From company's Overview

● Jamboree is a renowned educational institution that has successfully assisted numerous students in gaining admission to top colleges abroad. With their proven problem-solving methods, they have helped students achieve exceptional scores on exams like GMAT, GRE, and SAT with minimal effort.

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
df=pd.read_csv("/content/drive/MyDrive/Jamboree_Admission.csv")
df.head()
```

	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

Next steps: Generate code with df View recommended plots

```
df.shape
```

```
(500, 9)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 9 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Serial No.         500 non-null    int64
 1   GRE Score          500 non-null    int64
 2   TOEFL Score        500 non-null    int64
 3   University Rating  500 non-null    int64
 4   SOP                500 non-null    float64
 5   LOR                500 non-null    float64
 6   CGPA               500 non-null    float64
 7   Research           500 non-null    int64
 8   Chance of Admit    500 non-null    float64
dtypes: float64(4), int64(5)
memory usage: 35.3 KB
```

```
# statastical summary of entire dataset
display(df.describe())
```

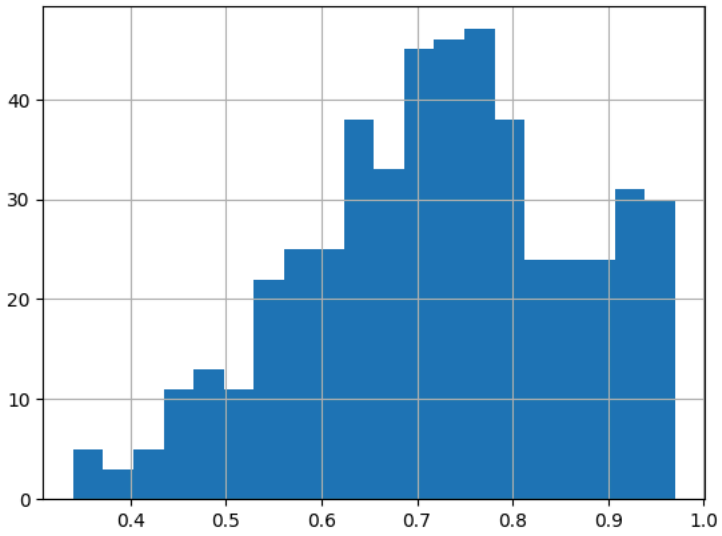
	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGP/
count	500.000000	500.000000	500.000000	500.000000	500.000000	500.00000	500.00000(
mean	250.500000	316.472000	107.192000	3.114000	3.374000	3.48400	8.57644(
std	144.481833	11.295148	6.081868	1.143512	0.991004	0.92545	0.60481:
min	1.000000	290.000000	92.000000	1.000000	1.000000	1.00000	6.80000(
25%	125.750000	308.000000	103.000000	2.000000	2.500000	3.00000	8.12750(
50%	250.500000	317.000000	107.000000	3.000000	3.500000	3.50000	8.56000(
75%	375.250000	325.000000	112.000000	4.000000	4.000000	4.00000	9.04000(

- GRE score range from [290-340]
- Tofel score range from [92-120]

Distribution in univarient Analysis

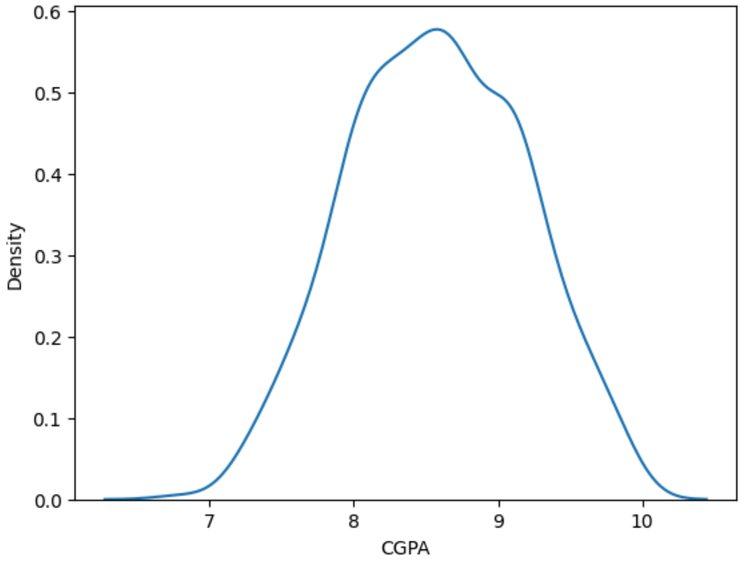
```
df['Chance of Admit '].hist(bins=20)
```

<Axes: >

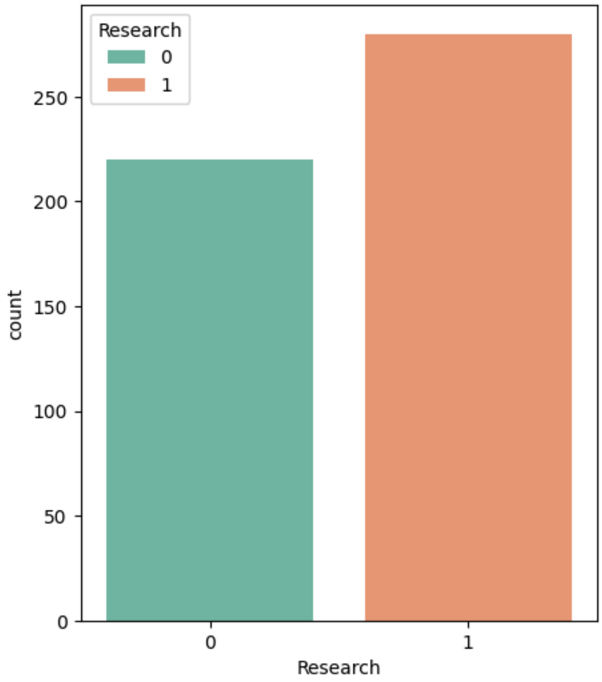



