```
import pandas as pd
import numpy as np
```

```
df=pd.read_excel('/content/drive/MyDrive/Colab Notebooks/DS & ML/Projects/8.jambore/Jambore.xlsx')
df
```

	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
0	1.0	337.0	118.0	4.0	4.5	4.5	9.65	1.0	0.92
1	2.0	324.0	107.0	4.0	4.0	4.5	8.87	1.0	0.76
2	3.0	316.0	104.0	3.0	3.0	3.5	8.00	1.0	0.72
3	4.0	322.0	110.0	3.0	3.5	2.5	8.67	1.0	0.80
4	5.0	314.0	103.0	2.0	2.0	3.0	8.21	0.0	0.65
...	...	...	...	...	...	...	...	...	...
495	496.0	332.0	108.0	5.0	4.5	4.0	9.02	1.0	0.87
496	497.0	337.0	117.0	5.0	5.0	5.0	9.87	1.0	0.96
497	498.0	330.0	120.0	5.0	4.5	5.0	9.56	1.0	0.93
498	499.0	312.0	103.0	4.0	4.0	5.0	8.43	0.0	0.73
499	500.0	327.0	113.0	4.0	4.5	4.5	9.04	0.0	0.84

500 rows × 9 columns

1. Define Problem statement & Exploratory analysis

Definition of Problem

The fetaure of this model is to predict whether a student gets an admission into a specific college or not based on the scores and the capability of a candidate

Observations and shape of data

```
df.head()
```

	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
0	1.0	337.0	118.0	4.0	4.5	4.5	9.65	1.0	0.92
1	2.0	324.0	107.0	4.0	4.0	4.5	8.87	1.0	0.76
2	3.0	316.0	104.0	3.0	3.0	3.5	8.00	1.0	0.72
3	4.0	322.0	110.0	3.0	3.5	2.5	8.67	1.0	0.80
4	5.0	314.0	103.0	2.0	2.0	3.0	8.21	0.0	0.65

```
df.shape
```

```
(500, 9)
```

Data types

```
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    float64
 1   GRE Score          500 non-null    float64
 2   TOEFL Score        500 non-null    float64
 3   University Rating  500 non-null    float64
 4   SOP                500 non-null    float64
 5   LOR                500 non-null    float64
 6   CGPA               500 non-null    float64
 7   Research           500 non-null    float64
 8   Chance of Admit    500 non-null    float64
dtypes: float64(9)
memory usage: 35.3 KB
```

```
df.drop(['Serial No.'],axis=1,inplace=True)
```

Among all the features, University rating and Research are categorical data

```
df['University Rating']=df['University Rating'].astype('category')
df['Research']=df['Research'].astype('category')
df['SOP']=df['SOP'].astype('category')
df['LOR']=df['LOR'].astype('category')
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 8 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   GRE Score          500 non-null    float64
 1   TOEFL Score        500 non-null    float64
 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(4)
memory usage: 18.8 KB
```

