Context

- Jamboree has helped thousands of students make it to top colleges abroad. Be it GMAT, GRE or SAT, their unique problem-solving methods ensure maximum scores with minimum effort.
- They recently launched a feature where students/learners can come to their website and check their probability of getting into the IVY league college. This feature estimates the chances of graduate admission from an Indian perspective.

Problem Statement :

- Help Jamboree in understanding what factors are important in graduate admissions and how these factors are interrelated among themselves. It will also help 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)
```

- Exploratory Data Analysis
- Linear Regression

In [ ]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
from matplotlib import figure

import warnings
warnings.filterwarnings('ignore')

import statsmodels.api as sm
```

In [ ]:
```
data = pd.read_csv("Jamboree_Admission.csv")
```

In [ ]:
```
data.sample(5)
```

Out[ ]:

	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
314	315	305	105	2	3.0	4.0	8.13	0	0.66
403	404	330	116	4	4.0	3.5	9.23	1	0.91
36	37	299	106	2	4.0	4.0	8.40	0	0.64
475	476	300	101	3	3.5	2.5	7.88	0	0.59
8	9	302	102	1	2.0	1.5	8.00	0	0.50

In [ ]:
```
data.shape
```

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

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

# dropping first  not required column "Serial No."
```

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

In [ ]:
```
# null values check
df.isna().sum()
```

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

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

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

No null values detected

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

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

University Rating,SOP,LOR,Research are seems to be categorical variables as the number of unique values are very small.

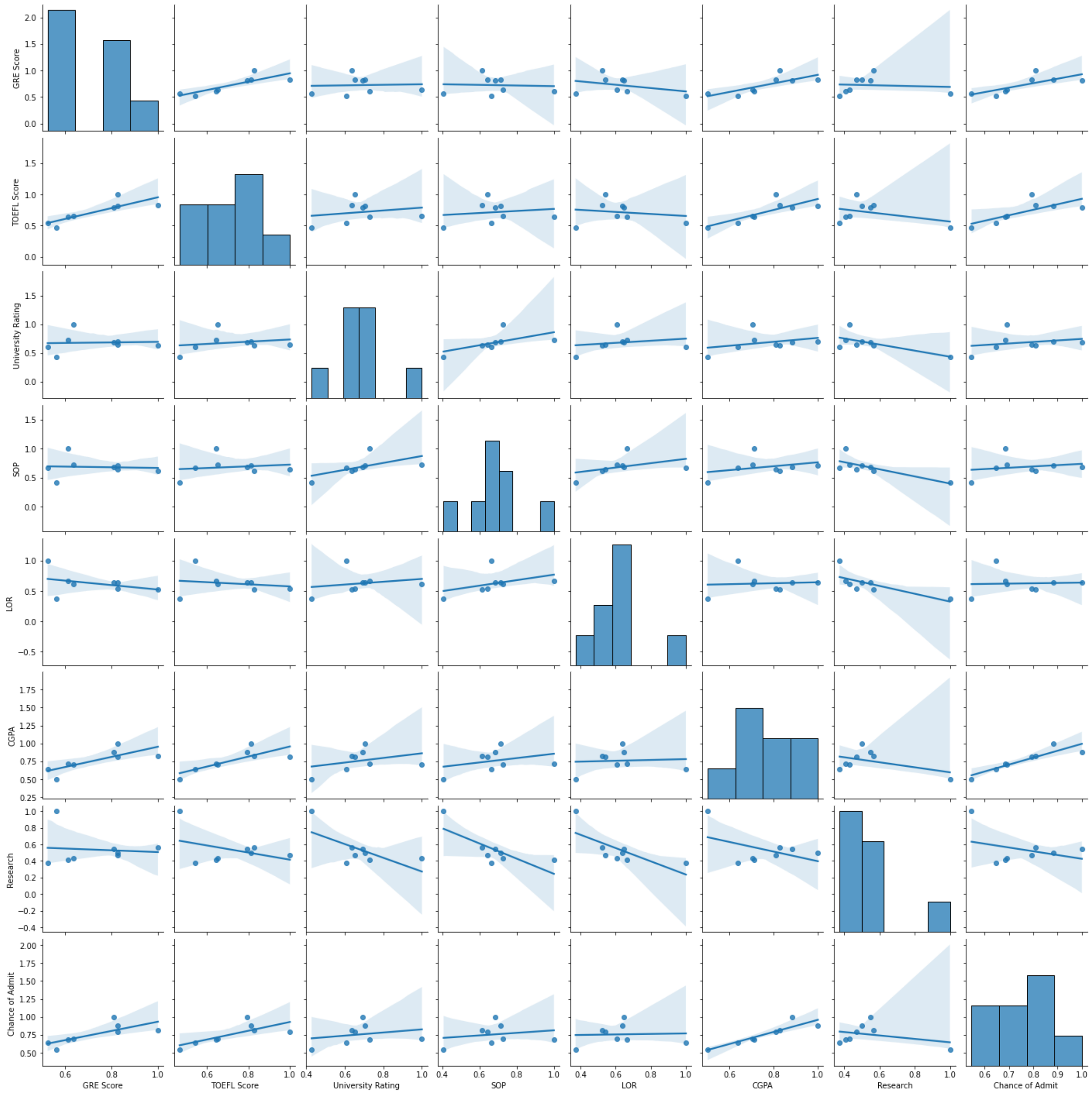
rest of the features are numeric , and ordinal . (University Rating,SOP,LOR,Research are discrete) and rest are continuous

also if SOP , University rating , LOR and research can be considered as numeric ordinal data.

Checking the overall linearity and correlation across all features using pairplot :

In [ ]:
```
sns.pairplot(df.corr(),kind= 'reg')
```

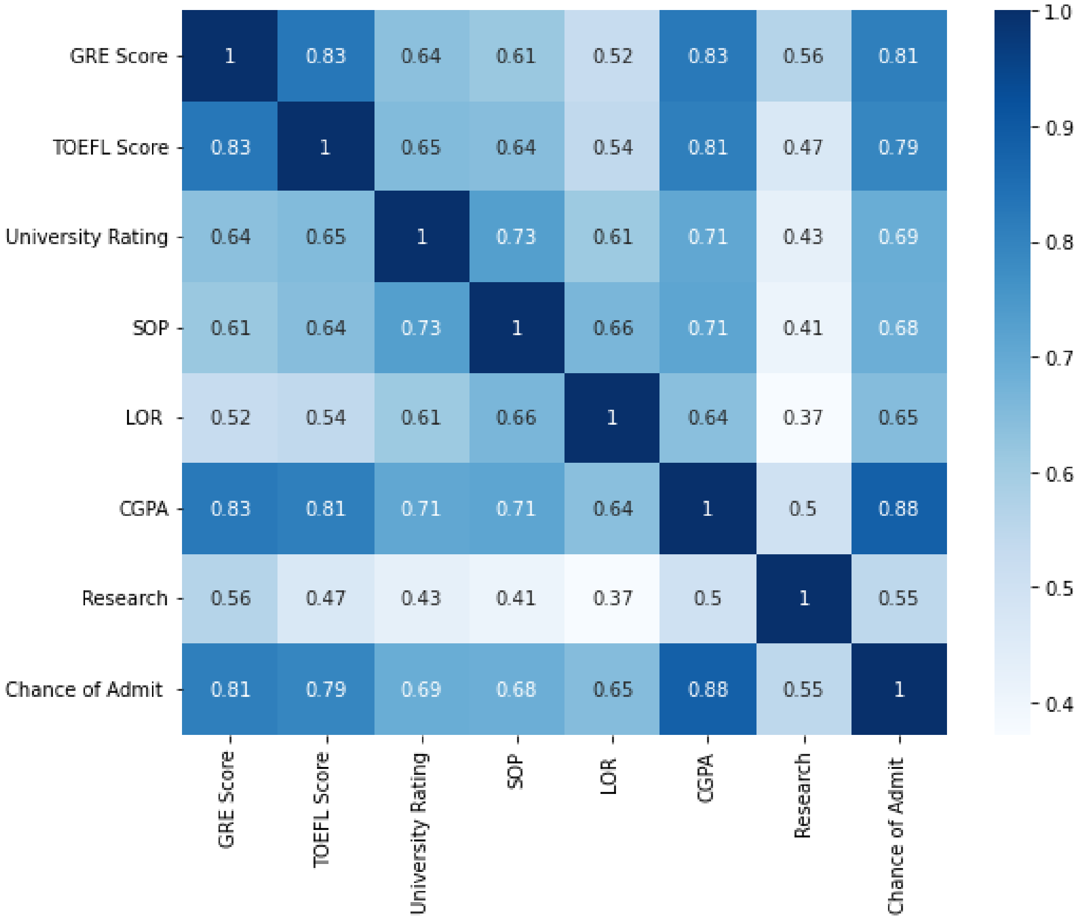
Out[ ]:
```
<seaborn.axisgrid.PairGrid at 0x29281f40c70>
```



Overall look at correlation :

In [ ]:
```
plt.figure(figsize=(9,7))
sns.heatmap(df.corr(),annot=True,cmap = "Blues")
```

Out[ ]: <AxesSubplot:>



- Independent Variables (Input data): GRE Score, TOEFL Score, University Rating, SOP, LOR, CGPA, Research
- Target/Dependent Variable : Chance of Admit (the value we want to predict)
- from above correlation heatmap , we can observe GRE score TOEFL score and CGPA have very high correlation with Change of admission.
- University rating, SOP ,LOR and Research have comparatively slightly less correlated than other features.

In [ ]:
```
df.columns
```
Out[ ]:
```
Index(['GRE Score', 'TOEFL Score', 'University Rating', 'SOP', 'LOR ', 'CGPA',
       'Research', 'Chance of Admit '],
      dtype='object')
```

In [ ]:
```
# changing / removing space between column names.
df.columns  = ['GRE_Score', 'TOEFL_Score', 'University_Rating', 'SOP', 'LOR', 'CGPA',
        'Research', 'Chance_of_Admit']
```

In [ ]:
```
df.sample(2)
```
Out[ ]:

	GRE_Score	TOEFL_Score	University_Rating	SOP	LOR	CGPA	Research	Chance_of_Admit
354	297	98	2	2.5	3.0	7.67	0	0.59
469	326	114	4	4.0	3.5	9.16	1	0.86

Outliers in the data :

In [ ]:
```
def detect_outliers(data):
    length_before = len(data)
    Q1 = np.percentile(data,25)
    Q3 = np.percentile(data,75)
    IQR = Q3-Q1
    upperbound = Q3+1.5*IQR
    lowerbound = Q1-1.5*IQR
    if lowerbound < 0:
        lowerbound = 0

    length_after = len(data[(data>lowerbound)&(data<upperbound)])
    return f"{np.round((length_before-length_after)/length_before,4)} % Outliers data fr
```

In [ ]:
```
for col in df.columns:
    print(col," : ",detect_outliers(df[col]))
```

