Problem statement

To 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.

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

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

	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
...	...	...	...	...	...	...	...	...	...
495	496	332	108	5	4.5	4.0	9.02	1	0.87
496	497	337	117	5	5.0	5.0	9.87	1	0.96
497	498	330	120	5	4.5	5.0	9.56	1	0.93
498	499	312	103	4	4.0	5.0	8.43	0	0.73
499	500	327	113	4	4.5	4.5	9.04	0	0.84

500 rows × 9 columns

```
df.shape
```

```
(500, 9)
```

```
df.info()
```

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

```
df.describe()
```

	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA
count	500.000000	500.000000	500.000000	500.000000	500.000000	500.00000	500.000000
mean	250.500000	316.472000	107.192000	3.114000	3.374000	3.48400	8.576440
std	144.481833	11.295148	6.081868	1.143512	0.991004	0.92545	0.604813
min	1.000000	290.000000	92.000000	1.000000	1.000000	1.00000	6.800000
25%	125.750000	308.000000	103.000000	2.000000	2.500000	3.00000	8.127500
50%	250.500000	317.000000	107.000000	3.000000	3.500000	3.50000	8.560000
75%	375.250000	325.000000	112.000000	4.000000	4.000000	4.00000	9.040000

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

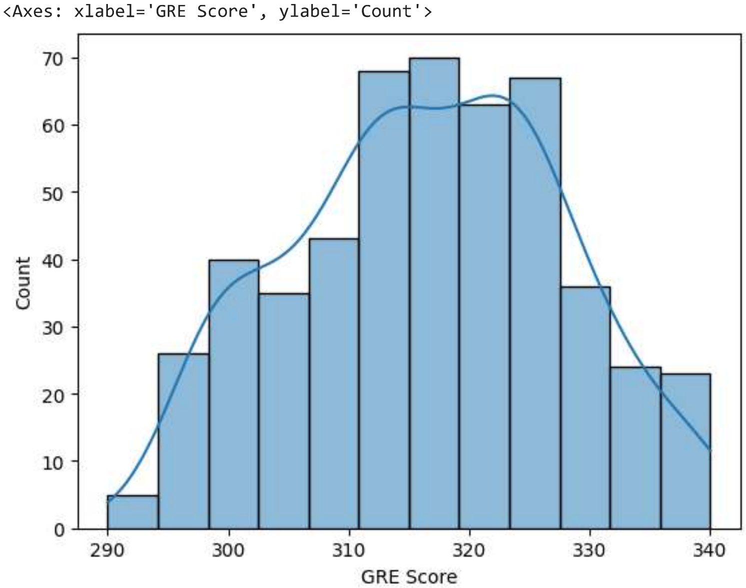
```
Serial No.           0
GRE Score            0
TOEFL Score          0
University Rating    0
SOP                  0
LOR                  0
CGPA                 0
Research             0
Chance of Admit      0
dtype: int64
```

```
cat_cols = ['University Rating', 'SOP', 'LOR ', 'Research']
num_cols = ['GRE Score', 'TOEFL Score', 'CGPA']
target = 'Chance of Admit '
```

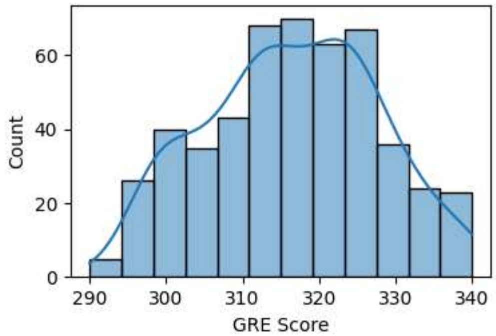
Univariate Analysis

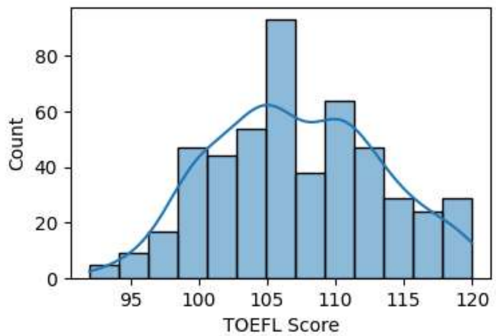
```
sns.histplot(df['GRE Score'], kde = True)
```

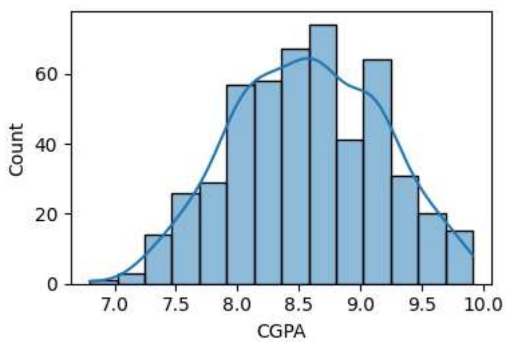
```
<Axes: xlabel='GRE Score', ylabel='Count'>
```




```
fig, axs = plt.subplots(len(num_cols), 1, figsize=(4, 8))

for i, col in enumerate(num_cols):
    sns.histplot(data=df[col], kde=True, ax=axs[i])

plt.tight_layout()
plt.show()
```



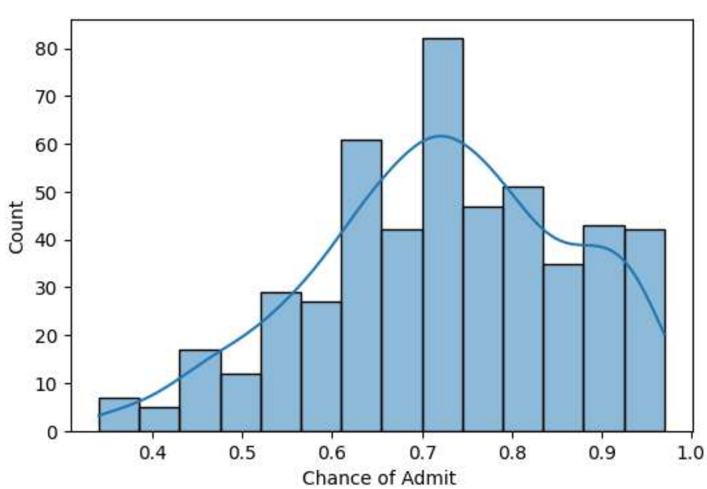





```
df.columns
```

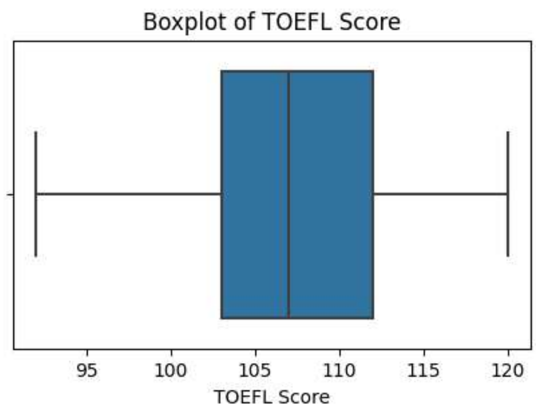
```
Index(['Serial No.', 'GRE Score', 'TOEFL Score', 'University Rating', 'SOP',
       'LOR ', 'CGPA', 'Research', 'Chance of Admit '],
      dtype='object')
```

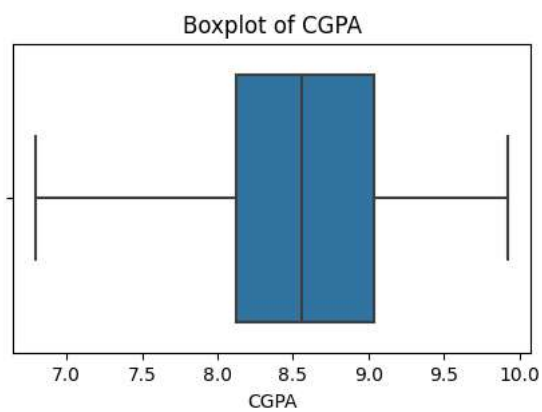
```
plt.figure(figsize = (6, 4))
sns.histplot(df[target], kde=True,)
plt.show()
```

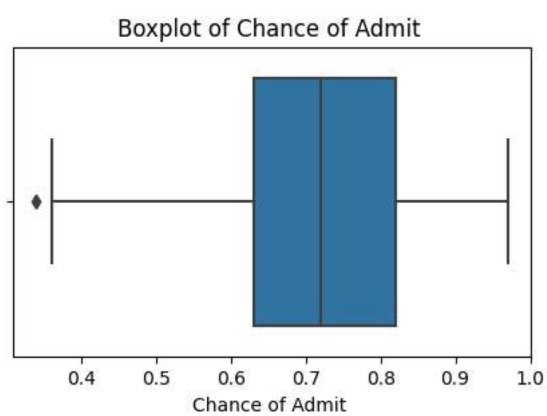


```
# check for outliers using boxplots
plt.figure(figsize=(5, 3))

for col in num_cols + [target]:
    plt.figure(figsize = (5, 3))
    sns.boxplot(x=df[col])
    plt.title(f'Boxplot of {col}')
    plt.show()
```

```
<Figure size 500x300 with 0 Axes>
```





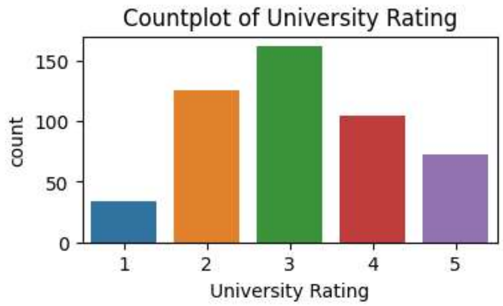


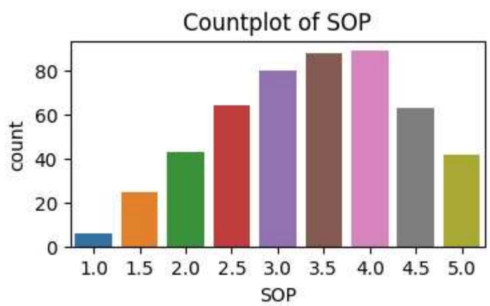
we can see that there are no outliers present

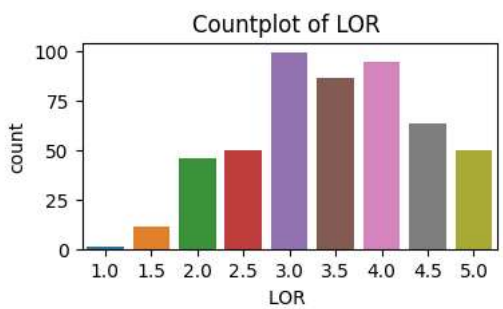
Countplot for categorical variables

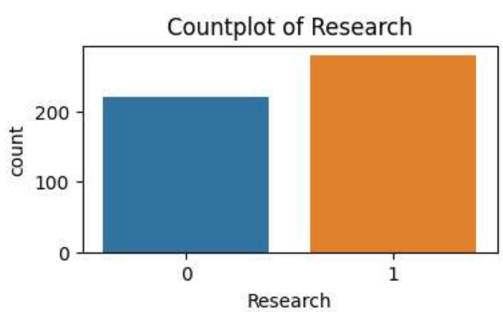
```
plt.figure(figsize = (6, 4))

for i in cat_cols:
  plt.figure(figsize=(4, 2))
  sns.countplot(x = df[i])
  plt.title(f'Countplot of {i}')
  plt.show()
```

```
<Figure size 600x400 with 0 Axes>
```







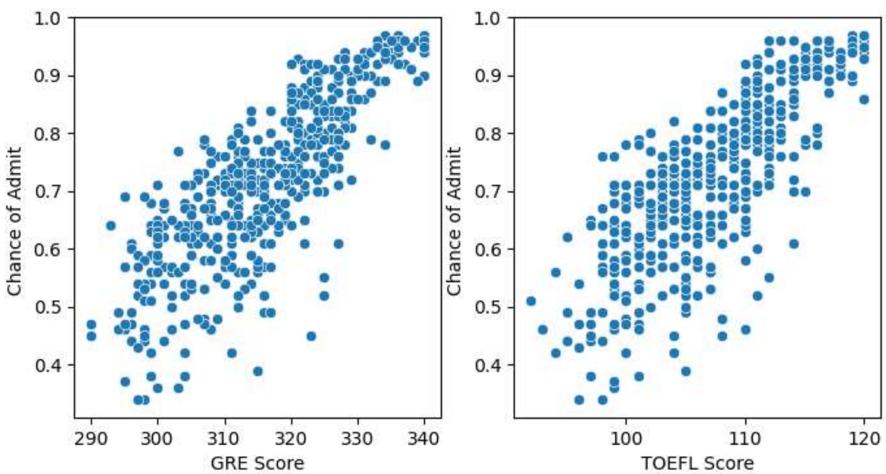


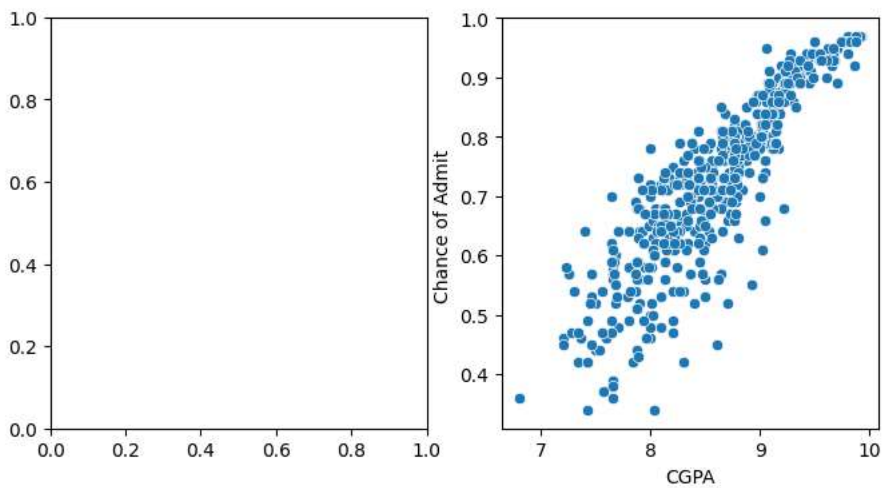

```
df.head()
```

	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
0	1	337	118	4	4.5	4.5	9.65	1	0.92
1	2	324	107	4	4.0	4.5	8.87	1	0.76

Bivariate analysis

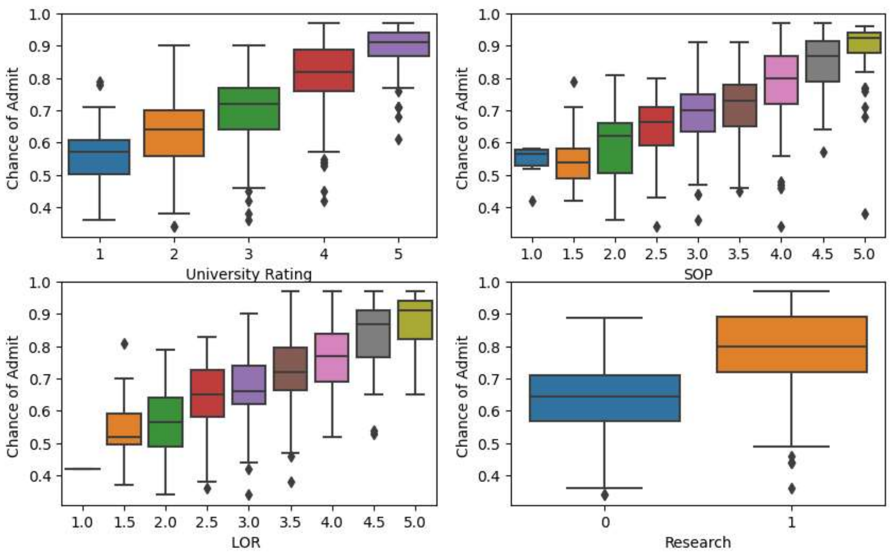
```
# check relation bw continuous variables & target variable

fig, axs = plt.subplots(1, 2, figsize = (8, 4))

sns.scatterplot(x = num_cols[0], y = target, data = df, ax = axs[0])
sns.scatterplot(x = num_cols[1], y = target, data = df, ax = axs[1])
plt.show()
fig, axs = plt.subplots(1, 2, figsize = (8, 4))
sns.scatterplot(x = num_cols[2], y = target, data = df)
plt.show()
```





Seems like there is a linear correlation between the continuous variables and the target variable.

```
rows, cols = 2,2
fig, axs = plt.subplots(rows, cols, figsize=(10,6))

index = 0
for row in range(rows):
    for col in range(cols):
        sns.boxplot(x=cat_cols[index], y=target, data=df, ax=axs[row,col])
        index += 1
```

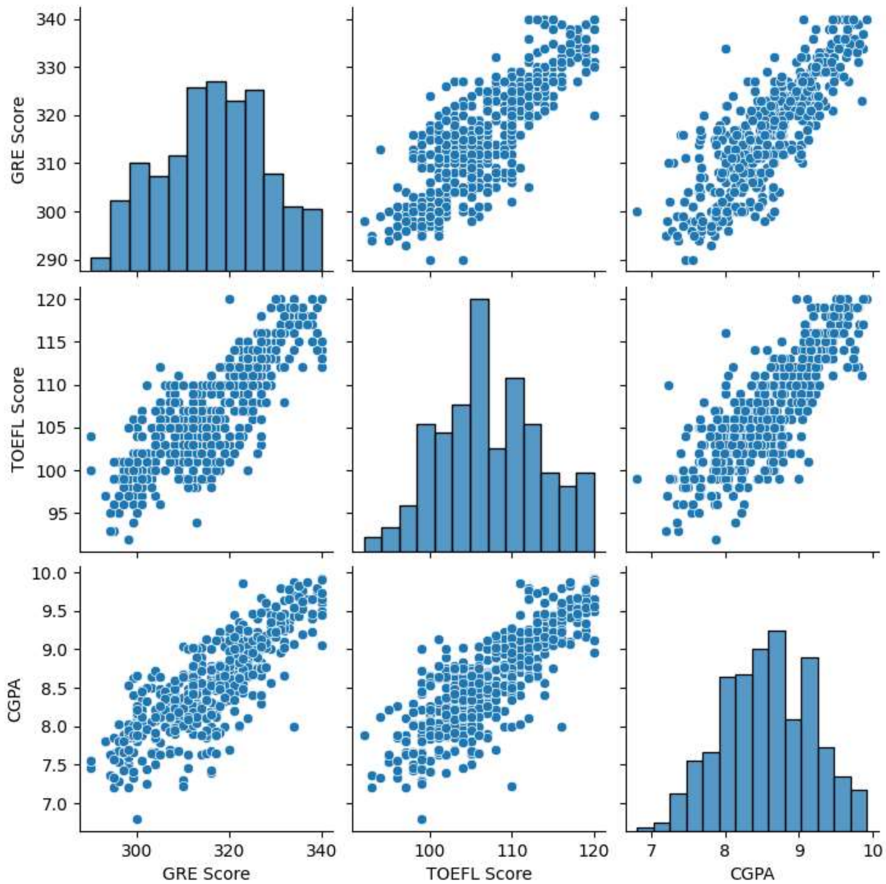


As you can see from the graphs, as the rating increases the Chance of Admit also increases.

Students who have the research experience have more chances of Admin as compared to other students who don't have the research experience.

Multivariate analysis

```
sns.pairplot(df[num_cols])
plt.show()
```

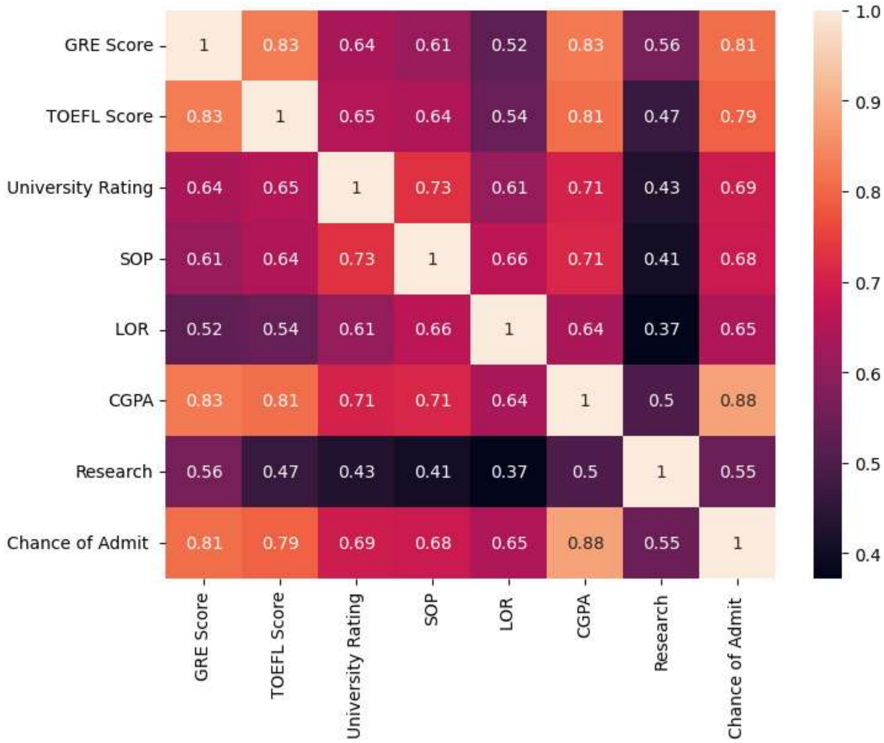


Independent continuous variables are also correlated with each other.

```
df.corr()
```

	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Rese
Serial No.	1.000000	-0.103839	-0.141696	-0.067641	-0.137352	-0.003694	-0.074289	-0.00
GRE Score	-0.103839	1.000000	0.827200	0.635376	0.613498	0.524679	0.825878	0.56
TOEFL Score	-0.141696	0.827200	1.000000	0.649799	0.644410	0.541563	0.810574	0.46
University Rating	-0.067641	0.635376	0.649799	1.000000	0.728024	0.608651	0.705254	0.42
SOP	-0.137352	0.613498	0.644410	0.728024	1.000000	0.663707	0.712154	0.40
LOR	-0.003694	0.524679	0.541563	0.608651	0.663707	1.000000	0.637469	0.37

```
plt.figure(figsize = (8, 6))
sns.heatmap(df.corr(), annot = True)
plt.show()
```



Data Preprocessing

```
# drop serial no column
df = df.drop(columns = ['Serial No.'], axis = 1)
```

```
# check for duplicates
df.duplicated().sum()
```

```
0
```

```
df.head(3)
```

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
0	337	118	4	4.5	4.5	9.65	1	0.92
1	324	107	4	4.0	4.5	8.87	1	0.76
2	316	104	3	3.0	3.5	8.00	1	0.72

There are no missing values, outliers and duplicates present in the dataset.

Data preparation for model building

```
X = df.drop(columns = [target])
y = df[target]
```

```
X.head(3)
```

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research
0	337	118	4	4.5	4.5	9.65	1
1	324	107	4	4.0	4.5	8.87	1
2	316	104	3	3.0	3.5	8.00	1

```
y.head()
```

```
0    0.92
1    0.76
```

```
2    0.72
3    0.80
4    0.65
Name: Chance of Admit , dtype: float64
```

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
```

```
# standardize the dataset
scaler = StandardScaler()
X = scaler.fit_transform(X)
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_state = 1)
```

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

```
(350, 7) (350,)
(150, 7) (150,)
```

Model Building

```
from sklearn.linear_model import LinearRegression, Lasso, Ridge
from sklearn.metrics import r2_score
```

```
def adjusted_r2(r2, p, n):
    """
    n: no of samples
    p: no of predictors
    r2: r2 score
    """
    adj_r2 = 1 - ((1-r2)*(n-1) / (n-p-1))
    return adj_r2

def get_metrics(y_true, y_pred, p=None):
    n = y_true.shape[0]
    mse = np.sum((y_true - y_pred)**2) / n
    rmse = np.sqrt(mse)
    mae = np.mean(np.abs(y_true - y_pred))
    score = r2_score(y_true, y_pred)
    adj_r2 = None
    if p is not None:
        adj_r2 = adjusted_r2(score, p, n)

    res = {
        "mean_absolute_error": round(mae, 2),
        "rmse": round(rmse, 2),
        "r2_score": round(score, 2),
        "adj_r2": round(adj_r2, 2)
    }
    return res
```

```
def train_model(X_train, y_train, X_test, y_test,cols, model_name="linear", alpha=1.0):
    model = None
    if model_name == "lasso":
        model = Lasso(alpha=alpha)
    elif model_name == "ridge":
        model = Ridge(alpha=alpha)
    else:
        model = LinearRegression()

    model.fit(X_train, y_train)
    y_pred_train = model.predict(X_train)
    y_pred_test = model.predict(X_test)
    p = X_train.shape[1]
    train_res = get_metrics(y_train, y_pred_train, p)
    test_res = get_metrics(y_test, y_pred_test, p)

    print(f"\n----   {model_name.title()} Regression Model  ----\n")
    print(f"Train MAE: {train_res['mean_absolute_error']} Test MAE: {test_res['mean_absolute_error']}")
    print(f"Train RMSE: {train_res['rmse']} Test RMSE: {test_res['rmse']}")
    print(f"Train R2_score: {train_res['r2_score']} Test R2_score: {test_res['r2_score']}")
    print(f"Train Adjusted_R2: {train_res['adj_r2']} Test Adjusted_R2: {test_res['adj_r2']}")
    print(f"Intercept: {model.intercept_}")
    #print(len(df.columns), len(model.coef_))
    coef_df = pd.DataFrame({"Column": cols, "Coef": model.coef_})
    print(coef_df)
    print("-"*50)
    return model
```

```
train_model(X_train, y_train, X_test, y_test,df.columns[:-1], "linear")
train_model(X_train, y_train, X_test, y_test,df.columns[:-1], "ridge")
train_model(X_train, y_train, X_test, y_test,df.columns[:-1], "lasso", 0.001)
```

```
----   Linear Regression Model  ----

Train MAE: 0.04 Test MAE: 0.04
Train RMSE: 0.06 Test RMSE: 0.06
Train R2_score: 0.82 Test R2_score: 0.82
Train Adjusted_R2: 0.82 Test Adjusted_R2: 0.81
Intercept: 0.724978121476996
              Column      Coef
0          GRE Score  0.018657
1        TOEFL Score  0.023176
2  University Rating  0.011565
3                SOP -0.000999
4               LOR   0.012497
5               CGPA  0.064671
6           Research  0.013968
--------------------------------------------------

----   Ridge Regression Model  ----

Train MAE: 0.04 Test MAE: 0.04
Train RMSE: 0.06 Test RMSE: 0.06
Train R2_score: 0.82 Test R2_score: 0.82
Train Adjusted_R2: 0.82 Test Adjusted_R2: 0.81
Intercept: 0.7249823645841696
              Column      Coef
0          GRE Score  0.018902
1        TOEFL Score  0.023252
2  University Rating  0.011594
3                SOP -0.000798
4               LOR   0.012539
5               CGPA  0.064004
6           Research  0.013990
--------------------------------------------------

----   Lasso Regression Model  ----

Train MAE: 0.04 Test MAE: 0.04
Train RMSE: 0.06 Test RMSE: 0.06
Train R2_score: 0.82 Test R2_score: 0.82
Train Adjusted_R2: 0.82 Test Adjusted_R2: 0.81
Intercept: 0.7249659139557142
              Column      Coef
0          GRE Score  0.018671
1        TOEFL Score  0.022770
2  University Rating  0.010909
3                SOP  0.000000
4               LOR   0.011752
5               CGPA  0.064483
6           Research  0.013401
--------------------------------------------------
▾      Lasso
Lasso(alpha=0.001)
```

```
Lasso(alpha=0.001)
```

```
▾      Lasso
Lasso(alpha=0.001)
```

Since model is not overfitting, Results for Linear, Ridge and Lasso are the same. R2_score and Adjusted_r2 are almost the same. Hence there are no unnecessary independent variables in the data.

Linear Regression Model - Assumption Test

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

```
# Mutlicollinearity Check
def vif(newdf):
    # VIF dataframe
    vif_data = pd.DataFrame()
    vif_data["feature"] = newdf.columns

    # calculating VIF for each feature
    vif_data["VIF"] = [variance_inflation_factor(newdf.values, i)
                          for i in range(len(newdf.columns))]
    return vif_data


res = vif(df.iloc[:,:-1])
res
```

	feature	VIF
0	GRE Score	1308.061089
1	TOEFL Score	1215.951898
2	University Rating	20.933361
3	SOP	35.265006
4	LOR	30.911476
5	CGPA	950.817985
6	Research	2.869493

```
# droping GRE Score and again calculate the VIF
res = vif(df.iloc[:, 1:-1])
res
```

	feature	VIF
0	TOEFL Score	639.741892
1	University Rating	19.884298
2	SOP	33.733613
3	LOR	30.631503
4	CGPA	728.778312
5	Research	2.863301

```
# # droping TOEFL Score and again calculate the VIF
res = vif(df.iloc[:,2:-1])
res
```

	feature	VIF
0	University Rating	19.777410
1	SOP	33.625178
2	LOR	30.356252
3	CGPA	25.101796
4	Research	2.842227

```
# droping the SOP and again calculate VIF
res = vif(df.iloc[:,2:-1].drop(columns=['SOP']))
res
```

	feature	VIF
0	University Rating	15.140770
1	LOR	26.918495
2	CGPA	22.369655
3	Research	2.819171

```
# droping the LOR as well
newdf = df.iloc[:,2:-1].drop(columns=['SOP'])
newdf = newdf.drop(columns=['LOR '], axis=1)
res = vif(newdf)
res
```

	feature	VIF
0	University Rating	12.498400
1	CGPA	11.040746
2	Research	2.783179

```
# droping the University Rating
newdf = newdf.drop(columns=['University Rating'])
res = vif(newdf)
res
```

	feature	VIF
0	CGPA	2.455008
1	Research	2.455008

```
# now again train the model with these only two features
X = df[['CGPA', 'Research']]
sc = StandardScaler()
X = sc.fit_transform(X)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=1)


model = train_model(X_train, y_train, X_test, y_test, ['CGPA', 'Research'], "linear")
train_model(X_train, y_train, X_test, y_test, ['CGPA', 'Research'], "ridge")
train_model(X_train, y_train, X_test, y_test, ['CGPA', 'Research'], "lasso", 0.001)
```

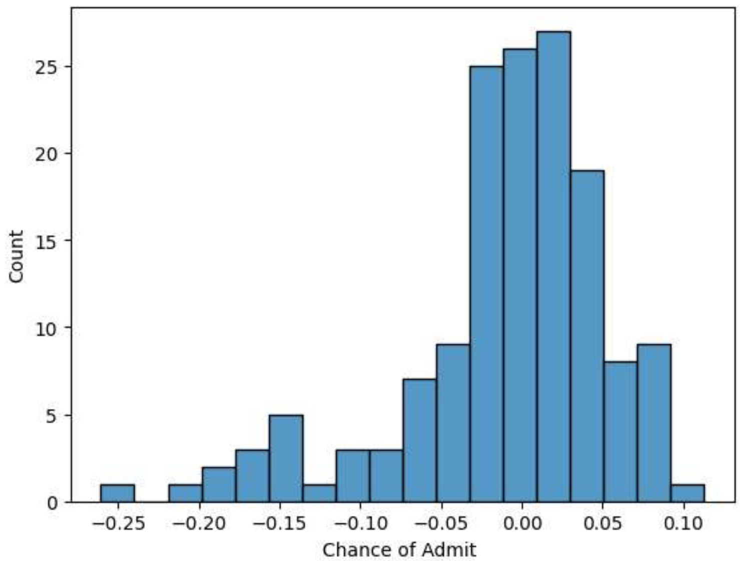
```
----   Linear Regression Model  ----

Train MAE: 0.05 Test MAE: 0.05
Train RMSE: 0.06 Test RMSE: 0.07
Train R2_score: 0.78 Test R2_score: 0.81
Train Adjusted_R2: 0.78 Test Adjusted_R2: 0.81
Intercept: 0.7247774222727991
     Column      Coef
0      CGPA  0.112050
1  Research  0.020205
--------------------------------------------------

----   Ridge Regression Model  ----

Train MAE: 0.05 Test MAE: 0.05
Train RMSE: 0.06 Test RMSE: 0.07
Train R2_score: 0.78 Test R2_score: 0.81
Train Adjusted_R2: 0.78 Test Adjusted_R2: 0.81
Intercept: 0.7247830300095277
     Column      Coef
0      CGPA  0.111630
1  Research  0.020362
--------------------------------------------------

----   Lasso Regression Model  ----

Train MAE: 0.05 Test MAE: 0.05
Train RMSE: 0.06 Test RMSE: 0.07
Train R2_score: 0.78 Test R2_score: 0.81
Train Adjusted_R2: 0.78 Test Adjusted_R2: 0.81
Intercept: 0.7247713356661623
     Column      Coef
0      CGPA  0.111344
1  Research  0.019571
--------------------------------------------------
▾     Lasso
Lasso(alpha=0.001)
```

After removing collinear features using VIF and using only two features. R2_score and Adjusted_r2 are still the same as before the testing dataset.

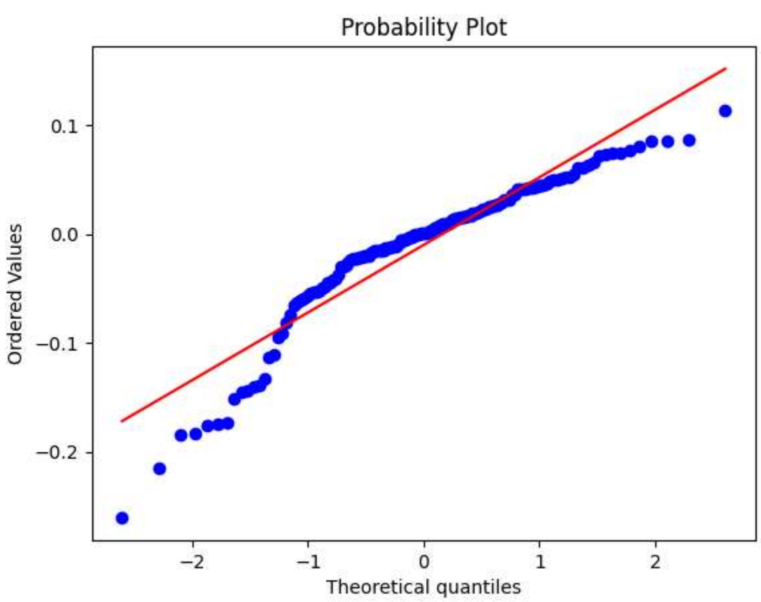
Mean of Residuals It is clear from RMSE that Mean of Residuals is almost zero.

Linearity of variables It is quite clear from EDA that independent variables are linearly dependent on the target variables.

```
# Normality of Residuals
y_pred = model.predict(X_test)
residuals = (y_test - y_pred)
sns.histplot(residuals)
plt.show()
```

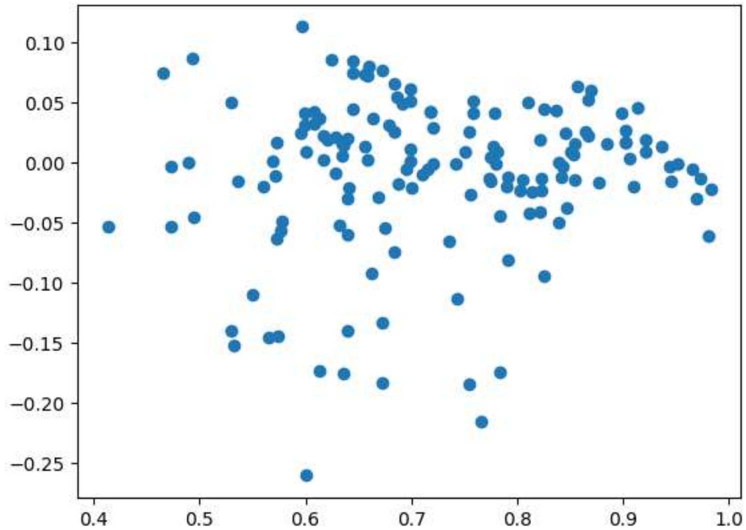



```
stats.probplot(residuals, plot=plt)
plt.show()
```



Test for Homoscedasticity

```
plt.scatter(y_pred, residuals)
plt.show()
```



Since the plot is not creating a cone type shape. Hence there is no homoscedasticity present in the data.

Insights Multicollinearity is present in the data.

After removing collinear features there are only two variables which are important in making predictions for the target variables.

Indepedent variables are linearly correlated with dependent variables.

Recommendations CGPA and Research are the only two variables which are important in making the prediction for Chance of Admit.

CGPA is the most important varibale in making the prediction for the Chance of Admit.

Following are the final model results on the test data:

RMSE: 0.07

MAE: 0.05

R2_score: 0.81

Adjusted_R2: 0.81