```
sns.kdeplot(df['CGPA'])
```

<Axes: xlabel='CGPA', ylabel='Density'>




```
fig = plt.figure(figsize=(5,6))
sns.countplot(x="Research",hue="Research",data=df,palette = "Set2")
plt.show()
```




```
abs_value=df["Research"].value_counts(ascending=False)
rel_value=df["Research"].value_counts(ascending=False,normalize=True).values*100
print(abs_value)
print(rel_value)
```

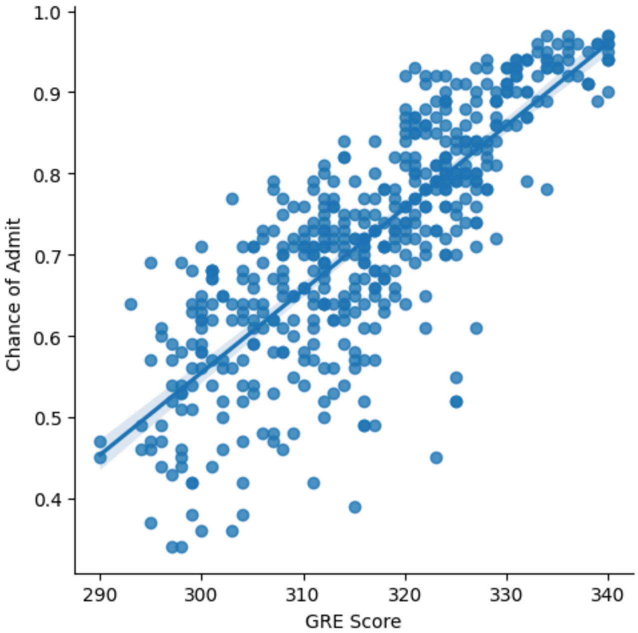
```
Research
1    280
0    220
Name: count, dtype: int64
[56. 44.]
```

1. Out of 500: 280(56%) student have research Experiance, 220(44%)student don`t have research experiance.
2. CGPA ranges from [6.80-9.92]
3. Chance of admit ranges from [0.34-0.97]

Distribution in Bivarient Analysis

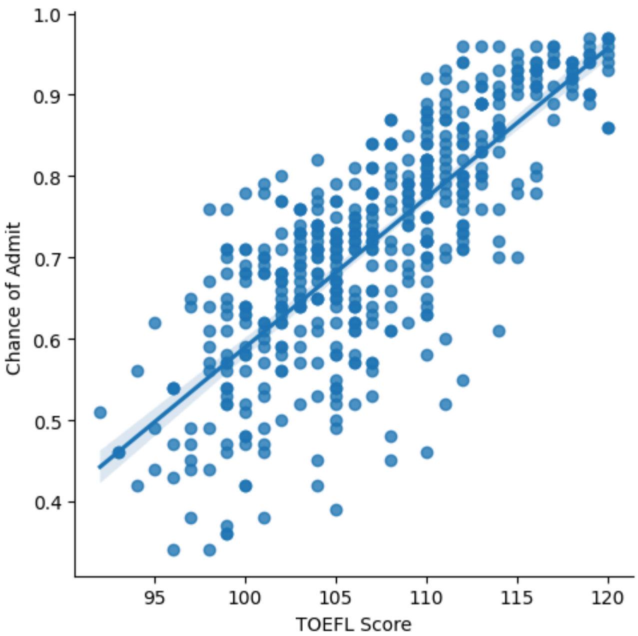
```
#creating function for linear plot and their correlation