```
GRE_Score  :  0.0 % Outliers data from input data found
TOEFL_Score  :  0.0 % Outliers data from input data found
University_Rating  :  0.0 % Outliers data from input data found
SOP  :  0.0 % Outliers data from input data found
LOR  :  0.024 % Outliers data from input data found
CGPA  :  0.0 % Outliers data from input data found
Research  :  0.44 % Outliers data from input data found
Chance_of_Admit  :  0.004 % Outliers data from input data found
```

In [ ]:
```
detect_outliers(df)
```

Out[ ]:
```
'0.0 % Outliers data from input data found'
```

there are no significant amount of outliers found in the data

Descriptive analysis of all numerical features :

In [ ]:
```
df.describe()
```

Out[ ]:

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

- chances of admit is a probability measure , which is within 0 to 1 which is good (no outliers or missleading data in column).
- Range of GRE score looks like between 290 to 340.
- range of TOEFL score is between 92 to 120.
- university rating , SOP and LOR are distributed between range of 1 to 5.
- CGPA range is between 6.8 to 9.92.

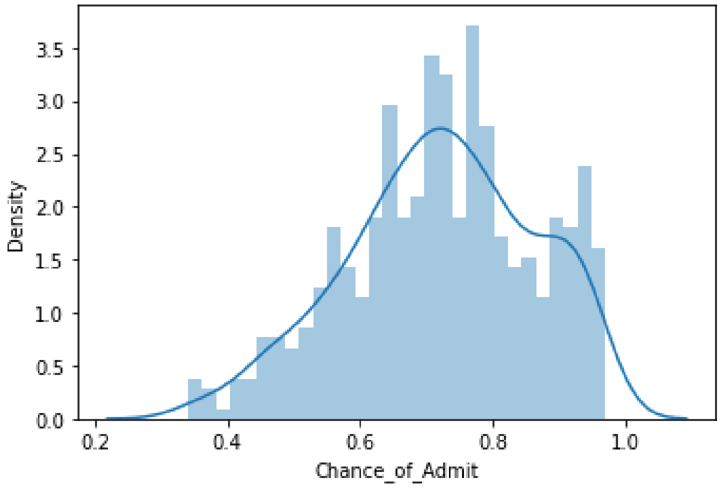
In [ ]:
```
df.columns
```

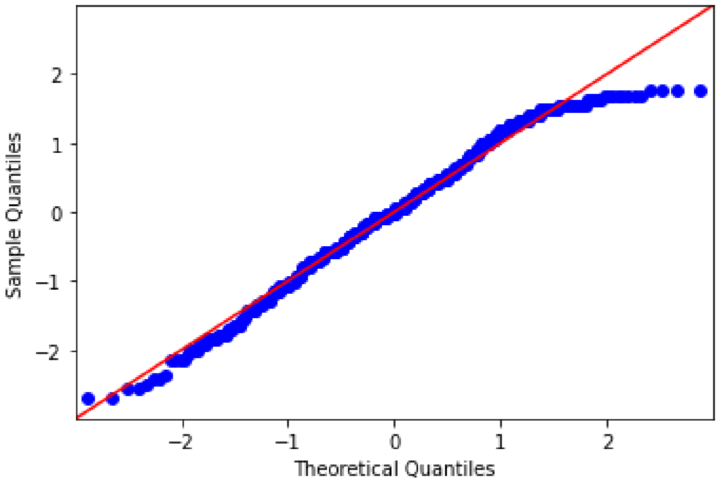
Out[ ]:
```
Index(['GRE_Score', 'TOEFL_Score', 'University_Rating', 'SOP', 'LOR', 'CGPA',
       'Research', 'Chance_of_Admit'],
      dtype='object')
```

Graphical Analysis :

Chance_of_Admit

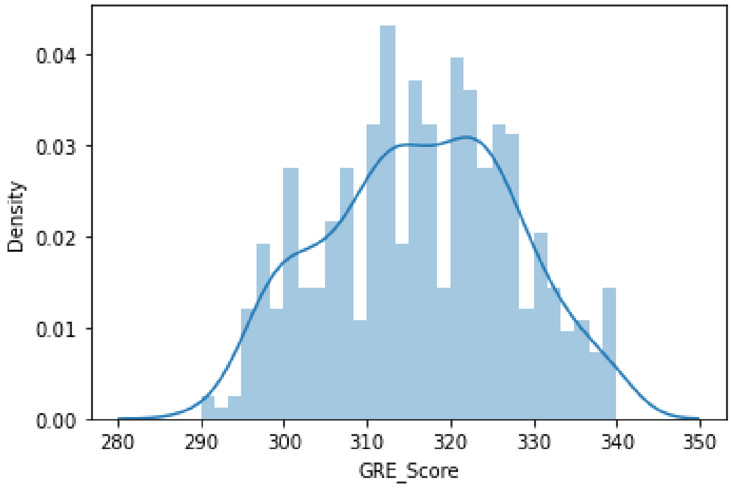
In [ ]:
```
sns.distplot(df["Chance_of_Admit"],bins = 30)
sm.qqplot(df["Chance_of_Admit"],fit=True, line="45")
plt.show()
```

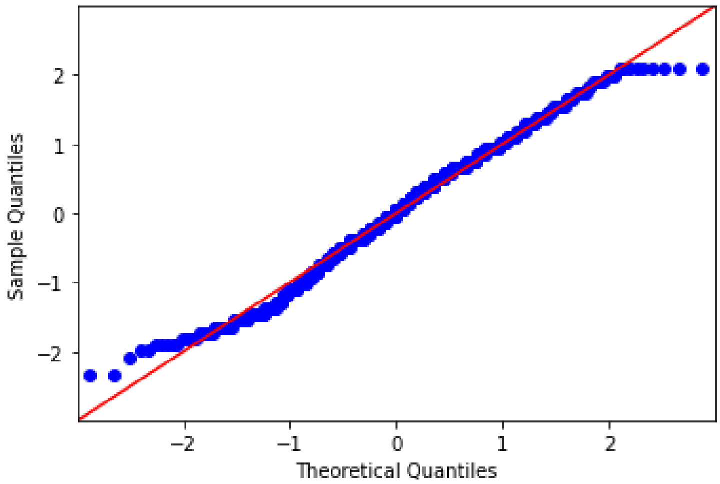




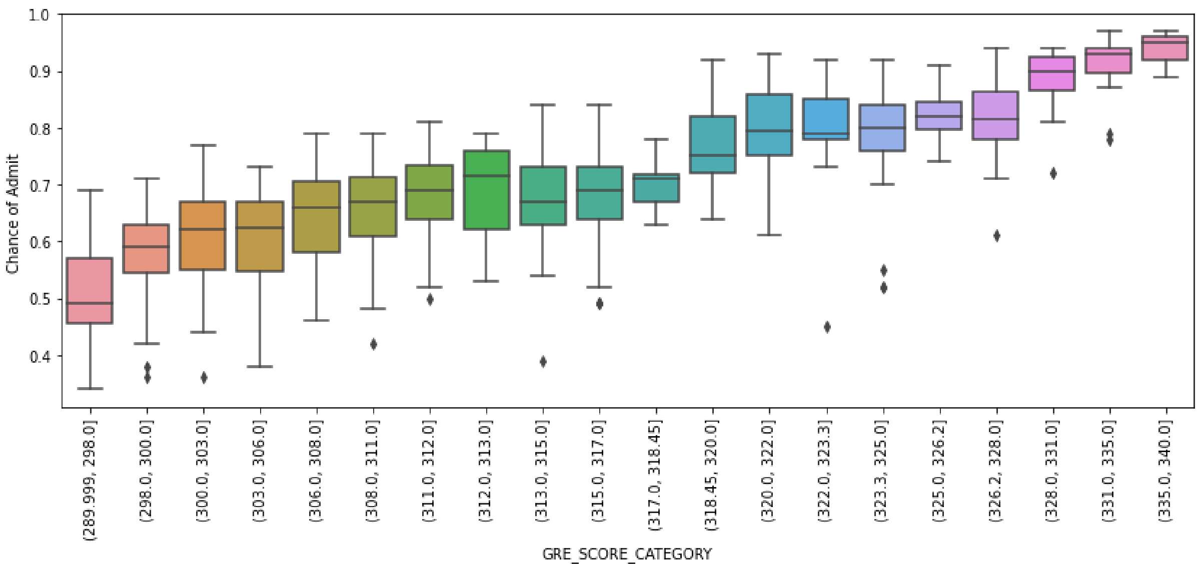
GRE_Score

In [ ]:
```
sns.distplot(df["GRE_Score"], bins = 30)
sm.qqplot(df["GRE_Score"],fit=True, line="45")
plt.show()
```





In [ ]:
```
data["GRE_SCORE_CATEGORY"]=pd.qcut(data["GRE Score"],20)
plt.figure(figsize=(14,5))
sns.boxplot(y = data["Chance of Admit "], x = data["GRE_SCORE_CATEGORY"])
plt.xticks(rotation = 90)
plt.show()
```

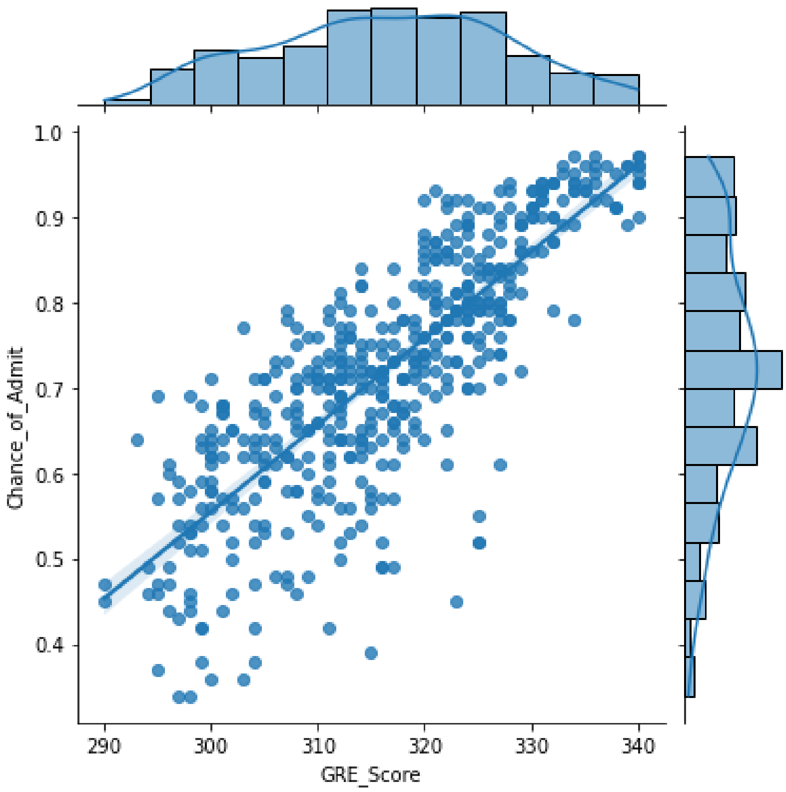


From above boxplot (distribution of chance of admition (probability of getting admition) as per GRE score) :

with higher GRE score , there is high probability of getting an admition .

In [ ]:
```
sns.jointplot(df["GRE_Score"],df["Chance_of_Admit"], kind = "reg" )
```

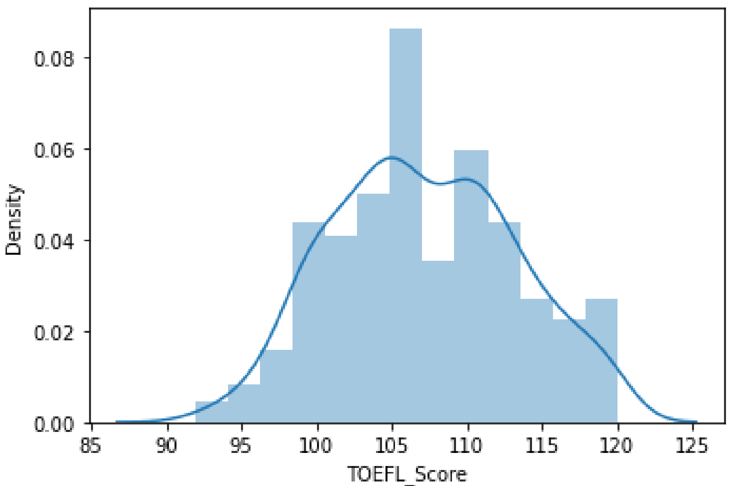
Out[ ]: <seaborn.axisgrid.JointGrid at 0x292873dfa90>

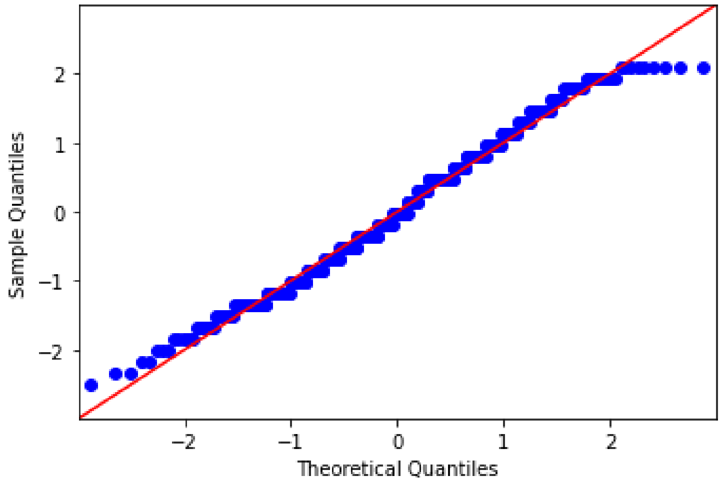


TOEFL_Score

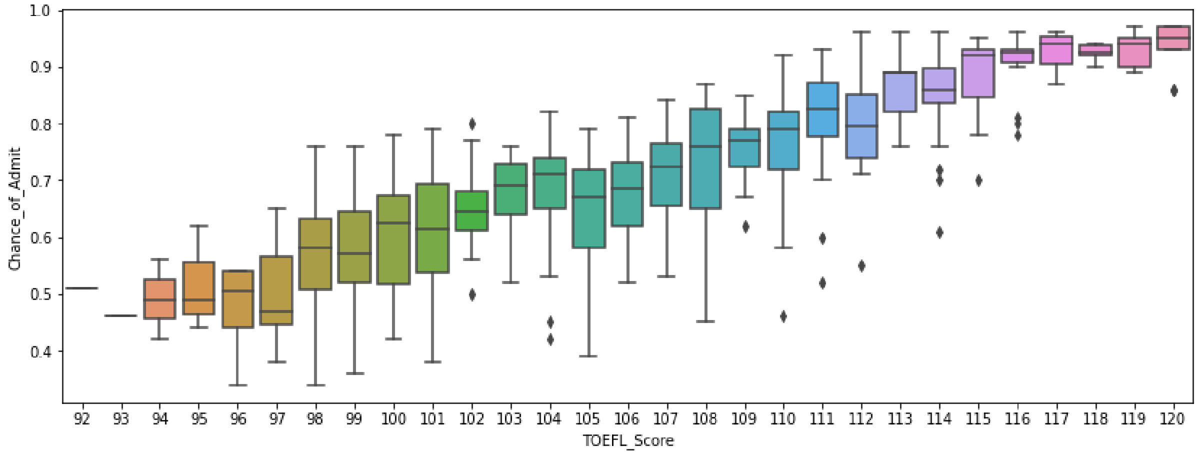
In [ ]:
```
# TOEFL_Score

