Jamboree_2

February 18, 2025

[1]:
```
!gdown https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/839/
↪original/Jamboree_Admission.csv
```

```
Downloading…
From: https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/839/ori
ginal/Jamboree_Admission.csv
To: /content/Jamboree_Admission.csv
   0% 0.00/16.2k [00:00<?, ?B/s] 100% 16.2k/16.2k [00:00<00:00, 49.5MB/s]
```

[2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

[3]:
```
df_main = pd.read_csv('/content/Jamboree_Admission.csv')
```

[4]:
```
df_main.head()
```

[4]:
```
   Serial No.  GRE Score  TOEFL Score  University Rating  SOP  LOR   CGPA  \
0           1        337          118                  4  4.5   4.5  9.65
1           2        324          107                  4  4.0   4.5  8.87
2           3        316          104                  3  3.0   3.5  8.00
3           4        322          110                  3  3.5   2.5  8.67
4           5        314          103                  2  2.0   3.0  8.21

   Research  Chance of Admit
0         1              0.92
1         1              0.76
2         1              0.72
3         1              0.80
4         0              0.65
```

[5]:
```
df_main.describe()
```

[5]:
```
       Serial No.   GRE Score  TOEFL Score  University Rating         SOP  \
count  500.000000  500.000000   500.000000         500.000000  500.000000
mean   250.500000  316.472000   107.192000           3.114000    3.374000
std    144.481833   11.295148     6.081868           1.143512    0.991004
min      1.000000  290.000000    92.000000           1.000000    1.000000
```

```
25%    125.750000  308.000000   103.000000          2.000000    2.500000
50%    250.500000  317.000000   107.000000          3.000000    3.500000
75%    375.250000  325.000000   112.000000          4.000000    4.000000
max    500.000000  340.000000   120.000000          5.000000    5.000000

             LOR        CGPA    Research  Chance of Admit
count  500.00000  500.000000  500.000000        500.00000
mean     3.48400    8.576440    0.560000          0.72174
std      0.92545    0.604813    0.496884          0.14114
min      1.00000    6.800000    0.000000          0.34000
25%      3.00000    8.127500    0.000000          0.63000
50%      3.50000    8.560000    1.000000          0.72000
75%      4.00000    9.040000    1.000000          0.82000
max      5.00000    9.920000    1.000000          0.97000
```

[6]:

```
df_main.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
```

[7]:

```
df_main.isna().sum()
```

[7]:

```
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
```

[8]:
```
def analyze_statistics(df):
    for column in df.select_dtypes(include=['float64', 'int64']):
        stats = df[column].describe()
        print(f"\nStatistical Analysis for {column}:")
        print(f"Skewness: {df[column].skew():.2f}")
        print(f"Kurtosis: {df[column].kurtosis():.2f}")
        print(f"Range: {stats['max'] - stats['min']:.2f}")

analyze_statistics(df_main)
```

```
Statistical Analysis for Serial No.:
Skewness: 0.00
Kurtosis: -1.20
Range: 499.00

Statistical Analysis for GRE Score:
Skewness: -0.04
Kurtosis: -0.71
Range: 50.00

Statistical Analysis for TOEFL Score:
Skewness: 0.10
Kurtosis: -0.65
Range: 28.00

Statistical Analysis for University Rating:
Skewness: 0.09
Kurtosis: -0.81
Range: 4.00

Statistical Analysis for SOP:
Skewness: -0.23
Kurtosis: -0.71
Range: 4.00

Statistical Analysis for LOR :
Skewness: -0.15
Kurtosis: -0.75
Range: 4.00

Statistical Analysis for CGPA:
Skewness: -0.03
Kurtosis: -0.56
Range: 3.12

Statistical Analysis for Research:
```

```
Skewness: -0.24
Kurtosis: -1.95
Range: 1.00

Statistical Analysis for Chance of Admit :
Skewness: -0.29
Kurtosis: -0.45
Range: 0.63
```

[9]:
```
# Checking for duplicate values
duplicates = df_main.duplicated().sum()
duplicates
```

[9]:
```
0
```

[10]:
```
def detect_outliers(df, columns):
    outliers = {}
    for col in columns:
        Q1 = df[col].quantile(0.25)
        Q3 = df[col].quantile(0.75)
        IQR = Q3 - Q1
        lower_bound = Q1 - 1.5 * IQR
        upper_bound = Q3 + 1.5 * IQR
        outliers[col] = df[(df[col] < lower_bound) | (df[col] > upper_bound)].
 ↪shape[0]
    return outliers

detect_outliers(df_main, df_main.select_dtypes(include=['float64', 'int64']).
 ↪columns)
```

[10]:
```
{'Serial No.': 0,
 'GRE Score': 0,
 'TOEFL Score': 0,
 'University Rating': 0,
 'SOP': 0,
 'LOR ': 1,
 'CGPA': 0,
 'Research': 0,
 'Chance of Admit ': 2}
```

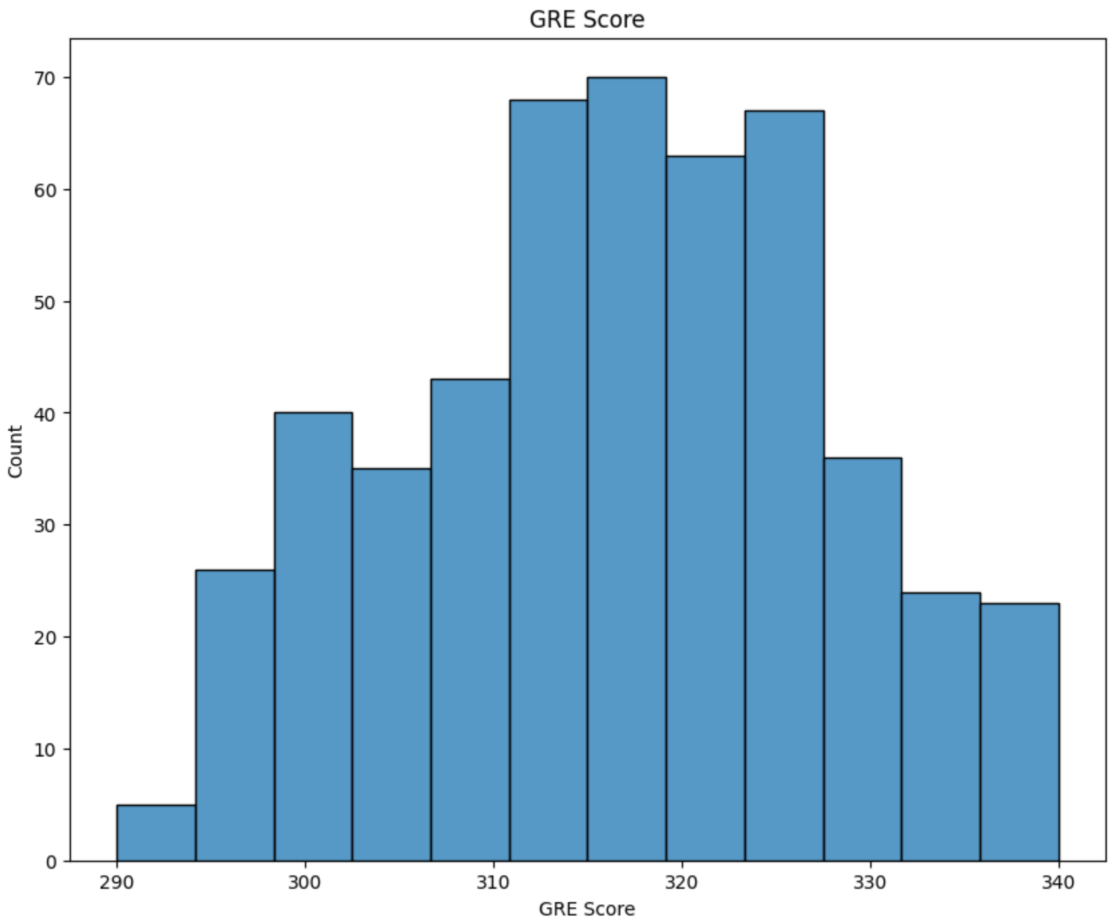
[11]:
```
df_main.drop(columns=['Serial No.'],axis=1, inplace=True)
```

