Business Case: Jamboree Education

Jamboree Education is the Asia's leading and largest test prep institute offering comprehensive classroom preparation programs for tests such as the GMAT, GRE, SAT, TOEFL, and IELTS.Jamboree has helped thousands of students make it to top colleges abroad. They recently launched a feature where learners can come to their website and check their probability of getting into the IVY league college.This case study anlayses the chances of graduate admission into the IVY league college with the help of Linear Regression. It also explores what factors are important in graduate admissions and how these factors are interrelated among themselves.

In [245…

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
import datetime
import time
warnings.simplefilter(action='ignore',category=Warning)
```

In [246…

```
df=pd.read_csv("jamboree.csv")
```

In [247…

```
df.shape
```

Out[247]:

```
(500, 9)
```

In [248…

```
df.columns
```

Out[248]:

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

In [249…

```
df.head()
```

Out[249]:

	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

In [250…

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

In [251…

```
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
```

We can see that there are no null records in the dataset.

In [252…

```
df.describe(include="all").T
```

Out[252]:

	count	mean	std	min	25%	50%	75%	max
GRE Score	500.0	316.47200	11.295148	290.00	308.0000	317.00	325.00	340.00
TOEFL Score	500.0	107.19200	6.081868	92.00	103.0000	107.00	112.00	120.00
University Rating	500.0	3.11400	1.143512	1.00	2.0000	3.00	4.00	5.00
SOP	500.0	3.37400	0.991004	1.00	2.5000	3.50	4.00	5.00
LOR	500.0	3.48400	0.925450	1.00	3.0000	3.50	4.00	5.00
CGPA	500.0	8.57644	0.604813	6.80	8.1275	8.56	9.04	9.92
Research	500.0	0.56000	0.496884	0.00	0.0000	1.00	1.00	1.00
Chance of Admit	500.0	0.72174	0.141140	0.34	0.6300	0.72	0.82	0.97

From analysis of data description, we can say that four of the independent variables are categorical:\ 1.University Rating\ 2.Research\ 3.SOP\ 4.LOR\ and three of them are continuous:\ 1.GRE Score\ 2.TOEFL Score\ 3.CGPA

In [167…

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

Out[167]:

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

There are no duplicate rows in the dataset

In [205…

```
# unique values in the dataset
for col in df:
    print(f'Number of unique values in the {col} column:',df[col].nunique())
```

```
Number of unique values in the GRE Score column: 49
Number of unique values in the TOEFL Score column: 29
Number of unique values in the University Rating column: 5
Number of unique values in the SOP column: 9
Number of unique values in the LOR  column: 9
Number of unique values in the CGPA column: 184
Number of unique values in the Research column: 2
Number of unique values in the Chance of Admit  column: 61
```

In [9]:

```
df[['University Rating']].value_counts()
```

```
Out[9]: University Rating
3                    162
2                    126
4                    105
5                     73
1                     34
dtype: int64
```

```
In [10]: df[['Research']].value_counts()
```

```
Out[10]: Research
1           280
0           220
dtype: int64
```

```
In [11]: df[['SOP']].value_counts()
```

```
Out[11]: SOP
4.0    89
3.5    88
3.0    80
2.5    64
4.5    63
2.0    43
5.0    42
1.5    25
1.0     6
dtype: int64
```

```
In [12]: df[['LOR ']].value_counts()
```

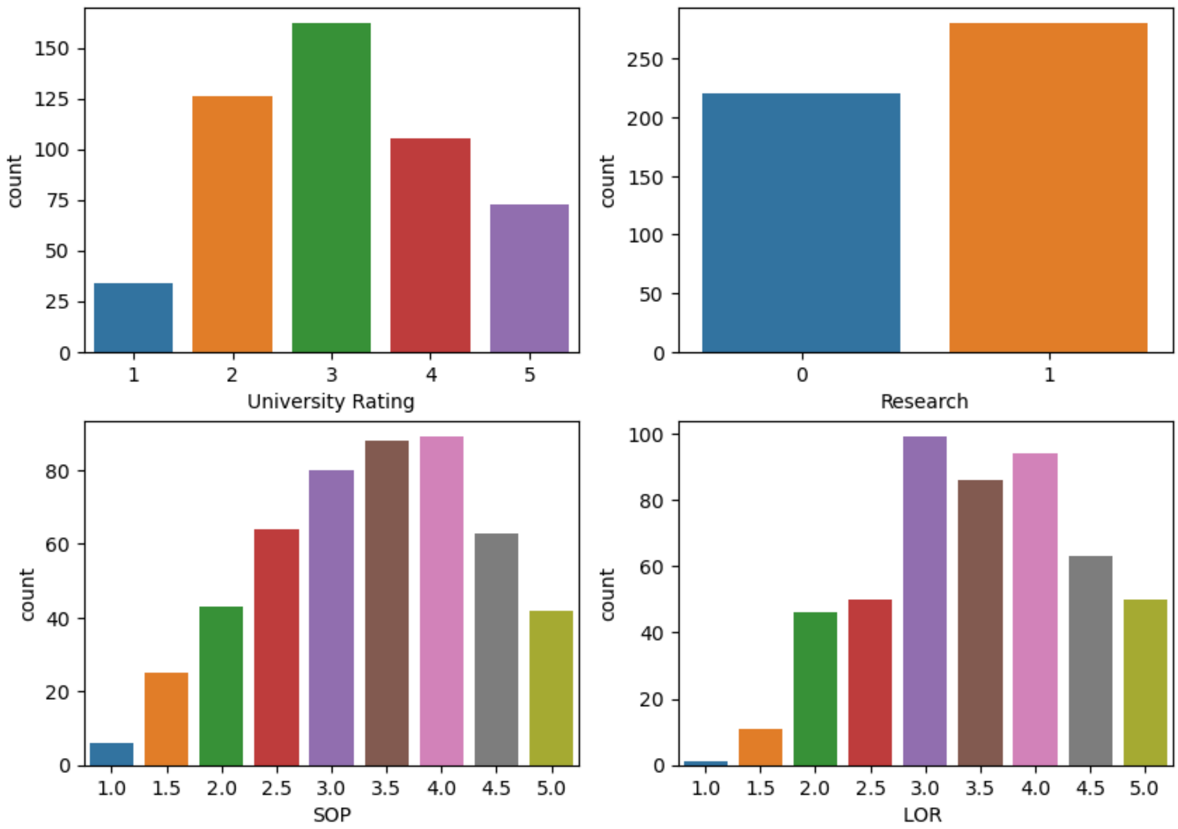
```
Out[12]: LOR
3.0     99
4.0     94
3.5     86
4.5     63
2.5     50
5.0     50
2.0     46
1.5     11
1.0      1
dtype: int64
```

Visual Analysis

Univariate Analysis

i.Categorical Variables

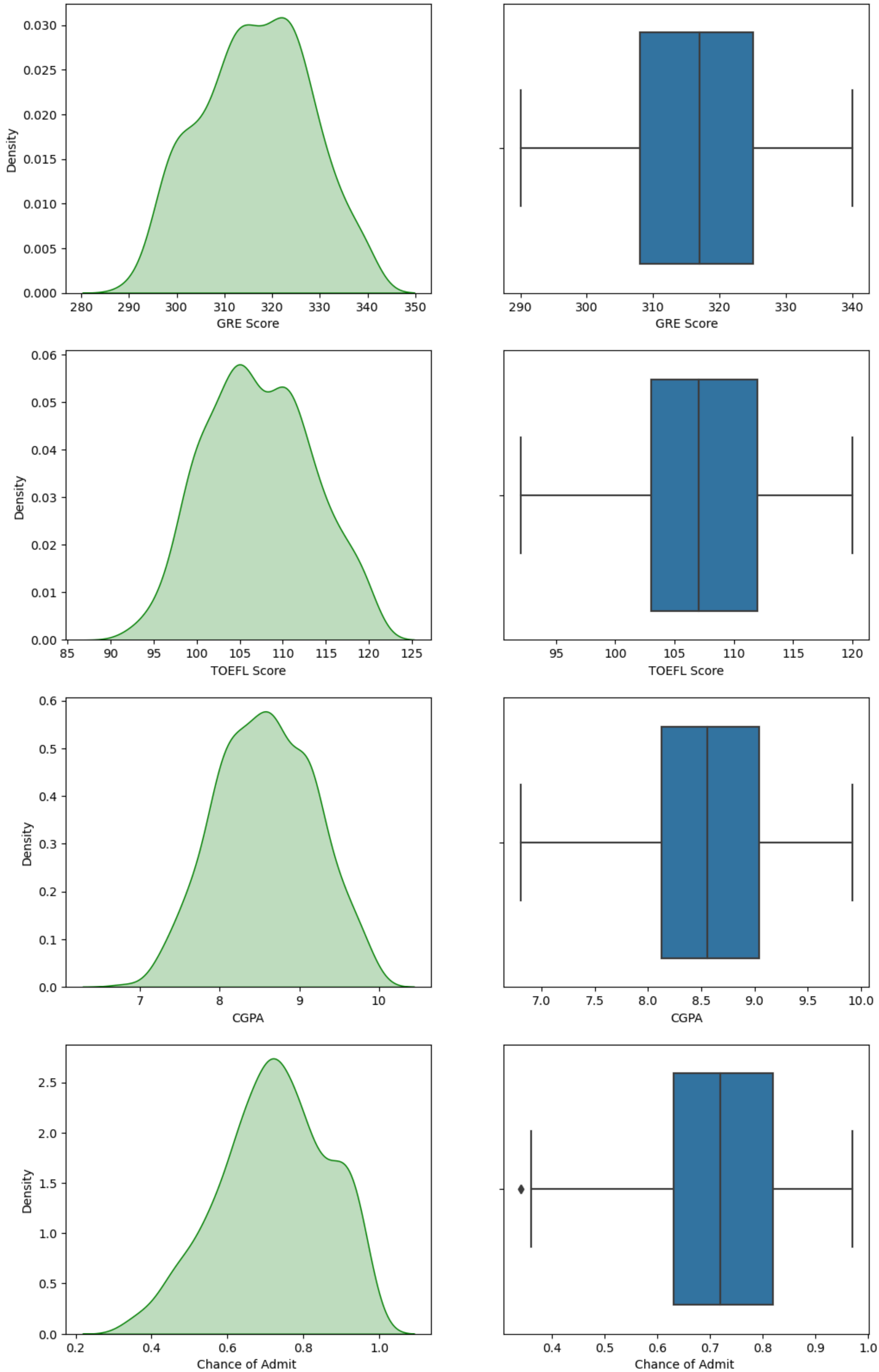
```
In [406…
fig,axis= plt.subplots(2,2,figsize=(10,7))
sns.countplot(data=df,x="University Rating",ax=axis[0][0])
sns.countplot(data=df,x="Research",ax=axis[0][1])
sns.countplot(data=df,x="SOP",ax=axis[1][0])
sns.countplot(data=df,x="LOR ",ax=axis[1][1])
plt.show()
```



ii. Continuous Variables

In [141…