sns.distplot(df["TOEFL_Score"])
sm.qqplot(df["TOEFL_Score"],fit=True, line="45")
plt.show()
plt.figure(figsize=(14,5))
sns.boxplot(y = df["Chance_of_Admit"], x = df["TOEFL_Score"])
```





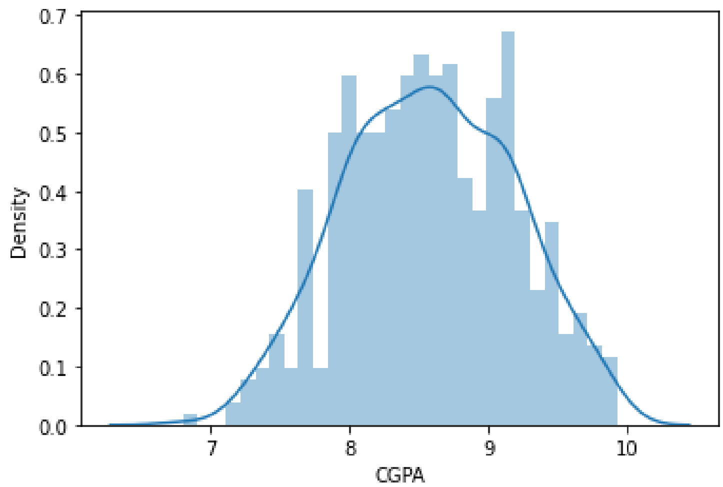
Out[ ]: <AxesSubplot:xlabel='TOEFL_Score', ylabel='Chance_of_Admit'>

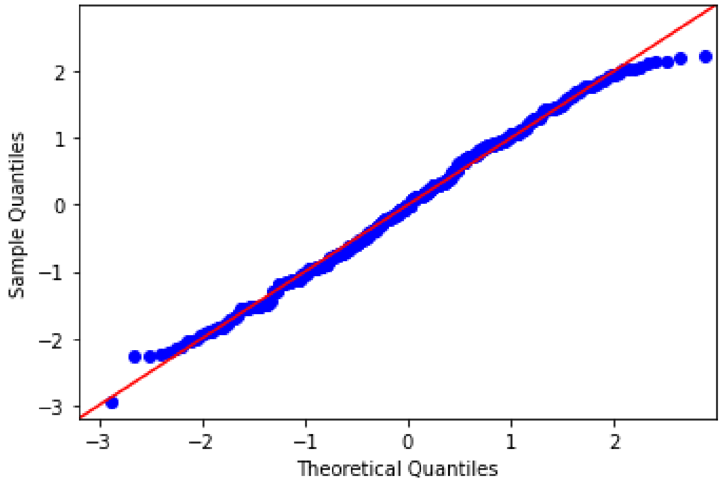


Students having high toefl score , has higher probability of getting admition .

CGPA

In [ ]:
```
sns.distplot(df["CGPA"], bins = 30)
sm.qqplot(df["CGPA"],fit=True, line="45")
plt.show()
```





Chance of admit and GRE score are nearly normally distrubted.

GRE score, TOEFL score and CGPA has a strong correlation with chance of addmission .

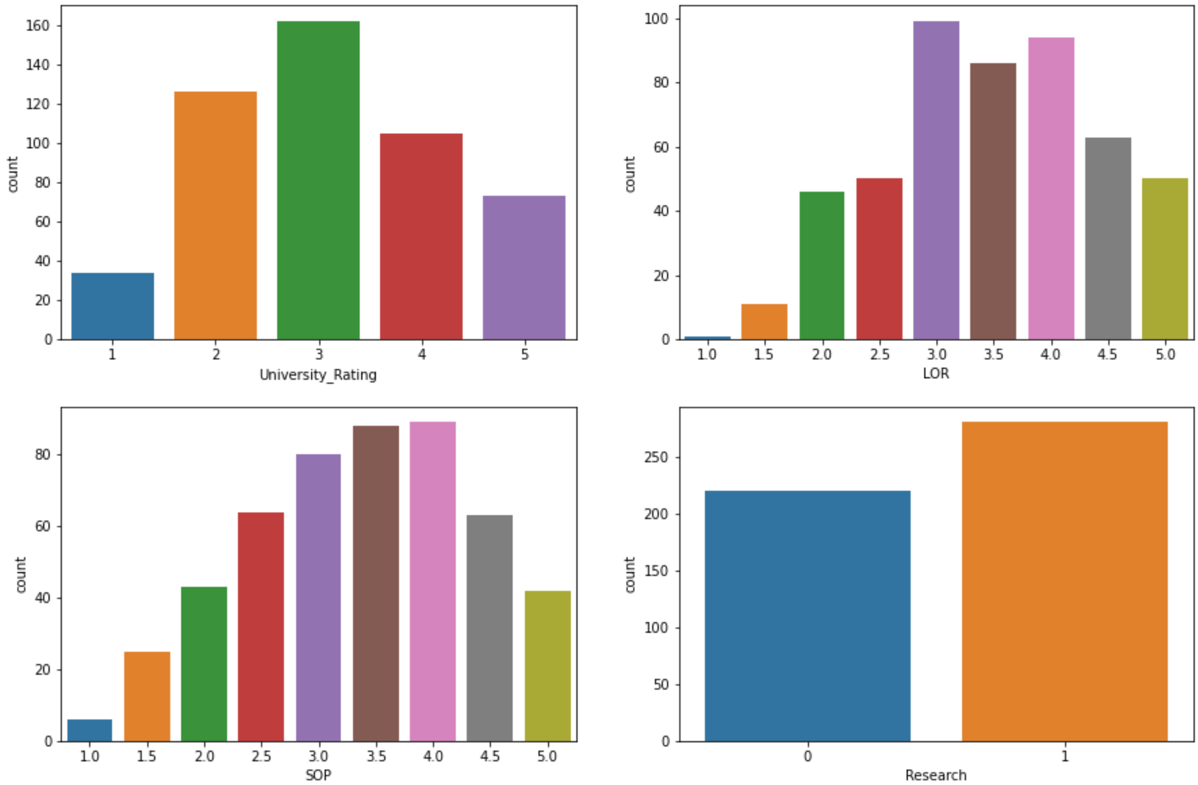
In [ ]:
```
df.columns
```

Out[ ]:
```
Index(['GRE_Score', 'TOEFL_Score', 'University_Rating', 'SOP', 'LOR', 'CGPA',
       'Research', 'Chance_of_Admit'],
      dtype='object')
```

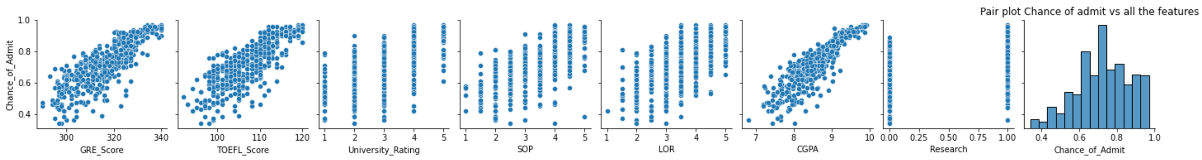
Distribution of all other categorical features :

In [ ]:
```
plt.figure(figsize=(15,10))
plt.subplot(2,2,1)
sns.countplot(df["University_Rating"])
plt.subplot(2,2,2)
sns.countplot(df["LOR"])
plt.subplot(2,2,3)
sns.countplot(df["SOP"])
plt.subplot(2,2,4)
sns.countplot(df["Research"])
```

Out[ ]:
```
<AxesSubplot:xlabel='Research', ylabel='count'>
```

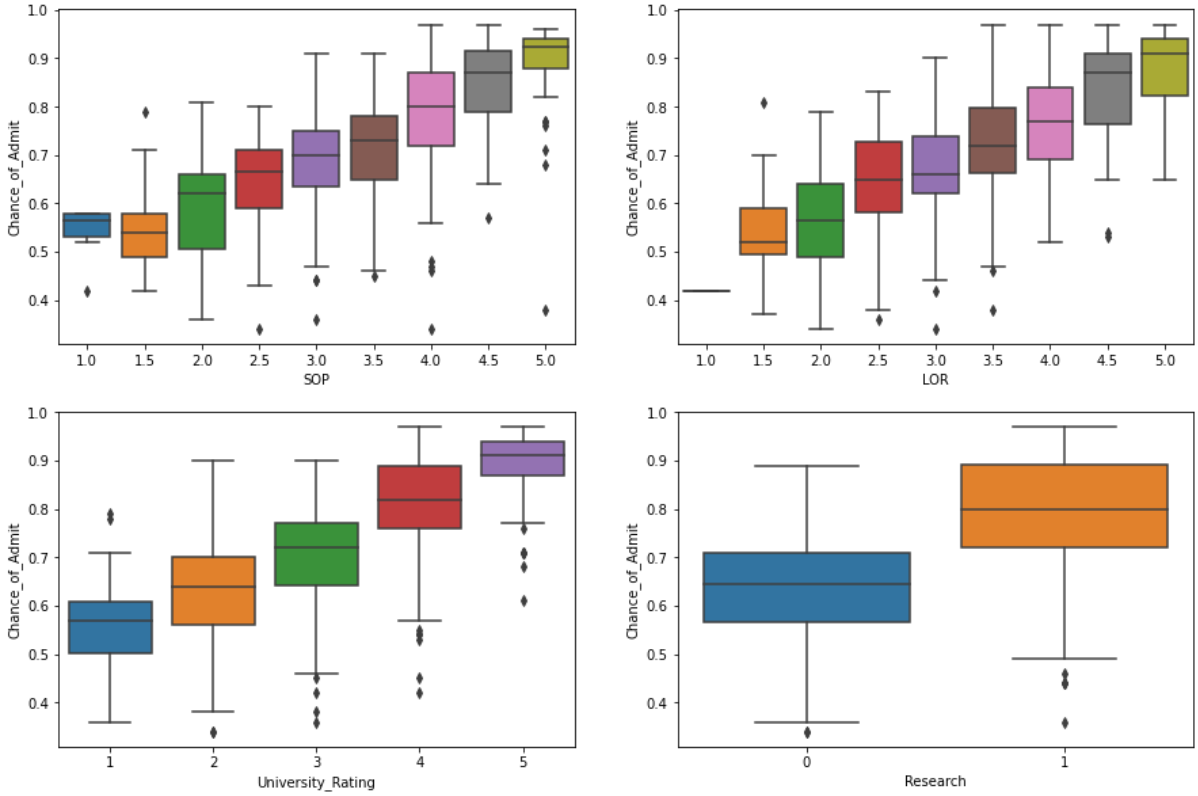


In [ ]:
```
sns.pairplot(df,y_vars = ["Chance_of_Admit"])
plt.title("Pair plot Chance of admit vs all the features")
plt.show()
```



Categorical features - vs - chances of admission boxplot :

In [ ]:
```
plt.figure(figsize=(15,10))
plt.subplot(2,2,1)
sns.boxplot(y = df["Chance_of_Admit"], x = df["SOP"])
plt.subplot(2,2,2)
sns.boxplot(y = df["Chance_of_Admit"], x = df["LOR"])
plt.subplot(2,2,3)
sns.boxplot(y = df["Chance_of_Admit"], x = df["University_Rating"])
plt.subplot(2,2,4)
sns.boxplot(y = df["Chance_of_Admit"], x = df["Research"])
plt.show()
```



from above plots, we can observe , statement of purpose SOP strength is positively correlated with Chance of Admission .

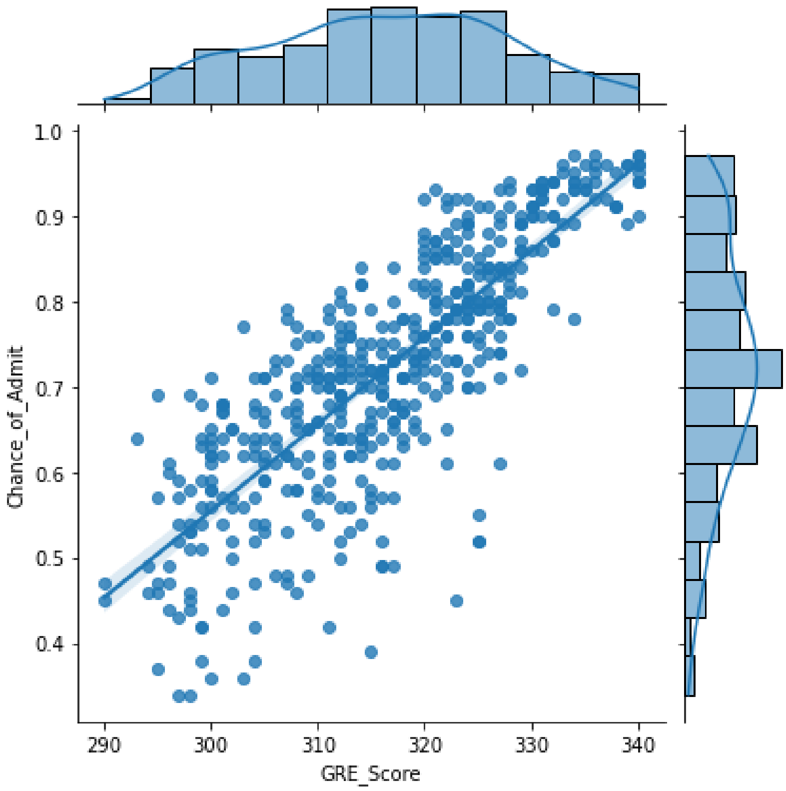
we can also similar pattern in Letter of Recommendation Stength and University rating , have positive correlation with Chaces of Admission .

Student having research has higher chances of Admission , but also we can observe some outliers within that caregory.

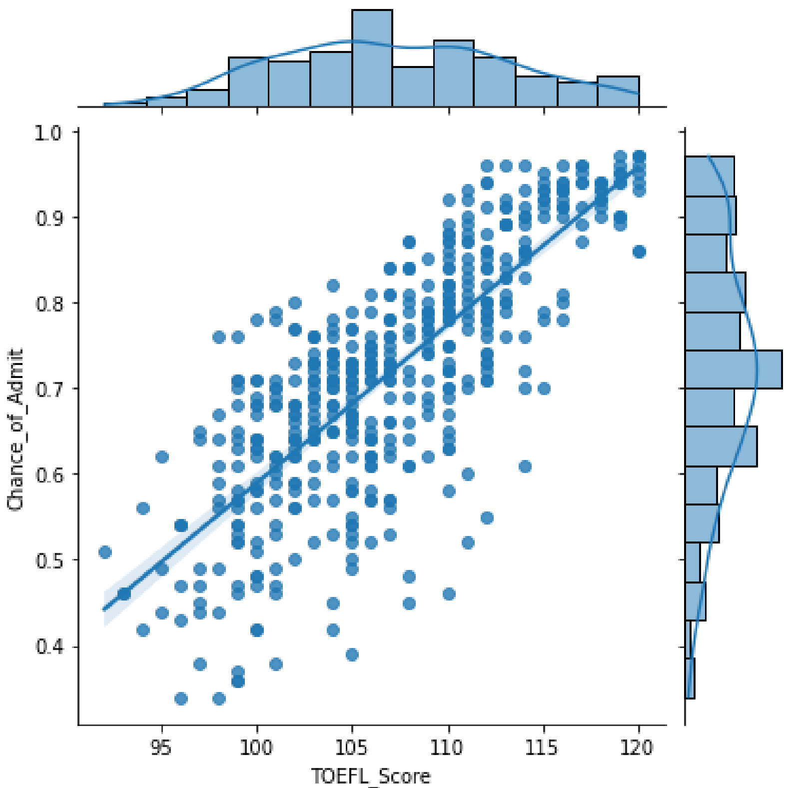
Linearity : How features are correlated with Target variable - chance of admit :

In [ ]:
```
for col in df.columns[:-1]:
    print(col)
    plt.figure(figsize=(3,3))
    sns.jointplot(df[col],df["Chance_of_Admit"],kind="reg")
    plt.show()
```

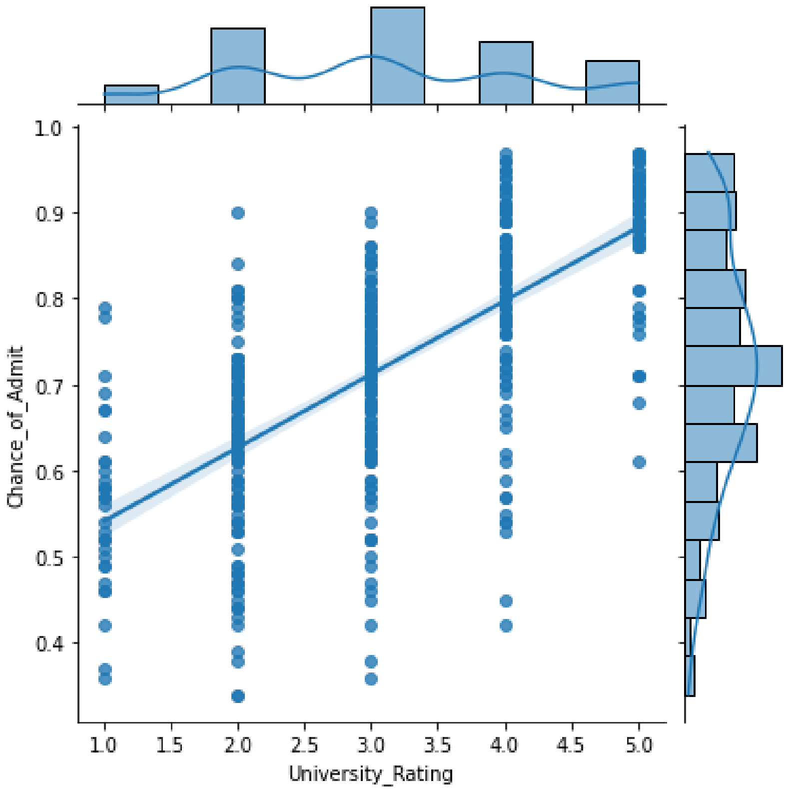
```
GRE_Score
<Figure size 216x216 with 0 Axes>
```



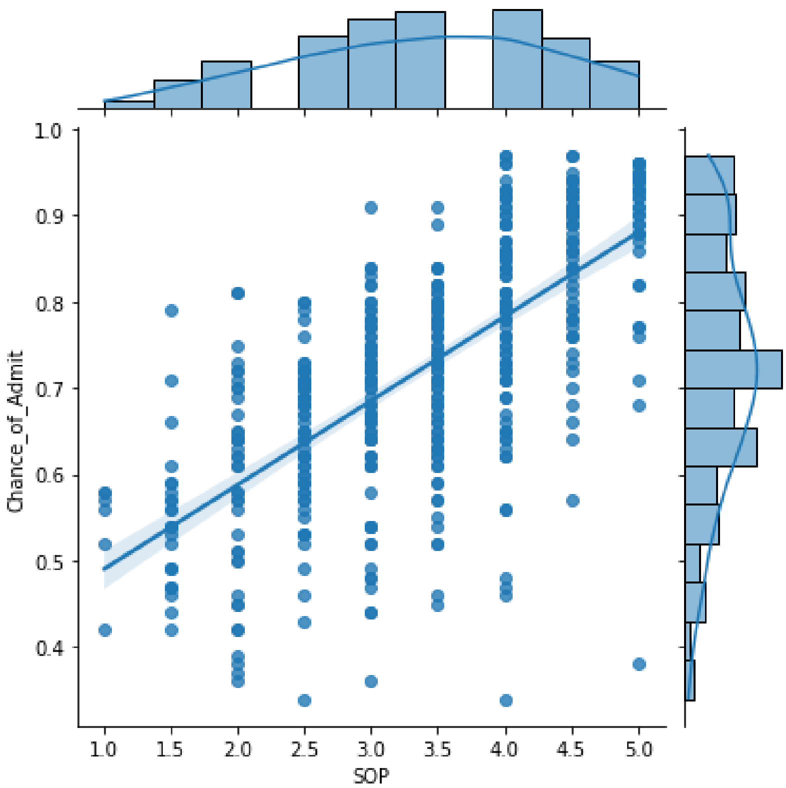