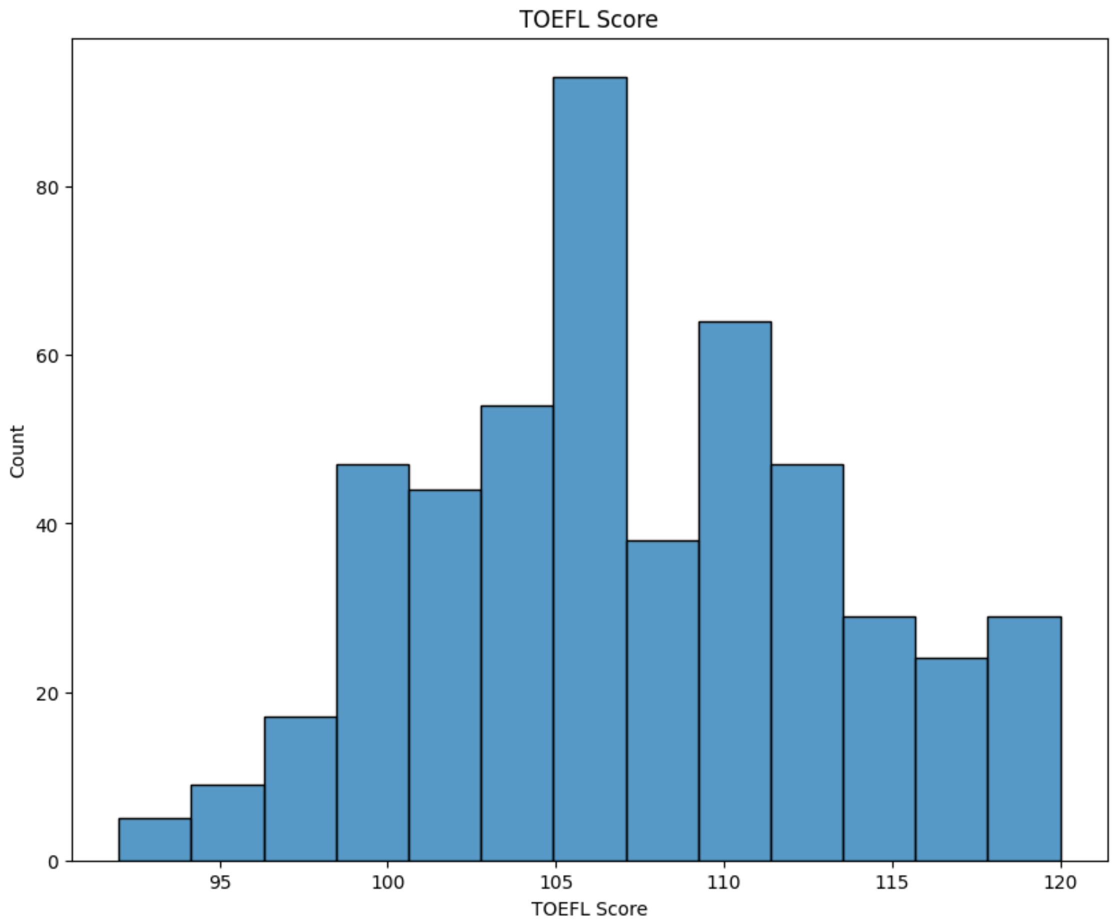
[12]:
```
df_main.head()
```

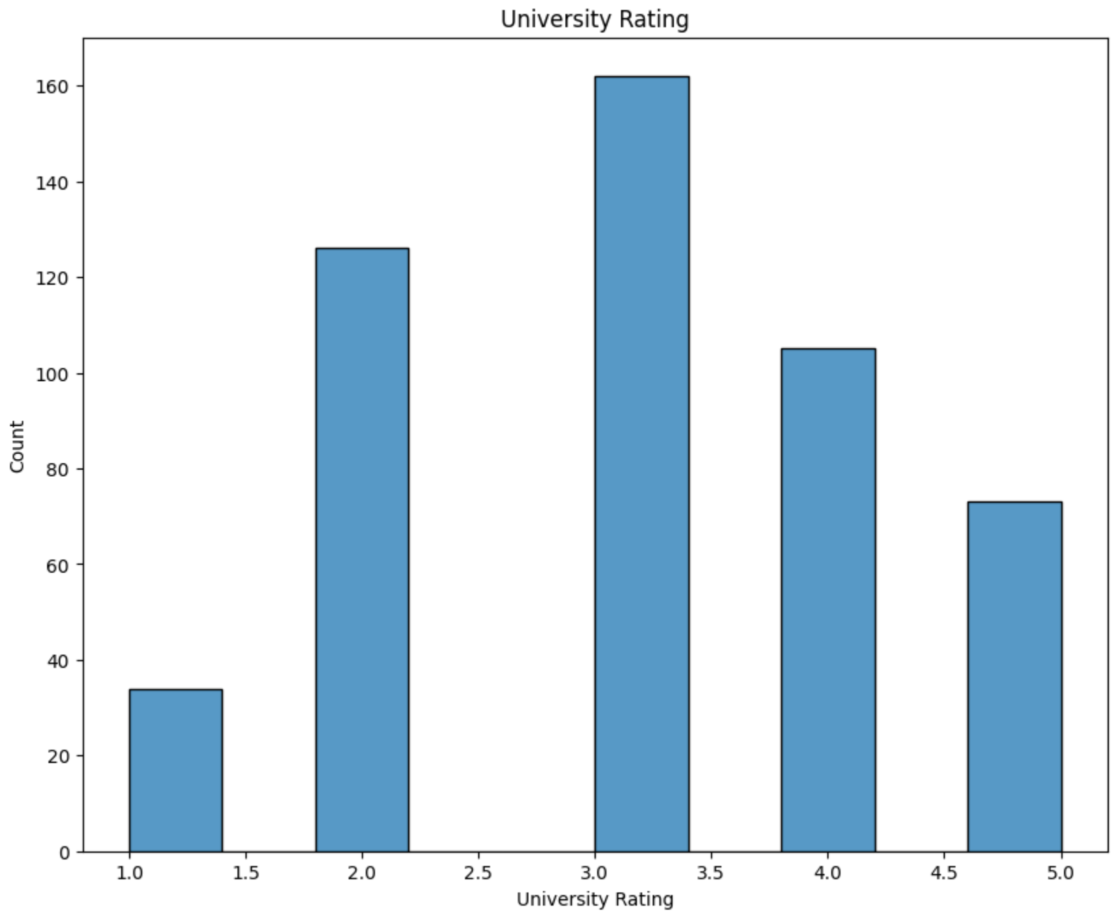
[12]:
```
   GRE Score  TOEFL Score  University Rating  SOP  LOR   CGPA  Research  \
0        337          118                  4  4.5   4.5  9.65         1
1        324          107                  4  4.0   4.5  8.87         1
```

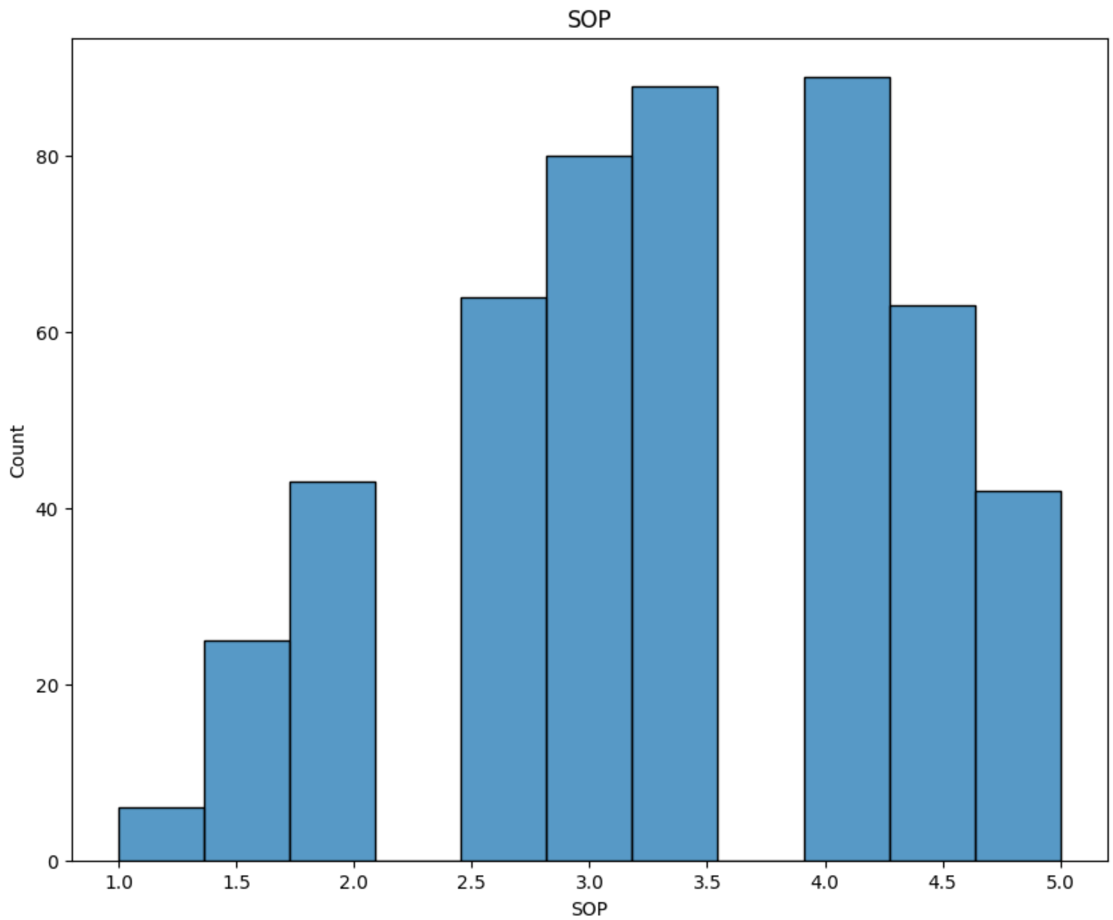
```
2        316          104                   3  3.0   3.5  8.00          1
3        322          110                   3  3.5   2.5  8.67          1
4        314          103                   2  2.0   3.0  8.21          0

   Chance of Admit
0             0.92
1             0.76
2             0.72
3             0.80
4             0.65
```

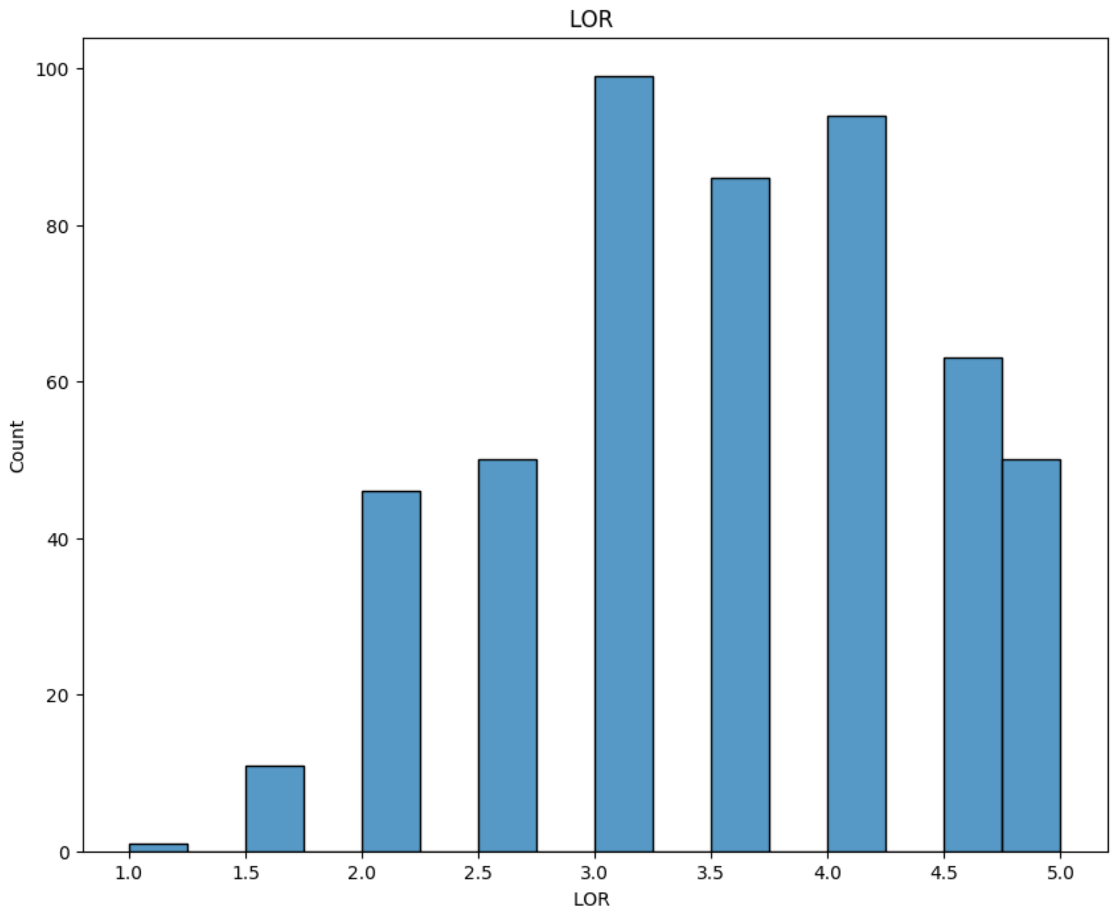
[13]:
```
import seaborn as sns
def check_distribution(col):
  plt.figure(figsize=(10,8))
  plt.title(col)
  if col == 'Research':
      data = df_main[col].value_counts()
      labels = data.index.map({1: "Yes", 0: "No"})
      plt.pie(data, labels=labels, autopct='%1.1f%%', startangle=90,␣
 ↪colors=['lightblue', 'lightcoral'])
  else:
    sns.histplot(data = df_main, x=col)


for col in df_main.iloc[:,:-1].columns:
  check_distribution(col)
```