Missing value detection

```
df[df.isna()].count()
```

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

NO missing values

Statistical summary

[ ] ↳ *1 cell hidden*

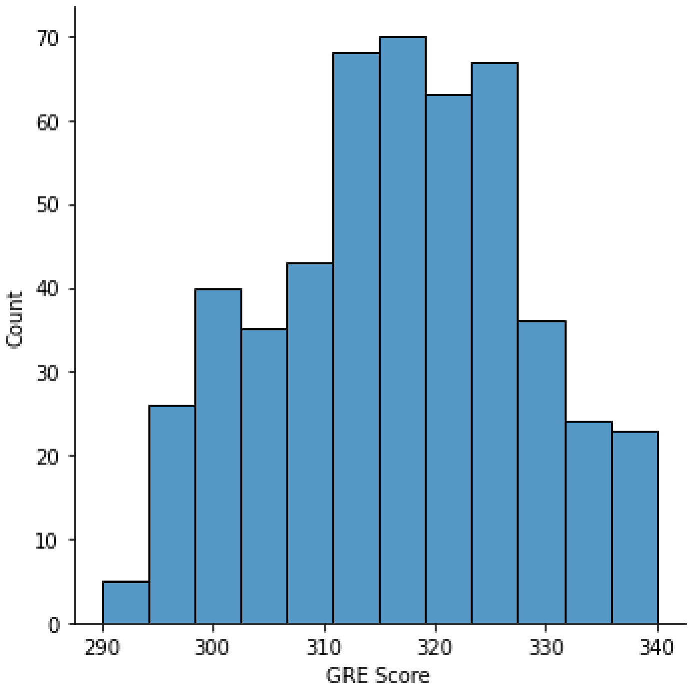
Univariate Analysis

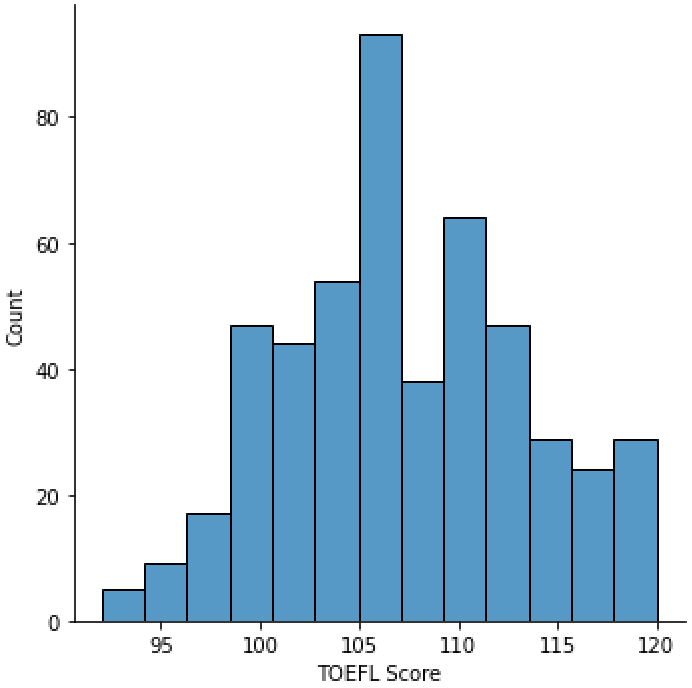
let's see the distribution of continuous variables like GRE, TOEFL score,CGPA,chance of admit

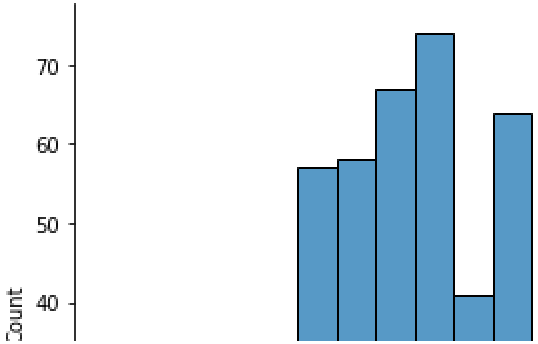
```
categorical_columns=df.select_dtypes(include='category').columns
numerical_columns=df.select_dtypes(include='number').columns
```

```
import matplotlib.pyplot as plt
import seaborn as sns
```

```
for i in numerical_columns:
  sns.displot(x=i,data=df)
  plt.show()
```

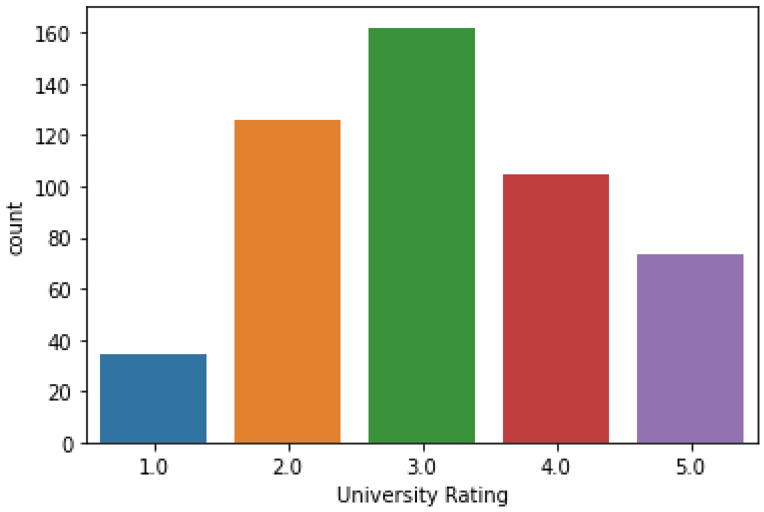

Count
GRE Score
0
10
20
30
40
50
60
70
290
300
310
320
330
340

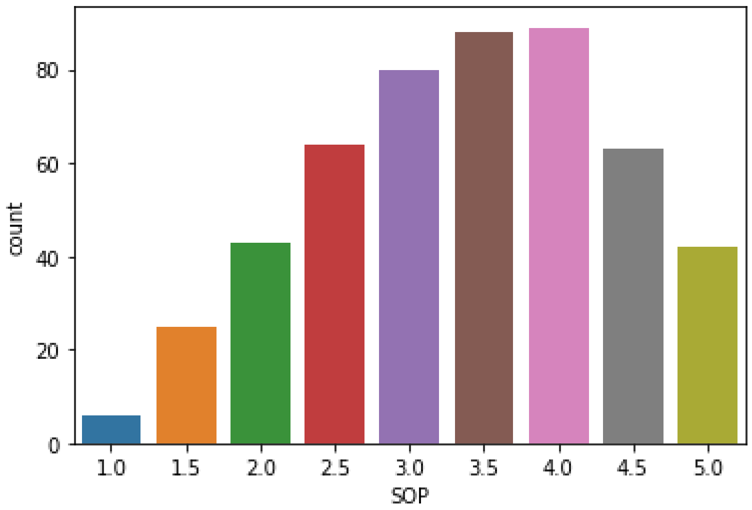

Count
TOEFL Score
0
20
40
60
80
95
100
105
110
115
120

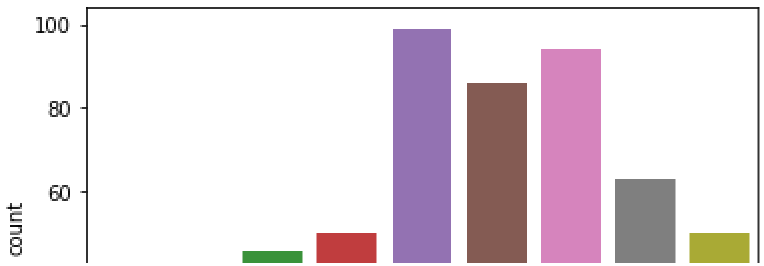


The ranges and high frequency or high repetative values can be observed

```
for i in categorical_columns:
  sns.countplot(x=i,data=df)
  plt.show()
```