```
TOEFL_Score
<Figure size 216x216 with 0 Axes>
```



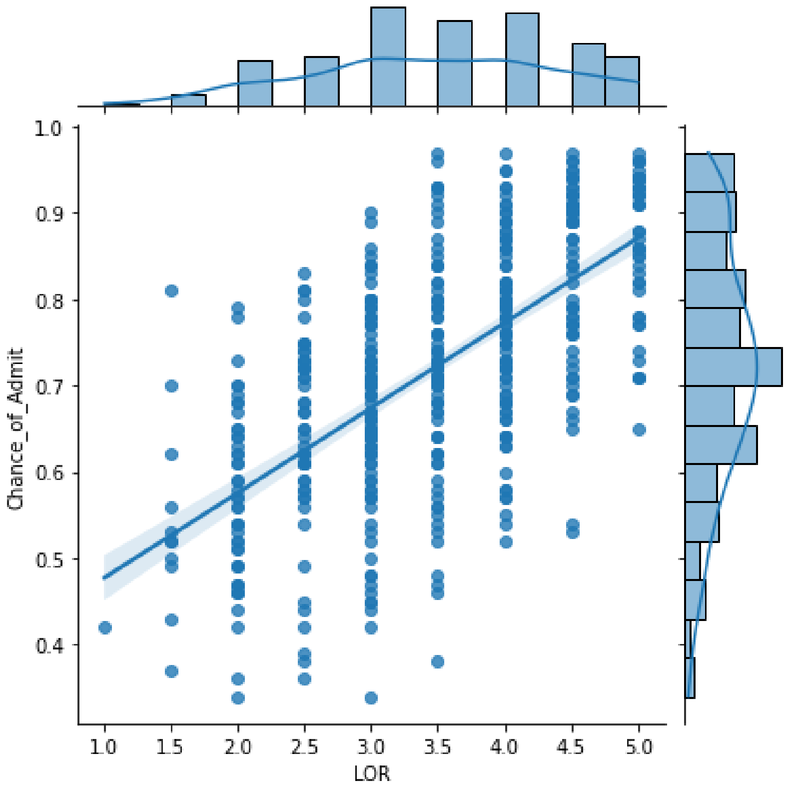

