1
```

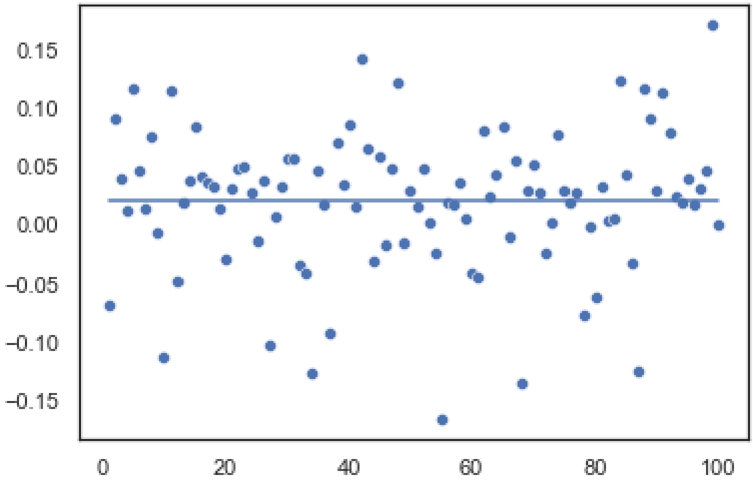


In [134]:

```
sns.scatterplot(np.arange(1,101,1),errors)
sns.lineplot(np.arange(1,101,1),errors.mean())
```

Out[134]:

```
<AxesSubplot:>
```

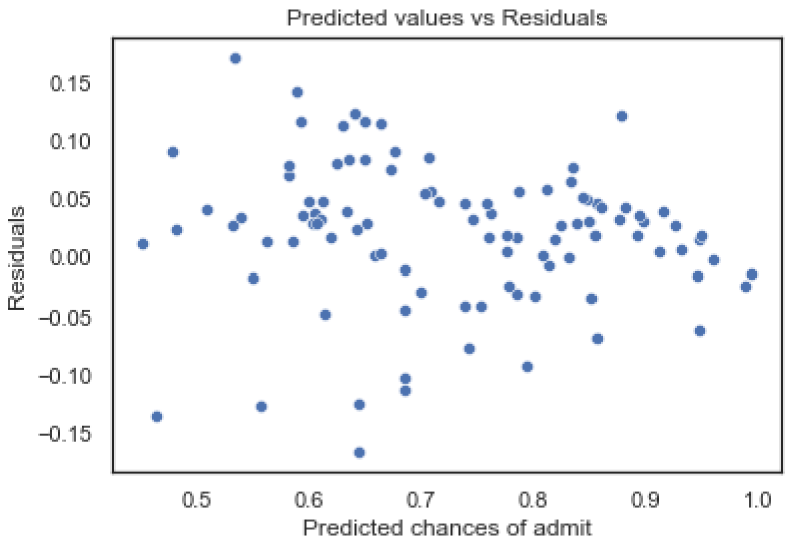


In [135]:

```
sns.scatterplot(y_preds,errors)
plt.xlabel("Predicted chances of admit")
plt.ylabel("Residuals")
plt.title("Predicted values vs Residuals")
```

Out[135]:

```
Text(0.5, 1.0, 'Predicted values vs Residuals')
```



4.Linearity of variables

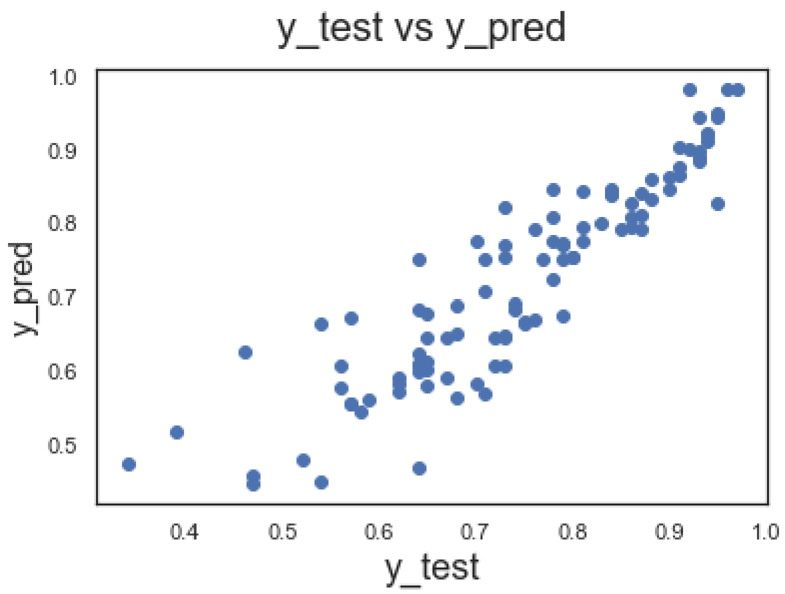
    - As there's a clear linear relationship between predicted values and given values
    for chance of admit, we can say that the variance of both the values is similar

In [136]:

```
# Plotting y_test and y_pred to understand the spread.
fig=plt.figure()
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)
```

Out[136]:

```
Text(0, 0.5, 'y_pred')
```



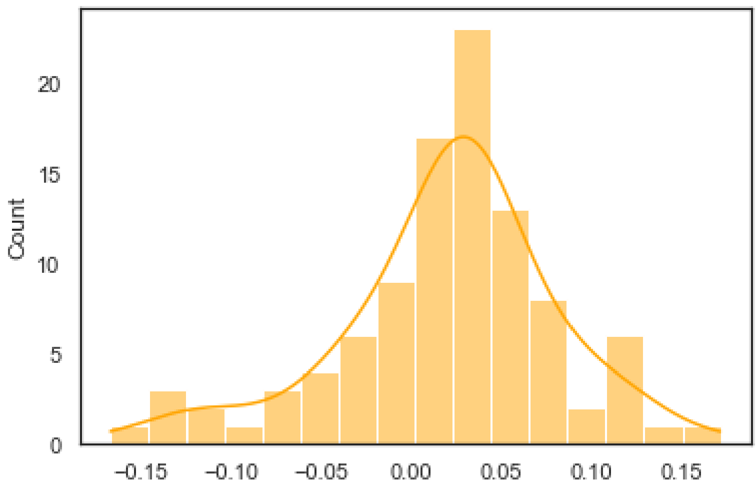
5.Normality of residuals

In [137]:

```
sns.histplot(errors,kde=True,color='orange')
```

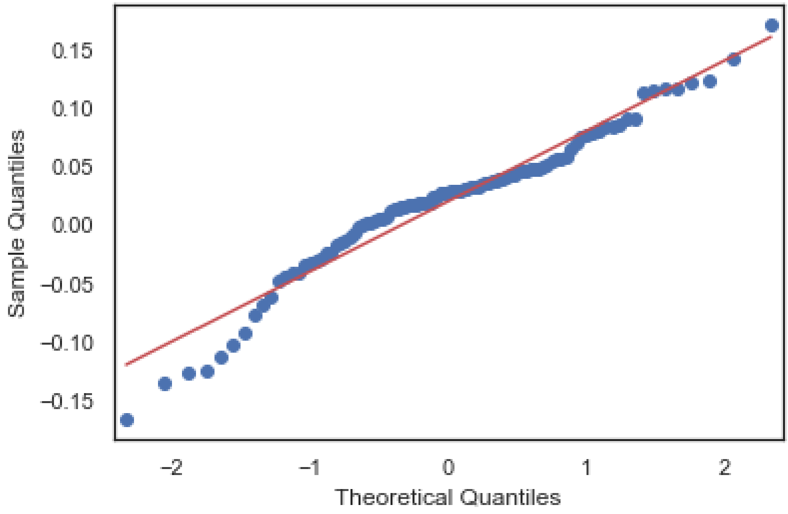
Out[137]:

```
<AxesSubplot:ylabel='Count'>
```



In [138]:

```
sm.qqplot(errors,line='s')
plt.show()
```



Observations for Model 2.3

- If only GRE score is considered out of GRE, TOEFL and CGPA, we are getting less R2 value (0.65)
- If only TOEFL score is considered out of GRE, TOEFL and CGPA, we are getting R2 value (0.666)
- If only CGPA is considered out of GRE, TOEFL and CGPA, we are getting less R2 value (0.791) and ajusted R2 as (0.790), which concludes that **CGPA is the best fit out of the three highly corelated features**
- If we are not including 'University Rating_2' then R2 is not having any drop at all -> 0.790, so we will remove it from our input variable.
- If we are not including 'Research_1' then R2 is dropping to 0.75, so we will keep it as our input variable.
- F-statistics has a very low p-value(practically low). Meaning that the model fit is statistically significant, and the explained variance isn’t purely by chance.
- No significant drop in adjusted R squared as compared to previous model.
- There's hardly any difference between the **R2(0.790) and adjusted R2(0.789)**. Meaning that 79% of the variance in chance for admit is explained by all the input variables (Research and CGPA). This is a decent R-squared value.

Observations from Multicollinearity check:

- All features have VIF < 5

Observations from Residual mean check:

- The mean of residuals is nearly zero (0.02)

Observations from Linearity of variables check:

- As there's a clear linear relationship between predicted values and given values for chance of admit, we can say that the variance of both the values is similar

Observations from test for Homoscedasticity check:

- No pattern in the residual plot

Observations from Normality of residuals check:

- The distribution looks normal

Actionable Insights & Recommendations:

- Although GRE Score, TOEFL Score, CGPA , University Rating , Research publications , Statement of Purpose and Letter of Recommendation Strength helps in predicting chance of admit, the most important factors in graduate admissions are **CGPA and Research Publications.**
- As there's a strong corelation between GRE Score, TOEFL Score and CGPA, any one of these three can be used to give similar predictions along with the Research criterion.
- The Research criteria is predominantly useful because of following reasons:
  - Students to Research papers have more chances of getting into Univeristies with top class ratings (4 & 5).
  - Students with higher ratings in LOR and SOP are the students with most number of research paper publications.
  - It shouldn't be surprising that the **students with higher scores in academics (GRE, TOEFL and CGPA) are the one's who are actively publishing** or had published Research papers in the past.
- Everything students do in high school can impact their admissions outcomes.Grades matters a lot.However, during the model building phase I noticed that **LOR (letter of recommendation) also is a strong feature which can be linked with student's behaiviour and extra curricular activities.** There are factors outside student's control that have an impact on their chances as colleges and universities build each freshman class to include a diverse array of students, and that means selecting for diverse racial, economic, and personal backgrounds can be considered for getting a **good LOR ratings which increases the chances of admission** given the rest of the variables.