The students with having research is more and the SOP, LOR the value of 3 to 4.0 and university rating of 3 is more

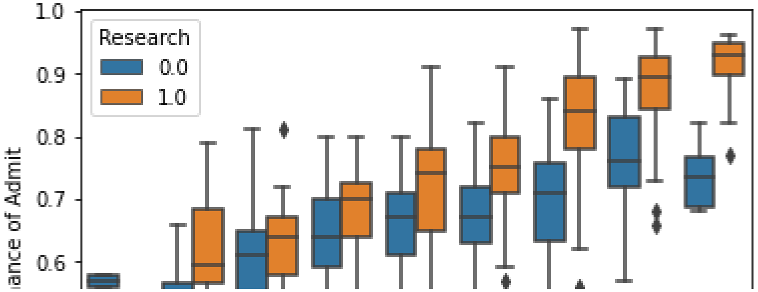
```
for i in categorical_columns:
  print(df[i].value_counts(normalize=True))
```

```
3.0    0.324
2.0    0.252
4.0    0.210
5.0    0.146
1.0    0.068
Name: University Rating, dtype: float64
4.0    0.178
3.5    0.176
3.0    0.160
2.5    0.128
4.5    0.126
2.0    0.086
5.0    0.084
1.5    0.050
1.0    0.012
Name: SOP, dtype: float64
3.0    0.198
4.0    0.188
3.5    0.172
4.5    0.126
2.5    0.100
5.0    0.100
2.0    0.092
1.5    0.022
1.0    0.002
Name: LOR, dtype: float64
1.0    0.56
0.0    0.44
Name: Research, dtype: float64
```

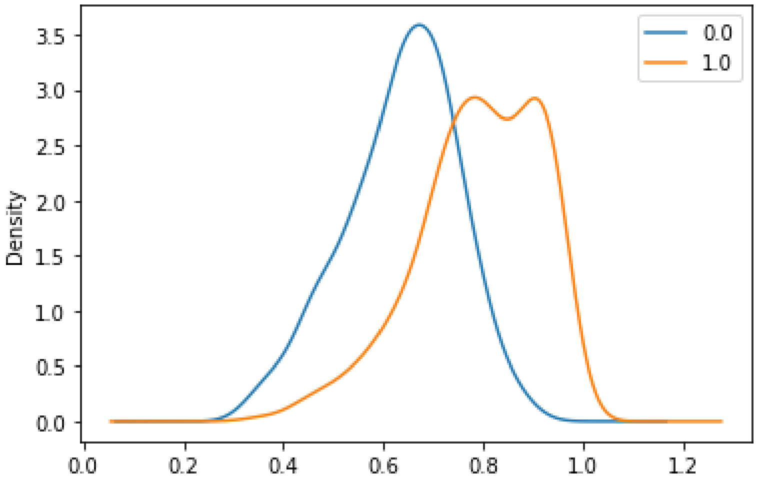
Bivariate analysis

```
for i in ['SOP','LOR','University Rating']:
```

```
sns.boxplot(x=i,y='Chance of Admit',data=df,hue='Research')
plt.show()
```




```
df.groupby(['Research'])['Chance of Admit'].plot.density()
plt.legend();
```



It shows the guys with research having more chances of getting admitted or getting good ratings for LOR and SOP

Insights

The GRE score range is 290 to 340 and the most frequent scores are between 310 to 328

The TOEFL score range is 90 to 120 and the most frequent score is about 100

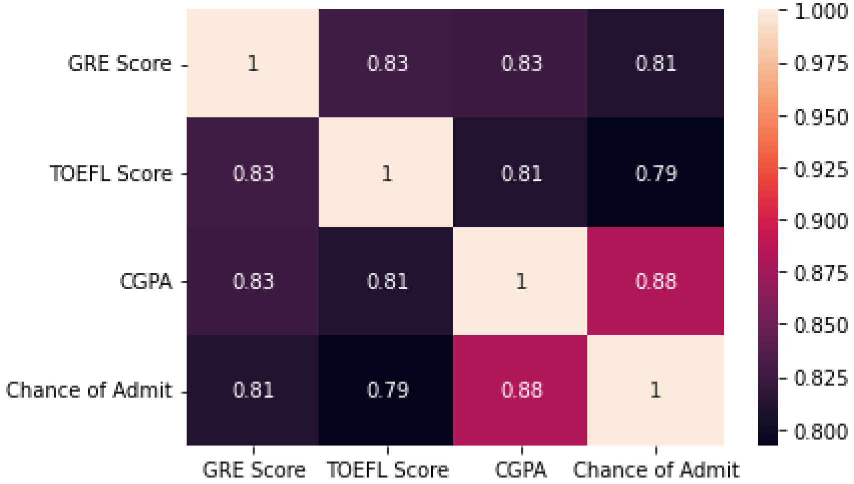
CGPA is between 6.8 to 10 and mostly occured is between 8 to 9