```
University_Rating
<Figure size 216x216 with 0 Axes>
```



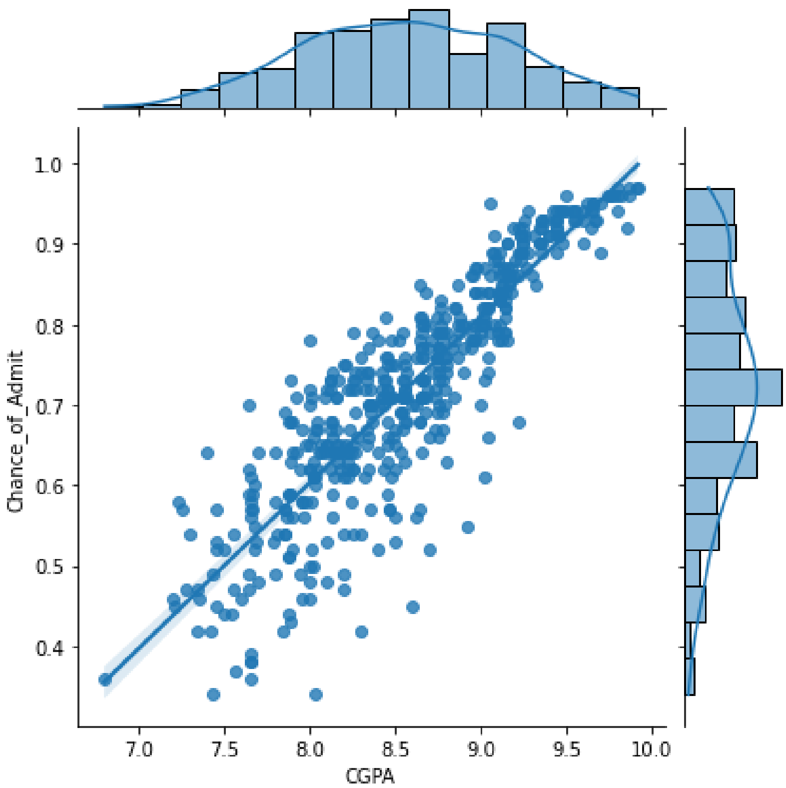

```
SOP
<Figure size 216x216 with 0 Axes>
```



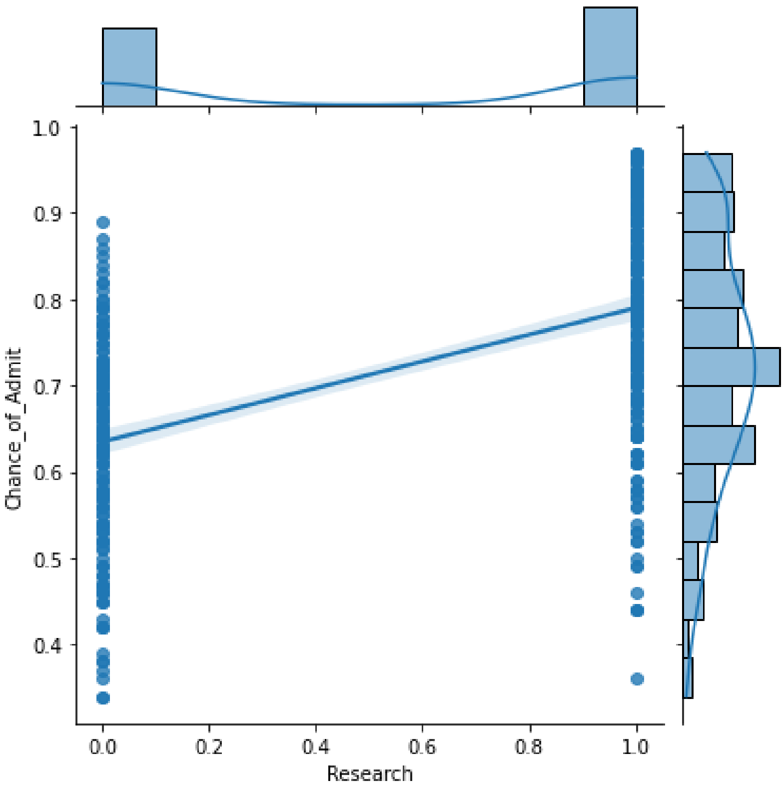

```
LOR
<Figure size 216x216 with 0 Axes>
```




```
CGPA
<Figure size 216x216 with 0 Axes>
```




```
Research
<Figure size 216x216 with 0 Axes>
```



Linear Regression :

In [ ]:
```
from sklearn.preprocessing import StandardScaler

from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split

from statsmodels.stats.outliers_influence import variance_inflation_factor

from sklearn.metrics import r2_score,mean_squared_error,mean_absolute_error, adjusted_mu
from sklearn.feature_selection import f_regression
```

In [ ]:
```
X = df.drop(["Chance_of_Admit"],axis = 1)  # independent variables
y = df["Chance_of_Admit"].values.reshape(-1,1) # target / dependent variables
```

Standardising data

In [ ]:
```
standardizer = StandardScaler()
standardizer.fit(X)
x = standardizer.transform(X)  # standardising the data
```

test train spliting :

In [ ]:
```
X_train , X_test, y_train , y_test = train_test_split(x,y,
                                                      random_state = 1,
                                                       test_size = 0.2
                                                      )                          # test tr
```

In [ ]:
```
X_train.shape,X_test.shape  # after spliting, checking for the shape of test and  train
```

Out[ ]:
```
((400, 7), (100, 7))
```

In [ ]:
```
y_train.shape, y_test.shape
```

Out[ ]: ((400, 1), (100, 1))

training the model

In [ ]:
```
LinearRegression = LinearRegression()    # training LinearRegression model
LinearRegression.fit(X_train,y_train)
```

Out[ ]: LinearRegression()

r2 score on train data :

In [ ]:
```
r2_score(y_train,LinearRegression.predict(X_train))
```

Out[ ]: 0.8215099192361265

r2 score on test data :

In [ ]:
```
r2_score(y_test,LinearRegression.predict(X_test) )
```

Out[ ]: 0.8208741703103732

All the feature's coefficients and Intercept :

In [ ]:
```
ws = pd.DataFrame(LinearRegression.coef_.reshape(1,-1),columns=df.columns[:-1])
ws["Intercept"] = LinearRegression.intercept_
ws
```

Out[ ]:

	GRE_Score	TOEFL_Score	University_Rating	SOP	LOR	CGPA	Research	Intercept
0	0.020675	0.019284	0.007001	0.002975	0.013338	0.070514	0.009873	0.722881

In [ ]:
```
LinearRegression_Model_coefs = ws
LinearRegression_Model_coefs
```

Out[ ]:

	GRE_Score	TOEFL_Score	University_Rating	SOP	LOR	CGPA	Research	Intercept
0	0.020675	0.019284	0.007001	0.002975	0.013338	0.070514	0.009873	0.722881

In [ ]:
```
def AdjustedR2score(R2,n,d):
    return 1-(((1-R2)*(n-1))/(n-d-1))
```

In [ ]:
```
y_pred = LinearRegression.predict(X_test)

print("MSE:",mean_squared_error(y_test,y_pred)) # MSE
print("RMSE:",np.sqrt(mean_squared_error(y_test,y_pred))) #RMSE
print("MAE :",mean_absolute_error(y_test,y_pred) ) # MAE
print("r2_score:",r2_score(y_test,y_pred)) # r2score
print("Adjusted R2 score :", AdjustedR2score(r2_score(y_test,y_pred),len(X),X.shape[1]))
```

```
MSE: 0.0034590988971363824
RMSE: 0.05881410457650769
MAE : 0.040200193804157944
r2_score: 0.8208741703103732
Adjusted R2 score : 0.8183256320830818
```

Assumptions of linear regression

- No multicollinearity

- The mean of residual is nearly zero.
- Linearity of Variables
- Test of homoscedasticity
- Normality of residual

Multicollinearity check :

- checking vif scores :

In [ ]:
```
vifs = []

for i in range(X_train.shape[1]):

    vifs.append((variance_inflation_factor(exog = X_train,
                                               exog_idx=i)))
vifs
```

Out[ ]:
```
[4.873264779539277,
 4.243883338617028,
 2.7982518885433794,
 2.9200455031169206,
 2.079334304516444,
 4.75138916638019,
 1.5081475402055675]
```

In [ ]:
```
pd.DataFrame({ "coef_name : " : X.columns ,
              "vif : ": np.around(vifs,2)})
```

Out[ ]:

	coef_name :	vif :
0	GRE_Score	4.87
1	TOEFL_Score	4.24
2	University_Rating	2.80
3	SOP	2.92
4	LOR	2.08
5	CGPA	4.75
6	Research	1.51

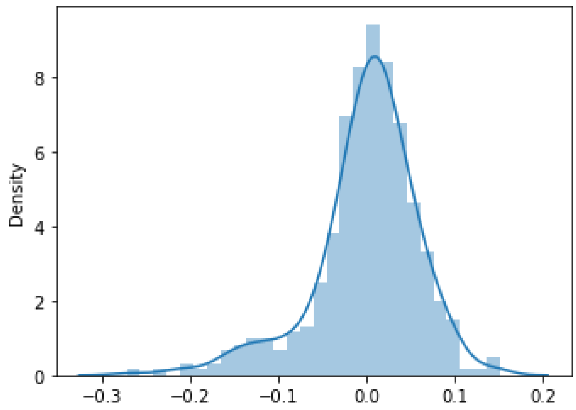
VIF score are all below 5 , doesnt seem to have very high multicolinearity.

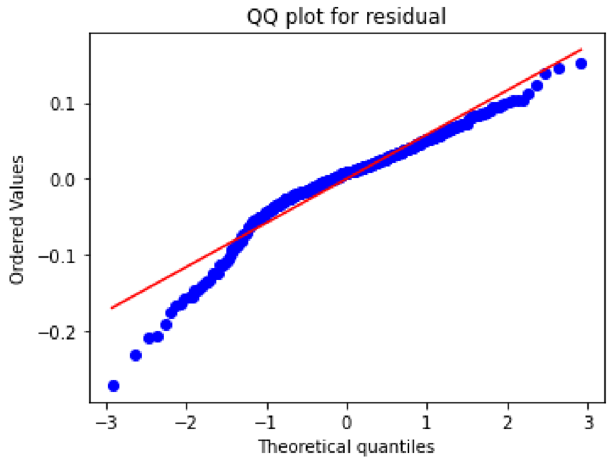
Residual analysis :

In [ ]:
```
y_predicted = LinearRegression.predict(X_train)
y_predicted.shape
```

Out[ ]:
```
(400, 1)
```

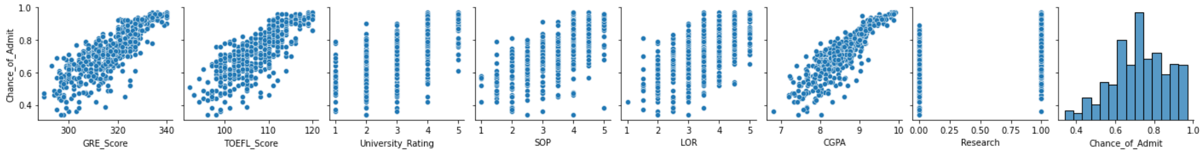
In [ ]:
```
residuals = (y_train - y_predicted)
plt.figure(figsize=(12,4))
plt.subplot(1,2,1)
sns.distplot(residuals)
plt.subplot(1,2,2)
stats.probplot(residuals.reshape(-1,), plot = plt)
plt.title('QQ plot for residual')
plt.show()
```





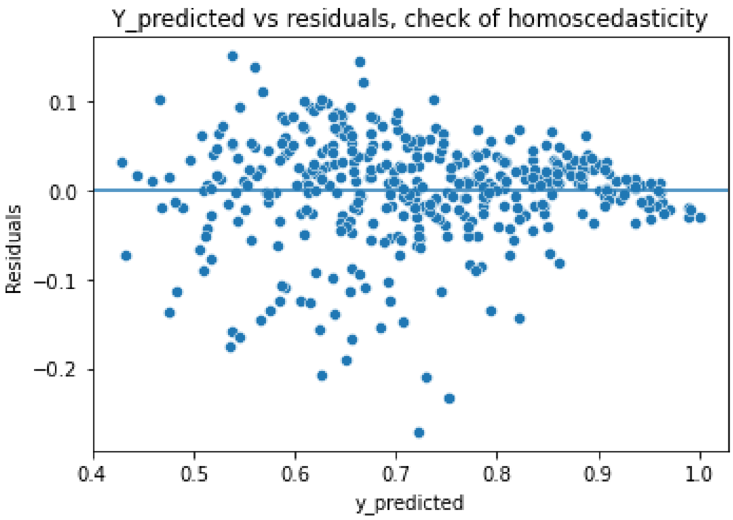
Linearity of varibales

In [ ]:
```
sns.pairplot(df,y_vars = ["Chance_of_Admit"])
plt.show()
```



Test of homoscedasticity | plotting y_predicted and residuals

In [ ]:
```
# Test of homoscedasticity
sns.scatterplot(y_predicted.reshape(-1,), residuals.reshape(-1,))
plt.xlabel('y_predicted')
plt.ylabel('Residuals')
plt.axhline(y=0)
plt.title("Y_predicted vs residuals, check of homoscedasticity")
plt.show()
```



Model Regularisation :

In [ ]:
```
from sklearn.linear_model import Ridge   # L2 regualrization
from sklearn.linear_model import Lasso   # L1 regualrization
from sklearn.linear_model import ElasticNet
```

L2 regularization

Ridge regression :

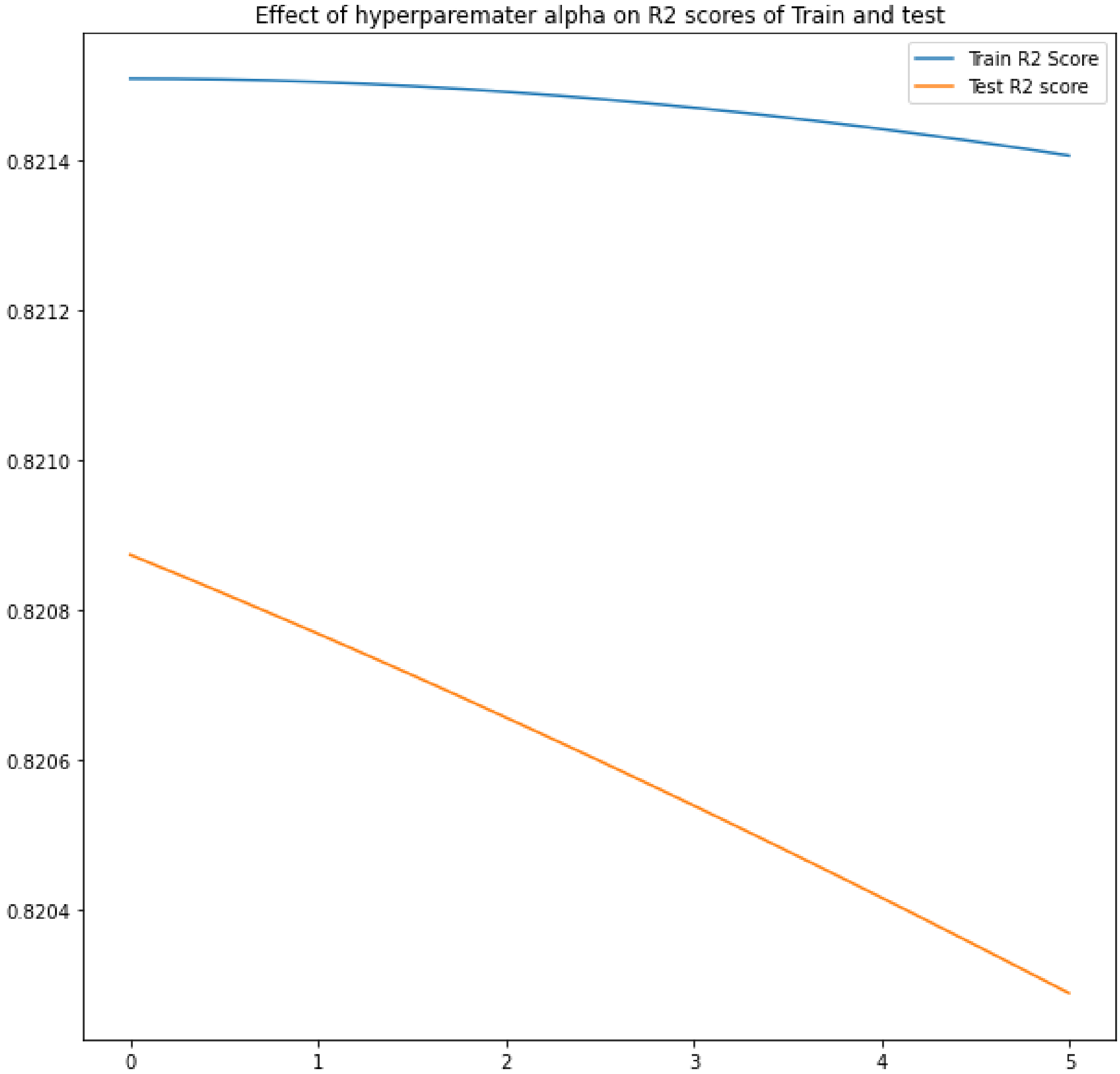
In [ ]:
```
## Hyperparameter Tuning : for appropriate lambda value :