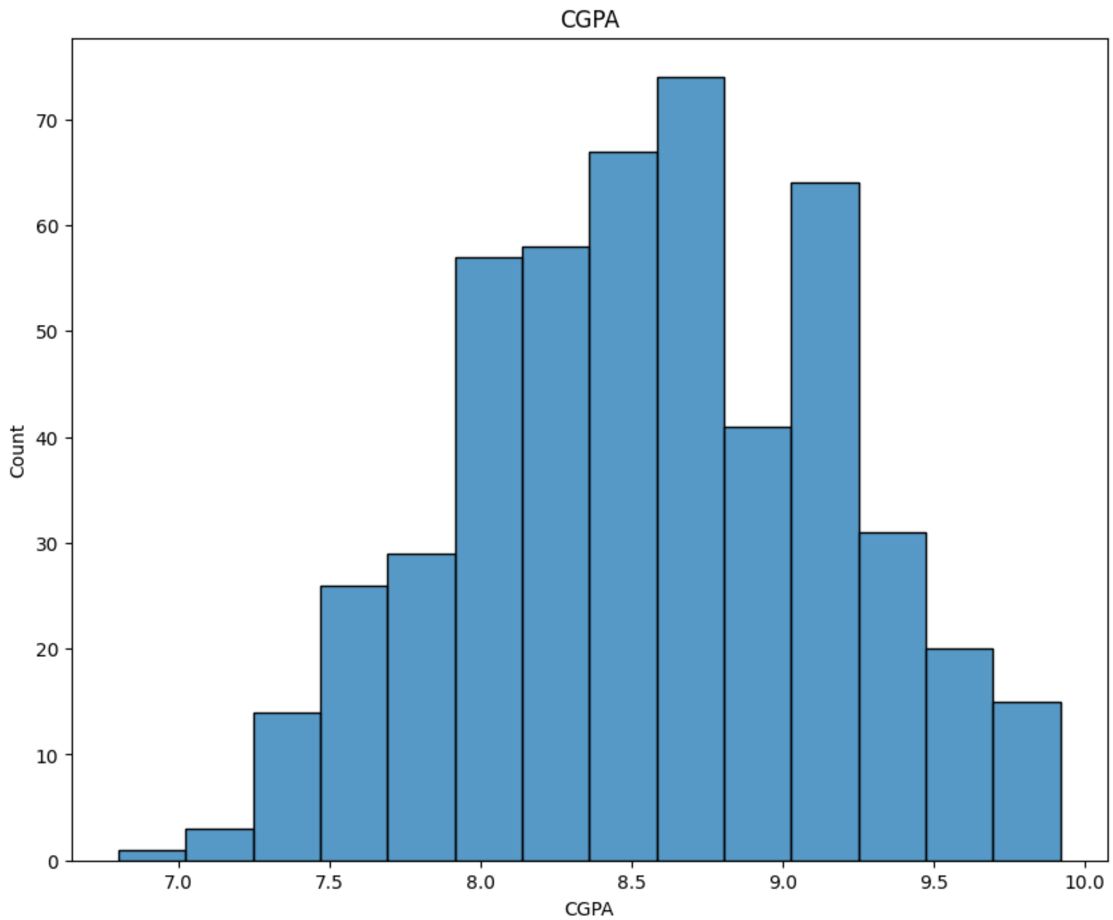

GRE Score
Count
GRE Score
0
10
20
30
40
50
60
70
290
300
310
320
330
340

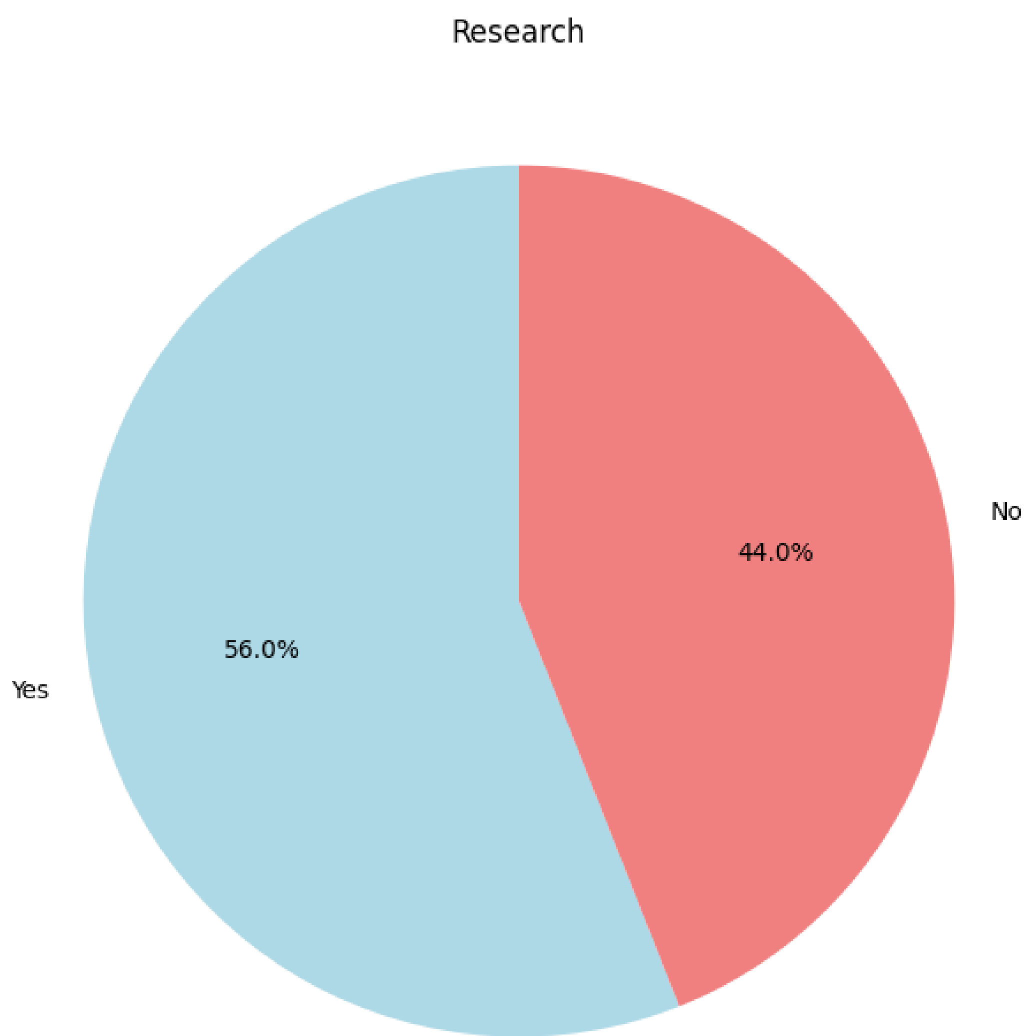

TOEFL Score
Count
0
20
40
60
80
95
100
105
110
115
120
TOEFL Score


University Rating
Count
160
140
120
100
80
60
40
20
0
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
University Rating


SOP
Count
0
20
40
60
80
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
SOP

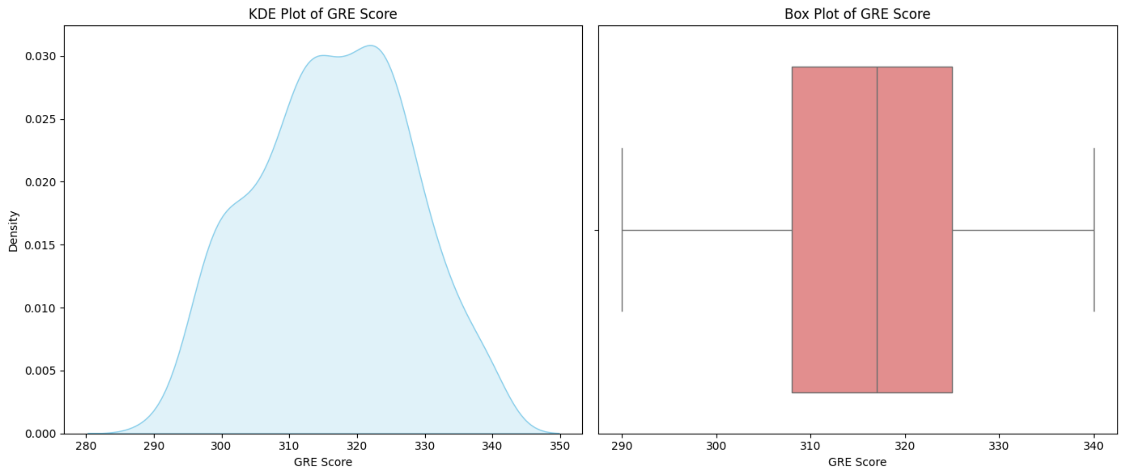

LOR
100
80
60
40
20
0
Count
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
LOR

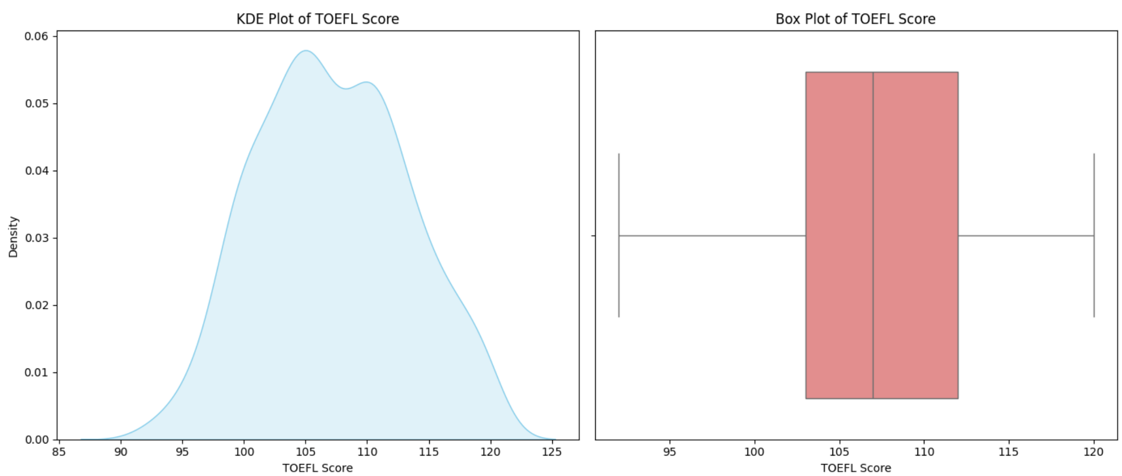

CGPA
Count
0
10
20
30
40
50
60
70
7.0
7.5
8.0
8.5
9.0
9.5
10.0
CGPA

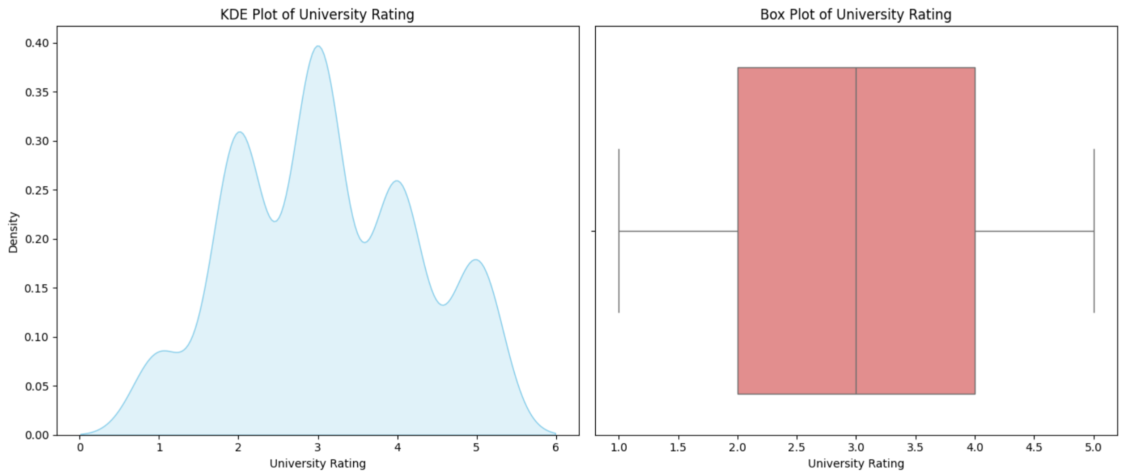


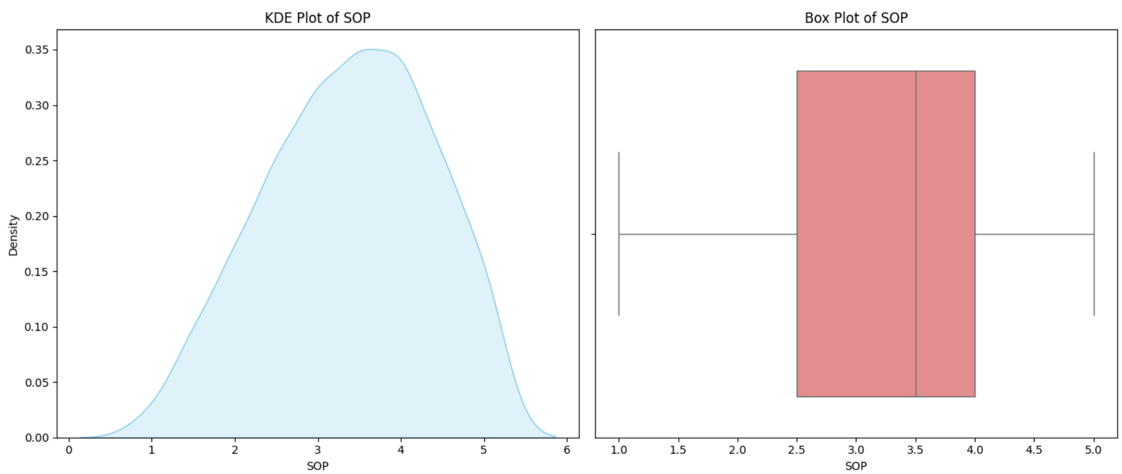
[79]:
```
def check_distribution_kde_boxplot(col):
    if col != 'Research':
      fig, axes = plt.subplots(1, 2, figsize=(14, 6))


      sns.kdeplot(data=df_main, x=col, ax=axes[0], fill=True, color="skyblue")
      axes[0].set_title(f"KDE Plot of {col}")


      sns.boxplot(data=df_main, x=col, ax=axes[1], color="lightcoral")
      axes[1].set_title(f"Box Plot of {col}")
```