Chance of admit is more of 0.6 to 1

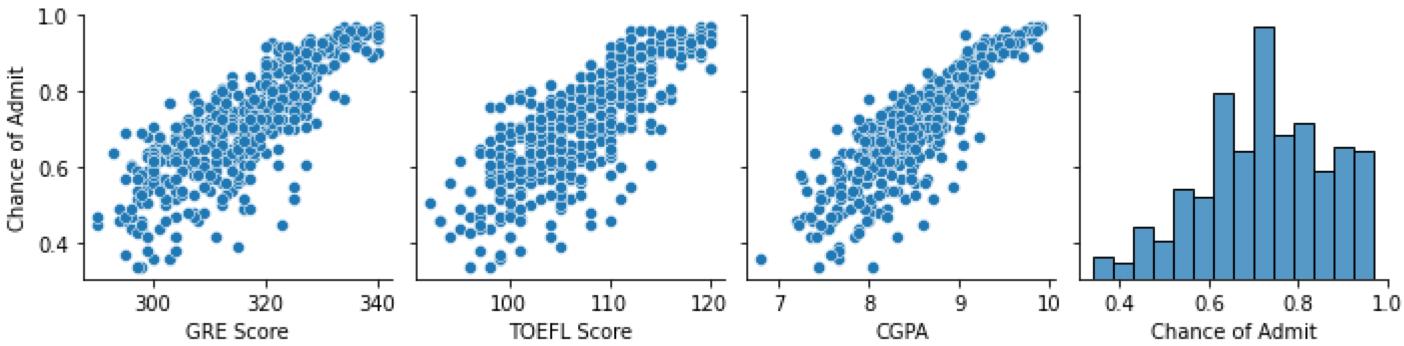
The chance of admit increases with SOP, LOR increases and who had done research has higher values of chance of admit

```
sns.heatmap(df.corr(),annot=True)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fc50d1942d0>
```




```
sns.pairplot(df, y_vars=["Chance of Admit"]);
```



So, the chance of admit increases with GRE score, TOEFL score, CGPA

Data Preprocessing

Duplicate value check

```
df[df.duplicated()]
```

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

There are no duplicates

Missing value treatment

There are no missing values

Outlier treatment

```
df.describe(include='all')
```

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
count	500.000000	500.000000	500.0	500.0	500.0	500.000000	500.0	500.00000
unique	NaN	NaN	5.0	9.0	9.0	NaN	2.0	NaN
top	NaN	NaN	3.0	4.0	3.0	NaN	1.0	NaN
freq	NaN	NaN	162.0	89.0	99.0	NaN	280.0	NaN
mean	316.472000	107.192000	NaN	NaN	NaN	8.576440	NaN	0.72174
std	11.295148	6.081868	NaN	NaN	NaN	0.604813	NaN	0.14114
min	290.000000	92.000000	NaN	NaN	NaN	6.800000	NaN	0.34000
25%	308.000000	103.000000	NaN	NaN	NaN	8.127500	NaN	0.63000

There are no outliers as it seems every data point is valid

Feature Engineering

There are no features which can be added up or derived from the existing features

```
# df=df2
```

Categorical Encoding

```
from sklearn.preprocessing import OrdinalEncoder
```

```
def feature_engineering(df,categorical_columns):
  ordinal_encoding_columns=categorical_columns
  for col in ordinal_encoding_columns:
```

```
        from sklearn.preprocessing import OrdinalEncoder
        enc = OrdinalEncoder()
        df[[col]]=enc.fit_transform(df[[col]])
        # df=pd.concat([df,pd.get_dummies(df[col],prefix=col).iloc[:,1:]],axis=1)
        # df = pd.concat([df, pd.get_dummies(df[column]).iloc[: , 1:]], axis=1)
      # df.drop(columns=ordinal_encoding_columns,inplace=True)
      return df

    for i in categorical_columns:
      # print([i])
      df=feature_engineering(df,[i])
      # df.head()


    df
```

```
df.columns
```

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

Scaling

```
# from sklearn.preprocessing import MinMaxScaler, StandardScaler
```

495	332.0	108.0	4.0	7.0	6.0	9.02	1.0	0.87

```
# scaler = StandardScaler()
# df = pd.DataFrame(scaler.fit_transform(df), columns=df.columns)
# df
```

498	312.0	103.0	3.0	6.0	8.0	8.43	0.0	0.73

```
# for i in df.columns:
#   print(df[i].max(),df[i].min())
```

500 rows × 8 columns

```
final_df=df
final_df.head()
```

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
0	337.0	118.0	3.0	7.0	7.0	9.65	1.0	0.92
1	324.0	107.0	3.0	6.0	7.0	8.87	1.0	0.76
2	316.0	104.0	2.0	4.0	5.0	8.00	1.0	0.72
3	322.0	110.0	2.0	5.0	3.0	8.67	1.0	0.80
4	314.0	103.0	1.0	2.0	4.0	8.21	0.0	0.65