train_R2_score = []
test_R2_score = []
lambdas = []
train_test_difference_Of_R2 =  []
lambda_ = 0
while lambda_ <= 5:
    lambdas.append(lambda_)
    RidgeModel = Ridge(lambda_)
    RidgeModel.fit(X_train,y_train)
    trainR2 = RidgeModel.score(X_train,y_train)
    testR2 = RidgeModel.score(X_test,y_test)
    train_R2_score.append(trainR2)
    test_R2_score.append(testR2)

    lambda_ += 0.01
```

In [ ]:
```
plt.figure(figsize = (10,10))
sns.lineplot(lambdas,train_R2_score,)
sns.lineplot(lambdas, test_R2_score)
plt.legend(['Train R2 Score','Test R2 score'])
plt.title("Effect of hyperparemater alpha on R2 scores of Train and test")


plt.show()
```



In [ ]:
```
RidgeModel = Ridge(alpha = 0.1)
RidgeModel.fit(X_train,y_train)
trainR2 = RidgeModel.score(X_train,y_train)
testR2 = RidgeModel.score(X_test,y_test)
```

In [ ]:
```
trainR2,testR2
```

Out[ ]:
```
(0.8215098726041209, 0.820863953615642)
```

In [ ]:
```
RidgeModel.coef_
```

Out[ ]:
```
array([[0.02069489, 0.01929637, 0.00700953, 0.00298992, 0.01334235,
        0.07044884, 0.00987467]])
```

In [ ]:
```
RidgeModel_coefs = pd.DataFrame(RidgeModel.coef_.reshape(1,-1),columns=df.columns[:-1])
RidgeModel_coefs["Intercept"] = RidgeModel.intercept_
RidgeModel_coefs
```

Out[ ]:

	GRE_Score	TOEFL_Score	University_Rating	SOP	LOR	CGPA	Research	Intercept
0	0.020695	0.019296	0.00701	0.00299	0.013342	0.070449	0.009875	0.722882

In [ ]:
```
LinearRegression_Model_coefs
```

Out[ ]:

	GRE_Score	TOEFL_Score	University_Rating	SOP	LOR	CGPA	Research	Intercept
0	0.020675	0.019284	0.007001	0.002975	0.013338	0.070514	0.009873	0.722881

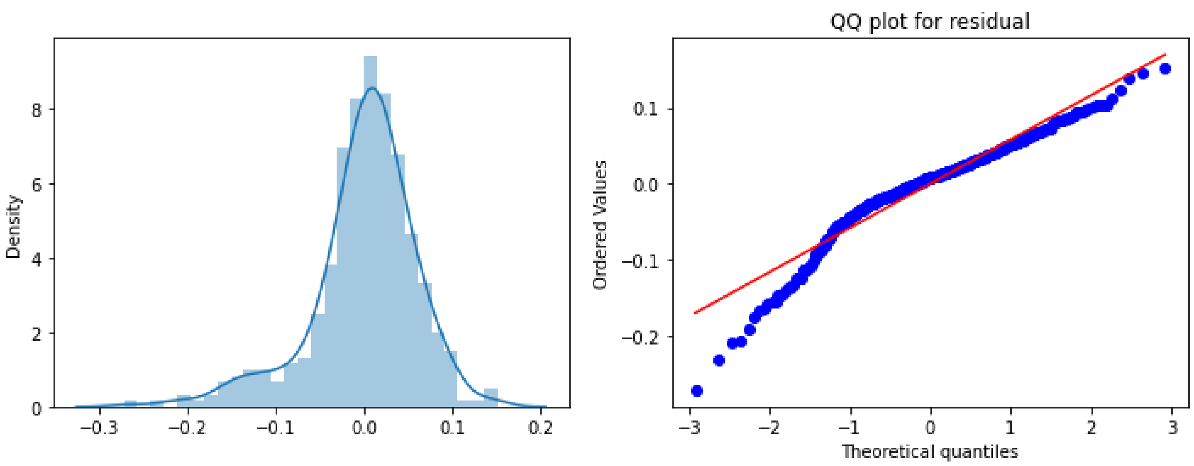
In [ ]:
```
y_pred = RidgeModel.predict(X_test)

print("MSE:",mean_squared_error(y_test,y_pred)) # MSE
print("RMSE:",np.sqrt(mean_squared_error(y_test,y_pred))) #RMSE
print("MAE :",mean_absolute_error(y_test,y_pred) ) # MAE
print("r2_score:",r2_score(y_test,y_pred)) # r2score
print("Adjusted R2 score :", AdjustedR2score(r2_score(y_test,y_pred),len(X),X.shape[1]))
```

```
MSE: 0.0034592961917283365
RMSE: 0.0588157818253599
MAE : 0.04020305511705699
r2_score: 0.820863953615642
Adjusted R2 score : 0.8183152700288727
```

In [ ]:
```
y_predicted = RidgeModel.predict(X_train)

residuals = (y_train - y_predicted)
plt.figure(figsize=(12,4))
plt.subplot(1,2,1)
sns.distplot(residuals)
plt.subplot(1,2,2)
stats.probplot(residuals.reshape(-1,), plot = plt)
plt.title('QQ plot for residual')
plt.show()
```



L1 regularization :

Lasso :

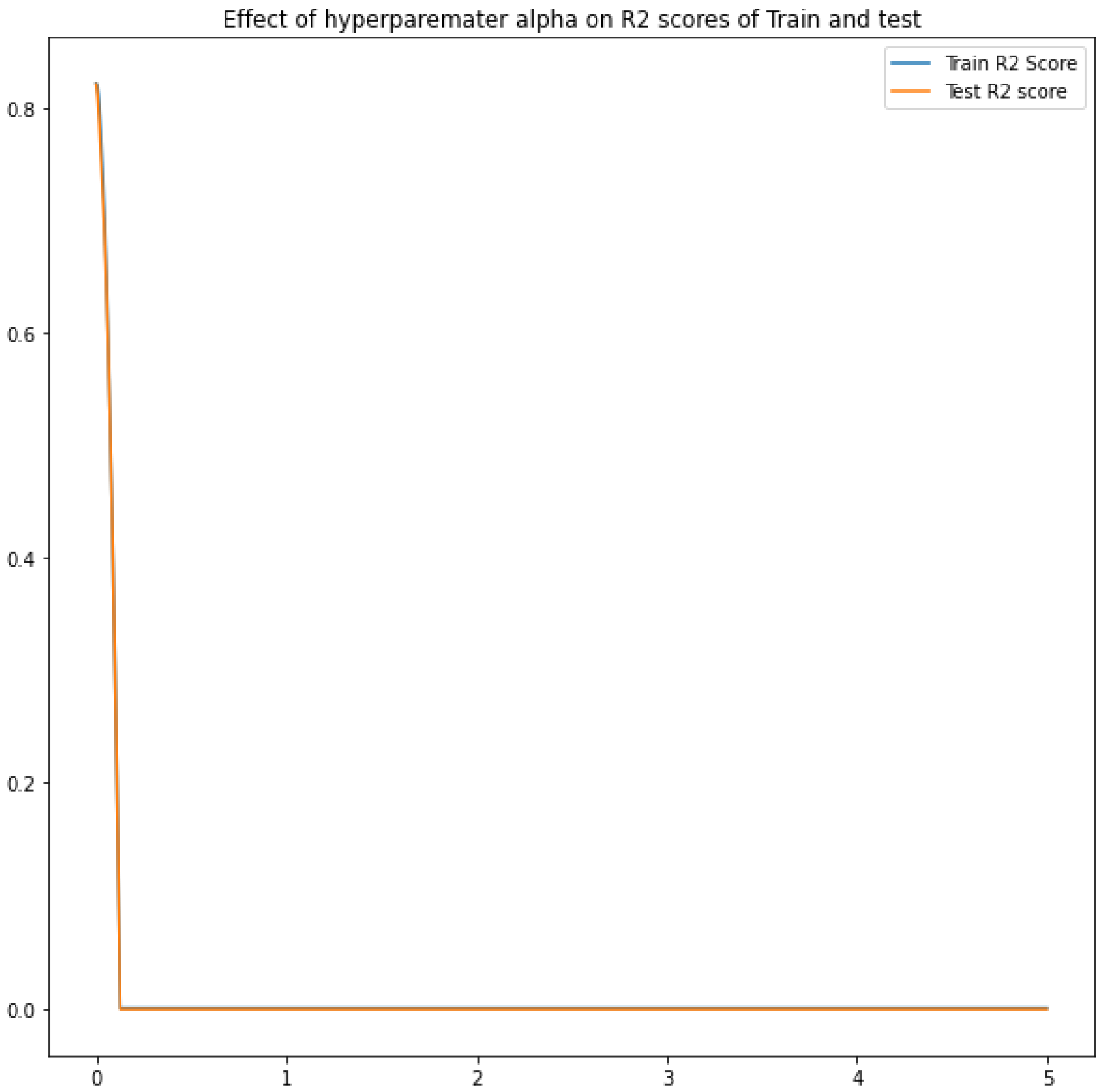
In [ ]:
```
## Hyperparameter Tuning : for appropriate lambda value :