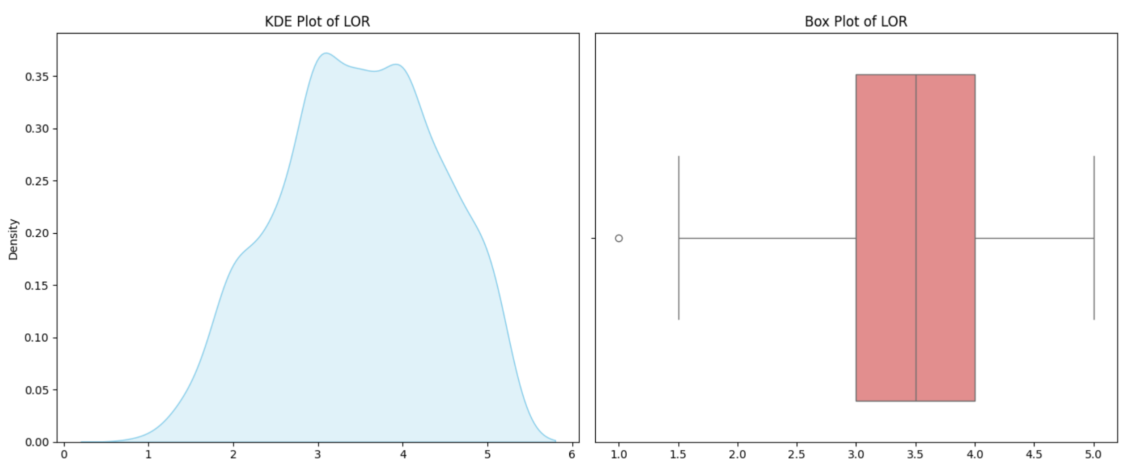
```
    plt.tight_layout()
    plt.show()

for col in df_main.iloc[:,:].columns:
  check_distribution_kde_boxplot(col)
```

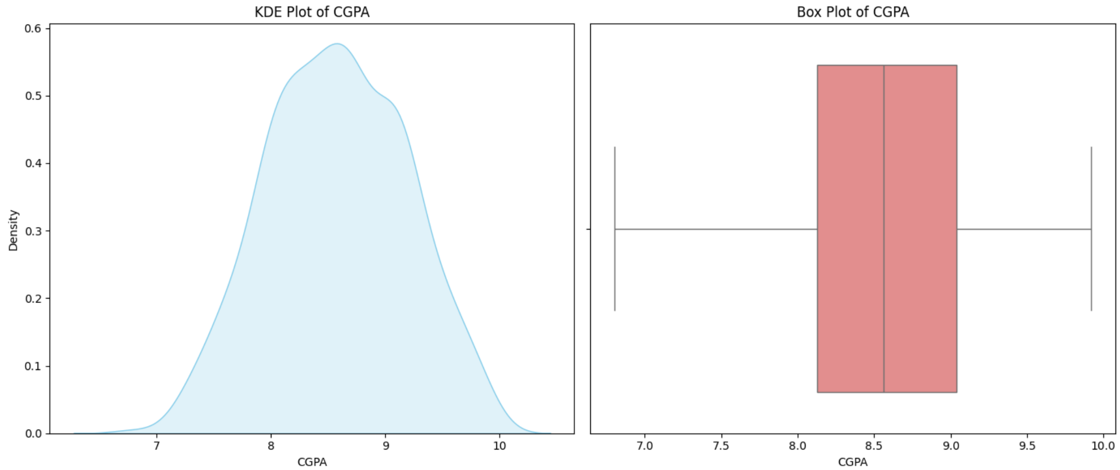


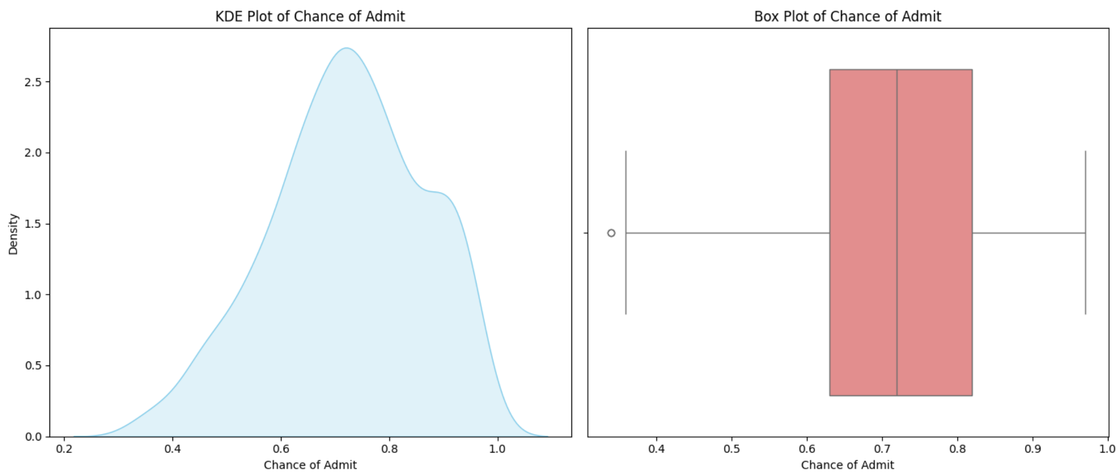


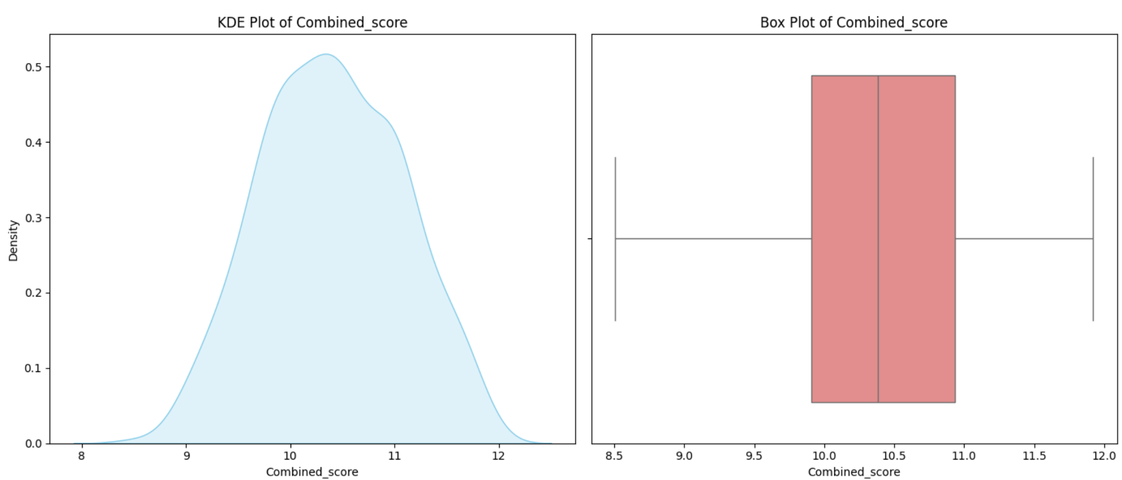

KDE Plot of University Rating
Density
University Rating
Box Plot of University Rating
University Rating


KDE Plot of SOP
Density
SOP
Box Plot of SOP
SOP


KDE Plot of LOR
Density
LOR
Box Plot of LOR
LOR

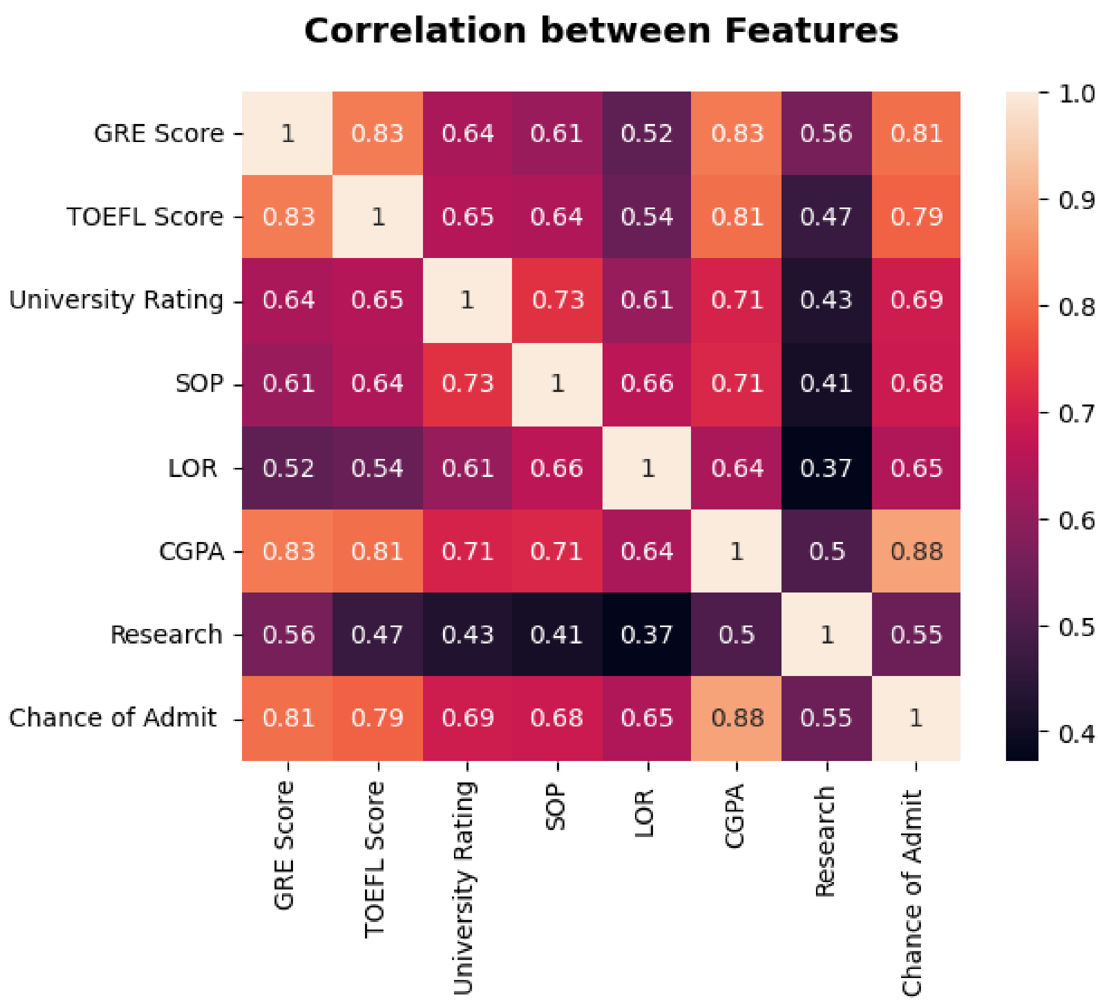

KDE Plot of CGPA
Density
CGPA
Box Plot of CGPA
CGPA


KDE Plot of Chance of Admit
Density
Chance of Admit
Box Plot of Chance of Admit
Chance of Admit


KDE Plot of Combined_score
Density
Combined_score
Box Plot of Combined_score
Combined_score

[15]:

```
sns.heatmap(df_main.corr(), annot=True)
plt.title('Correlation between Features', fontsize=14, fontweight='bold',␣
    ↪pad=20)
plt.show()
```



[16]:

```
df_main.columns = df_main.columns = df_main.columns.str.strip()
```

[17]:

```
X, y = df_main.drop('Chance of Admit', axis=1), df_main['Chance of Admit']
```

[18]:

```
X.head()
```

[18]:

	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
3        322        110                    3   3.5   2.5   8.67          1
4        314        103                    2   2.0   3.0   8.21          0
```

[19]:
```python
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)
len(X_train), len(X_test), len(y_train), len(y_test)
```

[19]:
```
(400, 100, 400, 100)
```

[20]:
```python
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaler.fit(X_train)
X_train_scaled = scaler.transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

[21]:
```python
scaled_df = pd.DataFrame(X_train_scaled, columns=X_train.columns)
scaled_df.head()
```

[21]:
```
   GRE Score  TOEFL Score  University Rating       SOP       LOR      CGPA  \
0   1.325906     1.931245           0.757101  1.610495  1.078640  1.064380
1   1.238676     0.785834           1.615006  0.621703  1.613945  1.969858
2   1.849290     1.767615           0.757101 -0.367089  1.078640  1.323088
3   0.366369    -0.850468          -0.100804  0.127307  0.543335  0.692488
4  -1.639937    -1.177728          -0.100804 -0.861485  0.543335 -1.021451

   Research
0  0.872992
1  0.872992
2  0.872992
3  0.872992
4  0.872992
```

[22]:
```python
# Linear Regression using sklearn
from sklearn.linear_model import LinearRegression
lr = LinearRegression()
lr.fit(X_train_scaled, y_train)
```

[22]:
```
LinearRegression()
```

[23]:
```python
lr.coef_
```

[23]:
```
array([0.01611005, 0.01789014, 0.00406069, 0.00404683, 0.01622322,
       0.07657168, 0.01364507])
```

[24]:
```python
lr.intercept_
```

[24]: 0.7234500000000001

[25]:
```
def plot_predictions(model, X_test, y_test):
  y_hat = model.predict(X_test)
  plt.figure(figsize=(8, 6))
  plt.scatter(y_test, y_hat, color='blue', alpha=0.6, label="Predicted Values")
  plt.scatter(y_test, y_test, color='red', alpha=0.6, label="Actual Values")

  plt.xlabel("Actual Values")
  plt.ylabel("Predicted Values")
  plt.legend()
  plt.title("Actual vs Predicted Values")
  plt.show()
```

[26]:
```
from sklearn.metrics import mean_squared_error, r2_score

def adjusted_r2(r2, sample_size, size):
    numerator = (1-r2)*(sample_size-1)
    denominator = sample_size - size - 1
    score = 1 - (numerator/denominator)
    return score



def evaluate_model(model, X_test, y_test,X_train, y_train):
  y_pred = model.predict(X_train)
  mse = mean_squared_error(y_train, y_pred)
  rmse = np.sqrt(mse)
  r2 = r2_score(y_train, y_pred)
  adj_r2 = adjusted_r2(r2, len(y_train), X_train.shape[1])
  print(f'''
  Training data statistics
    Mean squared error = {mse}
    Root mean squared error = {rmse}
    R2 Score = {r2}
    Adjusted R2 Score = {adj_r2}
  ''')
  y_pred = model.predict(X_test)
  mse = mean_squared_error(y_test, y_pred)
  rmse = np.sqrt(mse)
  r2 = r2_score(y_test, y_pred)
  adj_r2 = adjusted_r2(r2, len(y_test), X_test.shape[1])
  print(f'''
  Testing data statistics
    Mean squared error = {mse}
    Root mean squared error = {rmse}
    R2 Score = {r2}
```

```
    Adjusted R2 Score = {adj_r2}
  ''')
```

[27]:
```
evaluate_model(lr, X_test_scaled, y_test,X_train_scaled, y_train)
```

```
  Training data statistics
    Mean squared error = 0.0036436238661064603
    Root mean squared error = 0.06036243754278368
    R2 Score = 0.8245271132220857
    Adjusted R2 Score = 0.8213936688153373


  Testing data statistics
    Mean squared error = 0.0031881806465515637
    Root mean squared error = 0.056463976538599935
    R2 Score = 0.8042498554642961
    Adjusted R2 Score = 0.7893558227278838
```

[28]:
```
# Model does not perform well because of the very high correlation between
# CGPA GRE TOEFL

# Combine them into one feature
# Based on what transformations i applied to gre and toefl i got different␣
↪results
# checking online and trying myself i found this to be the best
df_main['Combined_score'] = (df_main['GRE Score'] / 340 + df_main['TOEFL␣
↪Score'] / 120) + df_main['CGPA']
# df_main['Combined_score'] = (df_main['GRE Score'] *10 / 340 + df_main['TOEFL␣
↪Score']*10 / 120) + df_main['CGPA']
```

[29]:
```
df_main.head()
```

[29]:
```
   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
3        322          110                  3  3.5  2.5  8.67         1
4        314          103                  2  2.0  3.0  8.21         0

   Chance of Admit  Combined_score
0             0.92       11.624510
1             0.76       10.714608
2             0.72        9.796078
3             0.80       10.533725
4             0.65        9.991863
```

[30]:
```
new_scaler = StandardScaler()
X_new = df_main.drop(columns=['Chance of Admit', 'GRE Score', 'TOEFL Score',␣
↪'CGPA'])
X_train, X_test, y_train, y_test = train_test_split(X_new, y, test_size=0.2,␣
↪random_state=42)
new_scaler.fit(X_train)
X_train_scaled = new_scaler.transform(X_train)
X_test_scaled = new_scaler.transform(X_test)
```

[31]:
```
X_train_scaled_df = pd.DataFrame(X_train_scaled, columns=X_new.columns)
X_train_scaled_df.head()
```

[31]:

	University Rating	SOP	LOR	Research	Combined_score
0	-0.098298	0.126796	0.564984	0.895434	0.437067
1	0.775459	0.633979	1.651491	-1.116777	-0.018460
2	-0.098298	0.126796	-0.521524	-1.116777	-0.247543
3	-0.972054	-0.887570	0.564984	-1.116777	-0.480729
4	-0.098298	0.126796	-1.064777	0.895434	-0.609268

[32]:
```
lr2 = LinearRegression()
lr2.fit(X_train_scaled, y_train)
```

[32]: LinearRegression()

[33]:
```
lr2.coef_
```

[33]: array([0.00582502, 0.00260901, 0.01373883, 0.01695661, 0.10142165])

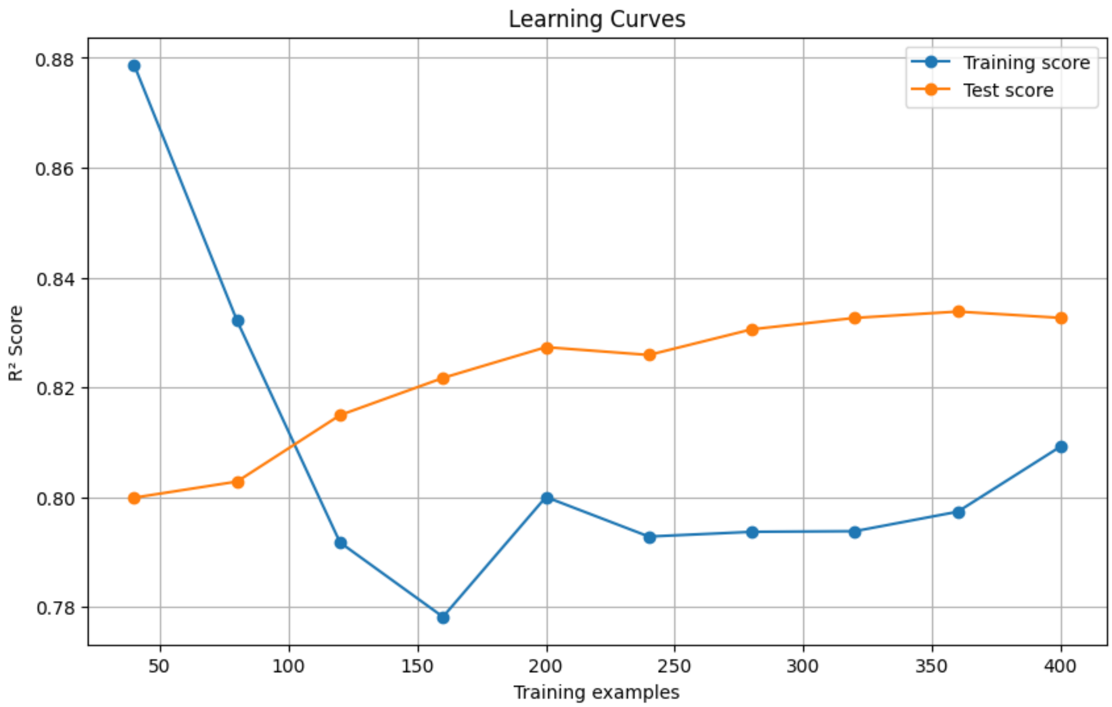
[34]:
```
lr2.intercept_
```

[34]: 0.7241749999999999

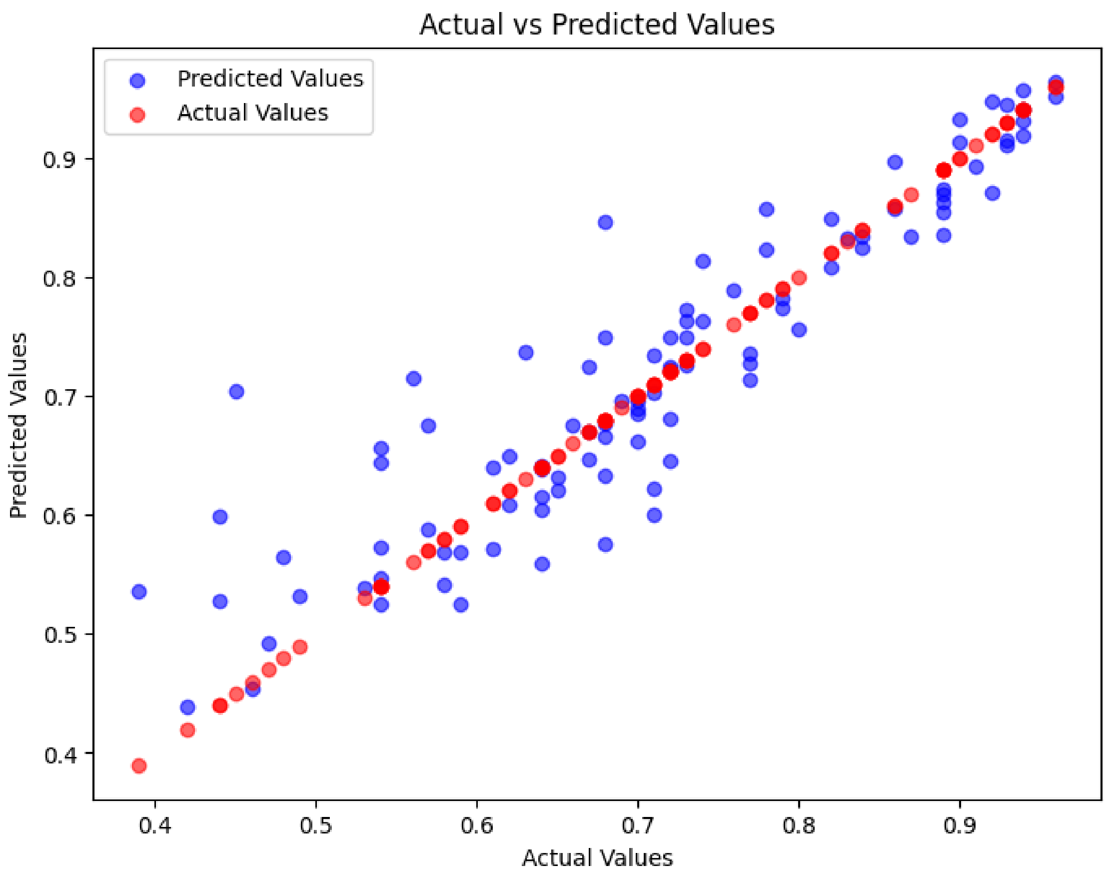
[35]:
```
evaluate_model(lr2, X_test_scaled, y_test,X_train_scaled, y_train)
```

```
 Training data statistics
   Mean squared error = 0.003759836606544623
   Root mean squared error = 0.06131750652582526
   R2 Score = 0.8092307542625382
   Adjusted R2 Score = 0.8068098247481034


 Testing data statistics
   Mean squared error = 0.0034223806865523038
   Root mean squared error = 0.05850111696841612
   R2 Score = 0.8326464211954864
   Adjusted R2 Score = 0.8237446350888633
```

