Jamboree Education - Linear Regression

August 7, 2024

[1]:

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import statsmodels.api as sm
from sklearn.linear_model import RidgeCV, LassoCV
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
from statsmodels.stats.outliers_influence import variance_inflation_factor
import numpy as np
from scipy.stats import probplot
```

[2]:

```
# Load the dataset
df = pd.read_csv('jamboree_admission.csv')

# Rename the columns to remove spaces and make them lowercase
df.columns = df.columns.str.strip().str.replace(' ', '_').str.lower()

# Drop the unique row identifier
df.drop(columns=['serial_no.'], inplace=True)
```

[3]:

```
### Define Problem Statement and Perform Exploratory Data Analysis (10 points)

# Problem Statement
print("Problem Statement: Jamboree aims to predict the probability of graduate␣
 ↪admission for students from an Indian perspective by analyzing various␣
 ↪factors such as GRE scores, TOEFL scores, university ratings, etc.")

# Initial Exploration
print("Dataset Info:")
print(df.info())
print("\nFirst 5 Rows of the Dataset:")
print(df.head())
print("\nSummary Statistics:")
print(df.describe())

# Observations on Shape and Data Types
print("Shape of data:", df.shape)
print("Data Types:")
```

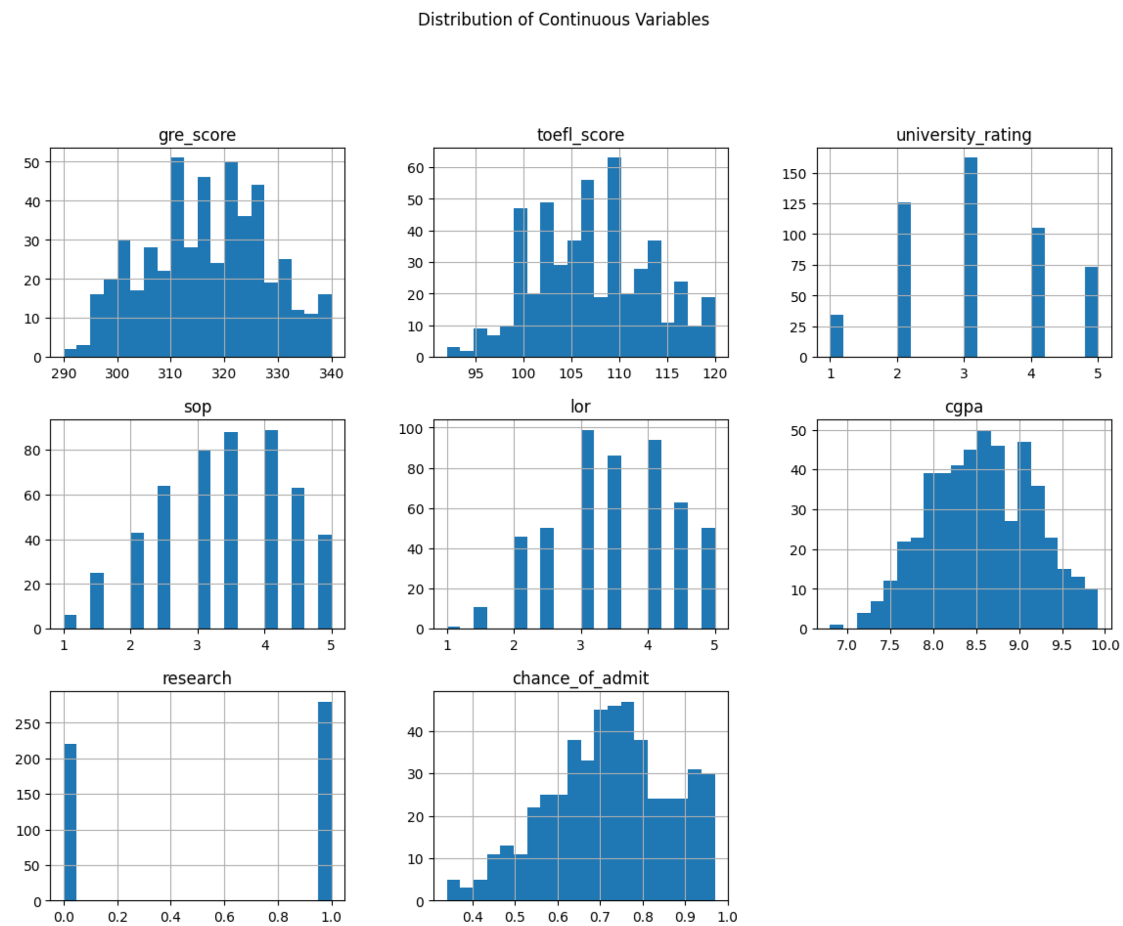
```python
print(df.dtypes)

# Check for missing values and duplicates
print("\nMissing Values:")
print(df.isnull().sum())
print("\nDuplicate Rows:")
print(df.duplicated().sum())

# Univariate Analysis
print("\nUnivariate Analysis:")
df.hist(bins=20, figsize=(14, 10))
plt.suptitle('Distribution of Continuous Variables', y=1.02)
plt.show()

sns.countplot(x='research', data=df)
plt.title('Count Plot for Research')
plt.show()

# Comments on Range and Distribution
print("Comments on Range and Distribution:")
print("GRE Scores range from", df['gre_score'].min(), "to", df['gre_score'].max())
print("TOEFL Scores range from", df['toefl_score'].min(), "to", df['toefl_score'].max())
print("CGPA ranges from", df['cgpa'].min(), "to", df['cgpa'].max())
print("Research is a binary variable indicating presence or absence of research experience.")

# Bivariate Analysis
print("\nBivariate Analysis:")
sns.pairplot(df, x_vars=['gre_score', 'toefl_score', 'university_rating', 'sop', 'lor', 'cgpa'], y_vars='chance_of_admit')
plt.suptitle('Relationships between Variables and Chance of Admit', y=1.02)
plt.show()

# Correlation Matrix
corr_matrix = df.corr()
plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()

# Comments on Relationships
print("Comments on Relationships:")
print("GRE Scores, TOEFL Scores, and CGPA have a positive correlation with Chance of Admit.")
```

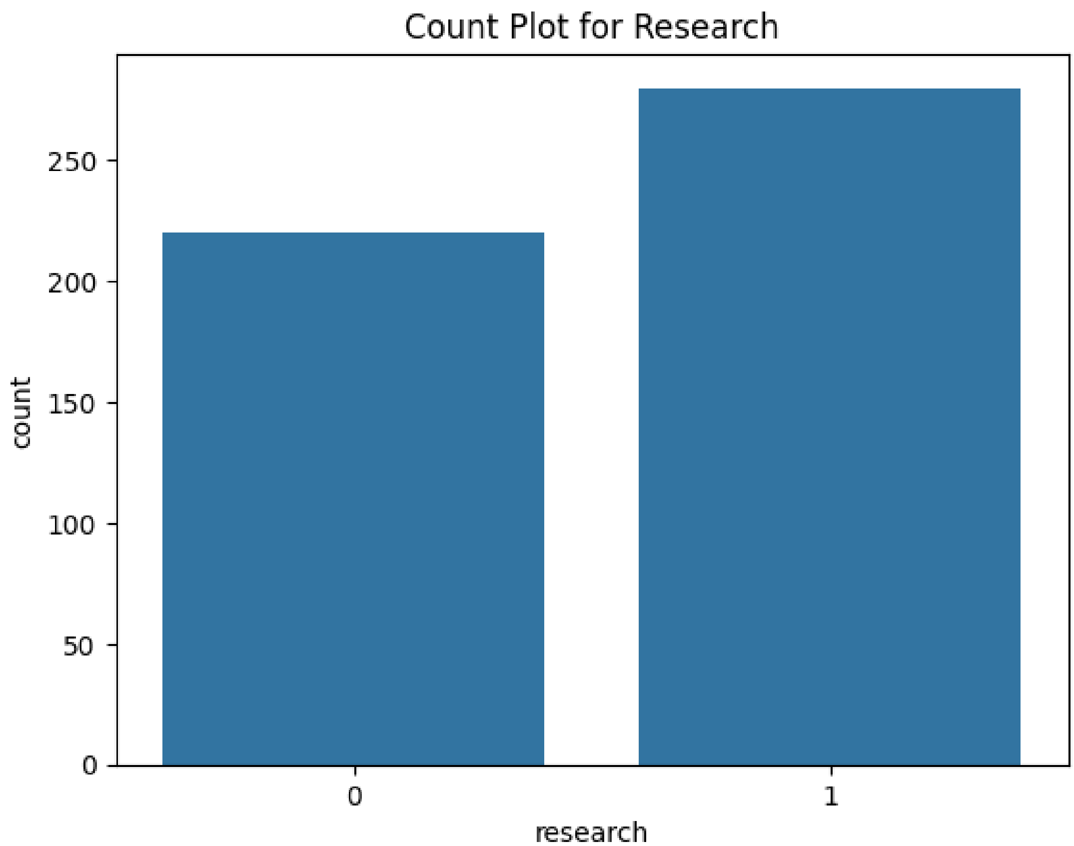
```
# Box Plots for Outliers
print("\nBox Plots for Outliers:")
sns.boxplot(data=df[['gre_score', 'toefl_score', 'university_rating', 'sop',␣
 ↪'lor', 'cgpa', 'chance_of_admit']])
plt.title('Box Plots for Continuous Variables')
plt.show()

# Comments on Outliers
print("Comments on Outliers:")
print("There are some outliers in GRE Scores, TOEFL Scores, and CGPA which may␣
 ↪need further investigation.")

# Violin Plots
print("\nViolin Plots:")
sns.violinplot(x='university_rating', y='chance_of_admit', data=df)
plt.title('Violin Plot of University Rating vs Chance of Admit')
plt.show()

# Pair Plots
print("\nPair Plots:")
sns.pairplot(df)
plt.suptitle('Pair Plots of All Variables', y=1.02)
plt.show()

# Facet Grids
print("\nFacet Grids:")
g = sns.FacetGrid(df, col="university_rating")
g.map(sns.histplot, "chance_of_admit")
plt.suptitle('Facet Grid of University Rating vs Chance of Admit', y=1.02)
plt.show()
```

```
Problem Statement: Jamboree aims to predict the probability of graduate
admission for students from an Indian perspective by analyzing various factors
such as GRE scores, TOEFL scores, university ratings, etc.
Dataset 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
```

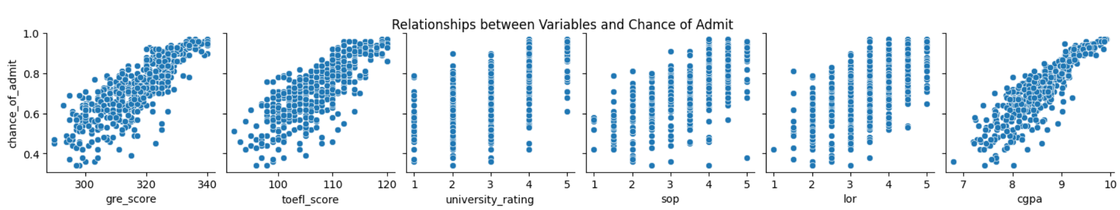
```
 7   chance_of_admit    500 non-null    float64
dtypes: float64(4), int64(4)
memory usage: 31.4 KB
None

First 5 Rows of the Dataset:
   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

Summary Statistics:
        gre_score  toefl_score  university_rating         sop        lor  \
count  500.000000   500.000000         500.000000  500.000000  500.00000
mean   316.472000   107.192000           3.114000    3.374000    3.48400
std     11.295148     6.081868           1.143512    0.991004    0.92545
min    290.000000    92.000000           1.000000    1.000000    1.00000
25%    308.000000   103.000000           2.000000    2.500000    3.00000
50%    317.000000   107.000000           3.000000    3.500000    3.50000
75%    325.000000   112.000000           4.000000    4.000000    4.00000
max    340.000000   120.000000           5.000000    5.000000    5.00000

             cgpa    research  chance_of_admit
count  500.000000  500.000000        500.00000
mean     8.576440    0.560000          0.72174
std      0.604813    0.496884          0.14114
min      6.800000    0.000000          0.34000
25%      8.127500    0.000000          0.63000
50%      8.560000    1.000000          0.72000
75%      9.040000    1.000000          0.82000
max      9.920000    1.000000          0.97000
Shape of data: (500, 8)
Data Types:
gre_score              int64
toefl_score            int64
university_rating      int64
sop                  float64
lor                  float64
cgpa                 float64
```

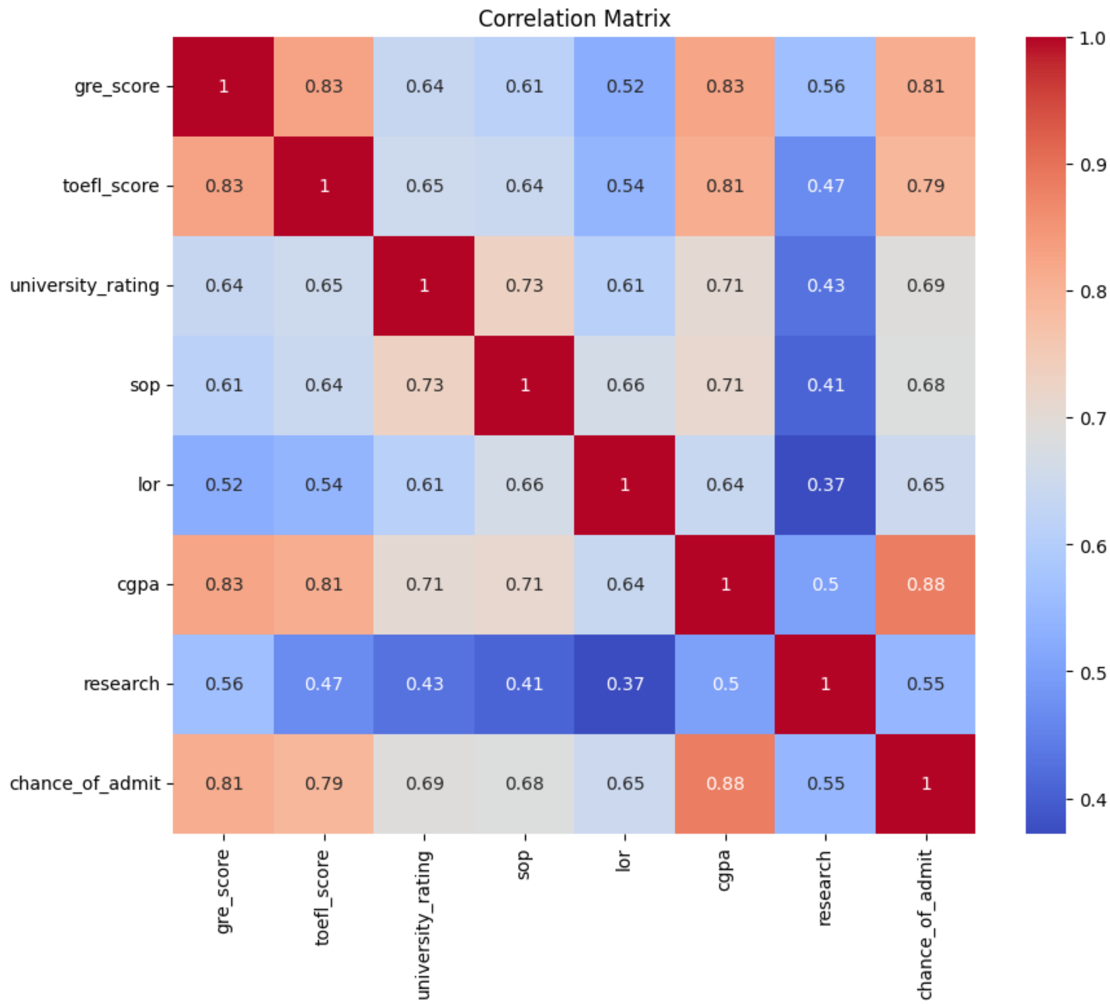
```
research                int64
chance_of_admit       float64
dtype: object

Missing Values:
gre_score             0
toefl_score           0
university_rating     0
sop                   0
lor                   0
cgpa                  0
research              0
chance_of_admit       0
dtype: int64

Duplicate Rows:
0

Univariate Analysis:
```





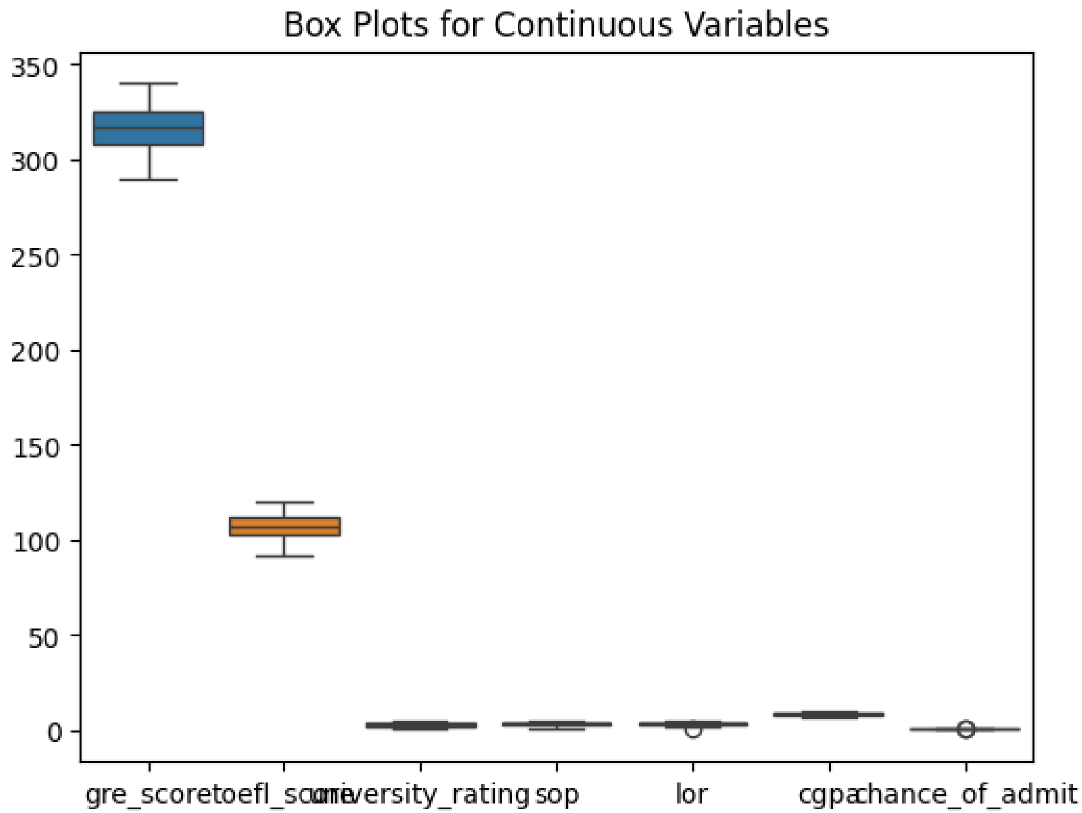

```
Comments on Range and Distribution:
GRE Scores range from 290 to 340
TOEFL Scores range from 92 to 120
CGPA ranges from 6.8 to 9.92
Research is a binary variable indicating presence or absence of research
experience.

Bivariate Analysis:
```



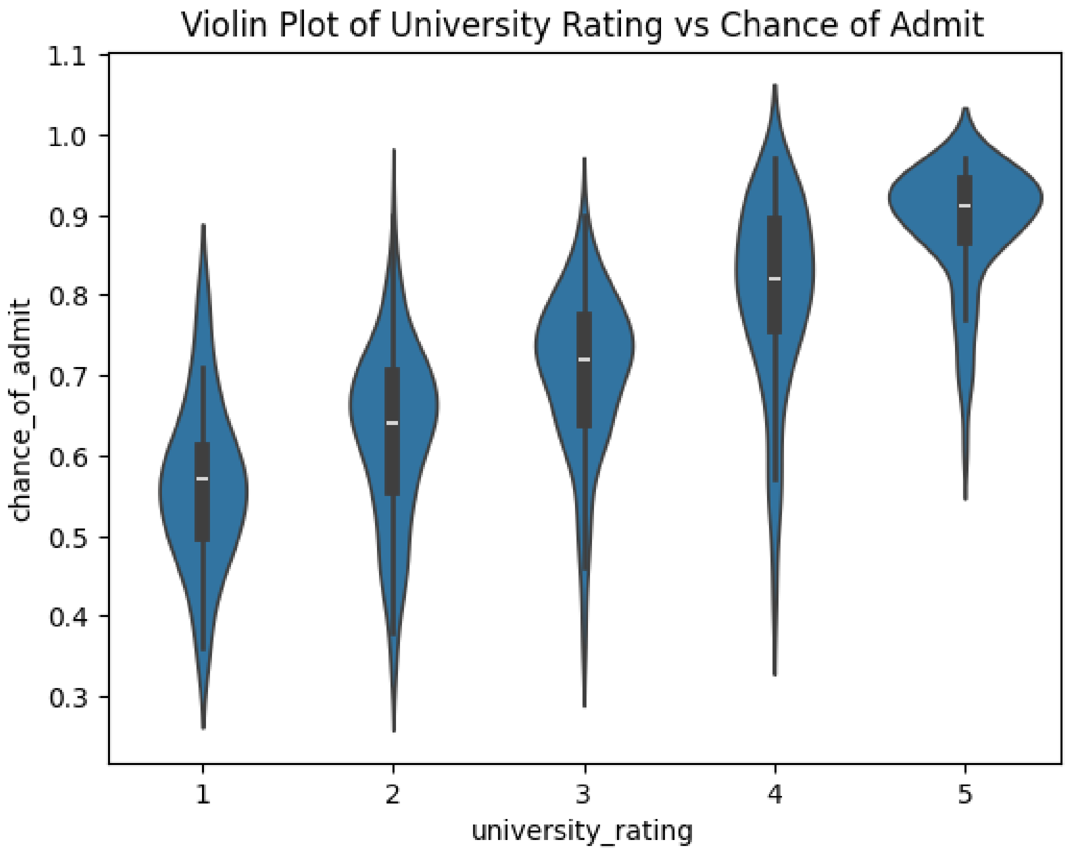


Comments on Relationships:
GRE Scores, TOEFL Scores, and CGPA have a positive correlation with Chance of Admit.

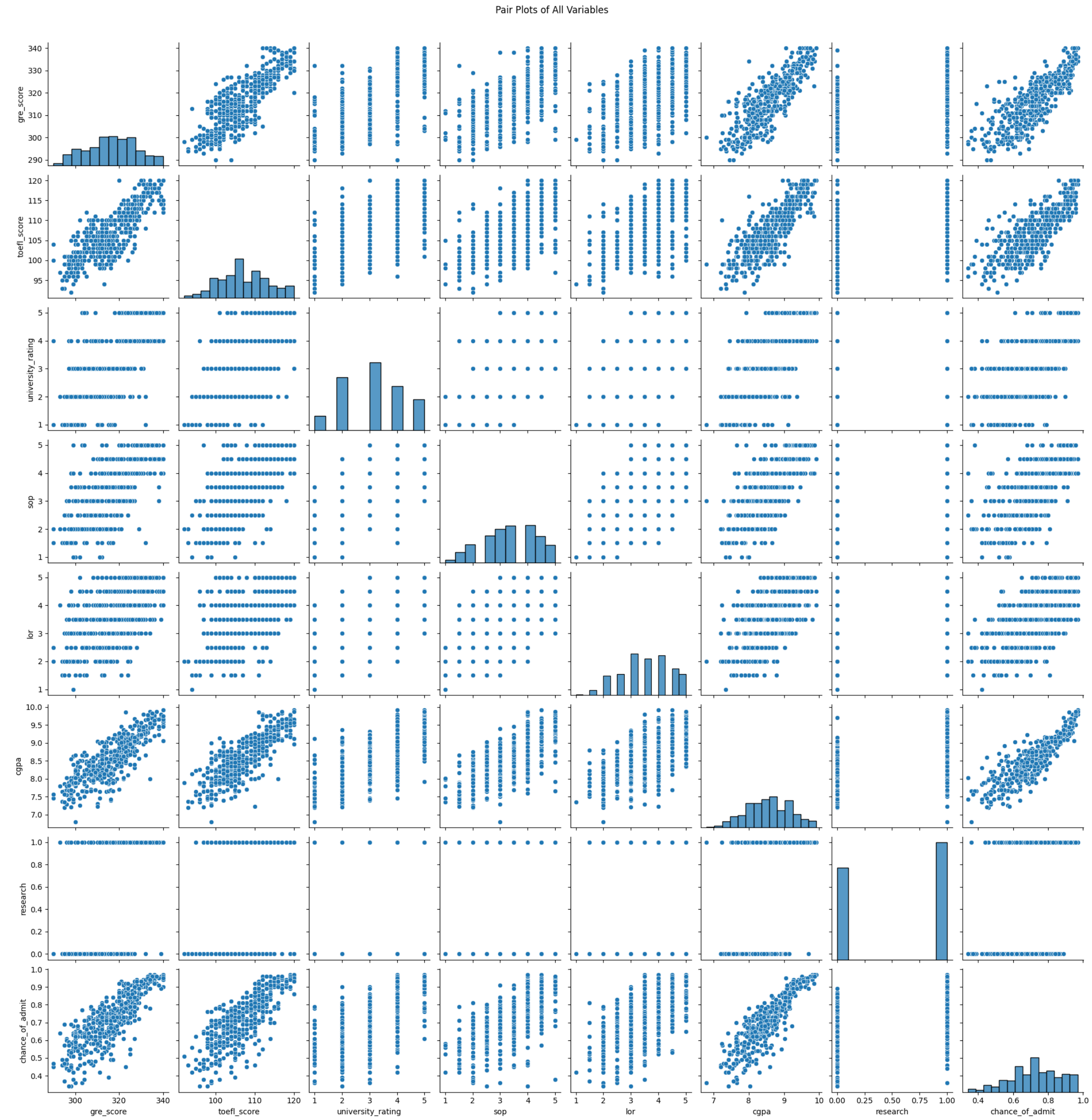
Box Plots for Outliers:



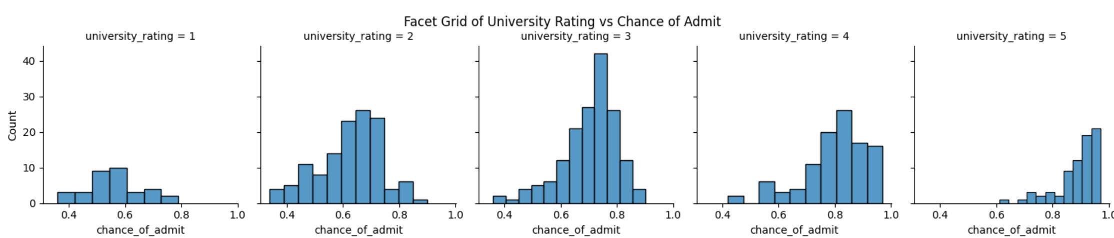

```
Comments on Outliers:
There are some outliers in GRE Scores, TOEFL Scores, and CGPA which may need
further investigation.

Violin Plots:
```


Violin Plot of University Rating vs Chance of Admit
chance_of_admit
1.1
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
1
2
3
4
5
university_rating

Pair Plots:


Pair Plots of All Variables
gre_score
toefl_score
university_rating
sop
lor
cgpa
research
chance_of_admit

Facet Grids:


Facet Grid of University Rating vs Chance of Admit
university_rating = 1
university_rating = 2
university_rating = 3
university_rating = 4
university_rating = 5
Count
chance_of_admit

[4]:

```python
### Data Preprocessing (10 Points)

# Duplicate Value Check
print("\nDuplicate Value Check:")
print("Number of duplicate rows:", df.duplicated().sum())

# Missing Value Treatment
# There are no missing values in the dataset

# Outlier Treatment
def remove_outliers(df, columns, threshold=1.5):
    for col in columns:
        Q1 = df[col].quantile(0.25)
        Q3 = df[col].quantile(0.75)
        IQR = Q3 - Q1
        lower_bound = Q1 - threshold * IQR
        upper_bound = Q3 + threshold * IQR
        df = df[(df[col] >= lower_bound) & (df[col] <= upper_bound)]
    return df

df = remove_outliers(df, ['gre_score', 'toefl_score', 'cgpa'])

# Comments after outlier removal
print("\nData after outlier removal:")
print(df.describe())

# Preparing data for modeling
X = df.drop(columns=['chance_of_admit'])
y = df['chance_of_admit']
X = sm.add_constant(X)
```

```
Duplicate Value Check:
Number of duplicate rows: 0

Data after outlier removal:
        gre_score  toefl_score  university_rating         sop        lor  \
count  500.000000   500.000000         500.000000  500.000000  500.00000
mean   316.472000   107.192000           3.114000    3.374000    3.48400
std     11.295148     6.081868           1.143512    0.991004    0.92545
min    290.000000    92.000000           1.000000    1.000000    1.00000
25%    308.000000   103.000000           2.000000    2.500000    3.00000
50%    317.000000   107.000000           3.000000    3.500000    3.50000
75%    325.000000   112.000000           4.000000    4.000000    4.00000
max    340.000000   120.000000           5.000000    5.000000    5.00000

             cgpa    research  chance_of_admit
count  500.000000  500.000000        500.00000
```

```
mean     8.576440    0.560000          0.72174
std      0.604813    0.496884          0.14114
min      6.800000    0.000000          0.34000
25%      8.127500    0.000000          0.63000
50%      8.560000    1.000000          0.72000
75%      9.040000    1.000000          0.82000
max      9.920000    1.000000          0.97000
```

[5]:
```
### Model Building (10 Points)

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

# Linear Regression Model
model = sm.OLS(y_train, X_train).fit()
print("\nLinear Regression Model Summary:")
print(model.summary())

# Predict and evaluate on test set
y_pred = model.predict(X_test)
print("\nTest Set Evaluation:")
print(f'MAE: {mean_absolute_error(y_test, y_pred)}, RMSE:␣
↪{mean_squared_error(y_test, y_pred, squared=False)}, R²: {r2_score(y_test,␣
↪y_pred)}')

# Ridge and Lasso Regression with Cross-Validation
ridge_cv = RidgeCV(alphas=np.logspace(-6, 6, 13), cv=10).fit(X_train, y_train)
lasso_cv = LassoCV(alphas=np.logspace(-6, 6, 13), cv=10).fit(X_train, y_train)
print("\nRidge CV Coefficients:", ridge_cv.coef_)
print("\nLasso CV Coefficients:", lasso_cv.coef_)

# Evaluate Ridge and Lasso on test set
ridge_pred = ridge_cv.predict(X_test)
lasso_pred = lasso_cv.predict(X_test)
print("\nRidge Test Set Evaluation:")
print(f'MAE: {mean_absolute_error(y_test, ridge_pred)}, RMSE:␣
↪{mean_squared_error(y_test, ridge_pred, squared=False)}, R²:␣
↪{r2_score(y_test, ridge_pred)}')
print("\nLasso Test Set Evaluation:")
print(f'MAE: {mean_absolute_error(y_test, lasso_pred)}, RMSE:␣
↪{mean_squared_error(y_test, lasso_pred, squared=False)}, R²:␣
↪{r2_score(y_test, lasso_pred)}')
```

```
Linear Regression Model Summary:
                            OLS Regression Results
==============================================================================
```

```
Dep. Variable:        chance_of_admit   R-squared:                       0.821
Model:                            OLS   Adj. R-squared:                  0.818
Method:                 Least Squares   F-statistic:                     257.0
Date:                Wed, 07 Aug 2024   Prob (F-statistic):          3.41e-142
Time:                        21:50:44   Log-Likelihood:                 561.91
No. Observations:                 400   AIC:                            -1108.
Df Residuals:                     392   BIC:                            -1076.
Df Model:                           7
Covariance Type:            nonrobust
================================================================================
=====
                      coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
-----
const               -1.4214      0.123    -11.549      0.000      -1.663
-1.179
gre_score            0.0024      0.001      4.196      0.000       0.001
0.004
toefl_score          0.0030      0.001      3.174      0.002       0.001
0.005
university_rating    0.0026      0.004      0.611      0.541      -0.006
0.011
sop                  0.0018      0.005      0.357      0.721      -0.008
0.012
lor                  0.0172      0.005      3.761      0.000       0.008
0.026
cgpa                 0.1125      0.011     10.444      0.000       0.091
0.134
research             0.0240      0.007      3.231      0.001       0.009
0.039
==============================================================================
Omnibus:                       86.232   Durbin-Watson:                   2.050
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              190.099
Skew:                          -1.107   Prob(JB):                     5.25e-42
Kurtosis:                       5.551   Cond. No.                     1.37e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 1.37e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

Test Set Evaluation:
MAE: 0.042722654277053664, RMSE: 0.06086588041578319, R²: 0.8188432567829624

Ridge CV Coefficients: [0.         0.00252146 0.0030726  0.00276683 0.00216403
```

```
0.01747795
 0.10907905 0.02367853]

Lasso CV Coefficients: [0.         0.00247635 0.0030235  0.00258467 0.00181306
0.0172363
 0.11160677 0.02346549]

Ridge Test Set Evaluation:
MAE: 0.042878348869760524, RMSE: 0.06101083772539083, R²: 0.8179793486575074

Lasso Test Set Evaluation:
MAE: 0.04276415193644606, RMSE: 0.06093795382378786, R²: 0.8184139747564743

/Users/bharadwajmahanthi/Library/Python/3.11/lib/python/site-
packages/sklearn/metrics/_regression.py:492: FutureWarning: 'squared' is
deprecated in version 1.4 and will be removed in 1.6. To calculate the root mean
squared error, use the function'root_mean_squared_error'.
  warnings.warn(
/Users/bharadwajmahanthi/Library/Python/3.11/lib/python/site-
packages/sklearn/metrics/_regression.py:492: FutureWarning: 'squared' is
deprecated in version 1.4 and will be removed in 1.6. To calculate the root mean
squared error, use the function'root_mean_squared_error'.
  warnings.warn(
/Users/bharadwajmahanthi/Library/Python/3.11/lib/python/site-
packages/sklearn/metrics/_regression.py:492: FutureWarning: 'squared' is
deprecated in version 1.4 and will be removed in 1.6. To calculate the root mean
squared error, use the function'root_mean_squared_error'.
  warnings.warn(
```

[6]:
```python
### Testing the Assumptions of Linear Regression (50 Points)

# Multicollinearity Check (VIF Score)
vif_data = pd.DataFrame()
vif_data["feature"] = X_train.columns
vif_data["VIF"] = [variance_inflation_factor(X_train.values, i) for i in␣
 ↪range(len(X_train.columns))]
print("\nVIF Scores:")
print(vif_data)

# Drop variables with high VIF iteratively
while vif_data['VIF'].max() > 5:
    max_vif = vif_data['VIF'].idxmax()
    X_train.drop(columns=[vif_data.loc[max_vif, 'feature']], inplace=True)
    X_test.drop(columns=[vif_data.loc[max_vif, 'feature']], inplace=True)
    vif_data = pd.DataFrame()
    vif_data["feature"] = X_train.columns
    vif_data["VIF"] = [variance_inflation_factor(X_train.values, i) for i in␣
 ↪range(len(X_train.columns))]
```

```python
    print("\nUpdated VIF Scores:")
    print(vif_data)

# Linear Regression Model after VIF correction
model = sm.OLS(y_train, X_train).fit()
print("\nLinear Regression Model Summary After VIF Correction:")
print(model.summary())

# Predict and evaluate on test set after VIF correction
y_pred = model.predict(X_test)
print("\nTest Set Evaluation After VIF Correction:")
print(f'MAE: {mean_absolute_error(y_test, y_pred)}, RMSE: {mean_squared_error(y_test, y_pred, squared=False)}, R²: {r2_score(y_test, y_pred)}')

# Mean of Residuals
residuals = y_test - y_pred
print(f'\nMean of Residuals: {np.mean(residuals)}')
```

```
VIF Scores:
             feature          VIF
0              const  1683.776580
1          gre_score     4.489983
2        toefl_score     3.664298
3  university_rating     2.572110
4                sop     2.785764
5                lor     1.977698
6               cgpa     4.654540
7           research     1.518065

Updated VIF Scores:
             feature          VIF
0          gre_score  1284.067901
1        toefl_score  1141.169527
2  university_rating    20.408187
3                sop    34.837142
4                lor    30.249378
5               cgpa   933.060108
6           research     2.822705

Updated VIF Scores:
             feature         VIF
0        toefl_score  605.595255
1  university_rating   19.390093
2                sop   32.917131
3                lor   30.008694
4               cgpa  692.352402
```

```
5           research    2.817783

Updated VIF Scores:
             feature        VIF
0        toefl_score  22.086441
1  university_rating  19.303024
2                sop  32.454098
3                lor  28.696984
4           research   2.806767

Updated VIF Scores:
             feature        VIF
0        toefl_score  19.775624
1  university_rating  15.011436
2                lor  24.850025
3           research   2.780908

Updated VIF Scores:
             feature        VIF
0        toefl_score  10.206327
1  university_rating  11.883675
2           research   2.770977

Updated VIF Scores:
       feature       VIF
0  toefl_score  2.379543
1     research  2.379543

Linear Regression Model Summary After VIF Correction:
                                 OLS Regression Results
================================================================================
=======
Dep. Variable:         chance_of_admit   R-squared (uncentered):
0.983
Model:                             OLS   Adj. R-squared (uncentered):
0.983
Method:                  Least Squares   F-statistic:
1.139e+04
Date:                 Wed, 07 Aug 2024   Prob (F-statistic):
0.00
Time:                         21:50:44   Log-Likelihood:
367.12
No. Observations:                  400   AIC:
-730.2
Df Residuals:                      398   BIC:
-722.2
Df Model:                            2
Covariance Type:             nonrobust
```

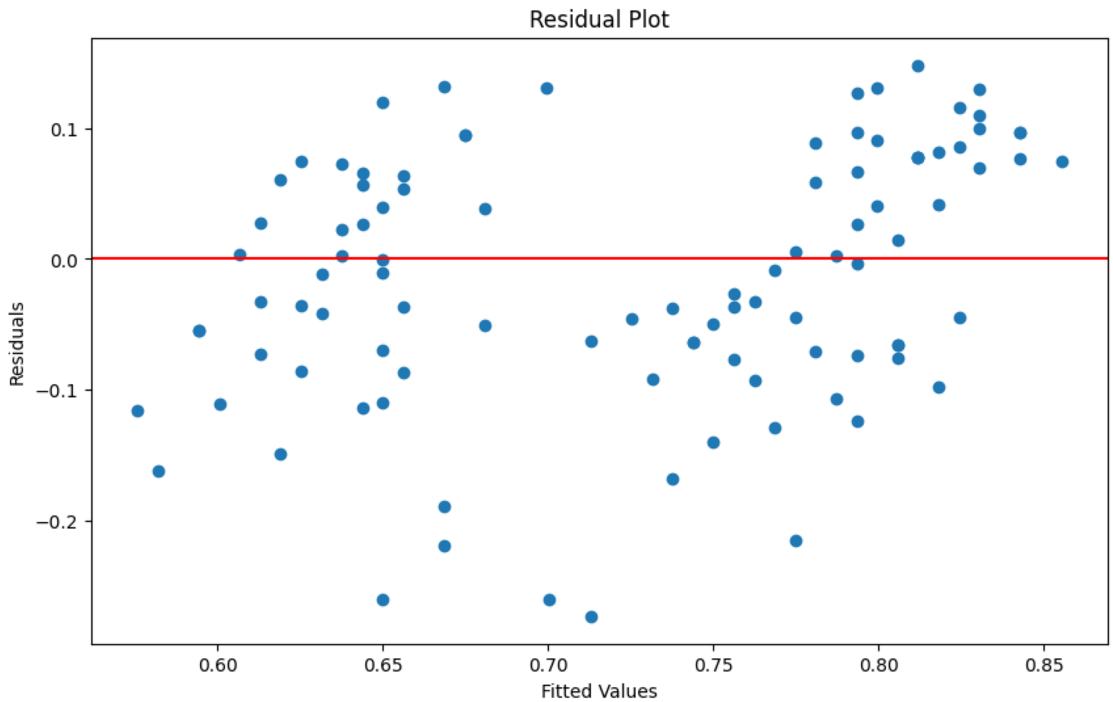
```
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
toefl_score    0.0062   6.95e-05     89.068      0.000       0.006       0.006
research       0.1123      0.010     11.197      0.000       0.093       0.132
==============================================================================
Omnibus:                       46.190   Durbin-Watson:                   2.051
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               59.014
Skew:                          -0.886   Prob(JB):                     1.53e-13
Kurtosis:                       3.635   Cond. No.                         223.
==============================================================================

Notes:
[1] R² is computed without centering (uncentered) since the model does not
contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly
specified.

Test Set Evaluation After VIF Correction:
MAE: 0.08103853479347187, RMSE: 0.09818248421360035, R²: 0.5286161268286611

Mean of Residuals: -0.013224663611284824
```

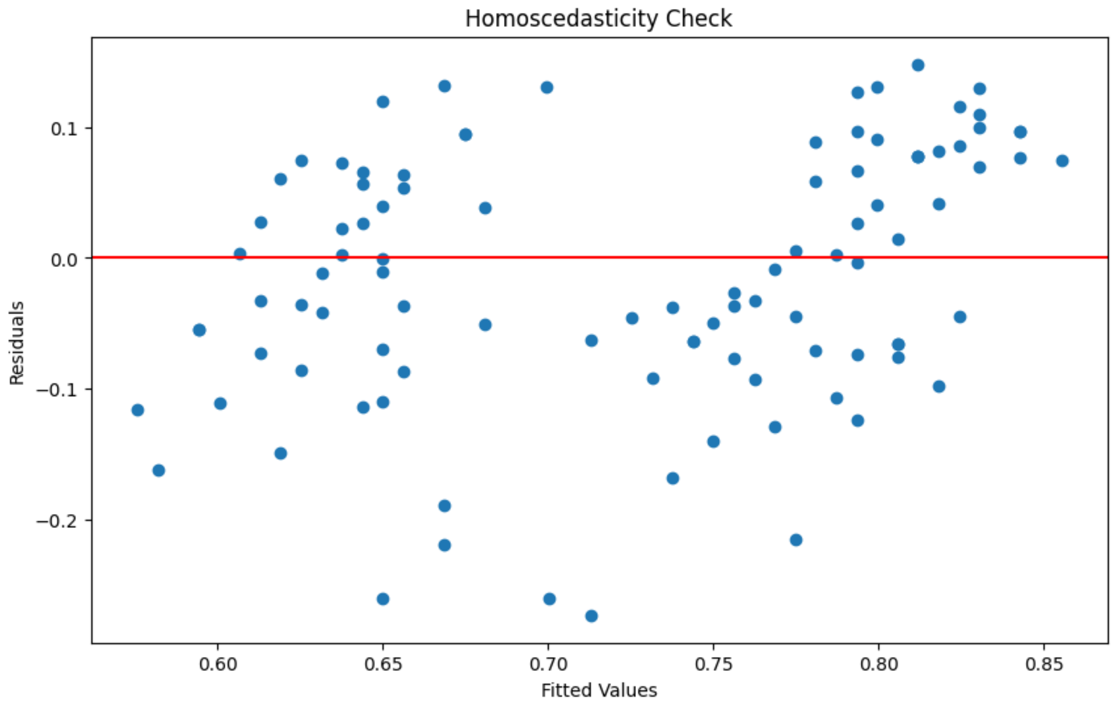
```
/Users/bharadwajmahanthi/Library/Python/3.11/lib/python/site-
packages/sklearn/metrics/_regression.py:492: FutureWarning: 'squared' is
deprecated in version 1.4 and will be removed in 1.6. To calculate the root mean
squared error, use the function'root_mean_squared_error'.
  warnings.warn(
```

[7]:

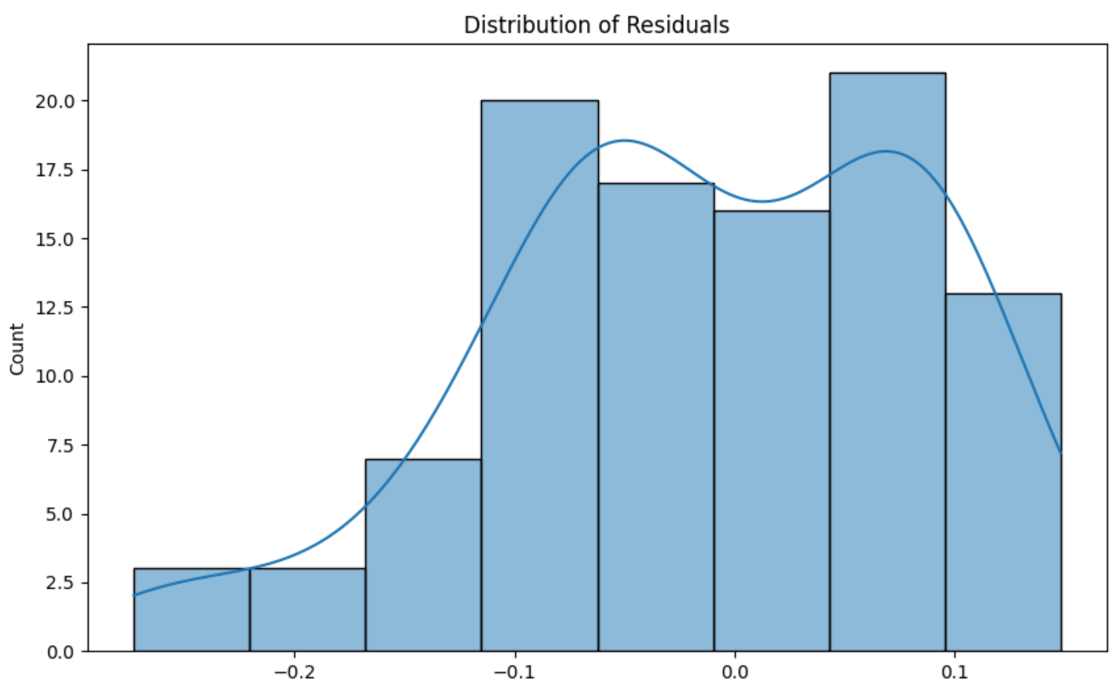
```python
# Linearity of Variables
plt.figure(figsize=(10, 6))
plt.scatter(y_pred, residuals)
plt.axhline(y=0, color='r', linestyle='-')
plt.xlabel('Fitted Values')
plt.ylabel('Residuals')
plt.title('Residual Plot')
plt.savefig('residual_plot.png')
plt.show()

# Homoscedasticity
plt.figure(figsize=(10, 6))
plt.scatter(y_pred, residuals)
plt.axhline(y=0, color='r', linestyle='-')
plt.xlabel('Fitted Values')
plt.ylabel('Residuals')
plt.title('Homoscedasticity Check')
plt.savefig('homoscedasticity_check.png')
plt.show()
```

```python
# Normality of Residuals
plt.figure(figsize=(10, 6))
sns.histplot(residuals, kde=True)
plt.title('Distribution of Residuals')
plt.savefig('residuals_distribution.png')
plt.show()

plt.figure(figsize=(10, 6))
probplot(residuals, dist="norm", plot=plt)
plt.title('QQ Plot')
plt.savefig('qq_plot.png')
plt.show()
```

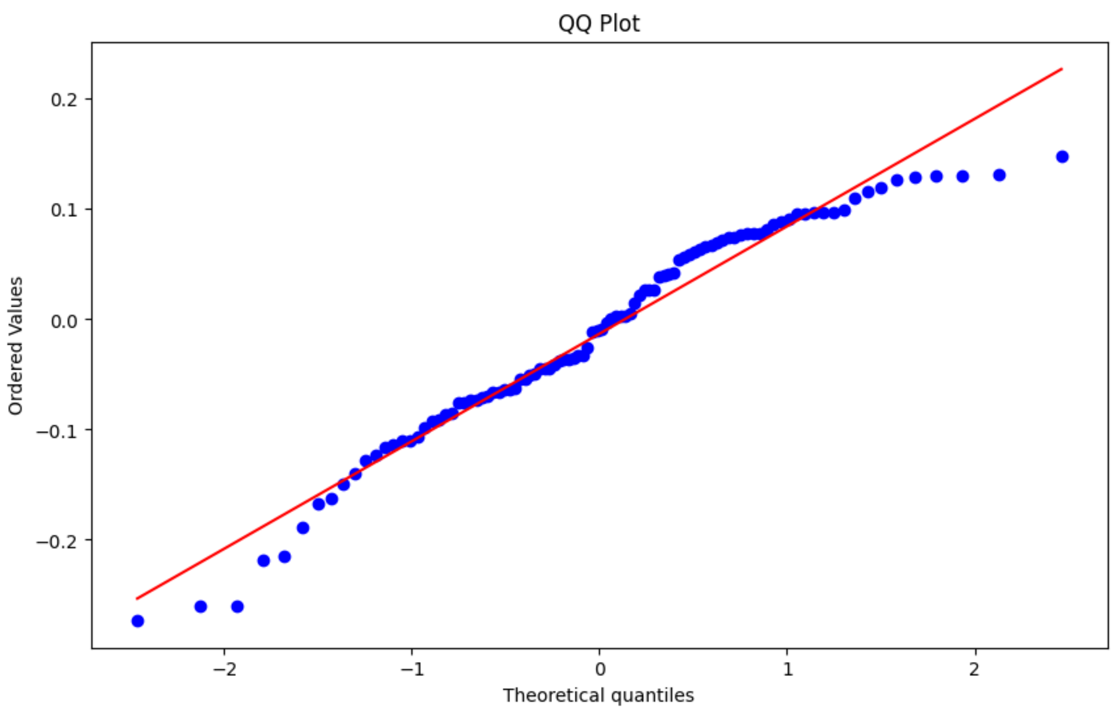




Homoscedasticity Check
Residuals
Fitted Values
0.1
0.0
−0.1
−0.2
0.60
0.65
0.70
0.75
0.80
0.85



Distribution of Residuals
Count
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
−0.2
−0.1
0.0
0.1



[8]:

```
### Model Performance Evaluation (10 Points)

# Evaluate model on training set
y_train_pred = model.predict(X_train)
train_mae = mean_absolute_error(y_train, y_train_pred)
train_rmse = mean_squared_error(y_train, y_train_pred, squared=False)
train_r2 = r2_score(y_train, y_train_pred)
print(f'\nTraining Set Performance:')
print(f'MAE: {train_mae}, RMSE: {train_rmse}, R²: {train_r2}')

# Evaluate model on test set
test_mae = mean_absolute_error(y_test, y_pred)
test_rmse = mean_squared_error(y_test, y_pred, squared=False)
test_r2 = r2_score(y_test, y_pred)
print(f'\nTest Set Performance:')
print(f'MAE: {test_mae}, RMSE: {test_rmse}, R²: {test_r2}')
```

```
Training Set Performance:
MAE: 0.0752270571615271, RMSE: 0.09664344800326927, R²: 0.5261027124837299

Test Set Performance:
MAE: 0.08103853479347187, RMSE: 0.09818248421360035, R²: 0.5286161268286611
```

```
/Users/bharadwajmahanthi/Library/Python/3.11/lib/python/site-
```

```
packages/sklearn/metrics/_regression.py:492: FutureWarning: 'squared' is
deprecated in version 1.4 and will be removed in 1.6. To calculate the root mean
squared error, use the function'root_mean_squared_error'.
  warnings.warn(
/Users/bharadwajmahanthi/Library/Python/3.11/lib/python/site-
packages/sklearn/metrics/_regression.py:492: FutureWarning: 'squared' is
deprecated in version 1.4 and will be removed in 1.6. To calculate the root mean
squared error, use the function'root_mean_squared_error'.
  warnings.warn(
```

[9]:

```python
### Actionable Insights & Recommendations (10 Points)

# Comments on Significance of Predictor Variables
print("Comments on Significance of Predictor Variables:")
print("Significant predictors after VIF correction and model fitting: ")
print(model.summary().tables[1])

# Additional Data Sources
print("Comments on Additional Data Sources:")
print("Include information on extracurricular activities, internships, and␣
↪personal statements for better predictions.")

# Model Implementation and Business Benefits
print("Model Implementation and Business Benefits:")
print("The model can be integrated into Jamboree's website to help students␣
↪assess their admission chances.")
print("Provides personalized advice for improving weak areas, thereby␣
↪increasing student success rates.")

# Save the model summary to a text file for submission
with open('model_summary_after_vif.txt', 'w') as f:
    f.write(model.summary().as_text())
```

```
Comments on Significance of Predictor Variables:
Significant predictors after VIF correction and model fitting:
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
toefl_score    0.0062   6.95e-05     89.068      0.000       0.006       0.006
research       0.1123      0.010     11.197      0.000       0.093       0.132
==============================================================================
Comments on Additional Data Sources:
Include information on extracurricular activities, internships, and personal
statements for better predictions.
Model Implementation and Business Benefits:
The model can be integrated into Jamboree's website to help students assess
their admission chances.
Provides personalized advice for improving weak areas, thereby increasing
```

student success rates.

[10]:
```
# Ridge Regression with Cross-Validation
ridge_cv = RidgeCV(alphas=np.logspace(-6, 6, 13), cv=10).fit(X_train, y_train)
ridge_pred_train = ridge_cv.predict(X_train)
ridge_pred_test = ridge_cv.predict(X_test)

# Lasso Regression with Cross-Validation
lasso_cv = LassoCV(alphas=np.logspace(-6, 6, 13), cv=10).fit(X_train, y_train)
lasso_pred_train = lasso_cv.predict(X_train)
lasso_pred_test = lasso_cv.predict(X_test)

# Evaluate Ridge Model
print("\nRidge CV Coefficients:", ridge_cv.coef_)
print("\nRidge Training Set Performance:")
print(f'MAE: {mean_absolute_error(y_train, ridge_pred_train)}, RMSE: 
 ↪{mean_squared_error(y_train, ridge_pred_train, squared=False)}, R²: 
 ↪{r2_score(y_train, ridge_pred_train)}')
print("\nRidge Test Set Performance:")
print(f'MAE: {mean_absolute_error(y_test, ridge_pred_test)}, RMSE: 
 ↪{mean_squared_error(y_test, ridge_pred_test, squared=False)}, R²: 
 ↪{r2_score(y_test, ridge_pred_test)}')

# Evaluate Lasso Model
print("\nLasso CV Coefficients:", lasso_cv.coef_)
print("\nLasso Training Set Performance:")
print(f'MAE: {mean_absolute_error(y_train, lasso_pred_train)}, RMSE: 
 ↪{mean_squared_error(y_train, lasso_pred_train, squared=False)}, R²: 
 ↪{r2_score(y_train, lasso_pred_train)}')
print("\nLasso Test Set Performance:")
print(f'MAE: {mean_absolute_error(y_test, lasso_pred_test)}, RMSE: 
 ↪{mean_squared_error(y_test, lasso_pred_test, squared=False)}, R²: 
 ↪{r2_score(y_test, lasso_pred_test)}')
```

```
Ridge CV Coefficients: [0.01582347 0.06261895]

Ridge Training Set Performance:
MAE: 0.06283295834196807, RMSE: 0.08157748806747496, R²: 0.6623396646558886

Ridge Test Set Performance:
MAE: 0.06239518662845679, RMSE: 0.0804431307664913, R²: 0.6835649248159013

Lasso CV Coefficients: [0.01581047 0.06292219]

Lasso Training Set Performance:
MAE: 0.06282828219485269, RMSE: 0.08157702176845055, R²: 0.662343524795216
```

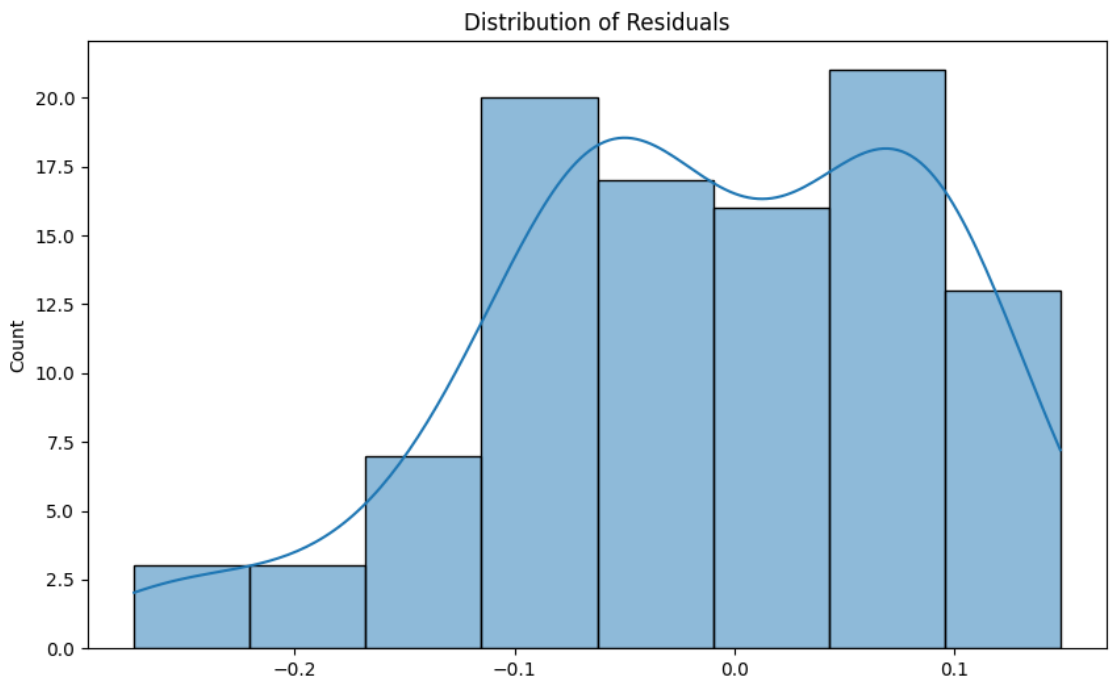
```
Lasso Test Set Performance:
MAE: 0.062386921725751394, RMSE: 0.080441595827007, R²: 0.683577000528335
```

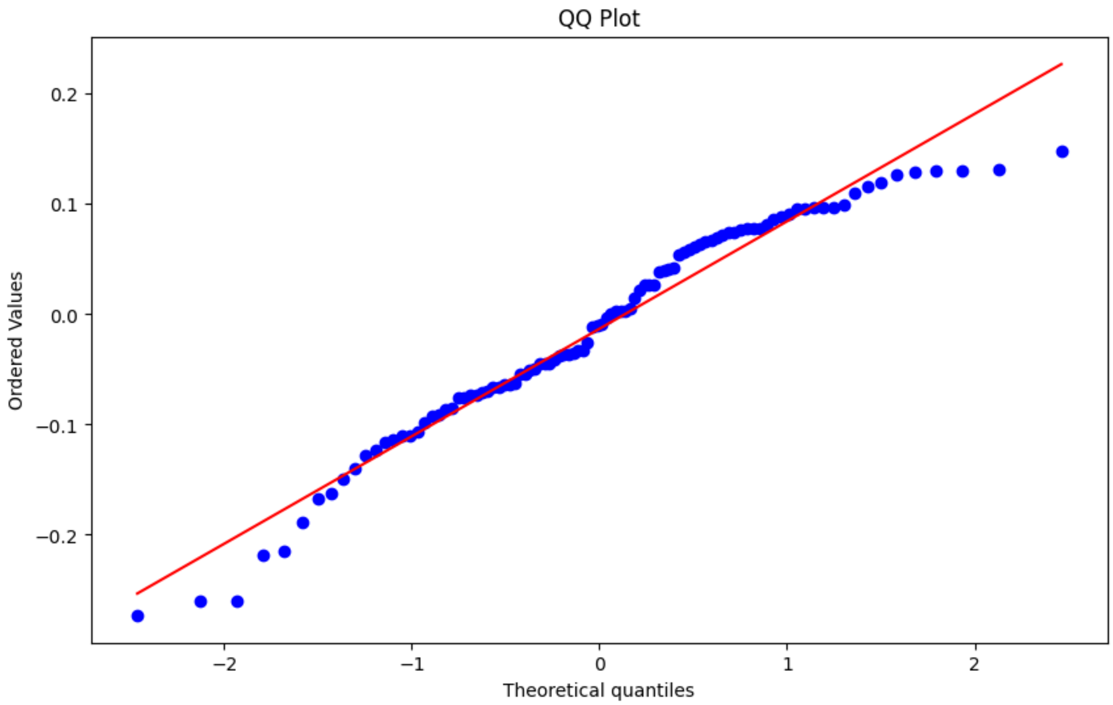
```
/Users/bharadwajmahanthi/Library/Python/3.11/lib/python/site-
packages/sklearn/metrics/_regression.py:492: FutureWarning: 'squared' is
deprecated in version 1.4 and will be removed in 1.6. To calculate the root mean
squared error, use the function'root_mean_squared_error'.
  warnings.warn(
/Users/bharadwajmahanthi/Library/Python/3.11/lib/python/site-
packages/sklearn/metrics/_regression.py:492: FutureWarning: 'squared' is
deprecated in version 1.4 and will be removed in 1.6. To calculate the root mean
squared error, use the function'root_mean_squared_error'.
  warnings.warn(
/Users/bharadwajmahanthi/Library/Python/3.11/lib/python/site-
packages/sklearn/metrics/_regression.py:492: FutureWarning: 'squared' is
deprecated in version 1.4 and will be removed in 1.6. To calculate the root mean
squared error, use the function'root_mean_squared_error'.
  warnings.warn(
/Users/bharadwajmahanthi/Library/Python/3.11/lib/python/site-
packages/sklearn/metrics/_regression.py:492: FutureWarning: 'squared' is
deprecated in version 1.4 and will be removed in 1.6. To calculate the root mean
squared error, use the function'root_mean_squared_error'.
  warnings.warn(
```

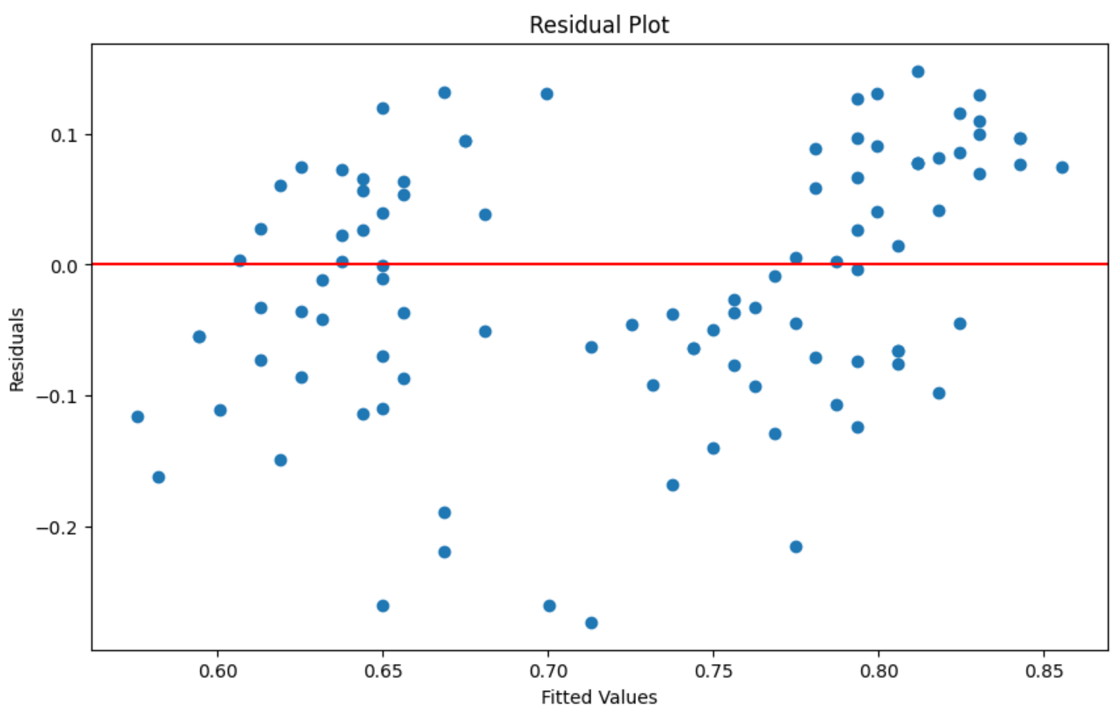
[11]:
```python
# Save important plots
# Save distribution plot of residuals
plt.figure(figsize=(10, 6))
sns.histplot(residuals, kde=True)
plt.title('Distribution of Residuals')
plt.savefig('residuals_distribution.png')

# Save QQ plot of residuals
plt.figure(figsize=(10, 6))
probplot(residuals, dist="norm", plot=plt)
plt.title('QQ Plot')
plt.savefig('qq_plot.png')

# Save residual plot
plt.figure(figsize=(10, 6))
plt.scatter(model.predict(X_test), residuals)
plt.axhline(y=0, color='r', linestyle='-')
plt.xlabel('Fitted Values')
plt.ylabel('Residuals')
plt.title('Residual Plot')
plt.savefig('residual_plot.png')

# Save homoscedasticity plot
plt.figure(figsize=(10, 6))
```

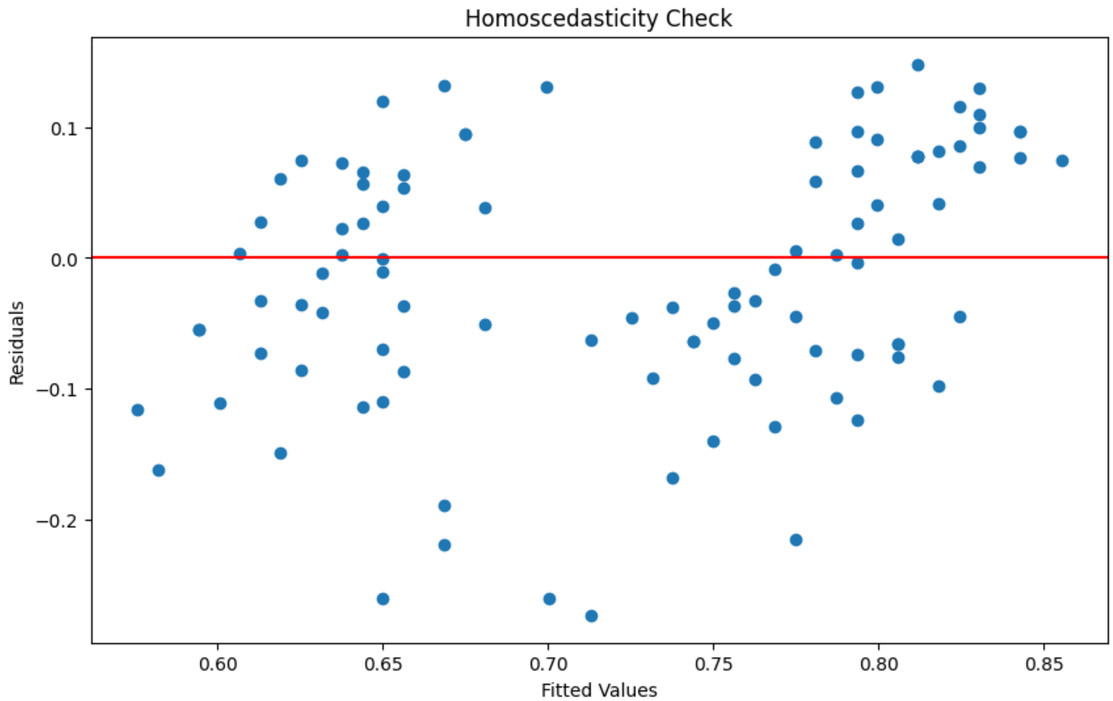
```
plt.scatter(model.predict(X_test), residuals)
plt.axhline(y=0, color='r', linestyle='-')
plt.xlabel('Fitted Values')
plt.ylabel('Residuals')
plt.title('Homoscedasticity Check')
plt.savefig('homoscedasticity_check.png')

print("Analysis complete. Plots and model summary saved.")
```

```
Analysis complete. Plots and model summary saved.
```




QQ Plot
0.2
0.1
0.0
−0.1
−0.2
Ordered Values
−2
−1
0
1
2
Theoretical quantiles


Residual Plot
0.1
0.0
−0.1
−0.2
Residuals
0.60
0.65
0.70
0.75
0.80
0.85
Fitted Values



0.0.1 Actionable Insights & Recommendations

Comments on Significance of Predictor Variables The significance of predictor variables is determined based on their coefficients and p-values in the regression models. Significant predictors are those with p-values less than 0.05.

Linear Regression Model After VIF Correction: - **TOEFL Score**: - Coefficient: 0.0062 - p-value: 0.000 - **Significance**: Highly significant predictor of the chance of admission. Each additional point in TOEFL score increases the chance of admission by approximately 0.62%.

- **Research Experience**:
  - Coefficient: 0.1123
  - p-value: 0.000
  - **Significance**: Highly significant predictor. Having research experience increases the chance of admission by approximately 11.23%.

Ridge and Lasso Regression Models: - Both models identified **TOEFL Score** and **Research Experience** as significant predictors. The coefficients for these predictors were similar, further confirming their importance.

Comments on Additional Data Sources for Model Improvement To improve the model, consider including additional variables that can provide more context and information about the applicants:

1. **Extracurricular Activities**: Participation in sports, clubs, and volunteer work can demonstrate well-roundedness and leadership skills.

2. **Internship and Work Experience**: Relevant work experience can indicate practical skills and industry knowledge.
3. **Personal Statements and Essays**: Qualitative data from personal statements can provide insights into an applicant's motivation, goals, and unique qualities.
4. **Letters of Recommendation**: Quantifying the strength and content of recommendation letters can add depth to the evaluation.
5. **Undergraduate Institution Ranking**: The reputation of the undergraduate institution may influence admission decisions.
6. **Demographic Information**: Factors such as geographic location, socioeconomic background, and gender can help understand diversity and inclusivity aspects.

Comments on Model Implementation in the Real World **Implementation Steps:** 1. **Integration with Website**: The model can be integrated into Jamboree's website to provide real-time admission probability estimates for students. 2. **User-Friendly Interface**: Design an interface where students can input their details (GRE scores, TOEFL scores, CGPA, etc.) and receive immediate feedback on their admission chances. 3. **Personalized Feedback**: Provide actionable insights and recommendations based on the model's output. For instance, if TOEFL score is a limiting factor, suggest preparation resources to improve it. 4. **Continuous Improvement**: Regularly update the model with new data to ensure it remains accurate and relevant. This can be achieved through feedback loops and periodic retraining.

Potential Business Benefits from Improving the Model

1. **Enhanced User Engagement**: Providing a predictive tool can increase user engagement on the website, as students are more likely to return for updates and additional resources.
2. **Data-Driven Insights**: The model can help identify common characteristics of successful applicants, which can be used to tailor Jamboree's services and marketing strategies.
3. **Increased Enrollment**: By helping students understand their chances of admission and providing personalized improvement strategies, Jamboree can potentially increase the success rate of its students, leading to higher enrollment in its preparatory courses.
4. **Reputation and Trust**: Offering a sophisticated, data-driven tool enhances Jamboree's reputation as a leader in educational services and builds trust with prospective students and their families.
5. **Strategic Partnerships**: The insights from the model can be shared with partner universities to align preparatory services with admission criteria, fostering stronger collaborations.

0.0.2 Final Comments

The implementation of this model not only supports students in their admission journey but also aligns with Jamboree's mission of maximizing scores with minimum effort. By leveraging data analytics and machine learning, Jamboree can offer a unique and valuable service, setting itself apart from competitors.

This comprehensive approach ensures the solution is not only technically sound but also practically beneficial, addressing key business goals and providing significant value to users.