train_R2_score = []
test_R2_score = []
lambdas = []
train_test_difference_Of_R2 =  []
lambda_ = 0
while lambda_ <= 5:
    lambdas.append(lambda_)
    LassoModel = Lasso(alpha=lambda_)
    LassoModel.fit(X_train , y_train)
    trainR2 = LassoModel.score(X_train,y_train)
    testR2 = LassoModel.score(X_test,y_test)
    train_R2_score.append(trainR2)
    test_R2_score.append(testR2)

    lambda_ += 0.001
```

In [ ]:
```
plt.figure(figsize = (10,10))
sns.lineplot(lambdas,train_R2_score,)
sns.lineplot(lambdas, test_R2_score)
plt.legend(['Train R2 Score','Test R2 score'])
plt.title("Effect of hyperparemater alpha on R2 scores of Train and test")


plt.show()
```



In [ ]:
```
LassoModel = Lasso(alpha=0.001)
LassoModel.fit(X_train , y_train)
trainR2 = LassoModel.score(X_train,y_train)
testR2 = LassoModel.score(X_test,y_test)
```

In [ ]:
```
trainR2,testR2
```

Out[ ]:
```
(0.82142983289567, 0.8198472607571161)
```

In [ ]:
```
Lasso_Model_coefs = pd.DataFrame(LassoModel.coef_.reshape(1,-1),columns=df.columns[:-1])
Lasso_Model_coefs["Intercept"] = LassoModel.intercept_
Lasso_Model_coefs
```

Out[ ]:

	GRE_Score	TOEFL_Score	University_Rating	SOP	LOR	CGPA	Research	Intercept
0	0.020616	0.019069	0.006782	0.002808	0.012903	0.070605	0.009278	0.722863

In [ ]:
```
RidgeModel_coefs
```

Out[ ]:

	GRE_Score	TOEFL_Score	University_Rating	SOP	LOR	CGPA	Research	Intercept
0	0.020695	0.019296	0.00701	0.00299	0.013342	0.070449	0.009875	0.722882

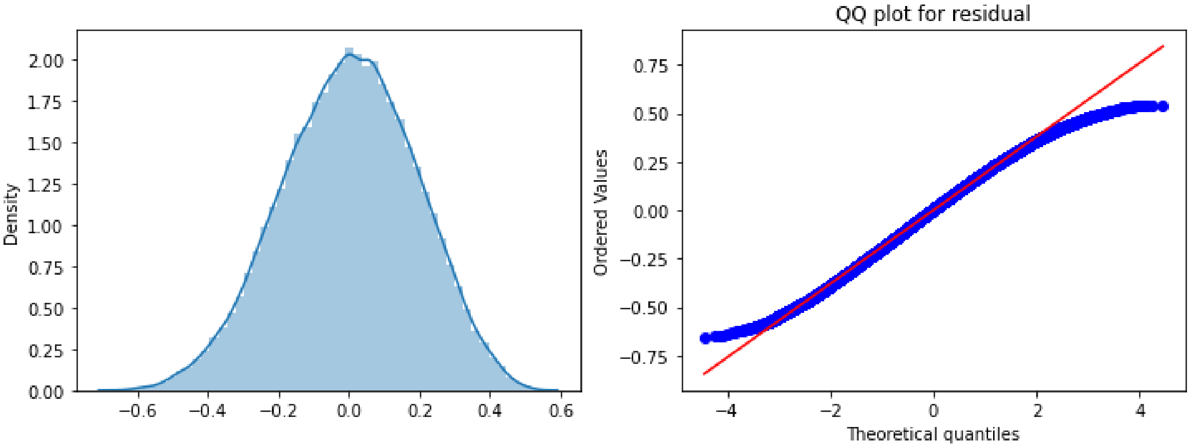
In [ ]:
```
LinearRegression_Model_coefs
```

Out[ ]:

	GRE_Score	TOEFL_Score	University_Rating	SOP	LOR	CGPA	Research	Intercept
0	0.020675	0.019284	0.007001	0.002975	0.013338	0.070514	0.009873	0.722881

In [ ]:
```
y_predicted = LassoModel.predict(X_train)

residuals = (y_train - y_predicted)
plt.figure(figsize=(12,4))
plt.subplot(1,2,1)
sns.distplot(residuals)
plt.subplot(1,2,2)
stats.probplot(residuals.reshape(-1,), plot = plt)
plt.title('QQ plot for residual')
plt.show()
```



In [ ]:
```
y_pred = LassoModel.predict(X_test)

print("MSE:",mean_squared_error(y_test,y_pred)) # MSE
print("RMSE:",np.sqrt(mean_squared_error(y_test,y_pred))) #RMSE
print("MAE :",mean_absolute_error(y_test,y_pred) ) # MAE
print("r2_score:",r2_score(y_test,y_pred)) # r2score
print("Adjusted R2 score :", AdjustedR2score(r2_score(y_test,y_pred),len(X),X.shape[1]))
```

```
MSE: 0.0034789295475193306
RMSE: 0.05898245118269781
MAE : 0.04022896061335951
r2_score: 0.8198472607571161
Adjusted R2 score : 0.8172841120280507
```

ElasticNet

L1 and L2 regularisation :

- ### Elastic net linear regression uses the penalties from both the lasso and ridge techniques to regularize regression models.

In [ ]:
```
## Hyperparameter Tuning : for appropriate lambda value :

train_R2_score = []
```

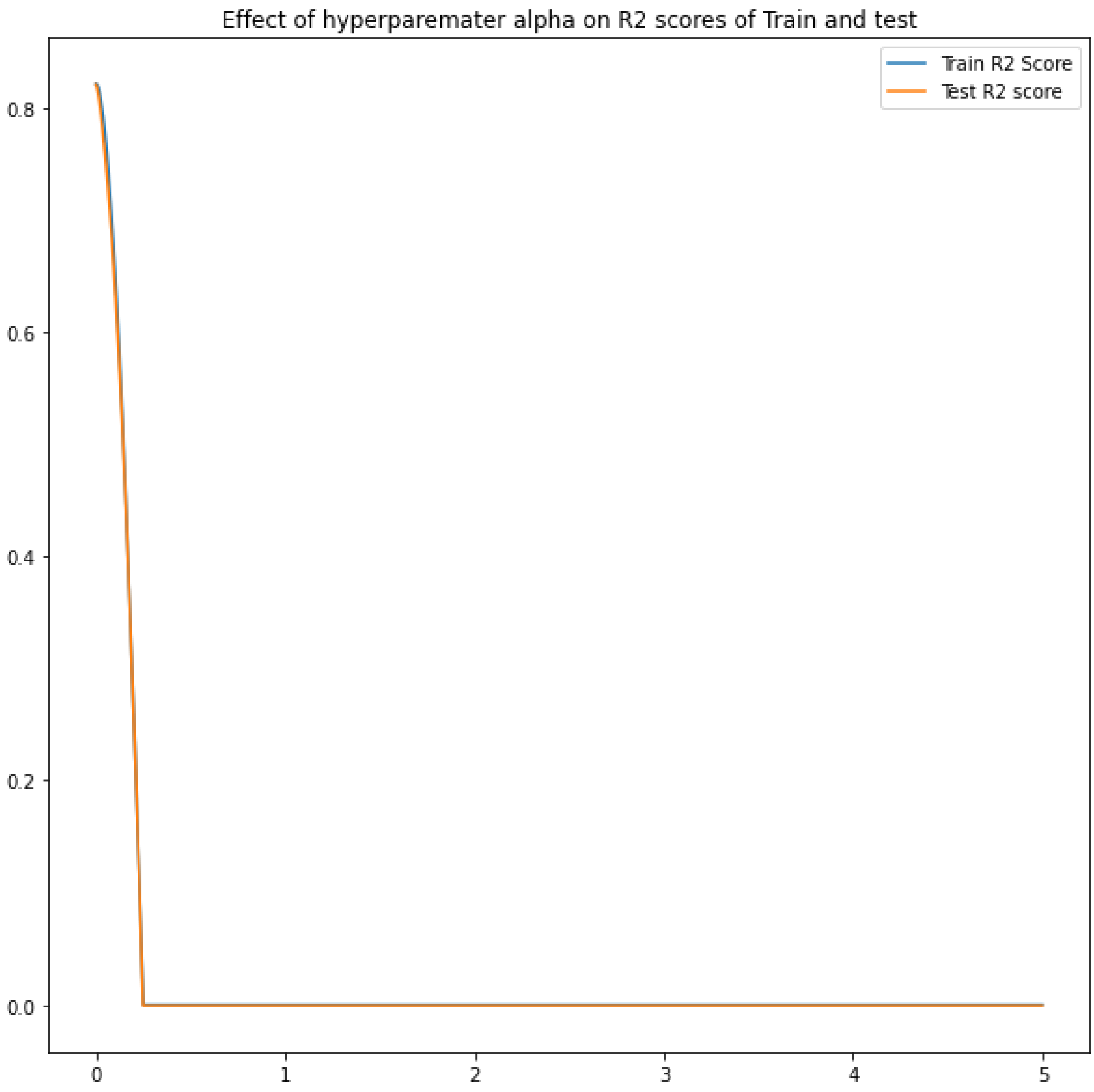
```
test_R2_score = []
lambdas = []
train_test_difference_Of_R2 =  []
lambda_ = 0
while lambda_ <= 5:
    lambdas.append(lambda_)
    ElasticNet_model = ElasticNet(alpha=lambda_)
    ElasticNet_model.fit(X_train , y_train)
    trainR2 = ElasticNet_model.score(X_train,y_train)
    testR2 = ElasticNet_model.score(X_test,y_test)
    train_R2_score.append(trainR2)
    test_R2_score.append(testR2)

    lambda_ += 0.001
```

In [ ]:

In [ ]:
```
plt.figure(figsize = (10,10))
sns.lineplot(lambdas,train_R2_score,)
sns.lineplot(lambdas, test_R2_score)
plt.legend(['Train R2 Score','Test R2 score'])
plt.title("Effect of hyperparemater alpha on R2 scores of Train and test")


plt.show()
```



In [ ]:
```
ElasticNet_model = ElasticNet(alpha=0.001)
ElasticNet_model.fit(X_train , y_train)
```

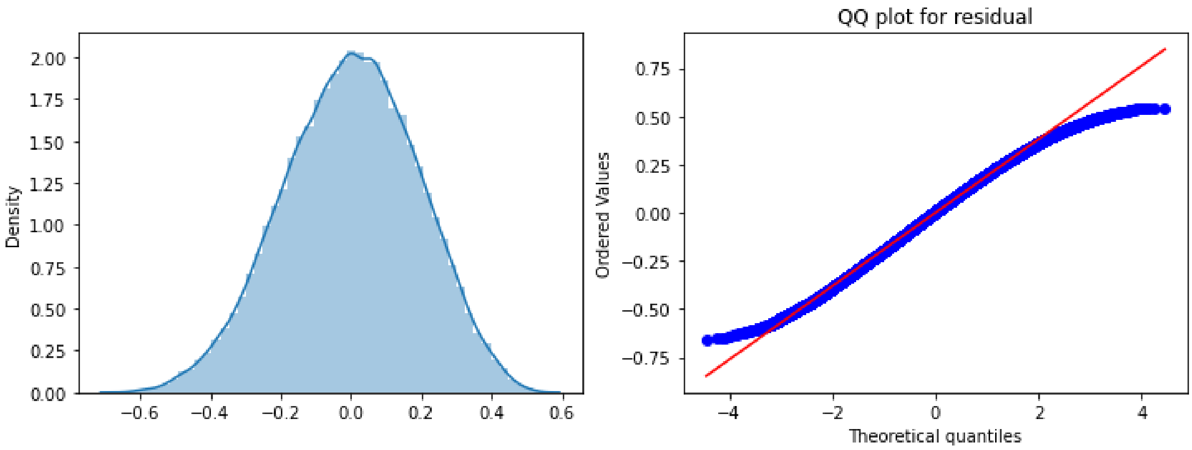
```
trainR2 = ElasticNet_model.score(X_train,y_train)
testR2 = ElasticNet_model.score(X_test,y_test)
```

In [ ]:
```
trainR2,testR2
```

Out[ ]:
```
(0.8214893364453533, 0.8203602261096284)
```

In [ ]:
```
y_predicted = ElasticNet_model.predict(X_train)

residuals = (y_train - y_predicted)
plt.figure(figsize=(12,4))
plt.subplot(1,2,1)
sns.distplot(residuals)
plt.subplot(1,2,2)
stats.probplot(residuals.reshape(-1,), plot = plt)
plt.title('QQ plot for residual')
plt.show()
```



In [ ]:
```
y_pred = ElasticNet_model.predict(X_test)

print("MSE:",mean_squared_error(y_test,y_pred)) # MSE
print("RMSE:",np.sqrt(mean_squared_error(y_test,y_pred))) #RMSE
print("MAE :",mean_absolute_error(y_test,y_pred) ) # MAE
print("r2_score:",r2_score(y_test,y_pred)) # r2score
print("Adjusted R2 score :", AdjustedR2score(r2_score(y_test,y_pred),len(X),X.shape[1]))
```