def plot_print_correlation(df,x_col,y_col):
  """
  df=dataframe containing data columns
  x_col= column name for x-axis
  y_col=column name for y-axis
  """
  sns.lmplot(data=df,x=x_col,y=y_col)
  correlation_coefficient=df[x_col].corr(df[y_col])
  print(f'correlation_coefficient between {x_col} and {y_col}:{round(correlation_coefficient,2)}')


plot_print_correlation(df,"GRE Score",'Chance of Admit ')
```

```
correlation_coefficient between GRE Score and Chance of Admit :0.81
```




```
plot_print_correlation(df,"TOEFL Score",'Chance of Admit ')
```

```
correlation_coefficient between TOEFL Score and Chance of Admit :0.79
```



1. Linear correlation is between GRE_score and Chance of admit and correaltion coefficient=0.81
2. Linear correlation is between Tofel_score and Chance of admit and correaltion coefficient=0.79
3. Both GRE_score and Tofel_score are important metric to get admission in university.

Data processing to check missing value,duplicates,outlier value

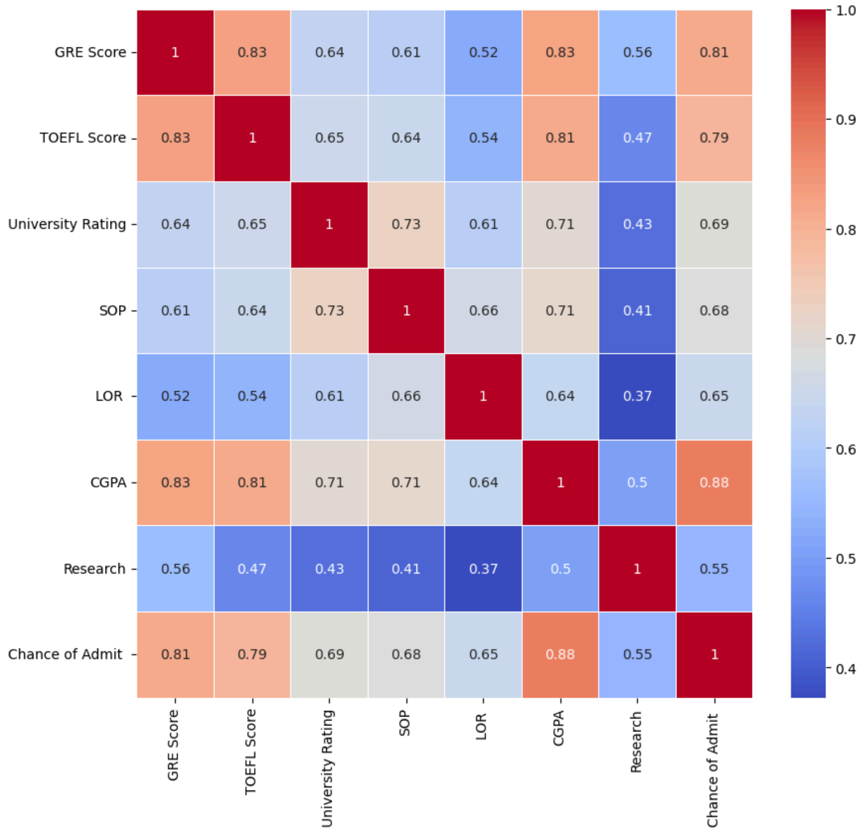
```
df.columns
```

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

```
data=df[["GRE Score","TOEFL Score",'University Rating','SOP','LOR ','CGPA','Research','Chance of Admit ']]
data=pd.DataFrame(data)
```

```
plt.figure(figsize=(10,9))
sns.heatmap(data.corr(),annot=True,cmap="coolwarm",linewidth=0.5)
```