X and Y separation

```
X = final_df[final_df.columns.drop('Chance of Admit')]
Y = final_df["Chance of Admit"]
```

```
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=1)
```

```
X_train,X_test
```

```
(     GRE Score  TOEFL Score  University Rating  SOP  LOR  CGPA  Research
 238      310.0        104.0                2.0  2.0  5.0  8.37       0.0
 438      318.0        110.0                0.0  3.0  5.0  8.54       1.0
 475      300.0        101.0                2.0  5.0  3.0  7.88       0.0
 58       300.0         99.0                0.0  4.0  2.0  6.80       1.0
 380      322.0        104.0                2.0  5.0  6.0  8.84       1.0
 ..         ...          ...                ...  ...  ...   ...       ...
 255      307.0        110.0                3.0  6.0  7.0  8.37       0.0
 72       321.0        111.0                4.0  8.0  8.0  9.45       1.0
 396      325.0        107.0                2.0  4.0  5.0  9.11       1.0
 235      326.0        111.0                4.0  7.0  6.0  9.23       1.0
 37       300.0        105.0                0.0  0.0  2.0  7.80       0.0

 [400 rows x 7 columns],
      GRE Score  TOEFL Score  University Rating  SOP  LOR  CGPA  Research
 304      313.0        106.0                1.0  3.0  2.0  8.43       0.0
 340      312.0        107.0                2.0  4.0  4.0  8.46       1.0
 47       339.0        119.0                4.0  7.0  6.0  9.70       0.0
 67       316.0        107.0                1.0  5.0  5.0  8.64       1.0
 479      325.0        110.0                3.0  7.0  6.0  8.96       1.0
 ..         ...          ...                ...  ...  ...   ...       ...
 11       327.0        111.0                3.0  6.0  7.0  9.00       1.0
 192      322.0        114.0                4.0  7.0  6.0  8.94       1.0
 92       298.0         98.0                1.0  6.0  4.0  8.03       0.0
 221      316.0        110.0                2.0  5.0  6.0  8.56       0.0
 110      305.0        108.0                4.0  4.0  4.0  8.48       0.0

 [100 rows x 7 columns])
```

```
Y_train, Y_test
```

```
(238    0.70
 438    0.67
 475    0.59
 58     0.36
 380    0.78
        ...
 255    0.79
 72     0.93
 396    0.84
 235    0.88
 37     0.58
 Name: Chance of Admit, Length: 400, dtype: float64, 304    0.62
 340    0.75
 47     0.89
 67     0.57
 479    0.79
        ...
 11     0.84
 192    0.86
 92     0.34
 221    0.75
 110    0.61
 Name: Chance of Admit, Length: 100, dtype: float64)
```

Model Building

```
# Scaling

from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
scaler.fit(X_train)
```

```
X_train_standardized = scaler.transform(X_train)
X_test_standardized = scaler.transform(X_test)
```

```
X_train_standardized
```

```
array([[-0.53736015, -0.51949116, -0.05463584, ...,  0.00933125,
        -0.32658176, -1.11114215],
       [ 0.16363964,  0.44925692, -1.8029826 , ...,  0.00933125,
        -0.04593523,  0.89997486],
       [-1.41360989, -1.0038652 , -0.05463584, ..., -1.05709751,
        -1.13550409, -1.11114215],
       ...,
       [ 0.77701445, -0.03511712, -0.05463584, ...,  0.00933125,
         0.89505605,  0.89997486],
       [ 0.86463943,  0.61071493,  1.69371093, ...,  0.54254563,
         1.09315948,  0.89997486],
       [-1.41360989, -0.35803314, -1.8029826 , ..., -1.59031189,
        -1.26757304, -1.11114215]])
```

```
from sklearn.linear_model import LinearRegression
```

```
model=LinearRegression()
model.fit(X_train_standardized,Y_train)
```

```
output=model.predict(X_test_standardized)
```

```
model.coef_,model.intercept_
```

```
(array([0.02091007, 0.01965792, 0.00701103, 0.00304937, 0.01352815,
        0.07069295, 0.00988992]), 0.7209250000000001)
```

```
model.score(X_train_standardized,Y_train)
```

```
0.8215099192361265
```

```
model.score(X_test_standardized,Y_test)
```

```
0.8208741703103731
```

```
# poly=PolynomialFeatures(2)

# X_train_2=poly.fit_transform(X_train)
# X_train_2
# scaler = StandardScaler()
# scaler.fit(X_train_2)
# X_train_2_standardized = scaler.transform(X_train_2)
```

```
# X_train_2.shape
```

```
import statsmodels.api as sm
X_train_1=pd.DataFrame(X_train_standardized, columns=X_train.columns)
X_train_1.set_index(pd.Index(X_train.index),inplace=True)
# Y_train_1=pd.DataFrame(Y_train,columns=['Chance of Admit']).reset_index().iloc[:,1]

X_sm = sm.add_constant(X_train_1)  #Statmodels default is without intercept, to add intercept we need to add constant

sm_model = sm.OLS(Y_train, X_sm).fit()
```

```
/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/tsatools.py:142: FutureWarning: In a future version of pandas all argume
  x = pd.concat(x[::order], 1)
```