```
MSE: 0.003469023673596966
RMSE: 0.058898418260569324
MAE : 0.04021407699792928
r2_score: 0.8203602261096284
Adjusted R2 score : 0.8178043756680987
```

In [ ]:
```
ElasticNet_model_coefs = pd.DataFrame(ElasticNet_model.coef_.reshape(1,-1),columns=df.cc
ElasticNet_model_coefs["Intercept"] = ElasticNet_model.intercept_
ElasticNet_model_coefs
```

Out[ ]:

	GRE_Score	TOEFL_Score	University_Rating	SOP	LOR	CGPA	Research	Intercept
0	0.020679	0.019199	0.006908	0.00292	0.013128	0.070437	0.009581	0.722873

In [ ]:
```
RidgeModel_coefs
```

Out[ ]:

	GRE_Score	TOEFL_Score	University_Rating	SOP	LOR	CGPA	Research	Intercept
0	0.020695	0.019296	0.00701	0.00299	0.013342	0.070449	0.009875	0.722882

In [ ]:
```
Lasso_Model_coefs
```

Out[ ]:

	GRE_Score	TOEFL_Score	University_Rating	SOP	LOR	CGPA	Research	Intercept
0	0.020616	0.019069	0.006782	0.002808	0.012903	0.070605	0.009278	0.722863

In [ ]:

```
LinearRegression_Model_coefs
```

Out[ ]:

	GRE_Score	TOEFL_Score	University_Rating	SOP	LOR	CGPA	Research	Intercept
0	0.020675	0.019284	0.007001	0.002975	0.013338	0.070514	0.009873	0.722881

In [ ]:

```
y_pred = ElasticNet_model.predict(X_test)
ElasticNet_model_metrics = []
ElasticNet_model_metrics.append(mean_squared_error(y_test,y_pred)) # MSE
ElasticNet_model_metrics.append(np.sqrt(mean_squared_error(y_test,y_pred))) #RMSE
ElasticNet_model_metrics.append(mean_absolute_error(y_test,y_pred) ) # MAE
ElasticNet_model_metrics.append(r2_score(y_test,y_pred)) # r2score
ElasticNet_model_metrics.append(AdjustedR2score(r2_score(y_test,y_pred),len(X),X.shape[1
```

In [ ]:

```
y_pred = LinearRegression.predict(X_test)
LinearRegression_model_metrics = []
LinearRegression_model_metrics.append(mean_squared_error(y_test,y_pred)) # MSE
LinearRegression_model_metrics.append(np.sqrt(mean_squared_error(y_test,y_pred))) #RMSE
LinearRegression_model_metrics.append(mean_absolute_error(y_test,y_pred) ) # MAE
LinearRegression_model_metrics.append(r2_score(y_test,y_pred)) # r2score
LinearRegression_model_metrics.append(AdjustedR2score(r2_score(y_test,y_pred),len(X),X.s
```

In [ ]:

```
y_pred = RidgeModel.predict(X_test)
RidgeModel_model_metrics = []
RidgeModel_model_metrics.append(mean_squared_error(y_test,y_pred)) # MSE
RidgeModel_model_metrics.append(np.sqrt(mean_squared_error(y_test,y_pred))) #RMSE
RidgeModel_model_metrics.append(mean_absolute_error(y_test,y_pred) ) # MAE
RidgeModel_model_metrics.append(r2_score(y_test,y_pred)) # r2score
RidgeModel_model_metrics.append(AdjustedR2score(r2_score(y_test,y_pred),len(X),X.shape[1
```

In [ ]:

```
y_pred = LassoModel.predict(X_test)
LassoModel_model_metrics = []
LassoModel_model_metrics.append(mean_squared_error(y_test,y_pred)) # MSE
LassoModel_model_metrics.append(np.sqrt(mean_squared_error(y_test,y_pred))) #RMSE
LassoModel_model_metrics.append(mean_absolute_error(y_test,y_pred) ) # MAE
LassoModel_model_metrics.append(r2_score(y_test,y_pred)) # r2score
LassoModel_model_metrics.append(AdjustedR2score(r2_score(y_test,y_pred),len(X),X.shape[1
```

In [ ]:

```
ElasticNet_model_metrics
```

Out[ ]:

```
[0.003469023673596966,
 0.058898418260569324,
 0.04021407699792928,
 0.8203602261096284,
 0.8178043756680987]
```

In [ ]:

```
A = pd.DataFrame([LinearRegression_model_metrics,LassoModel_model_metrics,RidgeModel_mod
A
```

Out[ ]:

	MSE	RMSE	MAE	R2_SCORE	ADJUSTED_R2
Linear Regression Model	0.003459	0.058814	0.040200	0.820874	0.818326
Lasso Regression Model	0.003479	0.058982	0.040229	0.819847	0.817284
Ridge Regression Model	0.003459	0.058816	0.040203	0.820864	0.818315
ElasticNet Regression Model	0.003469	0.058898	0.040214	0.820360	0.817804

In [ ]:
```
B = pd.DataFrame(LinearRegression_Model_coefs.append(Lasso_Model_coefs).append(RidgeMode
B.index = ["Linear Regression Model","Lasso Regression Model","Ridge Regression Model","
```

In [ ]:
```
REPORT = B.reset_index().merge(A.reset_index())
```

In [ ]:
```
REPORT = REPORT.set_index("index")
REPORT
```

Out[ ]:

index	GRE_Score	TOEFL_Score	University_Rating	SOP	LOR	CGPA	Research	Intercept
Linear Regression Model	0.020675	0.019284	0.007001	0.002975	0.013338	0.070514	0.009873	0.722881
Lasso Regression Model	0.020616	0.019069	0.006782	0.002808	0.012903	0.070605	0.009278	0.722863
Ridge Regression Model	0.020695	0.019296	0.007010	0.002990	0.013342	0.070449	0.009875	0.722882
ElasticNet Regression Model	0.020679	0.019199	0.006908	0.002920	0.013128	0.070437	0.009581	0.722873

Insights , Feature Importance and Interpretations and Recommendations :

- fist column was observed as unique row identifier which was dropped and was not required for model building.
- University Rating , SOP and LOR strength and research are seems to be discrete random Variables , but also ordinal numeric data.
- all the other features are numeric, ordinal and continuous.
- No null values were present in data.
- No Significant amount of outliers were found in data.
- Chance of admission(target variable) and GRE score(an independent feature) are nearly normally distrubted.

- Independent Variables (Input data): GRE Score, TOEFL Score, University Rating, SOP, LOR, CGPA, Research
- Target/Dependent Variable : Chance of Admit (the value we want to predict)

- from correlation heatmap , we can observe GRE score, TOEFL score and CGPA have very high correlation with Change of admission.

- University rating, SOP ,LOR and Research have comparatively slightly less correlated than other features.

- chances of admit is a probability measure , which is within 0 to 1 which is good (no outliers or missleading data in column).
- Range of GRE score looks like between 290 to 340.
- range of TOEFL score is between 92 to 120.
- university rating , SOP and LOR are distributed between range of 1 to 5.

- CGPA range is between 6.8 to 9.92.
- From boxplots (distribution of chance of admition (probability of getting admition) as per GRE score) : with higher GRE score , there is high probability of getting an admition .
- Students having high toefl score , has higher probability of getting admition .
- from count plots, we can observe , statement of purpose SOP strength is positively correlated with Chance of Admission .
- we can also similar pattern in Letter of Recommendation Stength and University rating , have positive correlation with Chaces of Admission .
- Student having research has higher chances of Admission , but also we can observe some outliers within that caregory.

Actionable Insights and Recommendations :

- education institute can not just help student to improve their CGPA score but also assist them writing good LOR and SOP thus helping them admit to better university.
- The education institute can not just help student to improve their GRE Score but can also assist them writing good LOR and SOP thus helping them admit to a better University.
- Awareness of CGPA and Reserach Capabilities : Seminars can be organised to increase the awareness regarding CGPA and Research Capablities to enhance the chance of admit.
- Any student can never change their current state of attributes so awareness and marketing campaign need to surveyed hence creating a first impression on student at undergraduate level, which wont just increase company's popularity but will also help sudent get prepared for future plans in advance.
- A dashboard can be created for students whenever they loged in into your website, hence allowing a healthy competition also to create a progress report for students.
- Additional features like number of hours they put in studing, watching lectures, assignments soved percentage, marks in mock test can result a better report for every student to judge themselves and improve on their own.

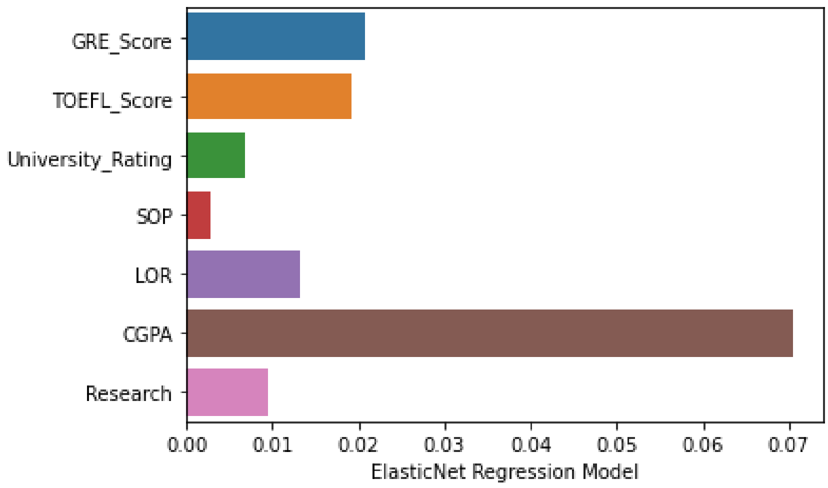
In [ ]:
```
REPORT
```

Out[ ]:

index	GRE_Score	TOEFL_Score	University_Rating	SOP	LOR	CGPA	Research	Intercept
Linear Regression Model	0.020675	0.019284	0.007001	0.002975	0.013338	0.070514	0.009873	0.722881
Lasso Regression Model	0.020616	0.019069	0.006782	0.002808	0.012903	0.070605	0.009278	0.722863
Ridge Regression Model	0.020695	0.019296	0.007010	0.002990	0.013342	0.070449	0.009875	0.722882
ElasticNet Regression Model	0.020679	0.019199	0.006908	0.002920	0.013128	0.070437	0.009581	0.722873

In [ ]:
```
sns.barplot(y  = REPORT.loc["ElasticNet Regression Model"][0:7].index,
            x = REPORT.loc["ElasticNet Regression Model"][0:7])
```

Out[ ]: <AxesSubplot:xlabel='ElasticNet Regression Model'>



Regression Analysis :

- from regression analysis (above bar chart and REPORT file), we can observe the CGPA is the most Important feature for prediciing the chances of admission.
- other important features are GRE and TOEFL score .

- after first Regression Model, checked for Multicolinearity . Getting all the VIF scores below 5 , showing there's no high multicolinearity.

- all the residuals are not perfectly normally distributed. and so residual plot we can observe some level of heteroscedasticity.
- regularised model ridge and lasso both give very similar results to Linear Regression Model.
- similarly ElasticNet (L1+L2) also returns very similar results. along with rest of all the model metrics.