```
<Axes: >
```

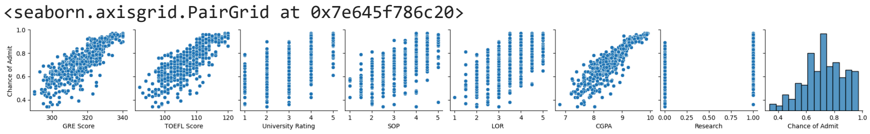


We see following correlation

1. GRE_score,Tofel_Score,CGPA have strong correlation > 0.8
2. University_rating ,SOP,LOR and Research experiance are equally important matrix for chance of admit.

```
sns.pairplot(data,y_vars=['Chance of Admit '])
```

```
<seaborn.axisgrid.PairGrid at 0x7e645f786c20>
```




```
df.isnull().sum()
```

```
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
```

```
df.duplicated().sum()
```

```
0
```

1. There is no null and duplicated values in dataset.

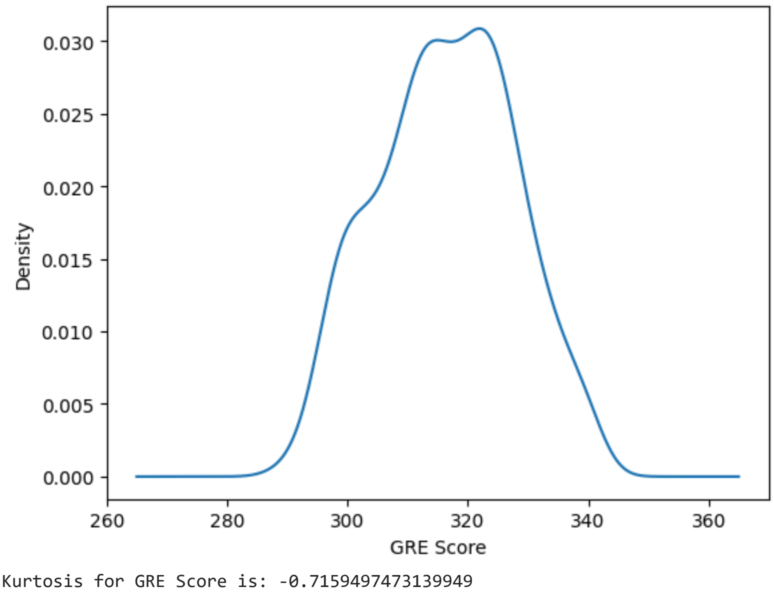
```
from scipy.stats import kurtosis,skew
TOFEL_skew=skew(df['TOEFL Score'],axis=0,bias=True)
TOFEL_skew
```

```
0.09531393010261811
```

- For a distribution having kurtosis < 3: It is called playkurtic.
- Both GRE=-0.7159 and TOfel=-0.6587 respectively hence dataset is playkurtic

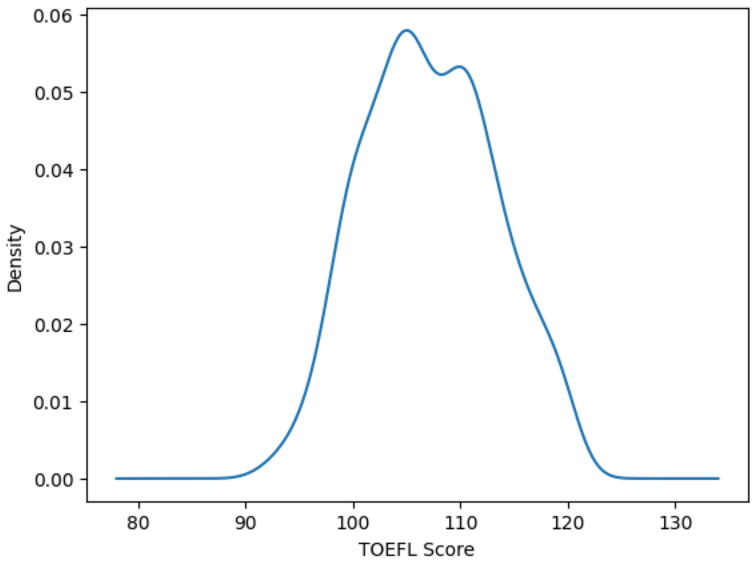
```
def skew_kurtosis(df,column_name):
  """
  creating normal distribution plot and calulating skewness and kurtosis for dataset
  """
  df[column_name].plot.density()
  plt.title=(f'Density plot for {column_name}')
  plt.xlabel(column_name)
  plt.ylabel("Density")
  plt.show()
# Calculate Kurtosis and skewness
  col_kurtosis=kurtosis(df[column_name],axis=0,bias=True)
  col_skew=skew(df[column_name],axis=0,bias=True)

  print(f'Kurtosis for {column_name} is: {col_kurtosis}')
  print(f'skew for {column_name} is: {col_skew}')
```