```
fig,axis= plt.subplots(4,2,figsize=(12,20))
sns.kdeplot(data=df,x="GRE Score",ax=axis[0][0],fill=True,color='green')
sns.boxplot(data=df,x="GRE Score",ax=axis[0][1])
sns.kdeplot(data=df,x="TOEFL Score",ax= axis[1][0],fill=True,color='green')
sns.boxplot(data=df,x="TOEFL Score",ax=axis[1][1])
sns.kdeplot(data=df,x="CGPA",ax=axis[2][0],fill=True,color='green')
sns.boxplot(data=df,x="CGPA",ax=axis[2][1])
sns.kdeplot(data=df,x="Chance of Admit ",ax=axis[3][0],fill=True,color='green')
sns.boxplot(data=df,x="Chance of Admit ",ax=axis[3][1])
plt.show()
```

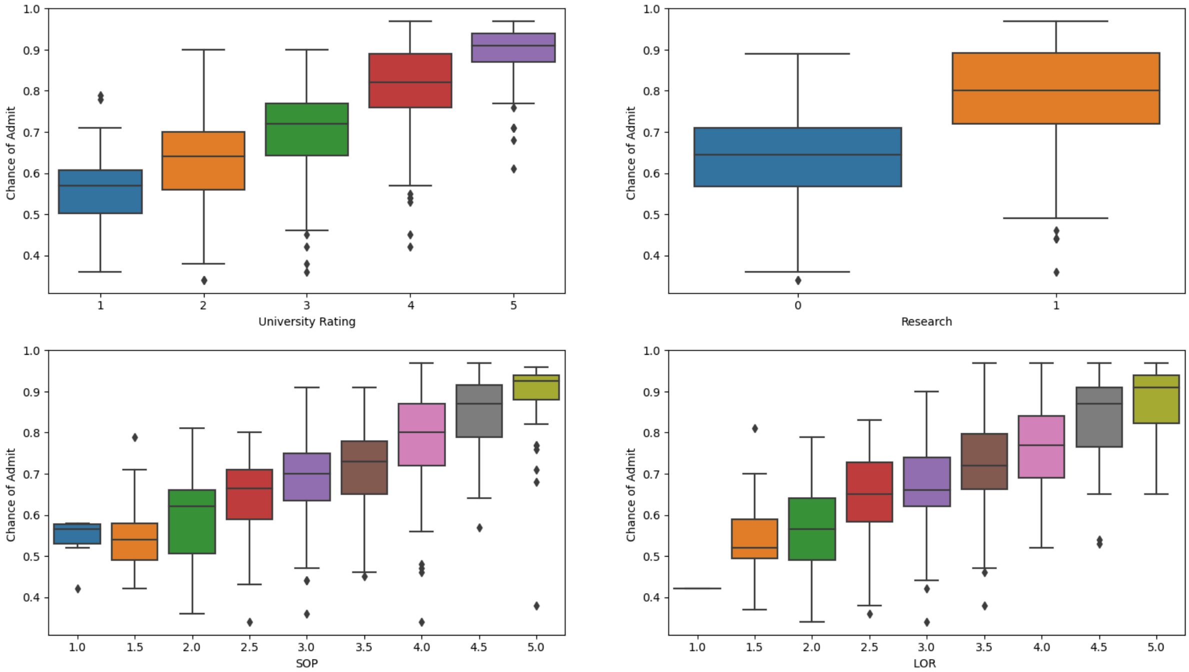


Bivariate Analysis

i.Categorical Variables

In [409…

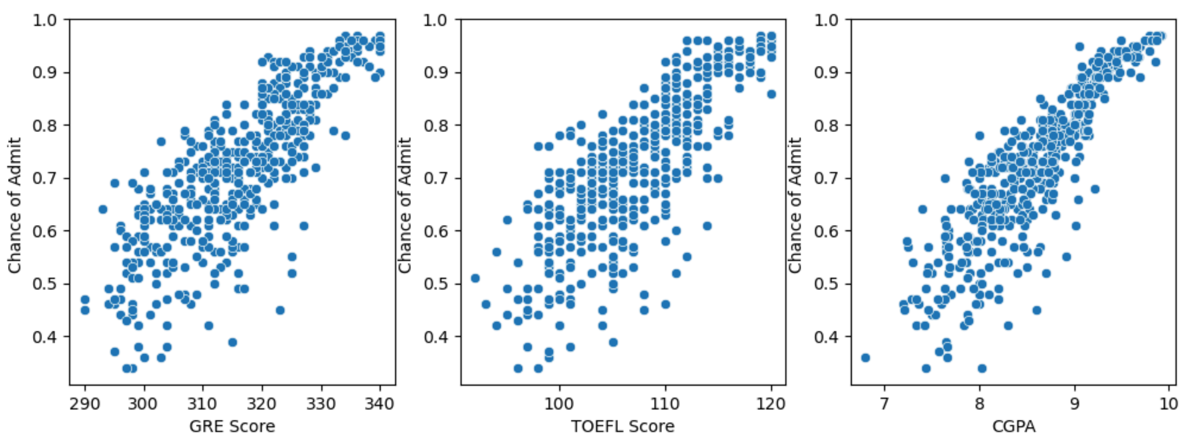
```
fig,axis= plt.subplots(2,2,figsize=(18,10))
sns.boxplot(data=df,x='University Rating',y="Chance of Admit ",ax=axis[0,0])
sns.boxplot(data=df,x="Research",y="Chance of Admit ",ax=axis[0,1])
sns.boxplot(data=df,x="SOP",y="Chance of Admit ",ax=axis[1,0])
sns.boxplot(data=df,x="LOR ",y="Chance of Admit ",ax=axis[1,1])
plt.show()
```



ii. Continuous Variables

In [509…

```
plt.figure(figsize=(12,4))
plt.subplot(1, 3, 1)
sns.scatterplot(data=df,x='GRE Score',y="Chance of Admit ")
plt.subplot(1, 3, 2)
sns.scatterplot(data=df,x="TOEFL Score",y="Chance of Admit ")
plt.subplot(1, 3, 3)
sns.scatterplot(data=df,x="CGPA",y="Chance of Admit ")
plt.show()
```

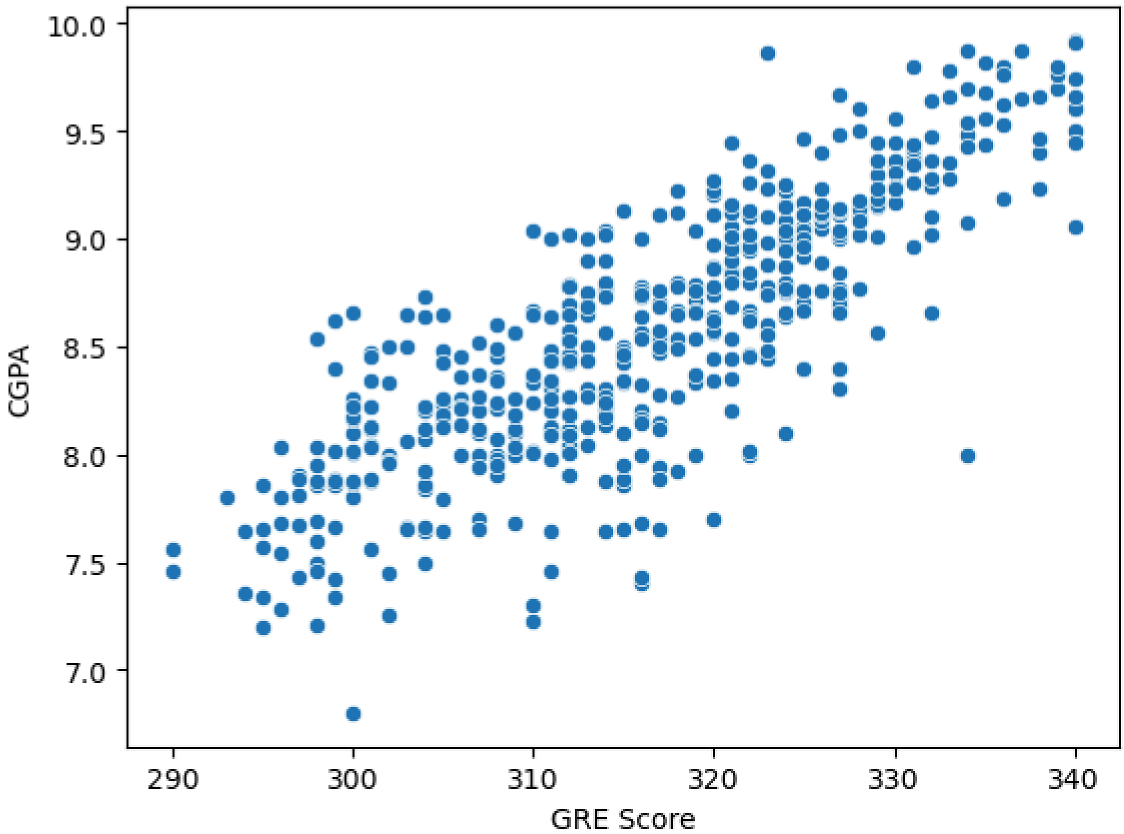


In [429…

```
sns.scatterplot(data=df,x='GRE Score',y="CGPA")
```

Out[429]:

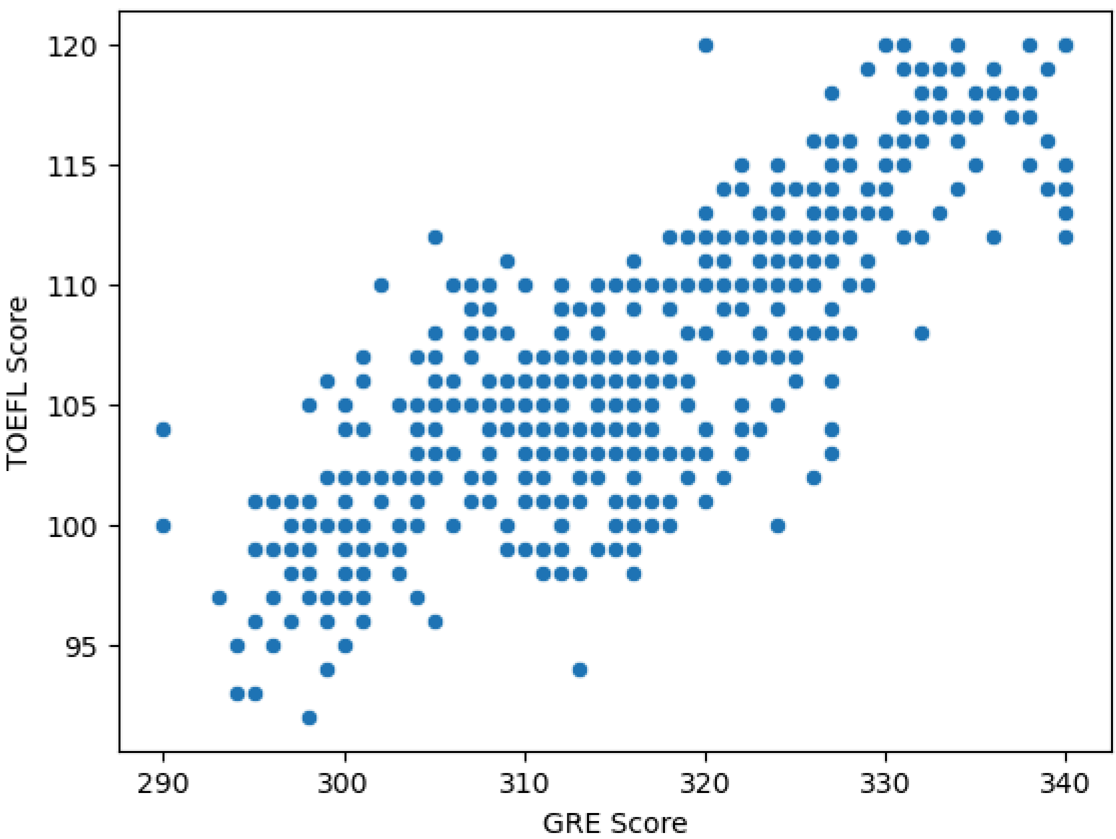
```
<AxesSubplot:xlabel='GRE Score', ylabel='CGPA'>
```



In [152…