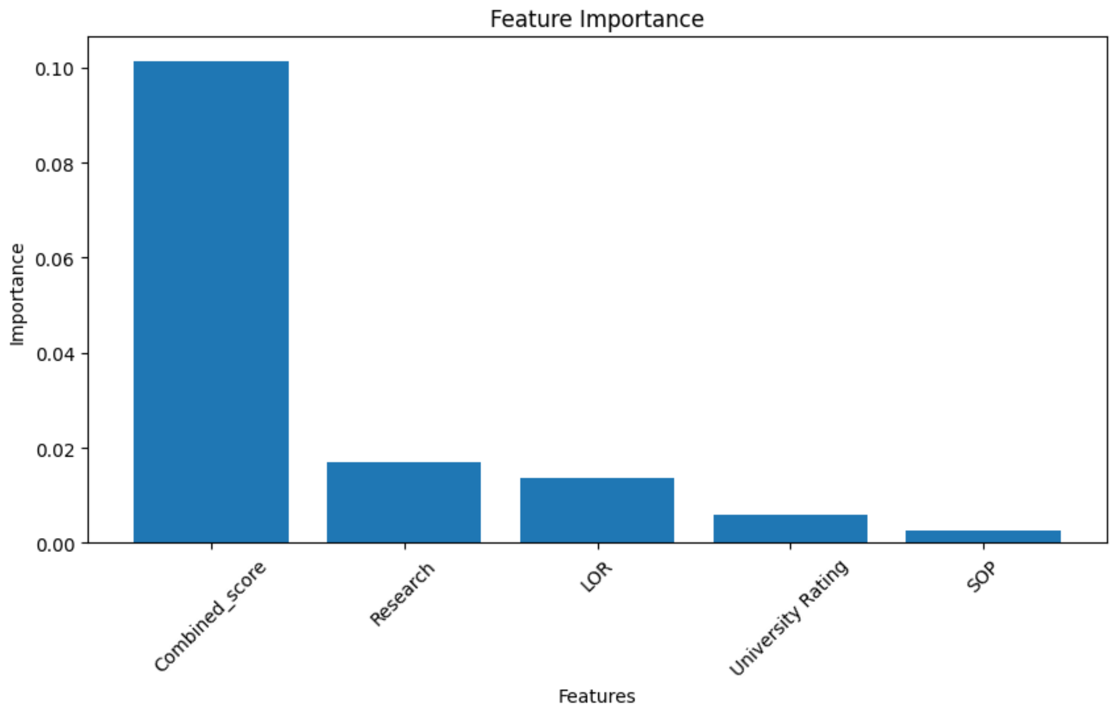
[36]:
```
from sklearn.model_selection import learning_curve
def plot_learning_curves(model, X_train, X_test, y_train, y_test):
    # Create arrays for different training set sizes
    train_sizes = np.linspace(0.1, 1.0, 10)
    train_scores = []
    test_scores = []

    for size in train_sizes:
        n_samples = int(len(X_train) * size)
        model.fit(X_train[:n_samples], y_train[:n_samples])
        train_score = model.score(X_train[:n_samples], y_train[:n_samples])
        test_score = model.score(X_test, y_test)
        train_scores.append(train_score)
        test_scores.append(test_score)

    plt.figure(figsize=(10, 6))
    plt.plot(train_sizes * len(X_train), train_scores, 'o-', label='Training␣
 ↪score')
    plt.plot(train_sizes * len(X_train), test_scores, 'o-', label='Test score')
    plt.xlabel('Training examples')
    plt.ylabel('R² Score')
    plt.title('Learning Curves')
    plt.legend(loc='best')
    plt.grid(True)
    plt.show()

plot_learning_curves(lr2, X_train_scaled, X_test_scaled, y_train, y_test)
```



[37]:
```
plot_predictions(lr2, X_test_scaled, y_test)
```



[38]:
```
coefficients = lr2.coef_
features = X_train_scaled_df.columns
sorted_indices = np.argsort(np.abs(coefficients))[::-1]
sorted_features = np.array(features)[sorted_indices]
sorted_coefficients = coefficients[sorted_indices]

plt.figure(figsize=(10, 5))
plt.bar(x=sorted_features, height=sorted_coefficients)
plt.title('Feature Importance')
plt.xlabel('Features')
plt.ylabel('Importance')
plt.xticks(rotation=45)
plt.show()
```



[38]:

```

```

[39]:

```
# Using OLS Model
import statsmodels.api as sm
X_train_sm = sm.add_constant(X_train_scaled)
model = sm.OLS(y_train, X_train_sm).fit()
```

[40]:

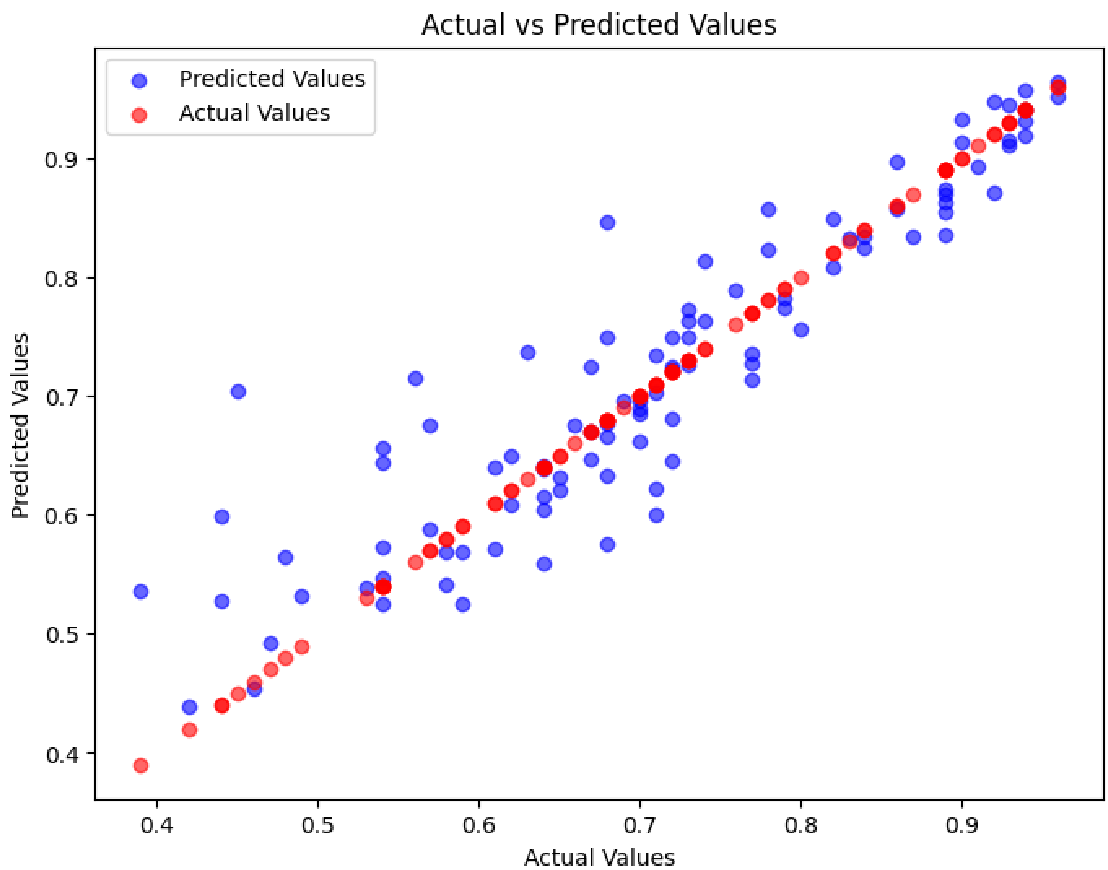
```
X_test_sm = sm.add_constant(X_test_scaled)
evaluate_model(model, X_test_sm, y_test, X_train_sm, y_train)
```

```
Training data statistics
  Mean squared error = 0.003759836606544624
  Root mean squared error = 0.061317506525825266
  R2 Score = 0.8092307542625382
  Adjusted R2 Score = 0.8063182466940273


Testing data statistics
  Mean squared error = 0.0034223806865523116
  Root mean squared error = 0.05850111696841618
  R2 Score = 0.832646421195486
  Adjusted R2 Score = 0.8218494161113239
```