```
skew_kurtosis(df,'GRE Score')
```




```
Kurtosis for GRE Score is: -0.7159497473139949
skew for GRE Score is: -0.03972223277299966
```

```
skew_kurtosis(df,'TOEFL Score')
```




```
Kurtosis for TOEFL Score is: -0.6587072628939645
skew for TOEFL Score is: 0.09531393010261811
```

- Both TOFEL_SCORE AND GRE_SCORE are platykturic distribution casue kurtosis < 3
- GRE_Score is left skew where as Tofel_score is Right skewed.

Prepating data for Modelling

```
#Scaling the data using Min_Max scaler
from sklearn.preprocessing import MinMaxScaler
scaler=MinMaxScaler()
df_scale=pd.DataFrame(scaler.fit_transform(df),columns=df.columns)
df_scale.head()
```

	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
0	0.000000	0.94	0.928571	0.75	0.875	0.875	0.913462	1.0	0.920635
1	0.002004	0.68	0.535714	0.75	0.750	0.875	0.663462	1.0	0.666667
2	0.004008	0.52	0.428571	0.50	0.500	0.625	0.384615	1.0	0.603175
3	0.006012	0.64	0.642857	0.50	0.625	0.375	0.599359	1.0	0.730159

Next steps: Generate code with `df_scale` View recommended plots

Splitting the data for train_test_split function

```
from sklearn.model_selection import train_test_split
df_train,df_test=train_test_split(df_scale,test_size=0.2,random_state=1)
```

```
df_train.shape
```

```
(400, 9)
```

```
df_test.shape
```

```
(100, 9)
```

```
y_train=df_train['Chance of Admit ']
x_train=df_train.drop(['Chance of Admit ','Serial No.'],axis=1)
y_train.shape,x_train.shape
```

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

```
y_test=df_test['Chance of Admit ']
x_test=df_test.drop(['Chance of Admit ','Serial No.'],axis=1)
y_test.shape,x_test.shape
```

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

```
from sklearn.linear_model import LinearRegression
model=LinearRegression()
model.fit(x_train, y_train)
```

```
▾ LinearRegression
LinearRegression()
```

```
model.coef_
```

```
array([0.14541621, 0.14106352, 0.03891338, 0.01907985, 0.09159877,
       0.57796411, 0.03157108])
```

```
model.intercept_
```

```
0.018693219780457793
```

Let's check the performance of our previously trained model on test data.

```
model.score(x_train,y_train)
```

```
0.8215099192361265
```

```
model.score(x_test,y_test)
```

```
0.8208741703103732
```

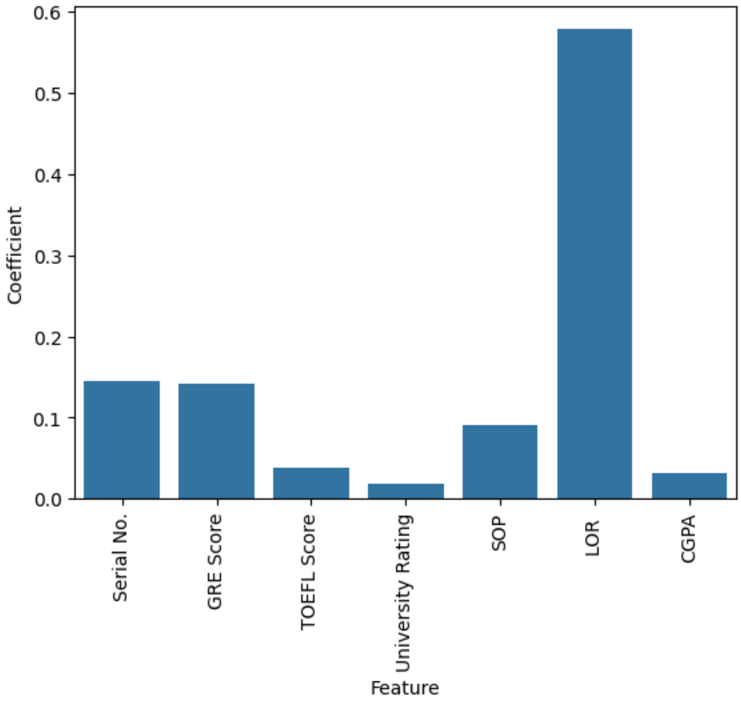
```
cols=df_scale.drop(columns=[df_scale.columns[-1]])
```