```
sns.scatterplot(data=df,x='GRE Score',y="TOEFL Score")
```

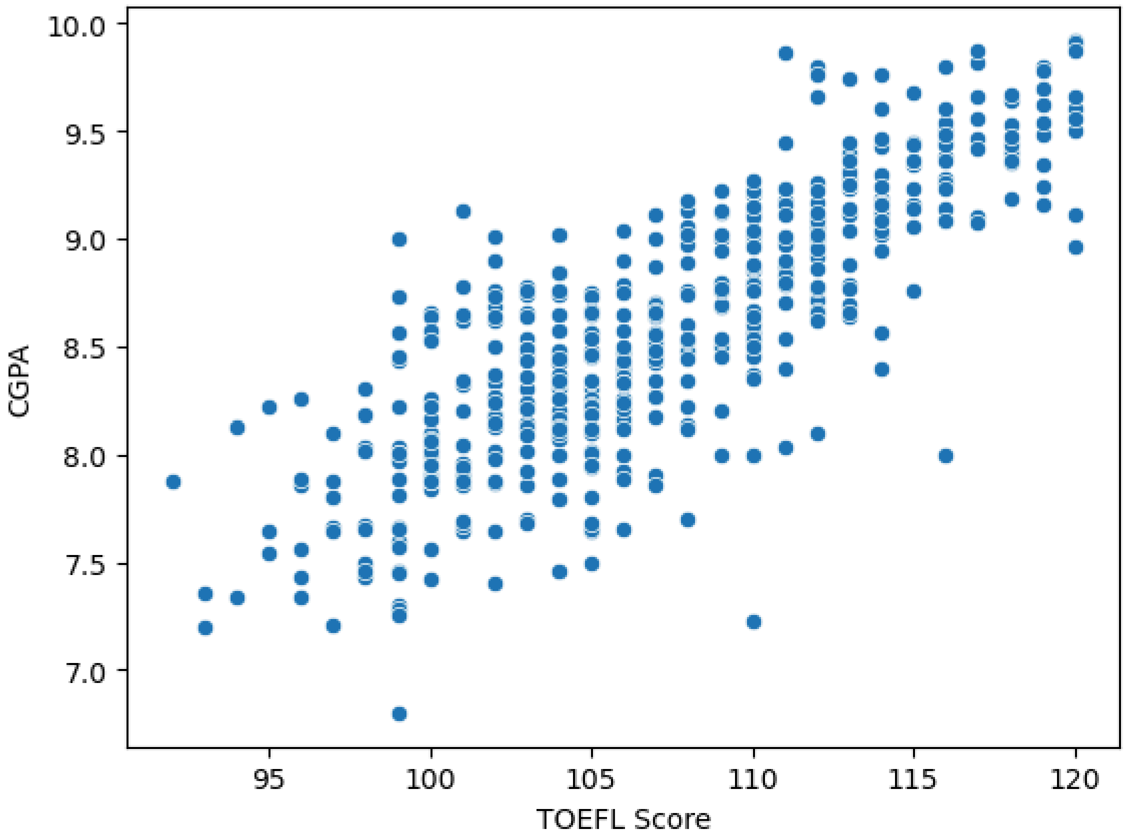
Out[152]: <AxesSubplot:xlabel='GRE Score', ylabel='TOEFL Score'>



In [153…

```
sns.scatterplot(data=df,x='TOEFL Score',y="CGPA")
```

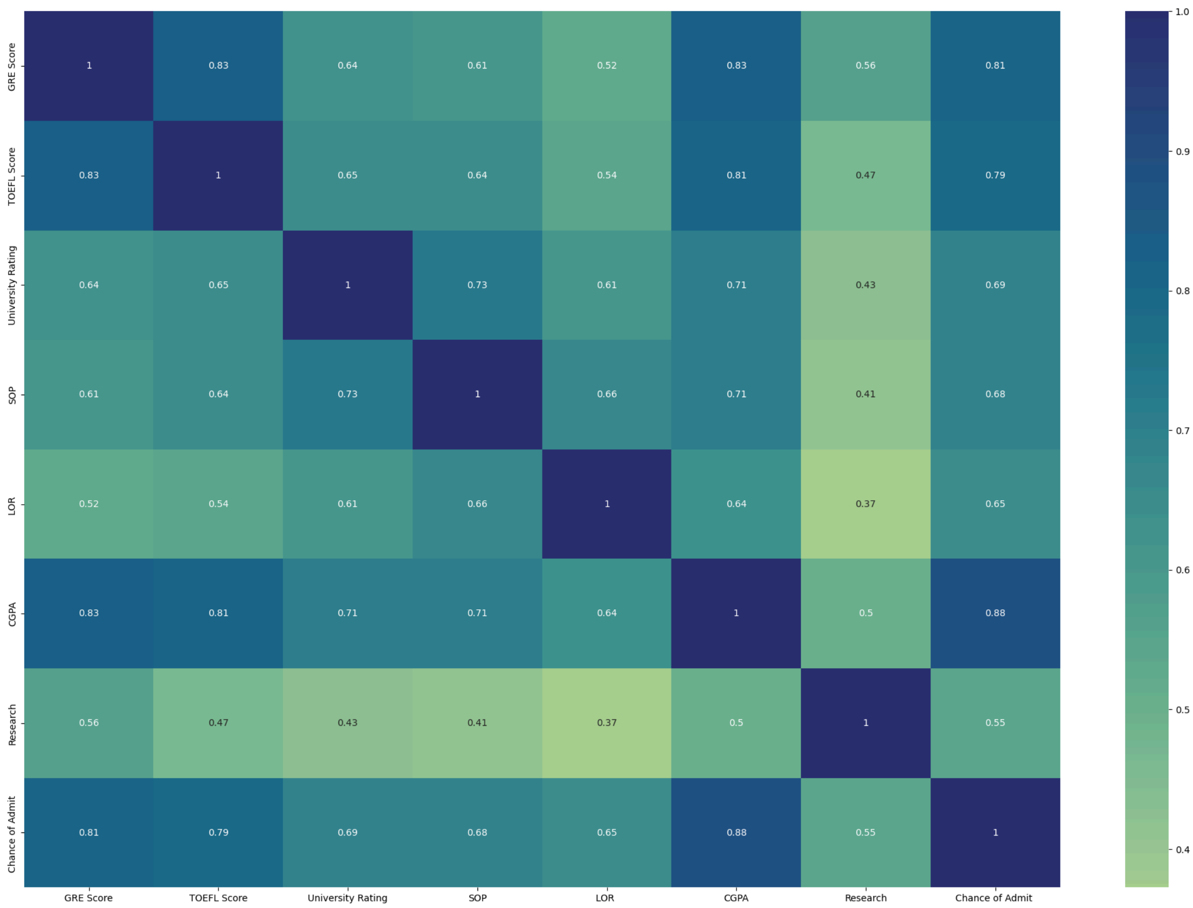
Out[153]: <AxesSubplot:xlabel='TOEFL Score', ylabel='CGPA'>



Multivariate Analysis

In [154…

```
plt.figure(figsize=(25,17))
sns.heatmap(df.corr(), cmap="crest",annot=True)
plt.show()
```

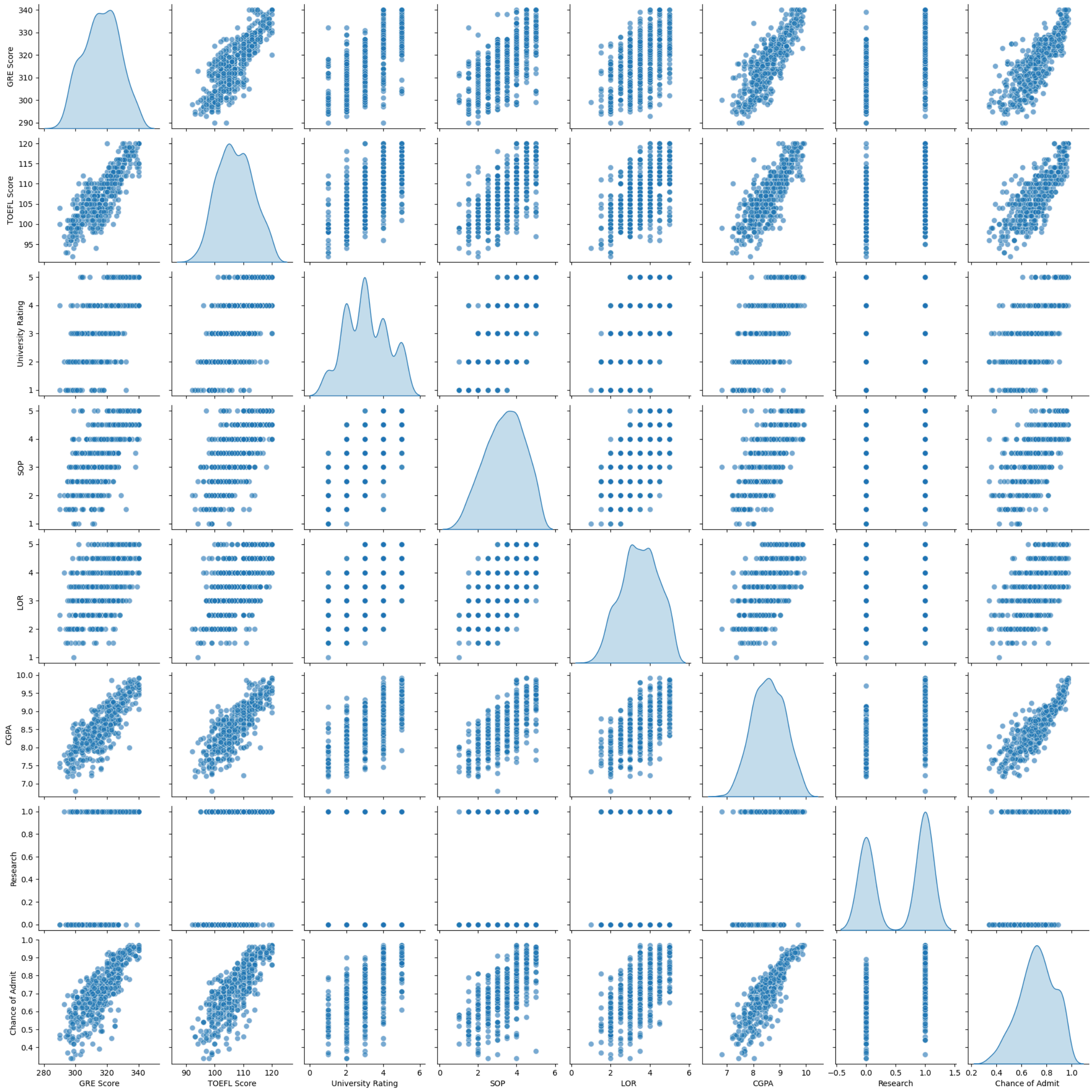


In [213…