Model statistics & coefficients

```
print(sm_model.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:                Tue, 01 Nov 2022   Prob (F-statistic):          2.10e-142
Time:                        07:09:31   Log-Likelihood:                 559.27
No. Observations:                 400   AIC:                            -1103.
Df Residuals:                     392   BIC:                            -1071.
Df Model:                           7
Covariance Type:            nonrobust
=====================================================================================
                        coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------
const                 0.7209      0.003    238.778      0.000       0.715       0.727
GRE Score             0.0209      0.007      3.135      0.002       0.008       0.034
TOEFL Score           0.0197      0.006      3.156      0.002       0.007       0.032
University Rating     0.0070      0.005      1.387      0.166      -0.003       0.017
SOP                   0.0030      0.005      0.591      0.555      -0.007       0.013
LOR                   0.0135      0.004      3.105      0.002       0.005       0.022
CGPA                  0.0707      0.007     10.743      0.000       0.058       0.084
Research              0.0099      0.004      2.668      0.008       0.003       0.017
==============================================================================
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.                         5.92
==============================================================================

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

From the model coefficients and the t statistic values only GRE, TOEFL, LOR, CGPA, Research features are important

```
from sklearn.preprocessing import PolynomialFeatures
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression

degrees = 6 # number of data-points
train_scores = []
```

```
test_scores = []
for degree in range(1, degrees):
  scaler = StandardScaler()
  polyreg_scaled = make_pipeline(PolynomialFeatures(degree), scaler, LinearRegression())
  polyreg_scaled.fit(X_train, Y_train)
  train_score = polyreg_scaled.score(X_train, Y_train)
  test_score = polyreg_scaled.score(X_test, Y_test)
  train_scores.append(train_score)
  test_scores.append(test_score)
```

```
train_scores,test_scores
```

```
([0.8215099192361265,
  0.8372870402475172,
  0.7894587469834955,
  0.6622897051187593,
  1.0],
 [0.8208741703103731,
  0.8237964531405697,
  0.48668364921591045,
  -9.303401405360034,
  -183.52056018729255])
```

By just increasing the degree the r2 score is decreasing and its negative, i.e. it is performing worst than the dumb model

From the test scores, the best model is 2 degree model and train, test performance is slightly better than degree 1 model

Lasso and Ridge Regression

```
from sklearn import linear_model
model_train_scores=[]
model_test_scores=[]
model_coefs=[]
model_intercepts=[]

alphas=[0.1,0.05,0.01,0.005,0.001,0.0005,0.0001]
```

```
for i in alphas:
  model=linear_model.Lasso(alpha=i)
  model.fit(X_train_standardized,Y_train)
  output=model.predict(X_test_standardized)
  model_coefs.append(model.coef_)
  model_intercepts.append(model.intercept_)
  model_train_scores.append(model.score(X_train_standardized,Y_train))
  model_test_scores.append(model.score(X_test_standardized,Y_test))

max_score_alpha_index=np.argmax(model_test_scores)
alpha=alphas[max_score_alpha_index]
model_test_scores[max_score_alpha_index],model_coefs[max_score_alpha_index],model_intercepts[max_score_alpha_index]
```

```
(0.8207818227394215,
 array([0.02089882, 0.01962888, 0.006992  , 0.00302528, 0.01348122,
        0.07071527, 0.00983233]),
 0.7209250000000001)
```

```
from sklearn import linear_model
model_train_scores=[]
model_test_scores=[]
model_coefs=[]
model_intercepts=[]

alphas=[0.1,0.05,0.01,0.005,0.001,0.0005,0.0001]
for i in alphas:
  model=linear_model.Ridge(alpha=i)
  model.fit(X_train_standardized,Y_train)
  output=model.predict(X_test_standardized)
  model_coefs.append(model.coef_)
  model_intercepts.append(model.intercept_)
  model_train_scores.append(model.score(X_train_standardized,Y_train))
  model_test_scores.append(model.score(X_test_standardized,Y_test))

max_score_alpha_index=np.argmax(model_test_scores)
```

```
alpha=alphas[max_score_alpha_index]
model_test_scores[max_score_alpha_index],model_coefs[max_score_alpha_index],model_intercepts[max_score_alpha_index]
```

```
(0.8208741602027321,
 array([0.02091009, 0.01965794, 0.00701104, 0.00304938, 0.01352815,
        0.07069288, 0.00988992]),
 0.7209250000000001)
```

Testing Linear regression assumptions

Multicollinearity

```
# VIF
from statsmodels.stats.outliers_influence import variance_inflation_factor


vif = pd.DataFrame()
X_t = pd.DataFrame(X_train_standardized)
vif['Features'] = X_train.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
```

	Features	VIF
0	GRE Score	4.88

There is no relation between the variables and one variable cannot be explained interms of linear relationship with another variable

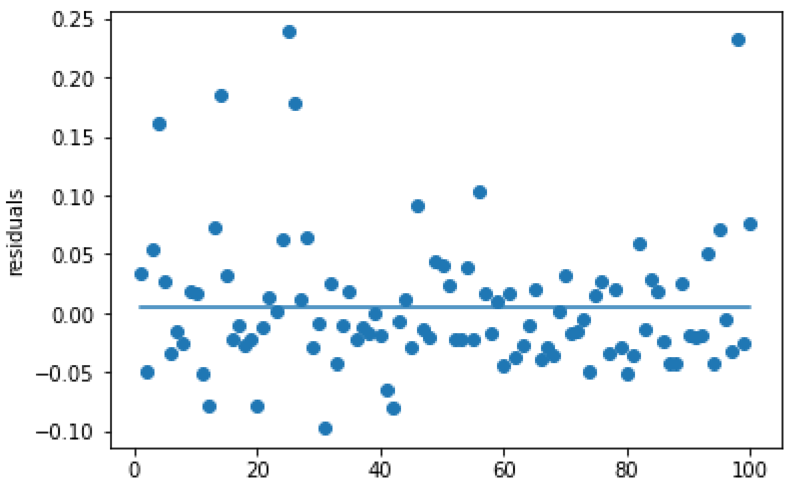
Mean of residuals