```
# Displaying column name with model coeffient
coeff_dict=dict(zip(cols.columns,model.coef_))
coeff_dict
```

```
{'Serial No.': 0.14541620599466432,
 'GRE Score': 0.1410635193731643,
 'TOEFL Score': 0.03891337690960878,
 'University Rating': 0.019079851592410282,
 'SOP': 0.09159876660812911,
 'LOR ': 0.5779641114318913,
 'CGPA': 0.03157107794156394}
```

```
imp=pd.DataFrame(list(coeff_dict.items()), columns=['Feature', 'Coefficient'])
sns.barplot(x='Feature',y='Coefficient',data=imp)
plt.xticks(rotation=90)
```

```
([0, 1, 2, 3, 4, 5, 6],
 [Text(0, 0, 'Serial No.'),
  Text(1, 0, 'GRE Score'),
  Text(2, 0, 'TOEFL Score'),
  Text(3, 0, 'University Rating'),
  Text(4, 0, 'SOP'),
  Text(5, 0, 'LOR '),
  Text(6, 0, 'CGPA')])
```




```
#Let's implement it for our earlier model and test data
y_hat=model.predict(x_test)
y_hat
```

```
array([0.49784861, 0.57211971, 0.95874419, 0.62120358, 0.75744731,
       0.51609063, 0.64359078, 0.59362311, 0.71227185, 0.50244074,
       0.52195512, 0.35262147, 0.70193023, 0.72317653, 0.68518869,
       0.82185736, 0.45902052, 0.66978499, 0.88489824, 0.52668273,
       0.45783759, 0.72047647, 0.7968502 , 0.4002296 , 0.71232259,
       0.36320112, 0.970822  , 0.48312348, 0.8258256 , 0.58861527,
       0.46562057, 0.75400178, 0.40910717, 0.90549255, 0.26652651,
       0.75896789, 0.55111319, 0.46540382, 0.50723991, 0.90745734,
       0.35829713, 0.50918643, 0.68626119, 1.00151975, 0.68540644,
       0.2894535 , 0.51902313, 0.46079161, 0.49782176, 0.50891734,
       0.78338084, 0.91827548, 0.85440056, 0.44333049, 0.67989432,
       0.48088514, 0.64709923, 0.41800985, 0.50699731, 0.56582297,
       0.15497635, 0.60613709, 0.65566715, 0.8081426 , 1.01612007,
       0.42944255, 0.62200407, 0.68880995, 0.9546544 , 0.57548434,
       0.41718373, 0.49862798, 0.76851132, 0.23976105, 0.92982374,
       0.40852008, 0.78857265, 0.95363212, 0.58919945, 0.68045127,
       0.78534311, 0.26971519, 0.91403047, 0.71327546, 0.72873205,
       0.5503102 , 0.85361701, 0.86804199, 0.35738891, 0.41390015,
       0.45909276, 0.70027409, 0.36702426, 0.58310661, 0.7307935 ,
       0.7847766 , 0.77489772, 0.36987656, 0.61110505, 0.54838994])
```

```
Adj_R= (1-model.score(x_test,y_test)*(len(y_test)-1)/(len(y_test)-x_test.shape[1]-1))
print("Adjusted R-squared:",Adj_R)
```

```
Adjusted R-squared: 0.11666801238340263
```

```
import statsmodels.api as sm
x_sm = sm.add_constant(x_train)
sm_model = sm.OLS(y_train,x_sm)
result = sm_model.fit()
# Print the summary statistics of the model
print(result.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:        Chance of Admit   R-squared:                       0.822
Model:                            OLS   Adj. R-squared:                  0.818
Method:                 Least Squares   F-statistic:                     257.7
Date:                Fri, 07 Jun 2024   Prob (F-statistic):          2.10e-142
Time:                        15:38:35   Log-Likelihood:                 374.46
No. Observations:                 400   AIC:                            -732.9
Df Residuals:                     392   BIC:                            -701.0
```