```
sns.pairplot(df, diag_kind="kde", markers="o", plot_kws={'alpha':0.6, 's':50})
```

Out[213]:

```
<seaborn.axisgrid.PairGrid at 0x21e00251310>
```



Data Splitting into Train and Test

In [253…

```
from sklearn.model_selection import train_test_split
```

In [254…

```
X = df.drop(columns='Chance of Admit ',axis=1)
```

In [92]:

```
y=df['Chance of Admit ']
```

In [255…

```
y.head(5)
```

Out[255]:

```
0    0.92
1    0.76
2    0.72
3    0.80
4    0.65
Name: Chance of Admit , dtype: float64
```

In [95]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y,test_size=0.2, random_stat
```

Standardization

In [15]:
```
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()
```

In [96]:
```
X_train = pd.DataFrame(scaler.fit_transform(X_train),columns = X_train.columns)
X_test = pd.DataFrame(scaler.transform(X_test),columns = X_test.columns)
```

In [97]:
```
print(X_train.shape)
print(X_test.shape)
```

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

In [256…
```
X_train.describe()
```

Out[256]:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA
count	4.000000e+02	4.000000e+02	4.000000e+02	4.000000e+02	4.000000e+02	4.000000e+02
mean	-1.792316e-15	1.082745e-15	-1.526557e-16	1.584843e-16	-4.241052e-16	-8.604228e-17
std	1.001252e+00	1.001252e+00	1.001252e+00	1.001252e+00	1.001252e+00	1.001252e+00
min	-2.376227e+00	-2.476689e+00	-1.893933e+00	-2.434351e+00	-2.715472e+00	-2.959850e+00
25%	-6.948823e-01	-6.983876e-01	-1.016096e+00	-9.355201e-01	-5.539023e-01	-7.467170e-01
50%	1.305255e-02	-5.173241e-02	-1.382593e-01	6.370030e-02	-1.350981e-02	6.216482e-02
75%	7.209874e-01	7.565865e-01	7.395777e-01	5.633105e-01	5.268827e-01	7.601846e-01
max	2.048365e+00	2.049897e+00	1.617415e+00	1.562531e+00	1.607668e+00	2.164436e+00

Linear Regression using Sklearn

In [257…
```
from sklearn.linear_model import LinearRegression
```

In [258…
```
model = LinearRegression()
```

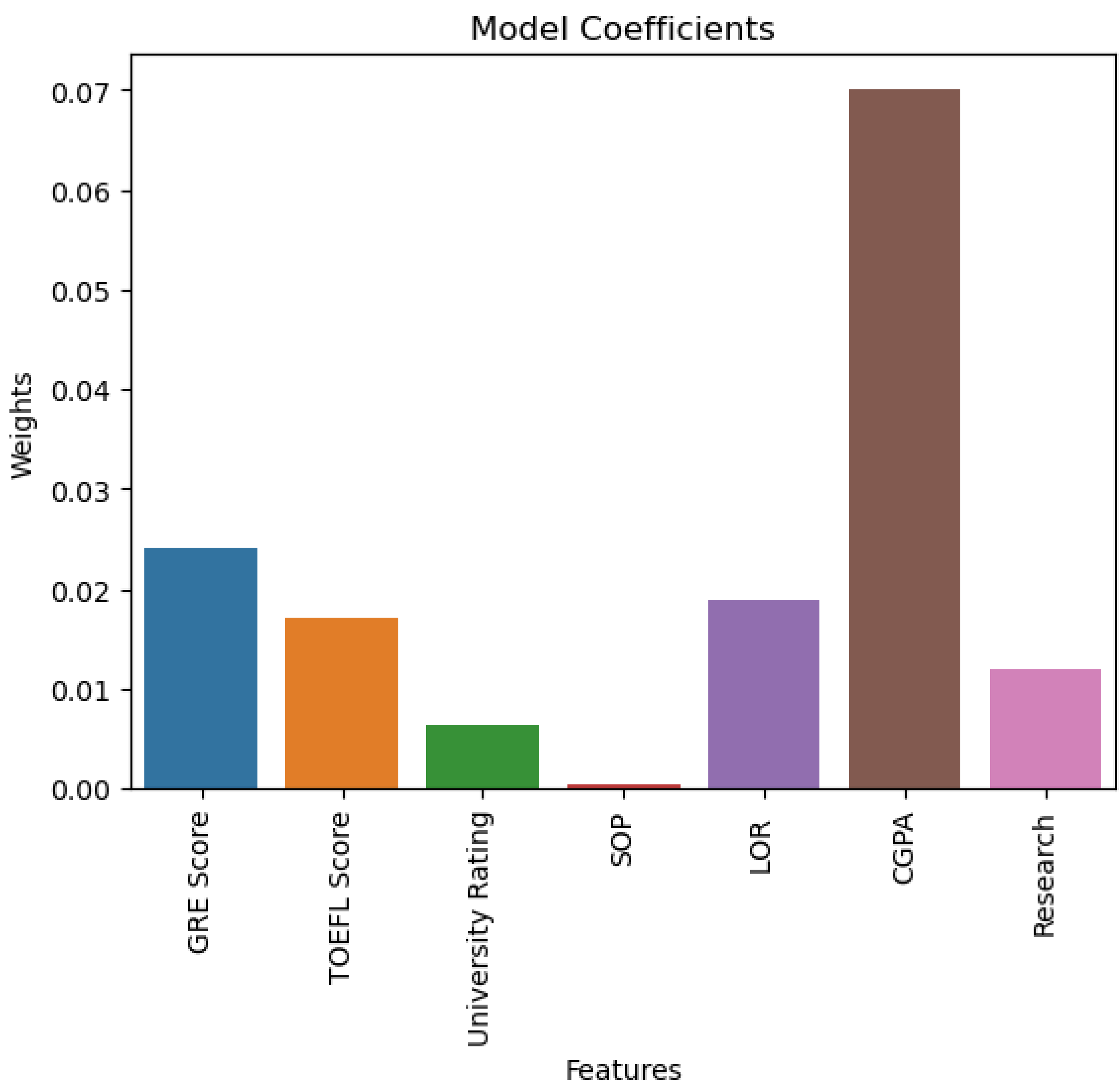
In [259…
```
model.fit(X_train,y_train)
```

Out[259]:
```
LinearRegression()
```

In [260…
```
print(f"Model Coefficients are: {model.coef_}")
print(f"Model Intercept is: {model.intercept_}")
```

```
Model Coefficients are: [0.024199   0.01713672 0.00633025 0.00051071 0.01888755 0.
07005237
 0.01187669]
Model Intercept is: 0.72655
```

In [261…
```
model_weights=zip(X_train.columns,model.coef_)
wts=pd.DataFrame(model_weights,columns=["Features","Weights"])
sns.barplot(data=wts,x="Features",y="Weights")
plt.title('Model Coefficients')
plt.ylabel('Weights')
plt.xticks(rotation=90)
plt.show()
```



Linear Regression using StatsModel Library

In [432…

```
import statsmodels.api as sm

X_train_sm = sm.add_constant(X_train)

ols_model = sm.OLS(np.array(y_train), X_train_sm).fit()
print(ols_model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.832
Model:                            OLS   Adj. R-squared:                  0.829
Method:                 Least Squares   F-statistic:                     277.5
Date:                Wed, 15 Jan 2025   Prob (F-statistic):          1.36e-147
Time:                        16:13:22   Log-Likelihood:                 568.04
No. Observations:                 400   AIC:                            -1120.
Df Residuals:                     392   BIC:                            -1088.
Df Model:                           7
Covariance Type:            nonrobust
==================================================================================
===
                        coef    std err          t      P>|t|      [0.025      0.9
75]
----------------------------------------------------------------------------------
---
const                 0.7266      0.003    245.975      0.000       0.721       0.
732
GRE Score             0.0242      0.006      3.852      0.000       0.012       0.
037
TOEFL Score           0.0171      0.006      2.950      0.003       0.006       0.
029
University Rating     0.0063      0.005      1.339      0.181      -0.003       0.
016
SOP                   0.0005      0.005      0.103      0.918      -0.009       0.
010
LOR                   0.0189      0.004      4.454      0.000       0.011       0.
027
CGPA                  0.0701      0.006     10.796      0.000       0.057       0.
083
Research              0.0119      0.004      3.354      0.001       0.005       0.
019
==============================================================================
Omnibus:                       89.207   Durbin-Watson:                   2.022
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              204.699
Skew:                          -1.126   Prob(JB):                     3.55e-45
Kurtosis:                       5.685   Cond. No.                         5.69
==============================================================================

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

Model Performance Evaluation

In [163…

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

In [271…

```python
def model_score(X,y_act,y_pred):
    mae=mean_absolute_error(y_act,y_pred)
    mse=mean_squared_error(y_act,y_pred)
    r2=r2_score(y_act,y_pred)
    adjusted_r2=1-(1-r2)*(X.shape[0]-1)/(X.shape[0]-X.shape[1]-1)

    print(f"Mean Absolute Error: {mae:.4f}")
    print(f"Root Mean Squared Error: {np.sqrt(mse):.4f}")
    print(f"R2 Score: {r2:.2f}")
    print(f"Adjusted R2 Score: {adjusted_r2:.2f}")
```

In [272…

```python
def model_eval(model,X_train,X_test,y_train,y_test):
    print("Training Set Evaluation:")
    ytr_pred = model.predict(X_train)
```