```
np.mean(output-Y_test)
```

```
0.0057065916355365405
```

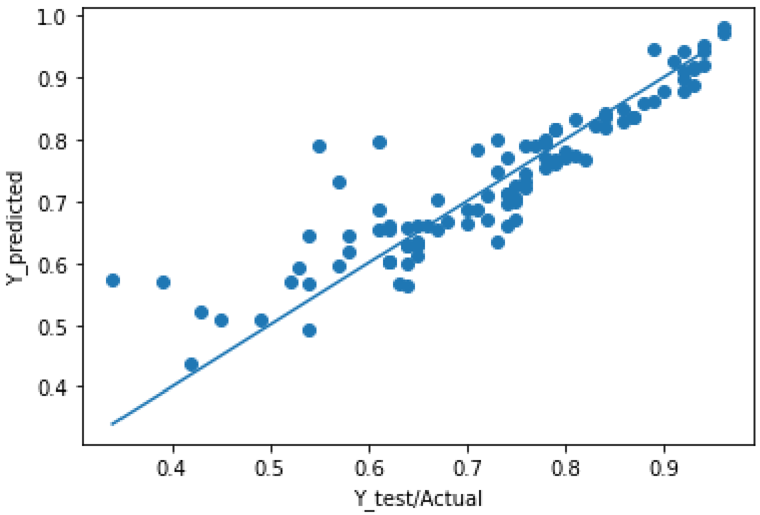
The mean of residuals is almost zero

```
plt.scatter(x=np.array(range(1,101)),y=output-Y_test)
plt.plot(np.array(range(1,101)),[np.mean(output-Y_test)]*100)
plt.ylabel('residuals')
plt.show()
```



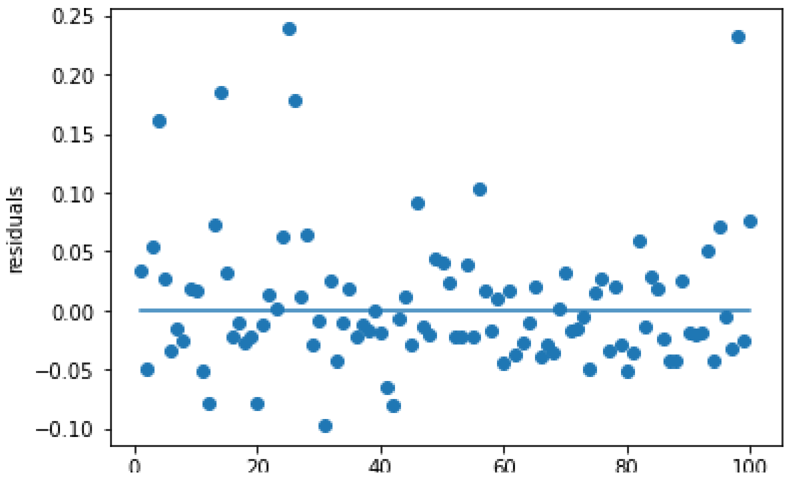
linearity of variables

```
plt.scatter(Y_test,output)
# plt.show()
min=np.min([Y_test.min(),output.min()])
max=np.max([Y_test.max(),output.max()])
plt.plot(np.arange(min,max,0.1),np.arange(min,max,0.1))
plt.xlabel('Y_test/Actual')
plt.ylabel('Y_predicted')
plt.show()
```



Test for Homoscedasticity

```
plt.scatter(x=np.array(range(1,101)),y=output-Y_test)
plt.plot(np.array(range(1,101)),[0]*100)
plt.ylabel('residuals')
plt.show()
```



There is almost constant variance

normality test

```
residuals=output-Y_test.values
```

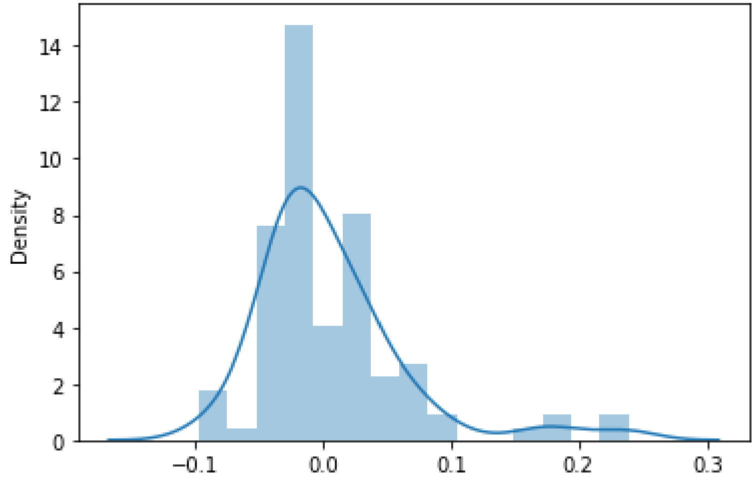
```
residuals
```