```
Df Model:                           7
Covariance Type:            nonrobust
=====================================================================================
                        coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------
const                 0.0187      0.016      1.155      0.249      -0.013       0.051
GRE Score             0.1454      0.046      3.135      0.002       0.054       0.237
TOEFL Score           0.1411      0.045      3.156      0.002       0.053       0.229
University Rating     0.0389      0.028      1.387      0.166      -0.016       0.094
SOP                   0.0191      0.032      0.591      0.555      -0.044       0.083
LOR                   0.0916      0.029      3.105      0.002       0.034       0.150
CGPA                  0.5780      0.054     10.743      0.000       0.472       0.684
Research              0.0316      0.012      2.668      0.008       0.008       0.055
==============================================================================
Omnibus:                       80.594   Durbin-Watson:                   1.932
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              167.116
Skew:                          -1.064   Prob(JB):                     5.14e-37
Kurtosis:                       5.346   Cond. No.                         23.4
==============================================================================

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

1. Model Summary R-squared (0.822): This indicates that approximately 82.2% of the variance in the dependent variable y y is explained by the independent variables in the model. This is a relatively high value, suggesting a good fit.
2. Adjusted R-squared (0.818): This value is slightly lower than the R-squared, accounting for the number of predictors in the model. It still indicates a good fit.

Coefficients and Significance

- GRE_score
- TOFEL_score and CGPA have higest significane

Multicoliearity and VIF

```
from sklearn.preprocessing import StandardScaler
from statsmodels.stats.outliers_influence import variance_inflation_factor
scaler = StandardScaler()
x_tr_scaled=scaler.fit_transform(x_train)
```

```
#VIF calculation
vif=pd.DataFrame()
x_t=pd.DataFrame(x_tr_scaled,columns=x_train.columns)
vif['Feature']=x_t.columns
vif['VIF']=[variance_inflation_factor(x_t.values,i) for i in range (x_t.shape[1])]
vif['VIF']=round(vif['VIF'],2)
vif=vif.sort_values(by='VIF',ascending=False)
vif
```

	Feature	VIF
0	GRE Score	4.88
5	CGPA	4.75
1	TOEFL Score	4.26
3	SOP	2.92
2	University Rating	2.80
4	LOR	2.08
6	Research	1.51

Next steps: Generate code with vif View recommended plots

```
cols2=vif['Feature'][1:].values
x2=pd.DataFrame(x_tr_scaled,columns=x_train.columns)[cols2]
x2_sm=sm.add_constant(x2) #Statmodels default is without intercept, to add intercept we need to add constant
sm_model=sm.OLS(list(y_train),x2_sm).fit()
print(sm_model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.817
Model:                            OLS   Adj. R-squared:                  0.814
Method:                 Least Squares   F-statistic:                     292.5
```

```
Date:                 Fri, 07 Jun 2024   Prob (F-statistic):          1.49e-141
Time:                         15:38:35   Log-Likelihood:                 369.51
No. Observations:                  400   AIC:                            -725.0
Df Residuals:                      393   BIC:                            -697.1
Df Model:                            6
Covariance Type:             nonrobust
=====================================================================================
                        coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------
const                 0.6046      0.005    124.773      0.000       0.595       0.614
CGPA                  0.1248      0.010     12.801      0.000       0.106       0.144
TOEFL Score           0.0468      0.009      5.421      0.000       0.030       0.064
SOP                   0.0027      0.008      0.323      0.747      -0.014       0.019
University Rating     0.0132      0.008      1.631      0.104      -0.003       0.029
LOR                   0.0208      0.007      2.982      0.003       0.007       0.035
Research              0.0210      0.006      3.690      0.000       0.010       0.032
==============================================================================
Omnibus:                       69.467   Durbin-Watson:                   1.922
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              125.834
Skew:                          -0.984   Prob(JB):                     4.74e-28
Kurtosis:                       4.918   Cond. No.                         4.82
==============================================================================

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

Error Distribution

```
sm_model=sm.OLS(y_train,x_sm).fit()
sm_model
```

```
<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x7e645833ed40>
```

```
y_hat=sm_model.predict(x_sm)
errors=y_hat- y_train
```

```
#Histogram of Residual
import seaborn as sns
sns.histplot(errors)
plt.xlabel("Residuals")
```

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