```
    model_score(X_train,y_train,ytr_pred)

    print("\nTesting Set Evaluation:")
    y_pred = model.predict(X_test)
    model_score(X_test,y_test,y_pred)
    return ytr_pred,y_pred
```

In [189…

```
ytr_pred,y_pred=model_eval(model,X_train,X_test,y_train,y_test)
```

```
Training Set Evaluation:
Mean Absolute Error: 0.0416
Root Mean Squared Error: 0.0585
R2 Score: 0.83
Adjusted R2 Score: 0.83

Testing Set Evaluation:
Mean Absolute Error: 0.0483
Root Mean Squared Error: 0.0639
R2 Score: 0.77
Adjusted R2 Score: 0.75
```

Assumptions of Linear Regression Model

1.Multicollinearity

In [35]:

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

In [337…

```
vif_list = [round(variance_inflation_factor(X_train,i),2) for i in range(len(X_trai
vif = zip(X_train.columns,vif_list)
vif_df = pd.DataFrame(vif,columns = ["feature","vif"]).sort_values(by="vif",ascendi
vif_df
```

Out[337]:

	feature	vif
5	CGPA	4.83
0	GRE Score	4.52
1	TOEFL Score	3.87
3	SOP	2.79
2	University Rating	2.56
4	LOR	2.06
6	Research	1.44

As the VIF scores of all columns are less than 5, there is no need to drop columns from the dataset to deal with multi-collinearity.

2.Mean of Residuals

In [378…

```
ytr_pred = model.predict(X_train)
residuals_tr = y_train - ytr_pred
residuals_tr.mean()
```

Out[378]:

```
3.3306690738754695e-18
```

In [406…

```
y_pred = model.predict(X_test)
residuals = y_test - y_pred
```

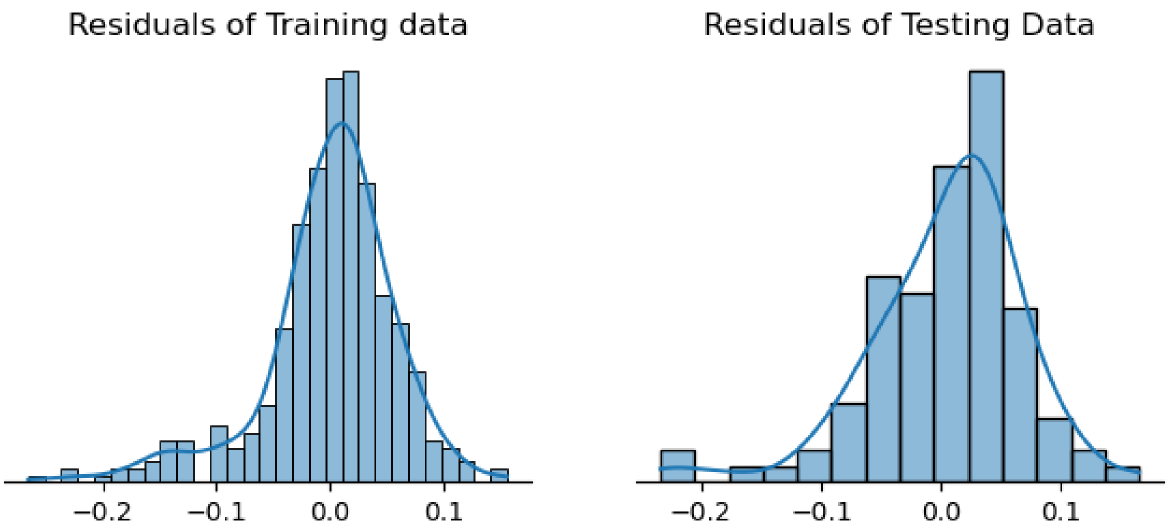
```
residuals.mean()
```

Out[406]:

```
0.004180930959275742
```

In [422…

```
plt.figure(figsize=(8,3))
plt.subplot(121)
sns.histplot(residuals_tr,kde=True)
plt.title("Residuals of Training data")
sns.despine(left=True)
plt.ylabel("")
plt.xlabel("")
plt.yticks([])
plt.subplot(122)
sns.histplot(residuals,kde=True)
plt.title("Residuals of Testing Data")
sns.despine(left=True)
plt.ylabel("")
plt.xlabel("")
plt.yticks([])
plt.show()
```



As we can see that the mean of residuals is nearly equal to 0 indicating the uniform distribution of residuals.

3.Linearity of variables

In [488…

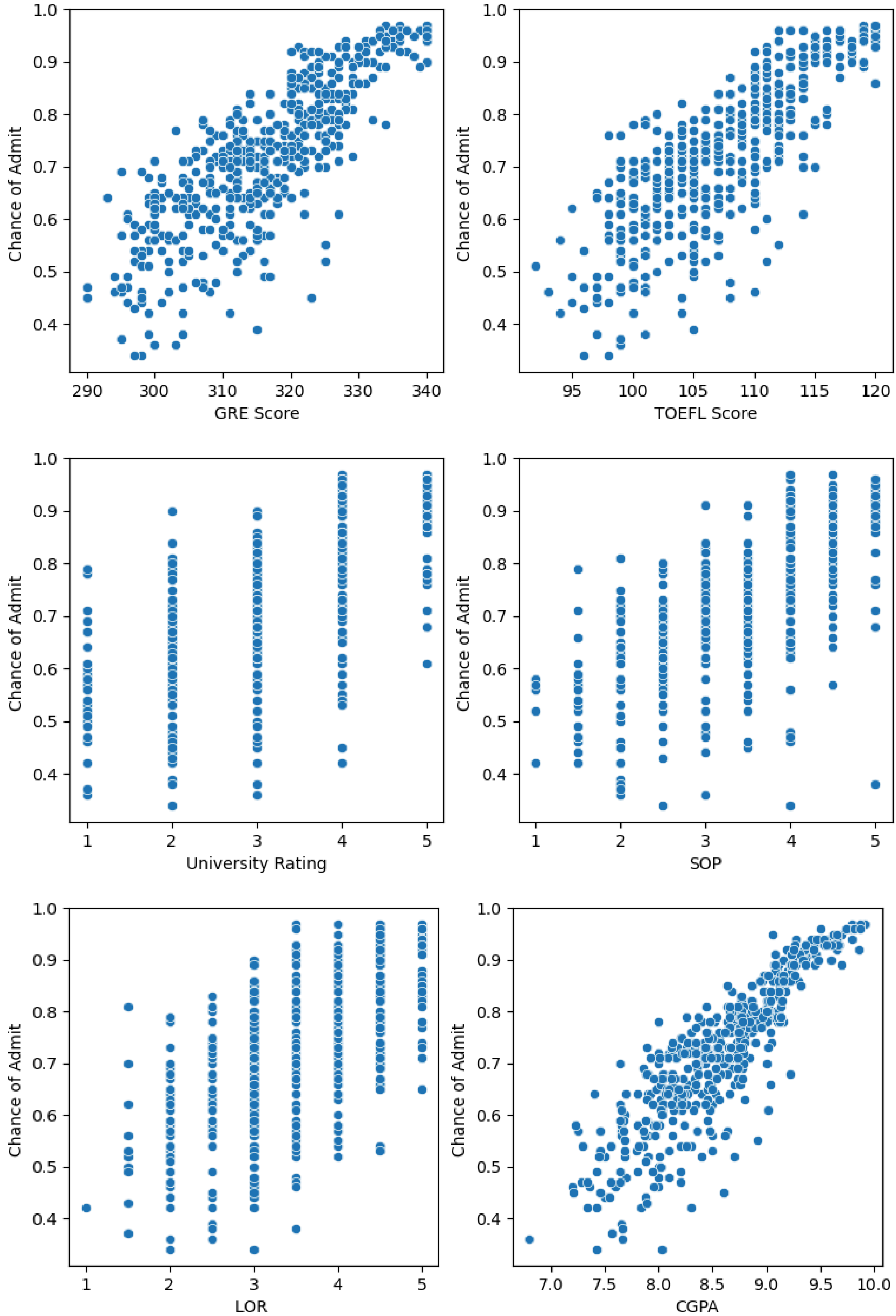
```
lst=[]
for i in range(0,X_train.shape[1],2):
    lst.append(X_train.columns[i:i+2])
lst
```

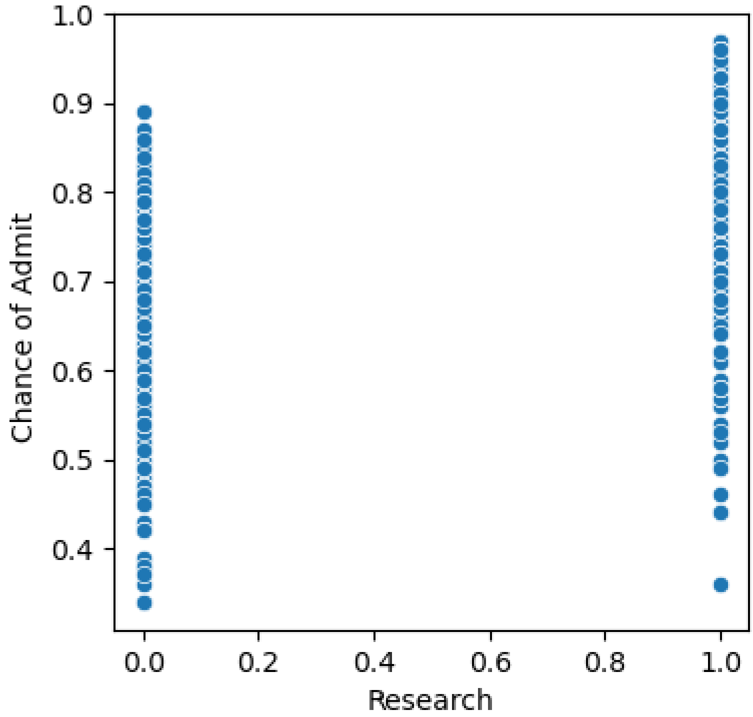
Out[488]:

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

In [487…

```
for i in lst:
    plt.figure(figsize=(9,4))
    plt.subplot(1,2,1)
    sns.scatterplot(data=df,x=i[0],y="Chance of Admit ")
    if str(i[0])!='Research':
        plt.subplot(1,2,2)
        sns.scatterplot(data=df,x=i[1],y="Chance of Admit ")
    plt.show()
```


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



In [476…

```
df.corr()["Chance of Admit "]
```

Out[476]:

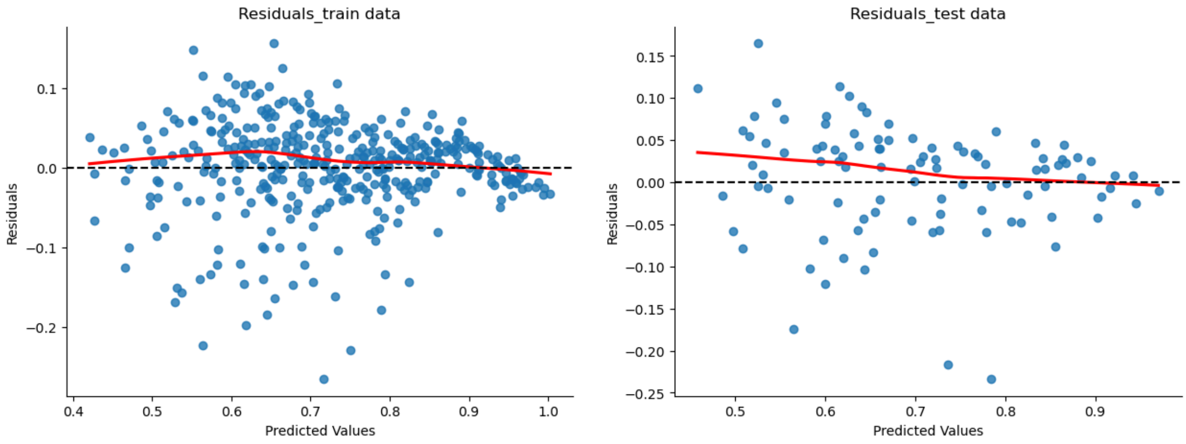
```
GRE Score            0.810351
TOEFL Score          0.792228
University Rating    0.690132
SOP                  0.684137
LOR                  0.645365
CGPA                 0.882413
Research             0.545871
Chance of Admit      1.000000
Name: Chance of Admit , dtype: float64
```

From above analysis with the help of scatter plots and correlation metric, relationship between dependent variables and independent variables seems to be linear.

4.Heteroscadisticity

In [421…

```
plt.figure(figsize=(15,5))
plt.subplot(121)
plt.title('Residuals_train data',fontsize=12)
sns.regplot(x=ytr_pred, y=residuals_tr, lowess=True,line_kws={'color': 'red'})
plt.axhline(y=0, color='k', linestyle='--')
plt.xlabel('Predicted Values')
plt.ylabel('Residuals')
plt.subplot(122)
plt.title('Residuals_test data',fontsize=12)
sns.regplot(x=y_pred, y=residuals, lowess=True,line_kws={'color': 'red'})
plt.axhline(y=0, color='k', linestyle='--')
plt.xlabel('Predicted Values')
plt.ylabel('Residuals')
sns.despine()
plt.show()
```

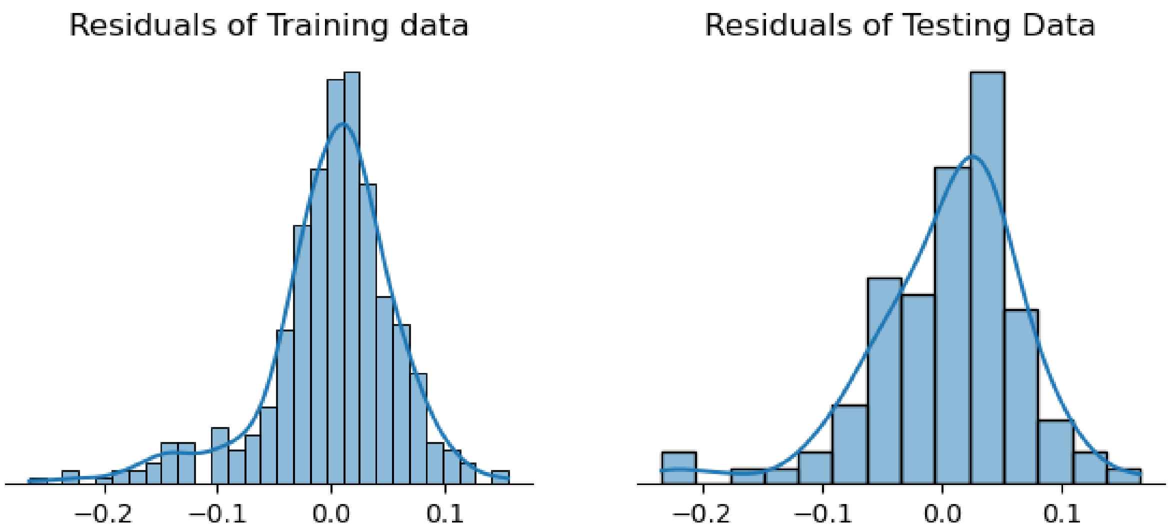


Here, we can see there is no significant pattern observed in the residuals plot indicating homoscedasticity which means Linear Regression is suitable as the model. If a pattern is observed in the residual plot, it may indicate that the linear regression model is not appropriate, and nonlinear regression or other modeling techniques should be considered.

5.Normality of Residuals

In [398…

```
plt.figure(figsize=(8,3))
plt.subplot(121)
sns.histplot(residuals_tr,kde=True)
plt.title("Residuals of Training data")
sns.despine(left=True)
plt.ylabel("")
plt.xlabel("")
plt.yticks([])
plt.subplot(122)
sns.histplot(residuals,kde=True)
plt.title("Residuals of Testing Data")
sns.despine(left=True)
plt.ylabel("")
plt.xlabel("")
plt.yticks([])
plt.show()
```



In [489…

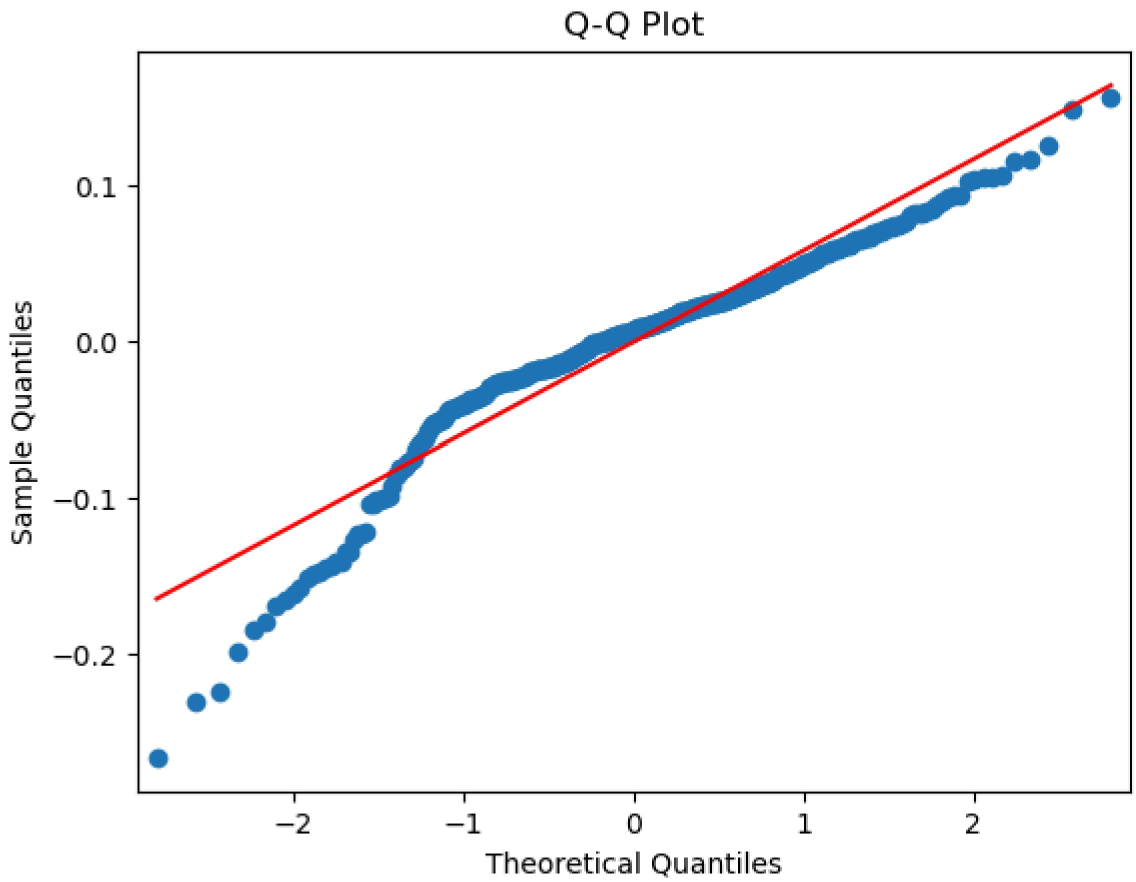
```
from scipy.stats import shapiro
stat,p_value = shapiro(residuals)
print(stat)
```

```
0.9390702247619629
```

High value of statistic indicates that residuals follows a normal distribution.

In [358…

```
# Q-Q Plot
from statsmodels.api import qqplot
qqplot(residuals,line="s")
plt.title("Q-Q Plot")
plt.show()
```



From the above analysis using residual charts, Shapiro-Wilk test and Q-Q plot, we can say that residuals follows a normal ditribution.

Lasso and Ridge Regression

In [355…

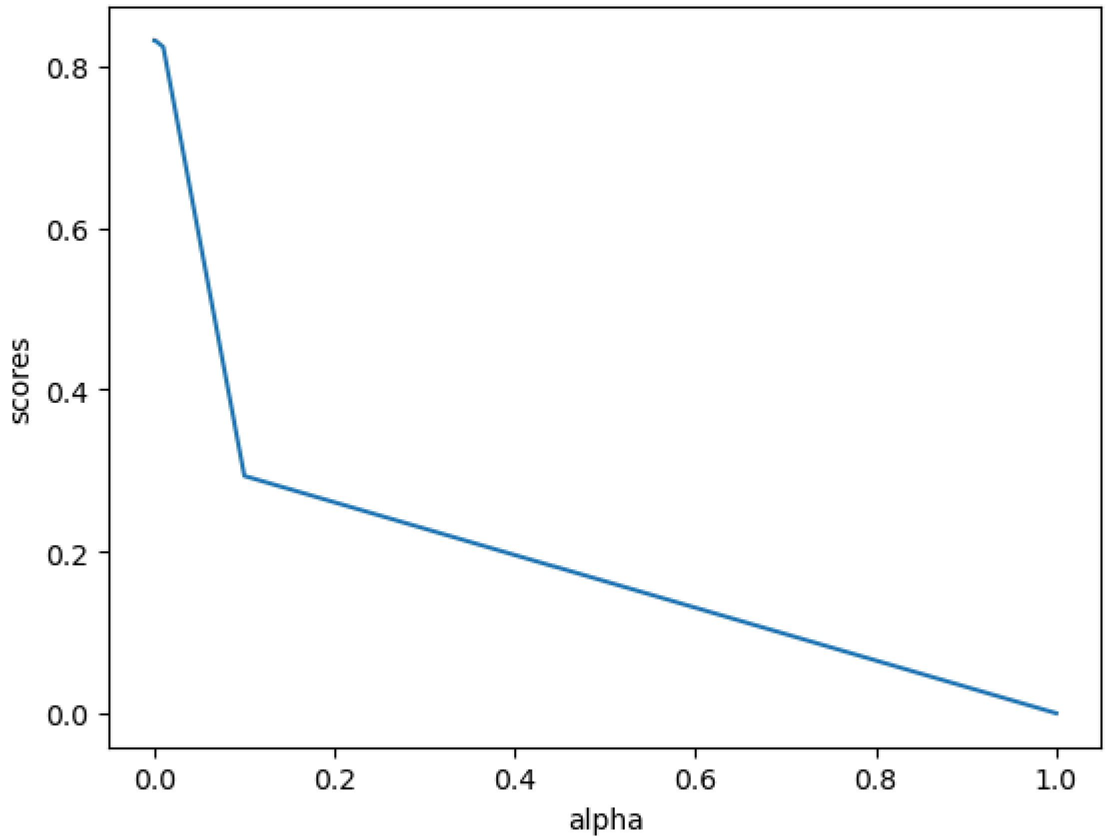
```
from sklearn.linear_model import Lasso,Ridge,ElasticNet
```

In [491…

```
alpha_val=[0.0001,0.001,0.01,0.1,1]
scores=[]
for i in alpha_val:
    mod=Lasso(alpha=i)
    mod.fit(X_train,y_train)
    score=mod.score(X_train,y_train)
    scores.append(score)
temp=pd.DataFrame(zip(alpha_val,scores),columns=["alpha","scores"])
sns.lineplot(data=temp,x="alpha",y="scores")
```

Out[491]:

```
<AxesSubplot:xlabel='alpha', ylabel='scores'>
```



In [493…

```
lasso = Lasso(alpha=0.001)
lasso.fit(X_train,y_train)
print(f"Model Coefficients are: {lasso.coef_}")
print(f"Model Intercept is: {lasso.intercept_}")
```

```
Model Coefficients are: [0.02409582 0.01684178 0.00610947 0.00029603 0.01844849 0.
07023694
 0.01129707]
Model Intercept is: 0.72655
```

In [494…

```
lasso_ytr_pred,lasso_y_pred=model_eval(lasso,X_train,X_test,y_train,y_test)
```

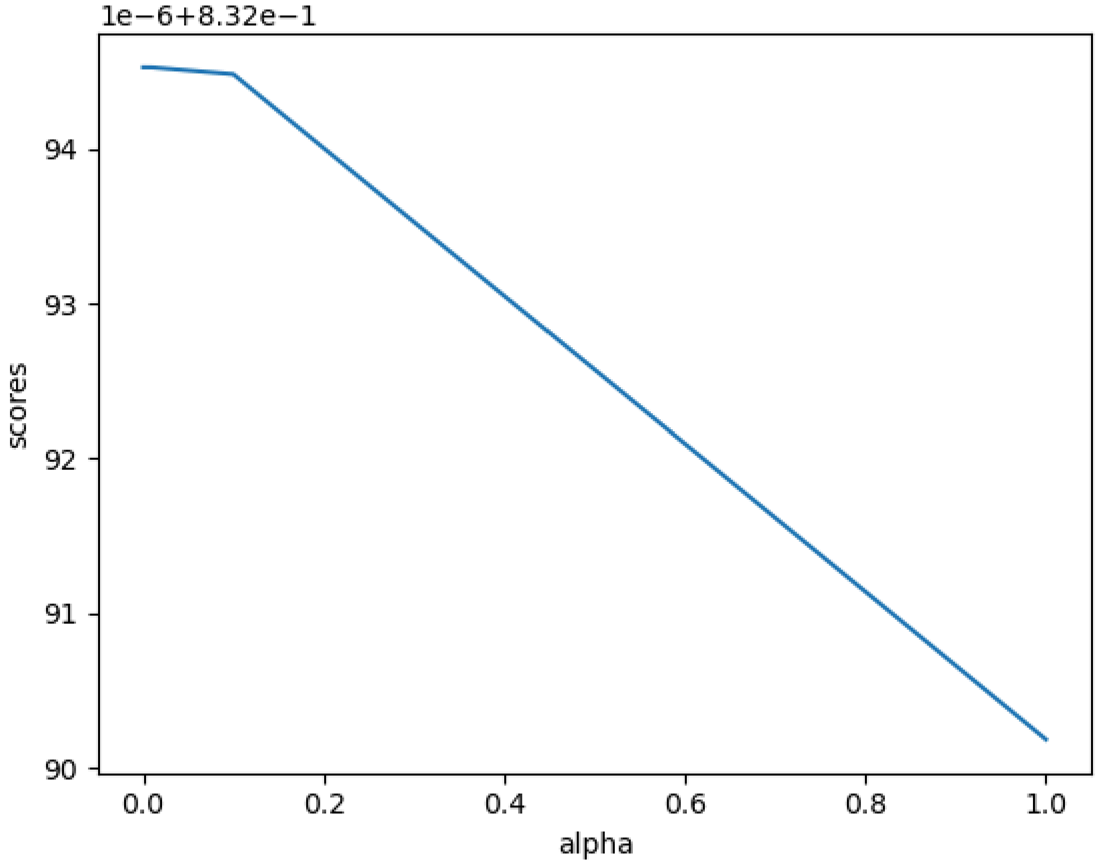
```
Training Set Evaluation:
Mean Absolute Error: 0.0415
Root Mean Squared Error: 0.0585
R2 Score: 0.83
Adjusted R2 Score: 0.83

Testing Set Evaluation:
Mean Absolute Error: 0.0480
Root Mean Squared Error: 0.0637
R2 Score: 0.77
Adjusted R2 Score: 0.75
```

In [495…

```
alpha_val=[0.0001,0.001,0.01,0.1,1]
scores=[]
for i in alpha_val:
    mod=Ridge(alpha=i)
    mod.fit(X_train,y_train)
    score=mod.score(X_train,y_train)
    scores.append(score)
temp=pd.DataFrame(zip(alpha_val,scores),columns=["alpha","scores"])
sns.lineplot(data=temp,x="alpha",y="scores")
```

Out[495]:

```
<AxesSubplot:xlabel='alpha', ylabel='scores'>
```



In [497…

```
temp
```

Out[497]:

	alpha	scores
0	0.0001	0.832095
1	0.0010	0.832095
2	0.0100	0.832095
3	0.1000	0.832094
4	1.0000	0.832090

In [499…

```
ridge = Ridge(alpha=1)
ridge.fit(X_train,y_train)
print(f"Model Coefficients are: {ridge.coef_}")
print(f"Model Intercept is: {ridge.intercept_}")
```

```
Model Coefficients are: [0.0243554  0.01729153 0.00641175 0.00067271 0.01891273 0.
06943147
 0.01188715]
Model Intercept is: 0.72655
```

In [500…

```
ridge_ytr_pred,ridge_y_pred=model_eval(ridge,X_train,X_test,y_train,y_test)
```

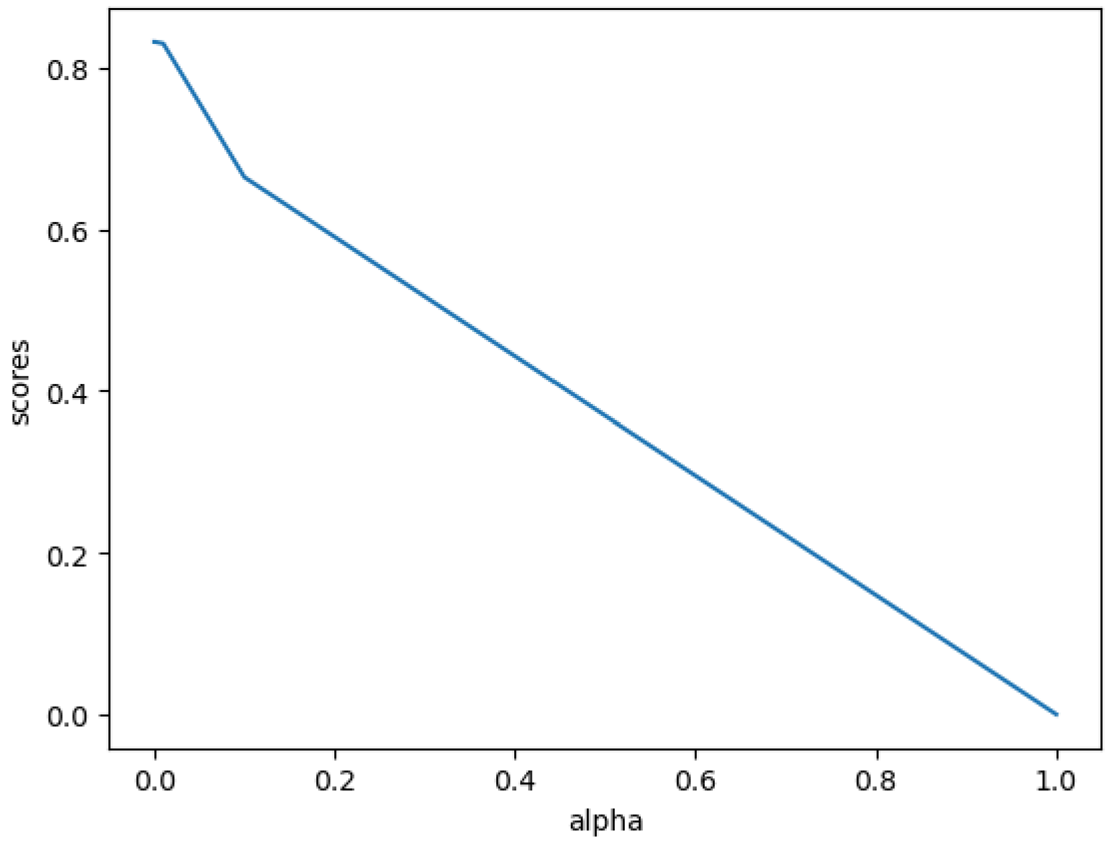
```
Training Set Evaluation:
Mean Absolute Error: 0.0416
Root Mean Squared Error: 0.0585
R2 Score: 0.83
Adjusted R2 Score: 0.83

Testing Set Evaluation:
Mean Absolute Error: 0.0483
Root Mean Squared Error: 0.0639
R2 Score: 0.77
Adjusted R2 Score: 0.75
```

In [334…

```
alpha_val=[0.0001,0.001,0.01,0.1,1]
scores=[]
for i in alpha_val:
    mod=ElasticNet(alpha=i)
    mod.fit(X_train,y_train)
    score=mod.score(X_train,y_train)
    scores.append(score)
temp=pd.DataFrame(zip(alpha_val,scores),columns=["alpha","scores"])
sns.lineplot(data=temp,x="alpha",y="scores")
```

Out[334]:

```
<AxesSubplot:xlabel='alpha', ylabel='scores'>
```



In [505…

```
elasticnet = ElasticNet(alpha=0.01)
elasticnet.fit(X_train , y_train)
elastic_ytr_pred,elastic_y_pred=model_eval(elasticnet,X_train,X_test,y_train,y_test
```

```
Training Set Evaluation:
Mean Absolute Error: 0.0415
Root Mean Squared Error: 0.0588
R2 Score: 0.83
Adjusted R2 Score: 0.83

Testing Set Evaluation:
Mean Absolute Error: 0.0472
Root Mean Squared Error: 0.0631
R2 Score: 0.77
Adjusted R2 Score: 0.75
```

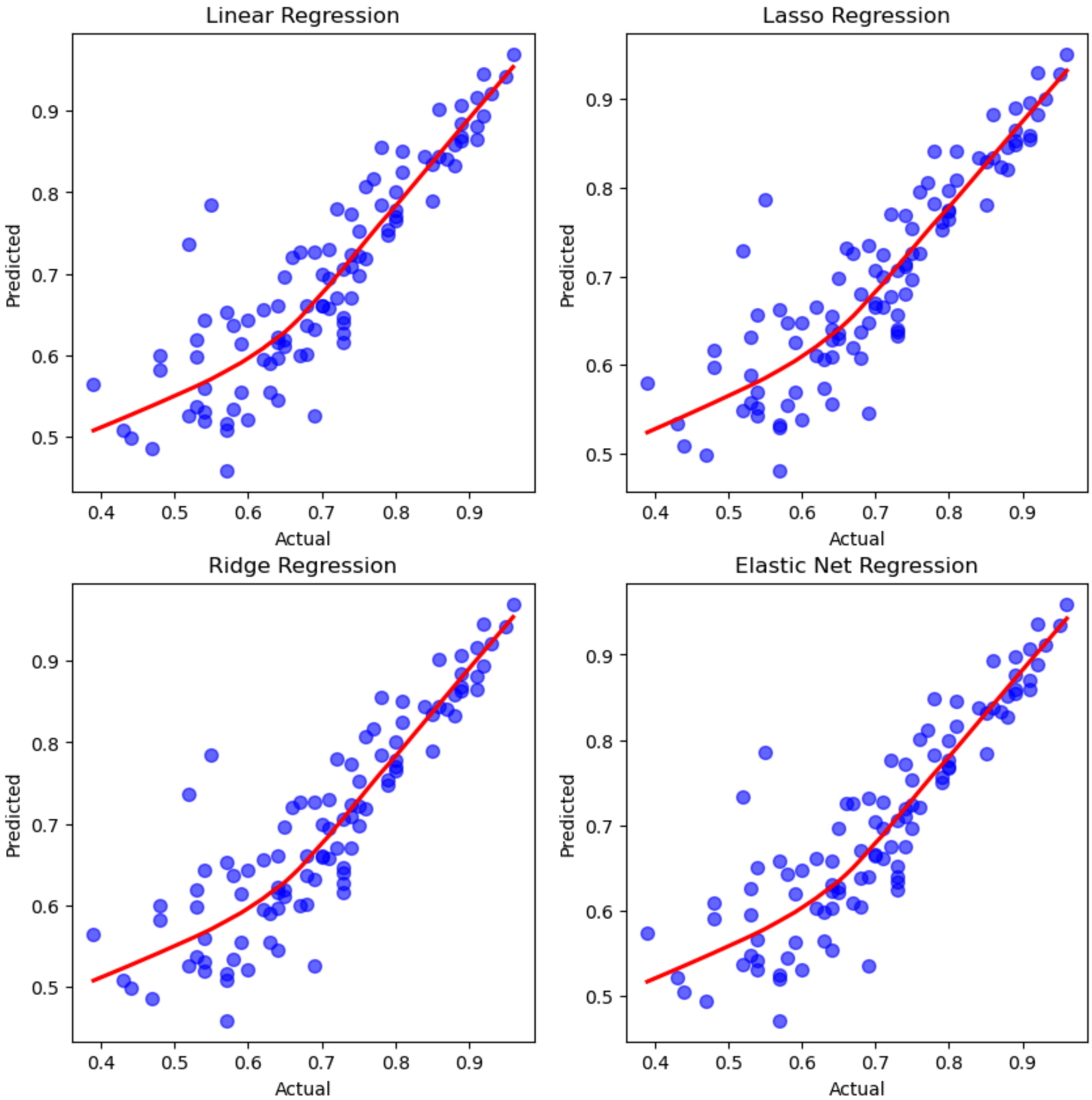
Actual vs Predicted

In [310…

```
fig,axis=plt.subplots(2,2,figsize=(10,10))
sns.regplot(x=y_test, y=y_pred, scatter_kws={'alpha': 0.6, 's': 50, 'color': 'blue'
sns.regplot(x=y_test, y=lasso_y_pred, scatter_kws={'alpha': 0.6, 's': 50, 'color':
sns.regplot(x=y_test, y=ridge_y_pred, scatter_kws={'alpha': 0.6, 's': 50, 'color':
sns.regplot(x=y_test, y=elastic_y_pred, scatter_kws={'alpha': 0.6, 's': 50, 'color'
axis[0,0].set(xlabel="Actual",ylabel="Predicted",title='Linear Regression')
axis[0,1].set(xlabel="Actual",ylabel="Predicted",title="Lasso Regression")
axis[1,0].set(xlabel="Actual",ylabel="Predicted",title="Ridge Regression")
axis[1,1].set(xlabel="Actual",ylabel="Predicted",title="Elastic Net Regression")
```

Out[310]:

```
[Text(0.5, 0, 'Actual'),
 Text(0, 0.5, 'Predicted'),
 Text(0.5, 1.0, 'Elastic Net Regression')]
```



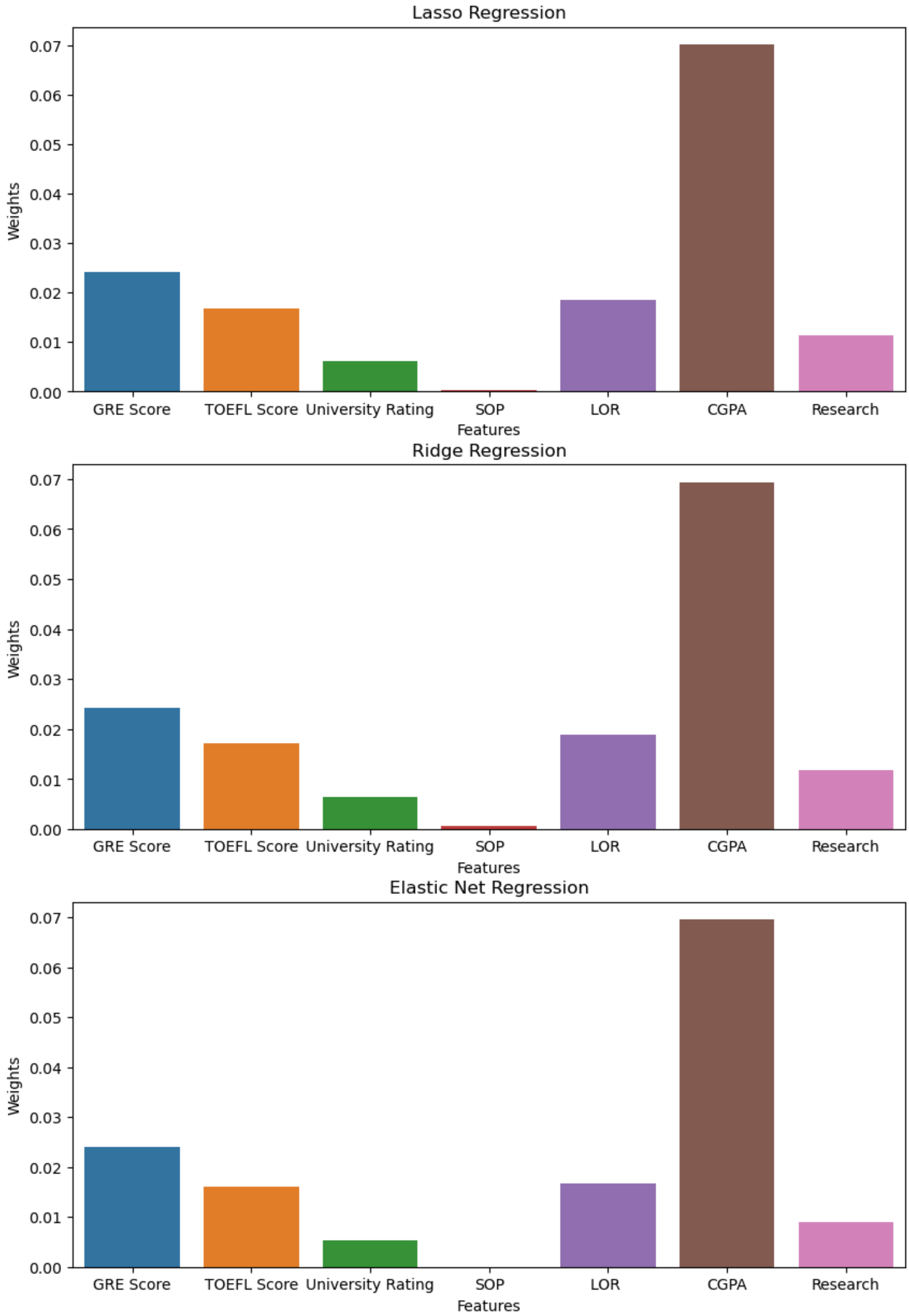
Features vs Weights

In [506…

```
lasso_wts=pd.DataFrame(zip(X_train.columns,lasso.coef_),columns=["Features","Weight
ridge_wts=pd.DataFrame(zip(X_train.columns,ridge.coef_),columns=["Features","Weight
elasticnet_wts=pd.DataFrame(zip(X_train.columns,elasticnet.coef_),columns=["Feature
fig,axis=plt.subplots(3,1,figsize=(10,15))
sns.barplot(data=lasso_wts, x="Features",y="Weights",ax=axis[0])
sns.barplot(data=ridge_wts, x="Features",y="Weights",ax=axis[1])
sns.barplot(data=elasticnet_wts,x="Features",y="Weights",ax=axis[2])
axis[0].set_title("Lasso Regression")
axis[1].set_title("Ridge Regression")
axis[2].set_title("Elastic Net Regression")
```

Out[506]:

```
Text(0.5, 1.0, 'Elastic Net Regression')
```



Insights:

1. According to feature weights, CGPA,TOEFL, GRE scores and LOR are the most important features for the Linear Regression model.
2. CGPA, TOEFL and GRE scores are highly correlated.
3. As per the analysis of assumptions of Linear Regression, features are not multi-collinear.

4. We are getting same accuracy scores in all models: Base Linear Regression,Lasso Regression,Ridge Regression and Elastic Net Regression.

Recommendation:

1. Students should focus on achieving higher GRE, TOEFL, LOR and CGPA scores.As the probability of getting admission increases based on these factors.
2. Since CGPA,TOEFL and GRE scores are highly correlated, more features can be included in the dataset to build a better model for prediction of admission chances
3. Features such as internship experience, hobbies, extra-curricular activities, etc. can be included in the analysis to get the improved version of Linear Regression Model.