```
array([ 0.0336446 , -0.04956458,  0.05400882,  0.16135824,  0.02719181,
       -0.03486292, -0.01453783, -0.02601738,  0.01873126,  0.01653774,
       -0.05116827, -0.07784847,  0.07221604,  0.18560119,  0.03166887,
       -0.02222985, -0.01081707, -0.0280355 , -0.02251413, -0.0781899 ,
       -0.01156232,  0.01390015,  0.00201561,  0.0621447 ,  0.23876323,
        0.17881676,  0.0116178 ,  0.0643678 , -0.0297299 , -0.00917237,
       -0.09665905,  0.02502109, -0.04226249, -0.00953971,  0.01791175,
       -0.02185026, -0.01279872, -0.0167956 , -0.00043886, -0.01830191,
       -0.06427282, -0.07921251, -0.00765546,  0.01095741, -0.02819392,
        0.09235569, -0.01301546, -0.01970124,  0.04362777,  0.04061795,
        0.02352994, -0.02148646, -0.02172766,  0.03929822, -0.02166665,
        0.10295764,  0.01767252, -0.01665377,  0.00940838, -0.0435315 ,
        0.01763511, -0.03813362, -0.02692968, -0.01087016,  0.02015561,
       -0.03945118, -0.02813741, -0.03604971,  0.00143225,  0.03255514,
```

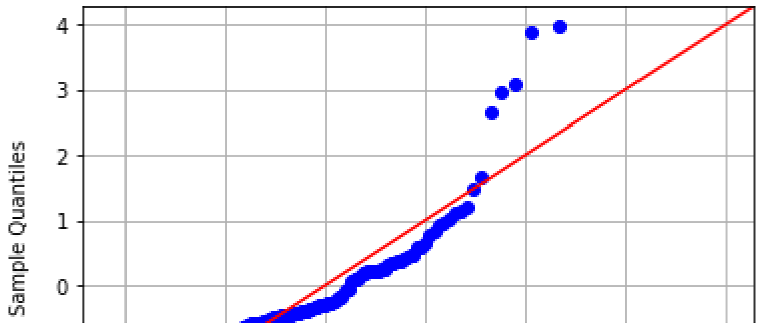
```
       -0.01717428, -0.01586437, -0.0058379 , -0.04895047,  0.01578893,
        0.0273677 , -0.03319921,  0.02078815, -0.02880435, -0.05131571,
       -0.03523384,  0.05992061, -0.01416081,  0.02936356,  0.0191012 ,
       -0.02330458, -0.0422213 , -0.04313355,  0.02515505, -0.01924291,
       -0.02077154, -0.01882737,  0.05122537, -0.04264278,  0.07039988,
       -0.00559074, -0.03181442,  0.23302224, -0.02500381,  0.07548566])
```

```
sns.distplot(residuals)
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a deprecated function and wi
  warnings.warn(msg, FutureWarning)
<matplotlib.axes._subplots.AxesSubplot at 0x7fc4ff6f3450>
```




```
import statsmodels.api as sm
fig = sm.qqplot(residuals, line='45', fit=True)
plt.grid()
```



Its not following normal distribution

Model performance evaluation

```
# R2 scoe for train
model.score(X_train_standardized,Y_train)       # for simple linear regrssionmodel
```

    0.8215099192360797

```
# R2 scoe for test
model.score(X_test_standardized,Y_test)       # for simple linear regrssionmodel
```

    0.8208741602027321

```
#Adjusted R2 score

1 - (1-model.score(X_train_standardized, Y_train))*(len(Y_train)-1)/(len(Y_train)-X.shape[1]-1)
```

    0.8183225963652955

```
np.mean((output-Y_test)**2)
```

    0.003459099909232504

```
# # MSE
# from sklearn.metrics import mean_squared_error
# mean_squared_error(Y_test, output)


# MAE
np.mean(abs(output-Y_test))
```

```
0.040200196655534464
```

Final comments

By considering R2 score, normality test, Linear regression is not best option we need another model to predict even better

Actionable Insights and recommendations

1. Among all the variables, the CGPA, GRE score, TOEFL score, LOR, Research are the major predictors and among all CGPA having highest weightage to predict.

2. With the given attributes and data, the model performance is moderate. We require even more data points or other attributes like Graduation comleted year, course opted in university, discipline of the candidate, graduated college of the candidate

3. With linear regression model, the test assumption of normal residuals is failed, and r2 score is also around 0.82, so, we need even more better model (with degree 2 the r2 score slightly increased, but not to a great extent)

4.There are much benefits if we predict out exactly, One can start eductaional training or coaching w.r.t GRE, TOEFL and also provide materials or necessary info to students to help in cracking their exams or college admissions

5.One can understand the flow of students who are willing to take up higher studies and plan online edtechs to fulfill their dreams