[41]:
```
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:        Chance of Admit   R-squared:                       0.809
Model:                            OLS   Adj. R-squared:                  0.807
Method:                 Least Squares   F-statistic:                     334.3
Date:                Tue, 18 Feb 2025   Prob (F-statistic):          2.79e-139
Time:                        01:10:13   Log-Likelihood:                 549.10
No. Observations:                 400   AIC:                            -1086.
Df Residuals:                     394   BIC:                            -1062.
Df Model:                           5
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.7242      0.003    234.427      0.000       0.718       0.730
x1             0.0058      0.005      1.185      0.237      -0.004       0.015
x2             0.0026      0.005      0.508      0.612      -0.007       0.013
x3             0.0137      0.004      3.178      0.002       0.005       0.022
x4             0.0170      0.004      4.696      0.000       0.010       0.024
x5             0.1014      0.005     19.524      0.000       0.091       0.112
==============================================================================
Omnibus:                       71.981   Durbin-Watson:                   2.019
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              137.626
Skew:                          -0.991   Prob(JB):                     1.30e-30
Kurtosis:                       5.081   Cond. No.                         3.53
==============================================================================

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

[42]:
```
plot_predictions(model, X_test_sm, y_test)
```



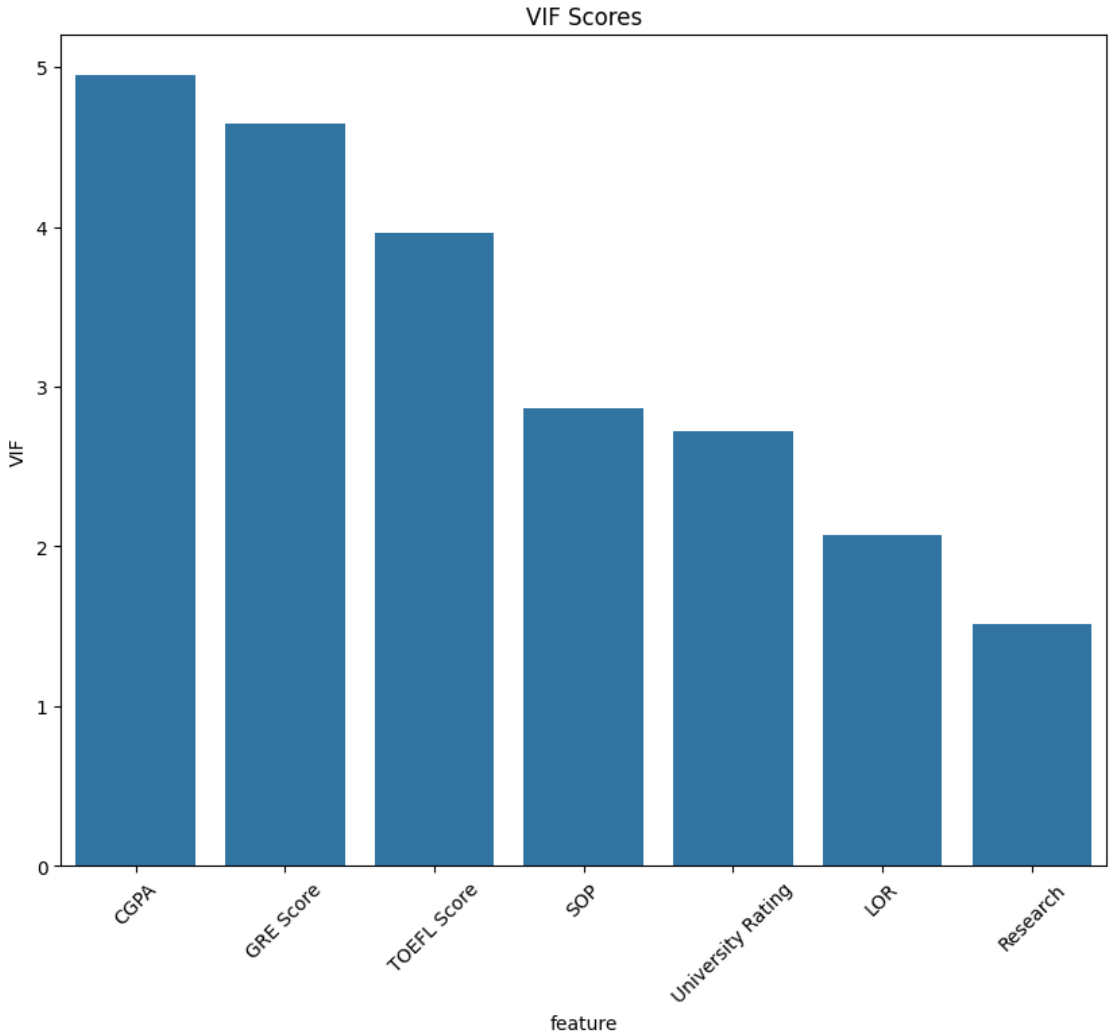
[43]:
```
# Before combining features
from statsmodels.stats.outliers_influence import variance_inflation_factor
vif_data = pd.DataFrame()
vif_data["feature"] = scaled_df.columns
vif_data["VIF"] = [variance_inflation_factor(scaled_df, i) for i in␣
↪range(scaled_df.shape[1])]
sorted_vif = vif_data.sort_values(by='VIF', ascending=False)
sorted_vif
```

[43]:

	feature	VIF
5	CGPA	4.951766
0	GRE Score	4.647707
1	TOEFL Score	3.961174
3	SOP	2.863042
2	University Rating	2.719241
4	LOR	2.071110
6	Research	1.512649

[44]:
```
plt.figure(figsize=(10,8))
plt.title("VIF Scores")
plt.xticks(rotation=45)
sns.barplot(data=sorted_vif,x='feature', y='VIF' )
```

[44]: `<Axes: title={'center': 'VIF Scores'}, xlabel='feature', ylabel='VIF'>`

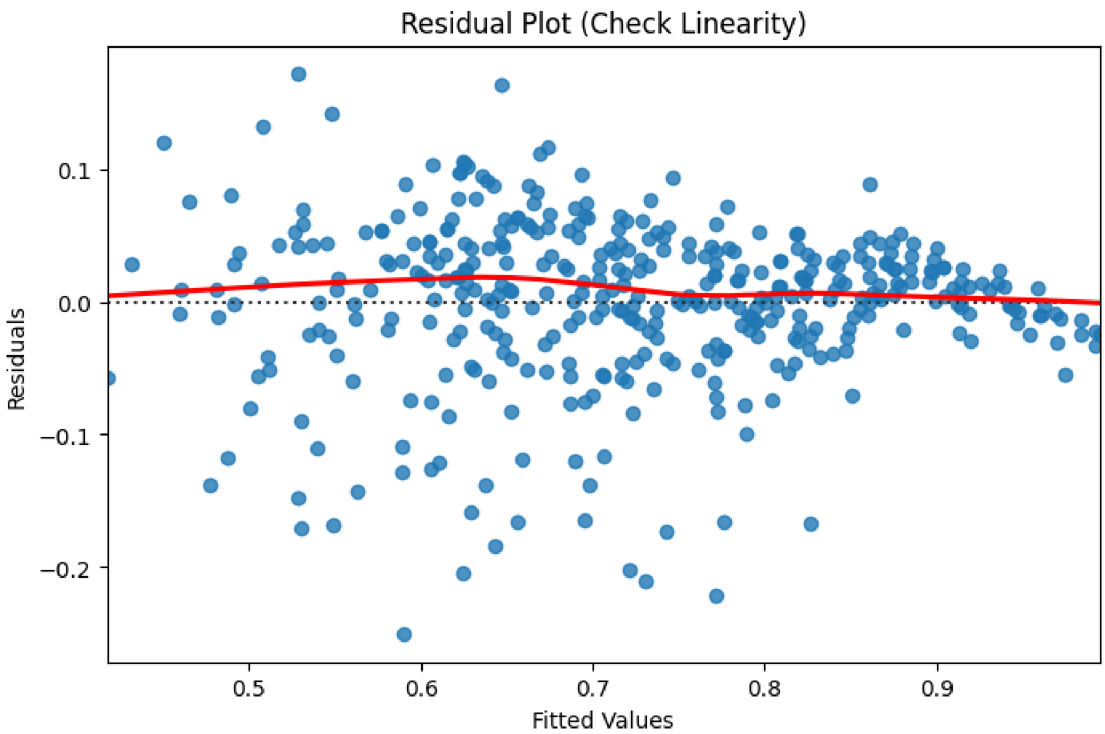


[45]:
```
# Mean of residuals
print("Mean of residuals",np.mean(model.resid))
```

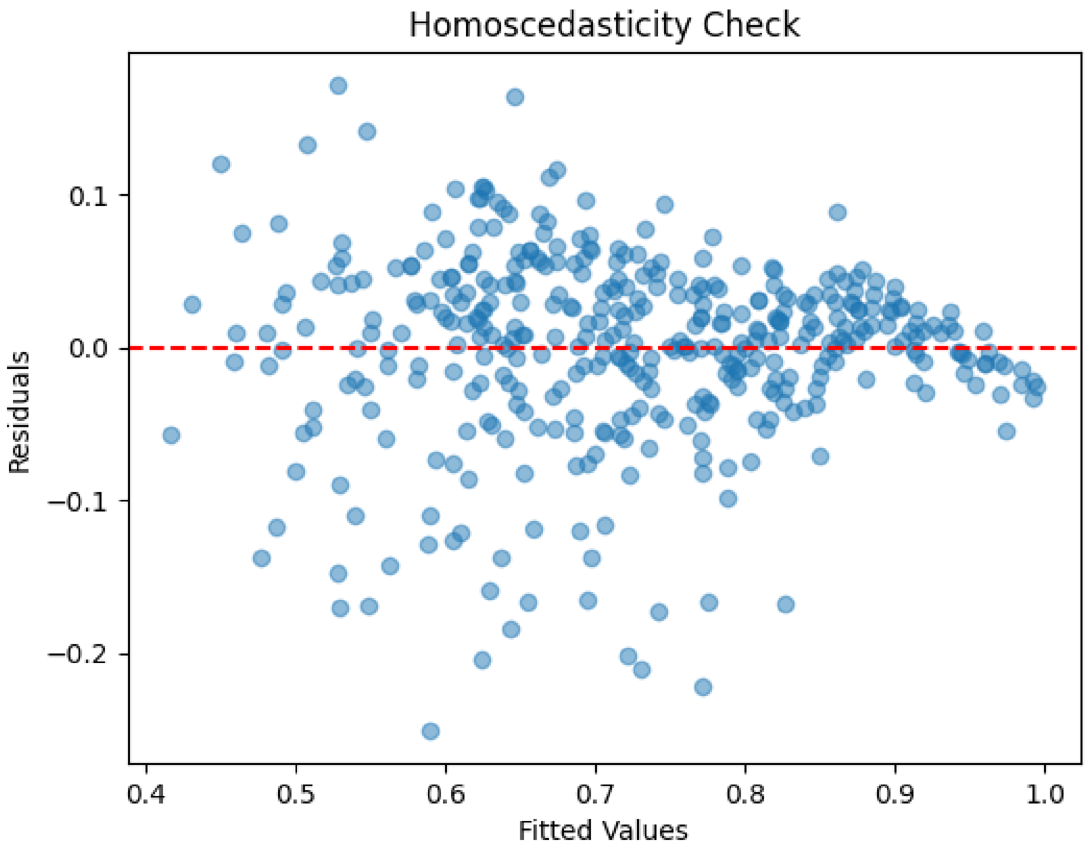
```
Mean of residuals -4.6074255521944e-16
```

[46]:
```
# residual plot

plt.figure(figsize=(8, 5))
```

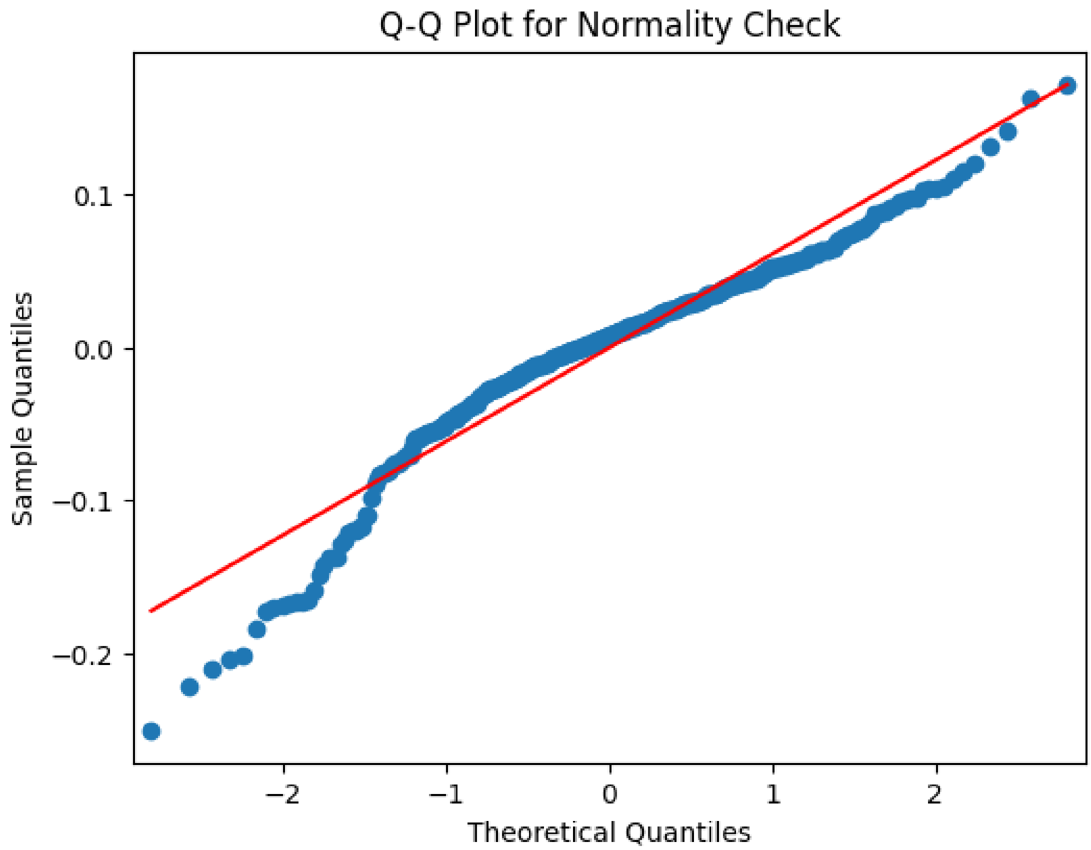
```
sns.residplot(x=model.fittedvalues, y=model.resid, lowess=True,␣
↪line_kws={"color": "red"})
plt.xlabel("Fitted Values")
plt.ylabel("Residuals")
plt.title("Residual Plot (Check Linearity)")
plt.show()
```



[47]:
```
# Homoscadasticity

plt.scatter(model.fittedvalues, model.resid, alpha=0.5)
plt.axhline(y=0, color='red', linestyle='--')
plt.xlabel("Fitted Values")
plt.ylabel("Residuals")
plt.title("Homoscedasticity Check")
plt.show()
```



[48]:
```
import scipy.stats as stats
sm.qqplot(model.resid, line='s')
plt.title("Q-Q Plot for Normality Check")
plt.show()
```



[49]:
```
# After combining features

from statsmodels.stats.outliers_influence import variance_inflation_factor
vif_data = pd.DataFrame()
vif_data["feature"] = X_train_scaled_df.columns
vif_data["VIF"] = [variance_inflation_factor(X_train_scaled_df, i) for i in␣
 ↪range(X_train_scaled_df.shape[1])]
sorted_vif = vif_data.sort_values(by='VIF', ascending=False)
sorted_vif
```

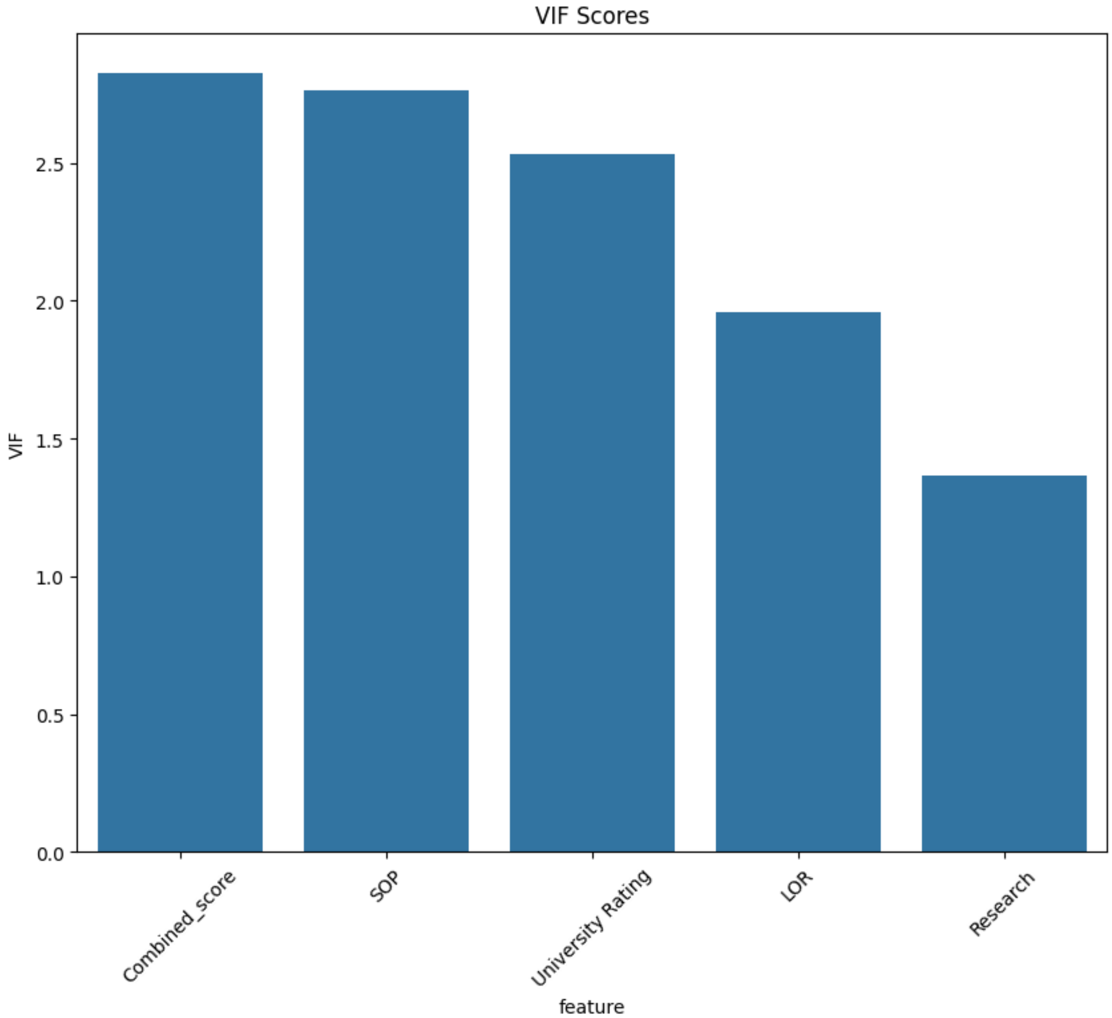
[49]:

	feature	VIF
4	Combined_score	2.827895
1	SOP	2.761665
0	University Rating	2.532827
2	LOR	1.958310
3	Research	1.366562

[50]:
```
plt.figure(figsize=(10,8))
plt.title("VIF Scores")
plt.xticks(rotation=45)
```

```
sns.barplot(data=sorted_vif,x='feature', y='VIF' )
```

[50]: <Axes: title={'center': 'VIF Scores'}, xlabel='feature', ylabel='VIF'>



[73]:
```
# Lasso and Ridge Regression
from sklearn.linear_model import Lasso, Ridge
lasso = Lasso(alpha=0.001)
```

[74]:
```
lasso.fit(X_train_scaled, y_train)
```

[74]: Lasso(alpha=0.001)

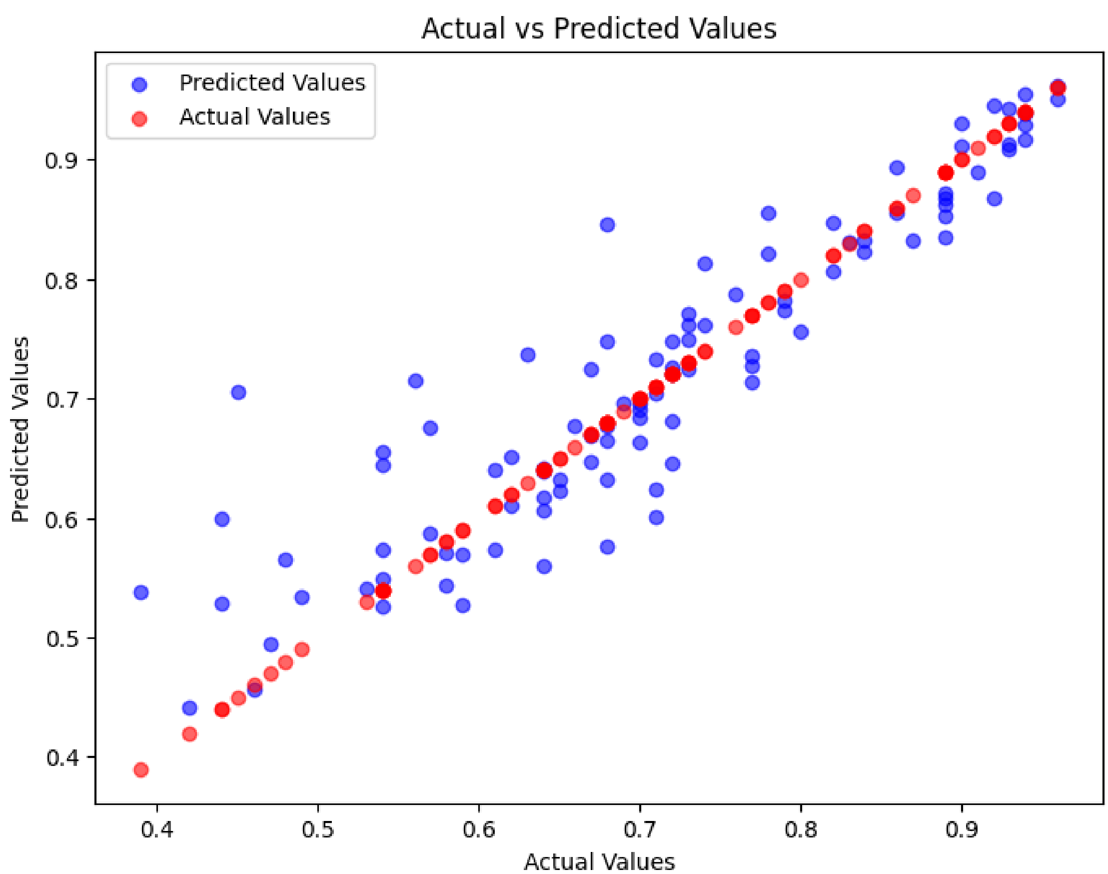
[75]:
```
evaluate_model(lasso, X_test_scaled, y_test, X_train_scaled, y_train)
```

Training data statistics

```
  Mean squared error = 0.0037614404980163742
  Root mean squared error = 0.061330583708427026
  R2 Score = 0.8091493748840359
  Adjusted R2 Score = 0.8067274126363714


Testing data statistics
  Mean squared error = 0.0034230548621705724
  Root mean squared error = 0.05850687875942941
  R2 Score = 0.8326134541725881
  Adjusted R2 Score = 0.8237099145009172
```

[76]:

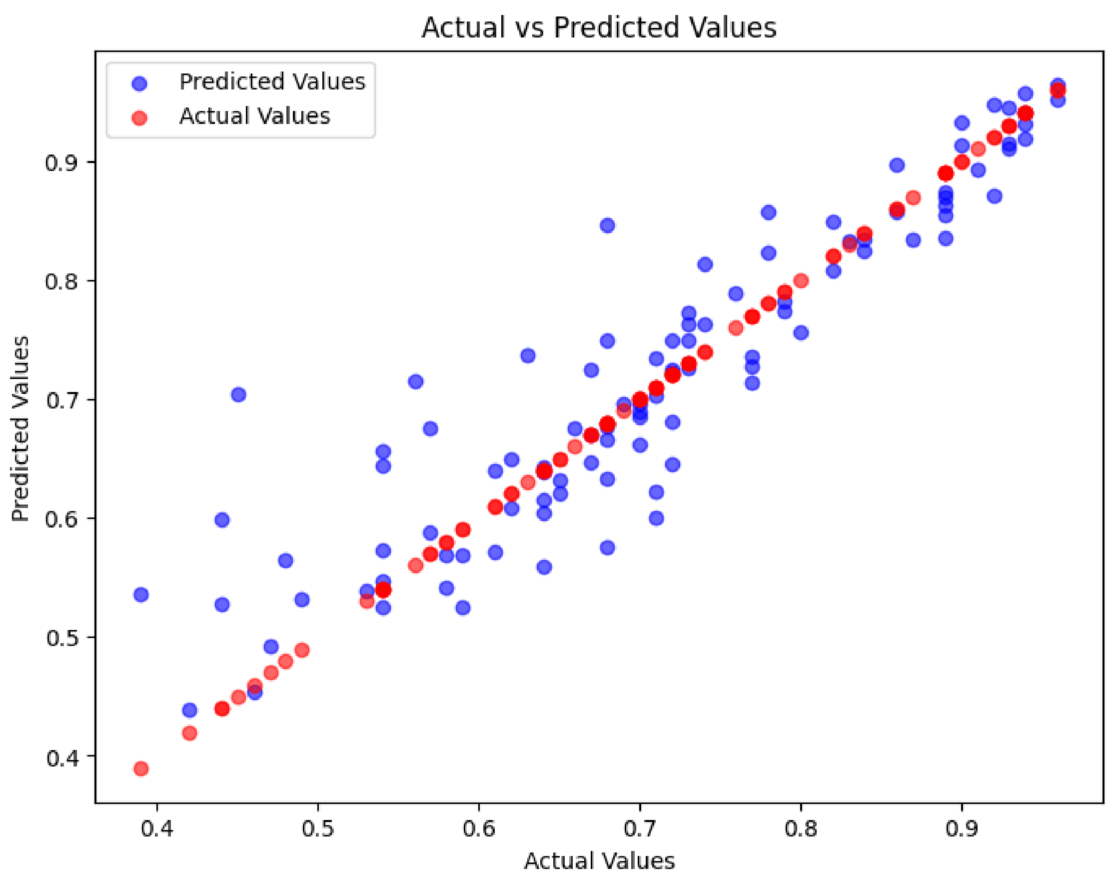
```
plot_predictions(lasso, X_test_scaled, y_test)
```



[78]:

```
ridge = Ridge(alpha=0.1)
ridge.fit(X_train_scaled, y_train)
evaluate_model(ridge, X_test_scaled, y_test, X_train_scaled, y_train)
plot_predictions(ridge, X_test_scaled, y_test)
```

```
Training data statistics
  Mean squared error = 0.0037598381676037483
  Root mean squared error = 0.06131751925513416
  R2 Score = 0.8092306750564175
  Adjusted R2 Score = 0.806809744536829


Testing data statistics
  Mean squared error = 0.0034220707471281416
  Root mean squared error = 0.058498467904109605
  R2 Score = 0.8326615771575481
  Adjusted R2 Score = 0.8237605972191198
```



[77]: