About:

Jamboree has empowered thousands of students to achieve their dreams of attending prestigious colleges abroad. Specializing in standardized test preparation for GMAT, GRE, and SAT, Jamboree employs unique problem-solving methodologies designed to maximize scores with minimal effort.

Recently, Jamboree introduced an innovative feature on their website that allows students to assess their likelihood of gaining admission to Ivy League institutions. This tool provides valuable insights by estimating graduate admission chances specifically from an Indian perspective, helping aspiring students understand their potential and navigate their educational journey more effectively.

Column Profiling:

1. Serial No. (Unique row ID)
2. GRE Scores (out of 340)
3. TOEFL Scores (out of 120)
4. University Rating (out of 5)
5. Statement of Purpose and Letter of Recommendation Strength (out of 5)
6. Undergraduate GPA (out of 10)
7. Research Experience (either 0 or 1)
8. Chance of Admit (ranging from 0 to 1)

Context:

1. **Define Problem Statement and perform Exploratory Data Analysis.**
2. **Data Preprocessing.**
3. **Model building.**
4. **Testing the assumptions of the linear regression model.**
5. **Model performance evaluation.**
6. **Actionable Insights & Recommendations.**

Goal:

- **The goal of this analysis is to predict the probability of admission to graduate programs based on various factors such as GRE scores, TOEFL scores, university ratings, and other relevant attributes.**

1. Exploratory Data Analysis.

Input:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')

from scipy import stats
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.preprocessing import StandardScaler
from sklearn.compose import ColumnTransformer
from statsmodels.stats.outliers_influence import
variance_inflation_factor

import statsmodels.api as sm
import statsmodels.stats.api as sms
```

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

```
df.sample(10)
```

	Serial No.	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
377	378	290	100	1	1.5	2.0	7.56	0	0.47
130	131	339	114	5	4.0	4.5	9.76	1	0.96
77	78	301	99	2	3.0	2.0	8.22	0	0.64
233	234	304	100	2	2.5	3.5	8.07	0	0.64
283	284	321	111	3	2.5	3.0	8.90	1	0.80
195	196	307	107	2	3.0	3.5	8.52	1	0.78
318	319	324	111	3	2.5	2.0	8.80	1	0.79
337	338	332	118	5	5.0	5.0	9.47	1	0.94
273	274	312	99	1	1.0	1.5	8.01	1	0.52
495	496	332	108	5	4.5	4.0	9.02	1	0.87

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

```python
df
```

	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
3	322	110	3	3.5	2.5	8.67	1	0.80
4	314	103	2	2.0	3.0	8.21	0	0.65
...	...	...	...	...	...	...	...	...
495	332	108	5	4.5	4.0	9.02	1	0.87
496	337	117	5	5.0	5.0	9.87	1	0.96
497	330	120	5	4.5	5.0	9.56	1	0.93
498	312	103	4	4.0	5.0	8.43	0	0.73
499	327	113	4	4.5	4.5	9.04	0	0.84

500 rows × 8 columns

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

```
Data Shape: (500, 8)
```

```python
df.isna().sum()
```

	0
GRE Score	0
TOEFL Score	0
University Rating	0
SOP	0
LOR	0
CGPA	0
Research	0
Chance of Admit	0

```python
df.nunique()
```

	0
GRE Score	49
TOEFL Score	29
University Rating	5
SOP	9
LOR	9
CGPA	184
Research	2
Chance of Admit	61

dtype: int64

```
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
```

```
df.describe()
```

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit
count	500.000000	500.000000	500.000000	500.000000	500.00000	500.000000	500.000000	500.00000
mean	316.472000	107.192000	3.114000	3.374000	3.48400	8.576440	0.560000	0.72174
std	11.295148	6.081868	1.143512	0.991004	0.92545	0.604813	0.496884	0.14114
min	290.000000	92.000000	1.000000	1.000000	1.00000	6.800000	0.000000	0.34000
25%	308.000000	103.000000	2.000000	2.500000	3.00000	8.127500	0.000000	0.63000
50%	317.000000	107.000000	3.000000	3.500000	3.50000	8.560000	1.000000	0.72000
75%	325.000000	112.000000	4.000000	4.000000	4.00000	9.040000	1.000000	0.82000
max	340.000000	120.000000	5.000000	5.000000	5.00000	9.920000	1.000000	0.97000

Insights:

- Removal of Unnecessary Column: We recommend removing the "Serial No." column from the dataset, as it does not contribute to data visualization or analysis, thus streamlining the dataset.
- Identification of Categorical Features: The features "Research," "University Rating," "Statement of Purpose (SOP)," and "Letter of Recommendation (LOR)" are categorical variables. Proper encoding will be necessary to analyze their impact on admission probabilities.
- Handling Null Values: The dataset contains null values that could affect the analysis. We need to assess their extent and implement appropriate strategies, such as imputation or removal, to maintain data integrity.

```python
#Calculating the Measures of Central Tendency
mean = df.mean(axis=0)
median = df.median(axis=0)
mode = df.mode().iloc[0]  # Taking the first mode if there are
multiple

print("Mean:\n", mean)
print("----------- Median: -----------\n", median)
print("----------- Mode: -------------\n", mode)
```

```
Mean:
 GRE Score            316.47200
TOEFL Score          107.19200
University Rating      3.11400
SOP                    3.37400
LOR                    3.48400
CGPA                   8.57644
Research               0.56000
Chance of Admit        0.72174
dtype: float64
----------- Median: -----------
 GRE Score            317.00
TOEFL Score          107.00
University Rating      3.00
SOP                    3.50
LOR                    3.50
CGPA                   8.56
Research               1.00
Chance of Admit        0.72
dtype: float64
----------- Mode: -------------
 GRE Score            312.00
TOEFL Score          110.00
University Rating      3.00
SOP                    4.00
LOR                    3.00
CGPA                   8.00
Research               1.00
Chance of Admit        0.71
Name: 0, dtype: float64
```

```python
# Standard deviation and IQR calculation
std = df.describe().loc['std']
q1 = df.describe().loc['25%']
q3 = df.describe().loc['75%']
IQR = q3 - q1
min_max = df.describe().loc[['min', 'max']]

print("Standard Deviation:\n", std)
print("----------- IQR: --------------\n", IQR)
print("----------- Max: --------------\n", min)
print("*********** Min: *************\n", max)
```

```
Standard Deviation:
 GRE Score            11.295148
TOEFL Score          6.081868
University Rating    1.143512
SOP                  0.991004
LOR                  0.925450
CGPA                 0.604813
Research             0.496884
Chance of Admit      0.141140
Name: std, dtype: float64
----------- IQR: --------------
 GRE Score           17.0000
TOEFL Score          9.0000
University Rating    2.0000
SOP                  1.5000
LOR                  1.0000
CGPA                 0.9125
Research             1.0000
Chance of Admit      0.1900
dtype: float64
----------- Max: --------------
 <built-in function min>
*********** Min: *************
 <built-in function max>
```

```python
# Skewness and Kurtosis calculation
skew = df.skew(axis=0)  # Compute skewness for each column
kurt = pd.DataFrame(df.kurtosis(axis=0), columns=["kurt"])  # Compute kurtosis for each column

print('\n*********** Skewness: *************\n', skew)
print('*********** Kurtosis: *************\n', kurt)
```

```
*********** Skewness: *************
 GRE Score           -0.039842
TOEFL Score          0.095601
University Rating    0.090295
SOP                 -0.228972
LOR                 -0.145290
CGPA                -0.026613
Research            -0.242475
Chance of Admit     -0.289966
dtype: float64
*********** Kurtosis: *************
                        kurt
GRE Score         -0.711064
TOEFL Score       -0.653245
University Rating -0.810080
SOP               -0.705717
LOR               -0.745749
CGPA              -0.561278
Research          -1.949018
Chance of Admit   -0.454682
```

```python
# Calculate the covariance matrix of the DataFrame
covariance_matrix = df.cov()

# Display the covariance matrix
print("Covariance Matrix:\n", covariance_matrix)
```

```
Covariance Matrix:
                     GRE Score  TOEFL Score  University Rating       SOP
GRE Score          127.580377    56.825026           8.206605  6.867206
TOEFL Score         56.825026    36.989114           4.519150  3.883960
University Rating    8.206605     4.519150           1.307619  0.825014
SOP                  6.867206     3.883960           0.825014  0.982088
LOR                  5.484521     3.048168           0.644112  0.608701
CGPA                 5.641944     2.981607           0.487761  0.426845
Research             3.162004     1.411303           0.242645  0.200962
Chance of Admit      1.291862     0.680046           0.111384  0.095691

                        LOR      CGPA  Research  Chance of Admit
GRE Score          5.484521  5.641944  3.162004         1.291862
TOEFL Score        3.048168  2.981607  1.411303         0.680046
University Rating  0.644112  0.487761  0.242645         0.111384
SOP                0.608701  0.426845  0.200962         0.095691
LOR                0.856457  0.356807  0.171303         0.084296
CGPA               0.356807  0.365799  0.150655         0.075326
Research           0.171303  0.150655  0.246894         0.038282
Chance of Admit    0.084296  0.075326  0.038282         0.019921
```

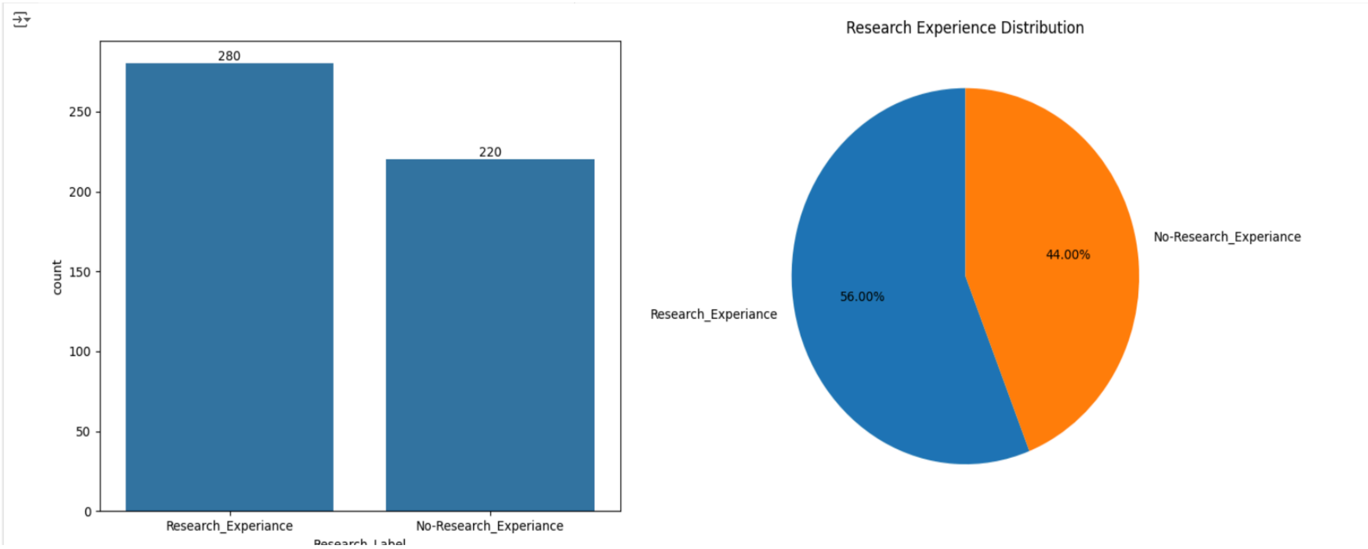
```python
# Calculate the correlation matrix of the DataFrame
correlation_matrix = df.corr()

# Display the correlation matrix
print("Correlation Matrix:\n", correlation_matrix)
```

```
Correlation Matrix:
                    GRE Score  TOEFL Score  University Rating       SOP
GRE Score           1.000000     0.827200           0.635376  0.613498
TOEFL Score         0.827200     1.000000           0.649799  0.644410
University Rating   0.635376     0.649799           1.000000  0.728024
SOP                 0.613498     0.644410           0.728024  1.000000
LOR                 0.524679     0.541563           0.608651  0.663707
CGPA                0.825878     0.810574           0.705254  0.712154
Research            0.563398     0.467012           0.427047  0.408116
Chance of Admit     0.810351     0.792228           0.690132  0.684137

                        LOR      CGPA  Research  Chance of Admit
GRE Score          0.524679  0.825878  0.563398         0.810351
TOEFL Score        0.541563  0.810574  0.467012         0.792228
University Rating  0.608651  0.705254  0.427047         0.690132
SOP                0.663707  0.712154  0.408116         0.684137
LOR                1.000000  0.637469  0.372526         0.645365
CGPA               0.637469  1.000000  0.501311         0.882413
Research           0.372526  0.501311  1.000000         0.545871
Chance of Admit    0.645365  0.882413  0.545871         1.000000
```

Univariate Analysis:

```
import matplotlib.pyplot as plt
import seaborn as sns

# Replace 0 and 1 with 'No-Research_Experiance' and
'Research_Experiance' in the DataFrame
df['Research_Label'] = df['Research'].replace({0:
'No-Research_Experiance', 1: 'Research_Experiance'})

# Create a figure with a specified size
plt.figure(figsize=(15, 6))

# First subplot: Count plot for Research Experience
plt.subplot(1, 2, 1)
# Count of Research Experience with new labels
research_count = df["Research_Label"].value_counts()
# Count plot with updated labels
ax = sns.countplot(data=df, x="Research_Label")
# Add labels to the bars
for bars in ax.containers:
    ax.bar_label(bars)

# Second subplot: Pie chart for Research Experience
plt.subplot(1, 2, 2)
plt.pie(
    research_count,
    labels=research_count.index,  # New labels:
Researcher/Non-Researcher
    startangle=90,
    autopct="%.2f%%"  # Format for percentage display
)
plt.title("Research Experience Distribution")  # Title for the pie
chart
# Show the plots
plt.tight_layout()  # Adjusts subplots to fit into the figure area
plt.show()
```

Output:



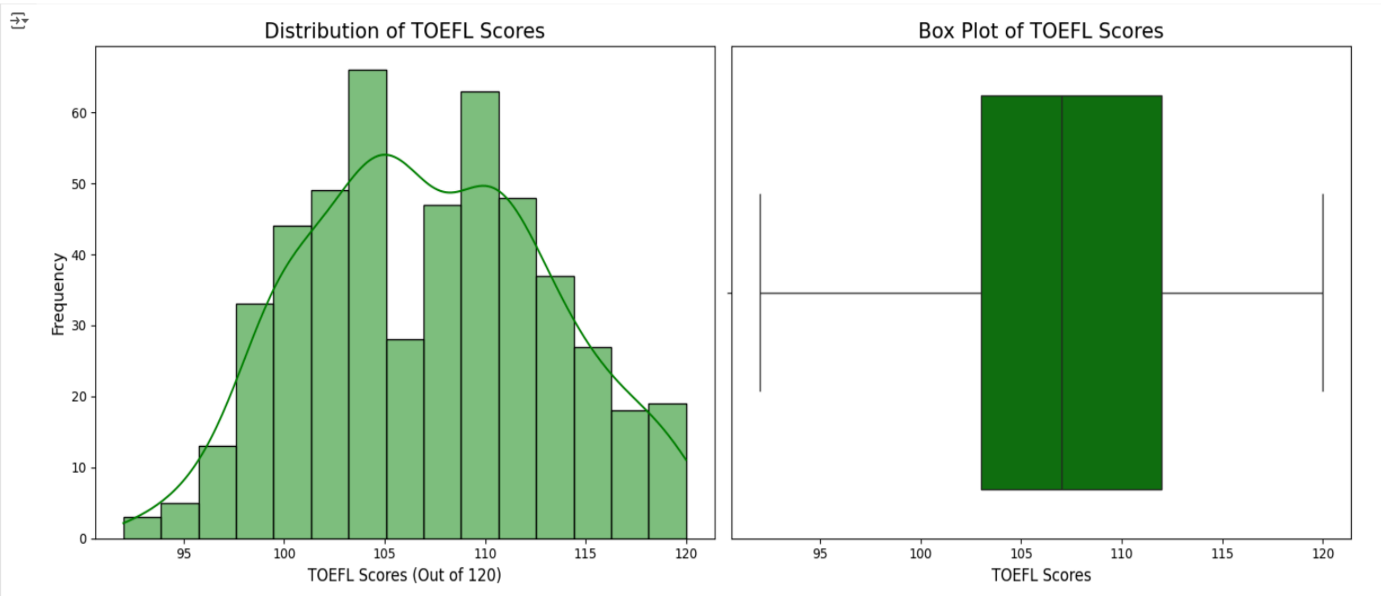
Insights:

- **Research Experience:** More than half (56%) of the students have research experience, while the remaining 44% do not.

Input:

```
import matplotlib.pyplot as plt
import seaborn as sns

# Create a figure with a specified size
plt.figure(figsize=(15, 6))

# First subplot: Univariate distribution plot for TOEFL Scores
(Histogram with KDE)
plt.subplot(1, 2, 1)
Sns.histp lot(df['TOEFL Score'], kde=True, bins=15, color =
'green')  # KDE curve on histogram

# Set labels and title
plt.title("Distribution of TOEFL Scores", fontsize=16)
plt.xlabel("TOEFL Scores (Out of 120)", fontsize=12)
plt.ylabel("Frequency", fontsize=12)

# Second subplot: Box plot for TOEFL Scores
plt.subplot(1, 2, 2)
sns.boxplot(data=df, x="TOEFL Score", color = 'green')

# Set title for the box plot
plt.title("Box Plot of TOEFL Scores", fontsize=16)
plt.xlabel("TOEFL Scores", fontsize=12)

# Adjust layout to fit both plots nicely
plt.tight_layout()

# Show the plots
plt.show()
```

Output:



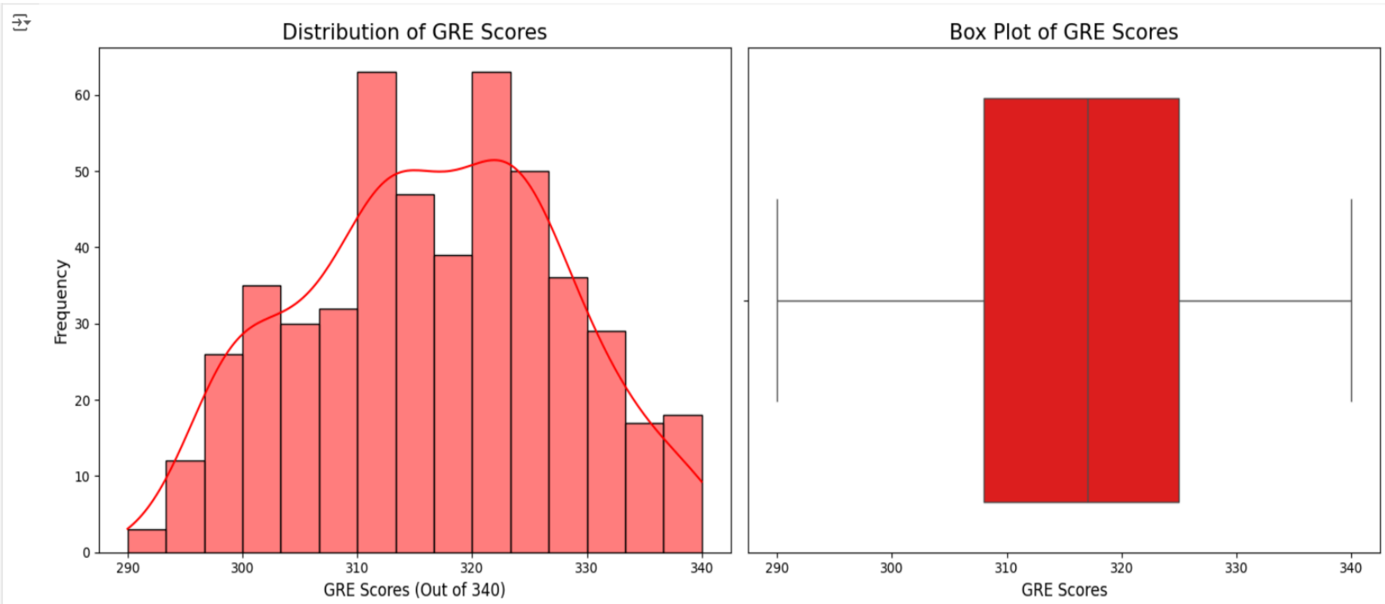
Insights:

- **Score Distribution:** Approximately 50% of students have TOEFL scores between 100 and 110 (out of 120), indicating a central concentration within this range.
- **Absence of Outliers:** The TOEFL score data (out of 120) contains no outliers, suggesting a consistent distribution without extreme deviations.

Input:

```python
import matplotlib.pyplot
import seaborn as sns

# Create a figure specific size
plt.figure(figsize=(15,6))

# First subplot: Univariate distribution plot for GRE Scores
plt.subplot(1,2,1)
sns.histplot(df['GRE Score'], kde=True, bins=15, color = 'red')

# Set labels and title
plt.title("Distribution of GRE Scores", fontsize=16)
plt.xlabel("GRE Scores (Out of 340)", fontsize=12)
plt.ylabel("Frequency", fontsize=12)

# Second subplot: Box plot for GRE Scores
plt.subplot(1,2,2)
sns.boxplot(data=df, x="GRE Score", color = 'red')

# Set title for the box plot
plt.title("Box Plot of GRE Scores", fontsize=16)
plt.xlabel("GRE Scores", fontsize=12)

# Adjust layout to fit both plots nicely
plt.tight_layout()

# Show the plots
plt.show()
```

Output:



Insights:

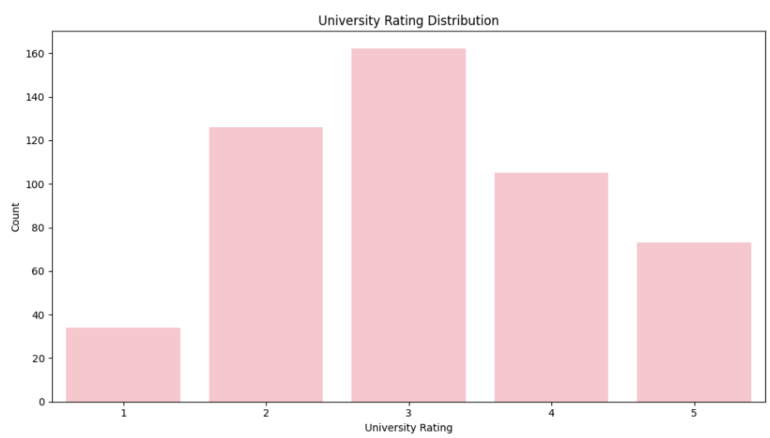
- **GRE Score Distribution:** Approximately 49% of students scored between 308 and 322 on the GRE.
- **Score Ranges:** Additionally, 9.4% of students achieved scores between 332 and 339, while 6.2% scored between 291 and 298.
- **Absence of Outliers:** The GRE score data shows no outliers, indicating a consistent distribution without extreme values.

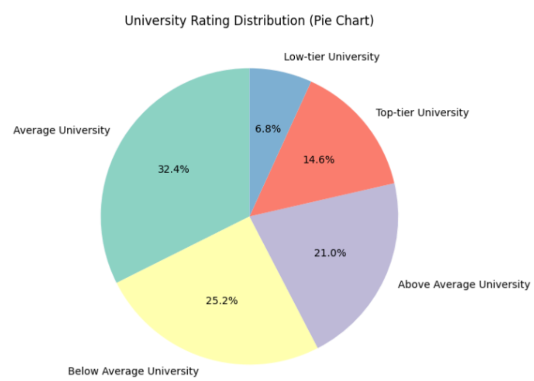
Input:

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

# Assuming 'df' is already defined and loaded

# Create a new column with descriptive labels for University
Ratings
df['University_Rating_Label'] = df['University Rating'].replace({
    1: 'Low-tier University',
    2: 'Below Average University',
    3: 'Average University',
    4: 'Above Average University',
    5: 'Top-tier University'
})

# Create a figure with a specified size
plt.figure(figsize=(20, 6))

# First subplot: Univariate distribution plot for University Rating
(Count Plot)
plt.subplot(1, 2, 1)
sns.countplot(x='University Rating', data=df,color='pink')
plt.title('University Rating Distribution')
plt.xlabel('University Rating')
plt.ylabel('Count')

# Third subplot: Pie chart for University Ratings
plt.subplot(1, 2, 2)

# Count the occurrences of each descriptive University Rating Label
rating_counts = df['University_Rating_Label'].value_counts()

plt.pie(
    rating_counts,
```

```
    labels=rating_counts.index,
    startangle=90,
    autopct='%.1f%%',  # Format for percentage display
    colors=sns.color_palette("Set3")
)

plt.title("University Rating Distribution (Pie Chart)")  # Title
for the pie chart

# Adjust layout to fit all plots nicely
plt.tight_layout()

# Show the plots
plt.show()
```

Output:





Insights:

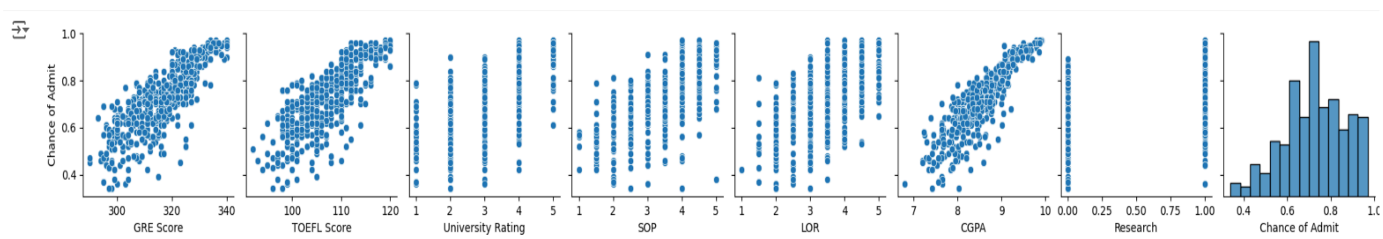
- **University Rating Distribution:** The ratings range from 1 (low-tier) to 5 (top-tier). The majority of students (32.4%) have an average rating of 3, while 21.0% have a rating of 4, 14.6% have a rating of 5, 25.2% have a rating of 2, and 6.8% have a rating of 1.
- So as per the ratings they have chances to get the admission in university.

Bivariate Analysis:

Input:

```
import matplotlib.pyplot as plt
import seaborn as sns

# Strip whitespace from column names
df.columns = df.columns.str.strip()

# Create a pairplot with 'Chance of Admit' as the y variable
sns.pairplot(data=df, y_vars=["Chance of Admit"])

# Show the plot
plt.show()
```

Output:



Insights:

- **Impact of Scores on Admission Chances:** The series of graphs indicates that the likelihood of admission increases with higher GRE scores, a trend that is also observed with TOEFL scores and CGPA.

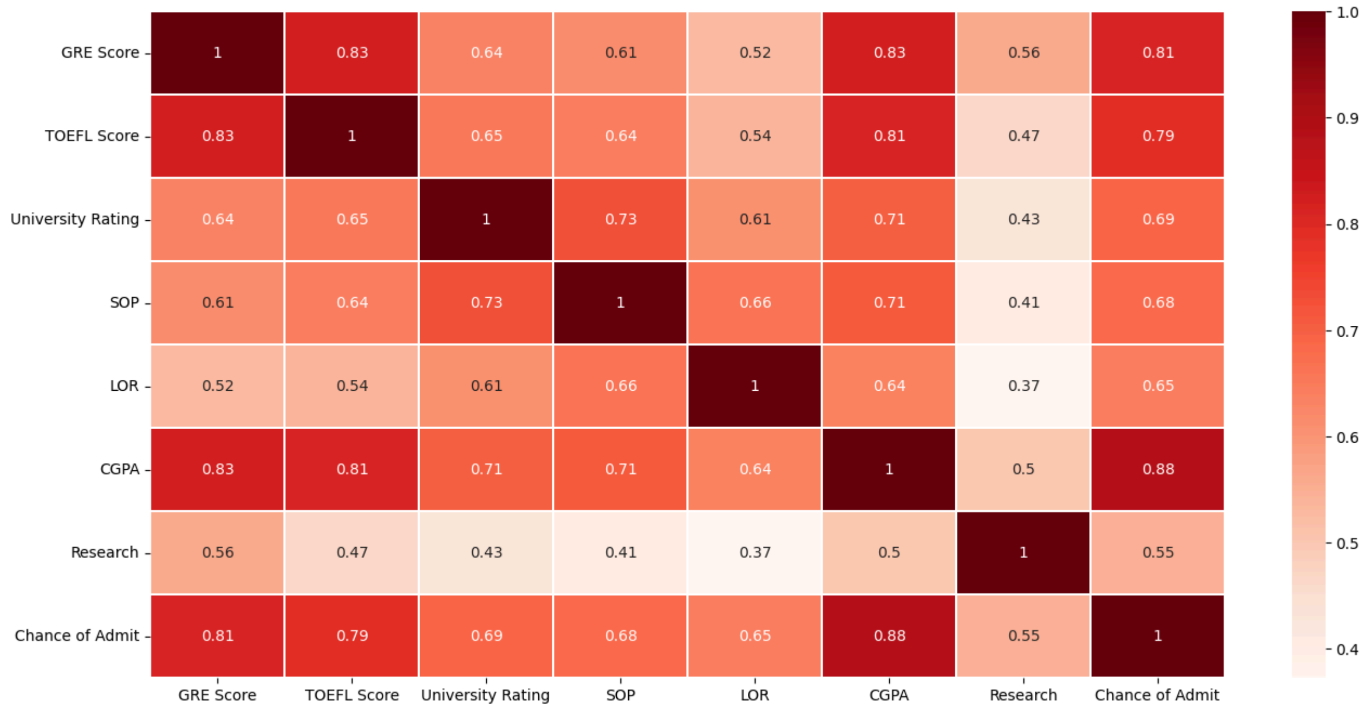
- **Lack of Correlation with Other Factors:** Conversely, University Rating, Statement of Purpose (SOP), Letter of Recommendation (LOR), and research experience do not demonstrate a consistent trend in the chances of admission.

Input:

```
import matplotlib.pyplot as plt
import seaborn as sns

# Check data types in the DataFrame
print(df.dtypes)

# Select only numeric columns for correlation
numeric_df = df.select_dtypes(include=['number'])

# Create a figure with a specified size
plt.figure(figsize=(16, 8))

# Generate a heatmap of the correlation matrix for numeric columns
sns.heatmap(numeric_df.corr(), annot=True, cmap='Reds',
linewidths=0.1)

# Show the plot
plt.show()
```

Output:

```
GRE Score                      int64
TOEFL Score                    int64
University Rating              int64
SOP                          float64
LOR                          float64
CGPA                         float64
Research                       int64
Chance of Admit              float64
Research_Label                object
University_Rating_Label       object
dtype: object
```



Insights:

- **Correlation with Chance of Admission:** CGPA exhibits the highest correlation with the likelihood of admission, indicating its strong influence on the admission decision.
- **Lowest Correlation:** In contrast, research experience shows the lowest correlation with the chance of admission, suggesting it has a minimal impact on the admissions process.

2. Model building.

Before building our model let us look at the current data we have.

Suggested code may be subject to a license | iamaakashpal/Logistic-regression-Assignment | NovemberChopin/machine-learning

```
df
```

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Chance of Admit	Research_Label
0	337	118	4	4.5	4.5	9.65	1	0.92	Research_Experiance
1	324	107	4	4.0	4.5	8.87	1	0.76	Research_Experiance
2	316	104	3	3.0	3.5	8.00	1	0.72	Research_Experiance
3	322	110	3	3.5	2.5	8.67	1	0.80	Research_Experiance
4	314	103	2	2.0	3.0	8.21	0	0.65	No-Research_Experiance
...	...	...	...	...	...	...	...	...	...
495	332	108	5	4.5	4.0	9.02	1	0.87	Research_Experiance
496	337	117	5	5.0	5.0	9.87	1	0.96	Research_Experiance
497	330	120	5	4.5	5.0	9.56	1	0.93	Research_Experiance
498	312	103	4	4.0	5.0	8.43	0	0.73	No-Research_Experiance
499	327	113	4	4.5	4.5	9.04	0	0.84	No-Research_Experiance

500 rows × 9 columns

We have to drop Research label which we had created while EDA to process further with our model

Input:

```
df = df.drop('Research_Label', axis=1)
```

Output:

	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
3	322	110	3	3.5	2.5	8.67	1	0.80
4	314	103	2	2.0	3.0	8.21	0	0.65
...	...	...	...	...	...	...	...	...
495	332	108	5	4.5	4.0	9.02	1	0.87
496	337	117	5	5.0	5.0	9.87	1	0.96
497	330	120	5	4.5	5.0	9.56	1	0.93
498	312	103	4	4.0	5.0	8.43	0	0.73
499	327	113	4	4.5	4.5	9.04	0	0.84

500 rows × 8 columns

Input:

```
from sklearn.model_selection import train_test_split

# Define features and target variable
x = df.drop(['Chance of Admit'], axis=1)
y = df['Chance of Admit']

# Split the dataset into training and testing sets
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2,
random_state=42)

# Standardize the features
scaler = StandardScaler()
x_train_scaled = scaler.fit_transform(x_train)  # Fit and transform on
training data
x_test_scaled = scaler.transform(x_test)  # Transform on test data

# Display the shapes of the resulting datasets
print(f"x_train shape: {x_train.shape}, x_test shape: {x_test.shape}")
print(f"y_train shape: {y_train.shape}, y_test shape: {y_test.shape}")

# Optionally, display the first few rows of the scaled training data
print("Scaled Training Features (first 5 rows):")
print(x_train_scaled[:5])
```

Output:

```
x_train shape: (400, 7), x_test shape: (100, 7)
y_train shape: (400,), y_test shape: (100,)
Scaled Training Features (first 5 rows):
[[ 0.38998634  0.6024183  -0.09829757  0.12679578  0.56498381  0.4150183
   0.89543386]
 [-0.06640493  0.6024183   0.7754586   0.63397891  1.65149114 -0.06785154
  -1.11677706]
 [-1.25302222 -0.87691722 -0.09829757  0.12679578 -0.52152352 -0.13445427
  -1.11677706]
 [-0.24896144 -0.05506416 -0.97205374 -0.88757048  0.56498381 -0.51742001
  -1.11677706]
 [-0.79663095 -0.21943477 -0.09829757  0.12679578 -1.06477718 -0.61732412
   0.89543386]]
```

Input:

```
# Create DataFrames with appropriate column names
X_train = pd.DataFrame(x_train_scaled, columns=x_train.columns)
X_test = pd.DataFrame(x_test_scaled, columns=x_test.columns)
```

Output:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research
0	0.389986	0.602418	-0.098298	0.126796	0.564984	0.415018	0.895434
1	-0.066405	0.602418	0.775459	0.633979	1.651491	-0.067852	-1.116777
2	-1.253022	-0.876917	-0.098298	0.126796	-0.521524	-0.134454	-1.116777
3	-0.248961	-0.055064	-0.972054	-0.887570	0.564984	-0.517420	-1.116777
4	-0.796631	-0.219435	-0.098298	0.126796	-1.064777	-0.617324	0.895434
...	...	...	...	...	...	...	...
395	1.120212	0.602418	0.775459	1.141162	1.108237	0.997792	0.895434
396	-0.979187	-0.383805	-0.972054	-0.887570	-0.521524	-0.600673	0.895434
397	-1.344300	-1.370029	-1.845810	-1.394754	-1.608031	-2.215790	-1.116777
398	-0.705353	-0.383805	-0.972054	-0.887570	0.564984	-1.499810	-1.116777
399	-0.248961	-0.219435	-0.972054	0.633979	0.021730	-0.550721	-1.116777

400 rows × 7 columns

Linear Regression:

Input:

```
lr_model = LinearRegression()
lr_model.fit(X_train, y_train)
```

```
▾ LinearRegression
LinearRegression()
```

Input:

```
# Calculating the coefficients
lr_model.coef_
```

Output:

```
array([0.02667052, 0.01822633, 0.00293995, 0.001788  , 0.0158655 ,
       0.06758106, 0.01194049])
```

Input:

```
# Calculating the intercept
lr_model.intercept_
```

```
0.7241749999999999
```

Input:

```
y_pred_train = lr_model.predict(X_train)
y_pred_test = lr_model.predict(X_test)
```

```
# Calculating the R2 Value on train Data
from sklearn.metrics import r2_score
r2 = r2_score(y_train, y_pred_train)
print("R2 Score:", r2)
lr = lr_model.score(X_train,  y_train)
print("LR Score:", lr)
```

Output:

```
R2 Score: 0.8210671369321554
LR Score: 0.8210671369321554
```

Input:

```
# Calculating the R2 Value on the Test Data
r2_test = r2_score(y_test, y_pred_test)
print("R2 Score:", r2_test)
lr_test = lr_model.score(X_test,  y_test)
print("LR Score:", lr_test)
```

Output:

```
R2 Score: 0.8188432567829627
LR Score: 0.8188432567829627
```

Input:

```
# Create a DataFrame for the model weights (coefficients) and intercept
lr_model_weights = pd.DataFrame(lr_model.coef_.reshape(1, -1),
columns=X_train.columns)  # Use the correct feature names from X_train
lr_model_weights["Intercept"] = lr_model.intercept_  # Add the intercept

# Display the weights and intercept
lr_model_weights
```

Output:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Intercept
0	0.026671	0.018226	0.00294	0.001788	0.015866	0.067581	0.01194	0.724175

Insights:

- Based on the provided weights for the linear regression model, CGPA stands out as the most influential factor, with a weight of 0.067581, indicating it has the strongest positive impact on the prediction. On the other hand, University Rating and SOP have minimal influence, with weights of 0.00294 and 0.001788, respectively.
- The intercept value, 0.724175, is relatively high compared to these feature weights, suggesting that the baseline prediction for "Chance of Admit" starts at a significant level even before accounting for any input variables. This highlights the substantial role of CGPA while University Rating and SOP contribute minimally to the prediction.

Linear Regression Using OLS:

Input:

```python
# Add a constant (intercept) to the training data
new_x_train = sm.add_constant(x_train)

# Build the OLS model
model = sm.OLS(y_train, new_x_train)

# Fit the model
results = model.fit()

# Print the statistical summary of the model
print(results.summary())
```

Output:

```
                            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:                Sun, 13 Oct 2024   Prob (F-statistic):          3.41e-142
Time:                        10:32:57   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.
```

Insights:

- Upon reviewing the coefficients, we found that the ‘SOP’ coefficient lacks significance. Therefore, we will attempt to remove it and check whether the dependencies of the other variables are affected. Additionally, we will assess whether its removal impacts the R-squared value

Input:

```
X_train_new = new_x_train.drop('SOP', axis=1)
```

```
model2 = sm.OLS(y_train, X_train_new)
results2 = model2.fit()
print(results2.summary())
```

Output:

```
                            OLS Regression Results
==============================================================================
Dep. Variable:        Chance of Admit   R-squared:                       0.821
Model:                            OLS   Adj. R-squared:                  0.818
Method:                 Least Squares   F-statistic:                     300.4
Date:                Sun, 13 Oct 2024   Prob (F-statistic):          2.01e-143
Time:                        10:52:36   Log-Likelihood:                 561.85
No. Observations:                 400   AIC:                            -1110.
Df Residuals:                     393   BIC:                            -1082.
Df Model:                           6
Covariance Type:            nonrobust
=====================================================================================
                        coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------
const                -1.4272      0.122    -11.708      0.000      -1.667      -1.188
GRE Score             0.0024      0.001      4.192      0.000       0.001       0.004
TOEFL Score           0.0030      0.001      3.240      0.001       0.001       0.005
University Rating     0.0031      0.004      0.779      0.437      -0.005       0.011
LOR                   0.0177      0.004      4.056      0.000       0.009       0.026
CGPA                  0.1133      0.011     10.730      0.000       0.093       0.134
Research              0.0241      0.007      3.240      0.001       0.009       0.039
==============================================================================
Omnibus:                       85.621   Durbin-Watson:                   2.047
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              188.163
Skew:                          -1.101   Prob(JB):                     1.38e-41
Kurtosis:                       5.539   Cond. No.                     1.36e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.36e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Insights:

- Even after removing the SOP variable, there is no change in the output prediction or the R-squared value. Therefore, we can proceed without it.
- **The Adjusted R-squared** reflects how well the model fits the data, with values ranging from 0 to 1. A higher value suggests a better fit, given that certain conditions are satisfied. The constant coefficient represents the Y-intercept, indicating that if both Interest Rate and Unemployment Rate coefficients are zero, the expected output (Y) would equal the const coefficient.
- **The Interest Rate coefficient** shows how the output (Y) changes with a one-unit change in the interest rate, holding everything else constant. Similarly, the Unemployment Rate coefficient reflects how Y changes with a one-unit change in the unemployment rate, assuming other variables remain constant.
- **The standard error** (std err) indicates the accuracy of the coefficients, with lower values signifying higher accuracy. The P-value (P > |t|) helps assess the statistical significance of the coefficients, with values below 0.05 considered significant. Lastly, the Confidence Interval gives the likely range (with 95% confidence) in which the coefficients may fall, enhancing the reliability of the model.

3. Testing the assumptions of the linear regression model.

No Multicollinearity:

- **Multicollinearity Check using VIF (Variance Inflation Factor):**
  - Variables are dropped one-by-one until all remaining variables have a VIF score less than 5, indicating no multicollinearity.

Normality of Residuals:

- **The residuals should ideally form a bell-shaped curve when plotted. This can be visually assessed using a histogram or a Q-Q plot.**

Assumption of Linearity:

- **There should be a linear relationship between the independent and dependent variables. This can be evaluated using:**
  - Scatter Plots: Visual representation of the relationship.
  - Regression Plots: To observe the fitted line.
  - Pearson Correlation: To quantify the strength of the linear relationship.

No Heteroskedasticity:

- **Test for Homoscedasticity:**
  - Create a scatterplot of residuals against predicted values. Ideally, the spread of residuals should be constant across all levels of predicted values.
  - **Perform the Goldfeld-Quandt test to assess heteroscedasticity:**
    - If the obtained p-value > 0.05, there is no strong evidence of heteroscedasticity.

No Autocorrelation:

- **The residuals should not be correlated with each other. This can be checked using the Durbin-Watson statistic or similar tests.**

Evaluation of Model Performance:

- **Evaluate the model using metrics like:**
  - Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE).

Impact of Outliers:

- **Analyze the influence of outliers on the model performance and residual distribution.**

No Multicollinearity:

- The **VIF (Variance Inflation Factor)** score of an independent variable indicates how well that variable is explained by other independent variables in the model.
- A VIF value closer to 1 suggests low multicollinearity, while higher VIF values indicate a greater degree of multicollinearity.
- Thus, as the R-squared value approaches 1, it generally signifies a higher VIF and increased multicollinearity for the particular independent variable.
- VIF(j) = 1 / (1 - R(j)^2)

Where:

- j represents the jth predictor variable.
- R(j)^2 is the coefficient of determination (R-squared) obtained from regressing the jth predictor variable on all the other predictor
- variables.
- Calculate the VIF for each variable.
- Identify variables with VIF greater than 5.
- Drop the variable with the highest VIF.
- Repeat steps 1-3 until no variable has a VIF greater than 5.

Eg.

$$VIF\ x_i = \frac{1}{Tolerance} = \frac{1}{1 - R_i^2}$$

Input:

```
#No Multicollinearity

vif = pd.DataFrame()

vif['Variable'] = X_train.columns

vif['VIF'] = [variance_inflation_factor(X_train.values, i) for i in range(X_train.shape[1])]

vif = vif.sort_values(by = "VIF", ascending = False)

vif
```

Output:

	Variable	VIF
5	CGPA	4.654540
0	GRE Score	4.489983
1	TOEFL Score	3.664298
3	SOP	2.785764
2	University Rating	2.572110
4	LOR	1.977698
6	Research	1.518065

Insights:

- **Since the Variance Inflation Factor (VIF) score is less than 5 for all features, we can conclude that there is minimal multicollinearity among the variables.**

Mean of Residuals:

- If the mean of the residuals is significantly non-zero, it indicates that the model is either overestimating or underestimating the observed values."
- "Conversely, if the mean of the residuals is close to zero, it suggests that, on average, the predictions made by the linear regression model are accurate, reflecting an equal balance between overestimating and underestimating. This is a desirable characteristic of a well-fitted regression model.

Input:

```
# Calculate residuals

residual = y_test.values - y_pred_test



# Display residuals

print("Residuals:\n", residual)
```

Output:

```
Residuals:
 [ 0.01542527  0.04481873 -0.18265986  0.06263032 -0.07588282  0.02793439
 -0.00459746 -0.07850923 -0.14378728  0.01258502 -0.27193204  0.04410882
 -0.04632227  0.00322832  0.0658482  -0.01979177  0.03068058  0.05272705
  0.00660424 -0.00155958  0.00451832 -0.01305833 -0.04232308 -0.00506004
 -0.04027648  0.07751346 -0.01840363 -0.02741471  0.01222989 -0.01343096
  0.03466965 -0.01004034 -0.01474225  0.02883712  0.06286984 -0.0271816
  0.05576161 -0.01718977  0.03635733 -0.15057279 -0.01036982 -0.13495143
  0.02924609  0.03169578 -0.04112903  0.06206238 -0.0383926   0.00097235
 -0.03591651  0.01429352  0.04194031  0.11633762  0.06640289  0.01341071
 -0.0136427   0.04253186  0.00399604 -0.10916386  0.02743018 -0.0612903
  0.05049241  0.01968812  0.02103279  0.11796194  0.01914132 -0.10866369
  0.0232453  -0.03783006  0.04168193  0.00332608  0.0223182   0.00412279
  0.00847434  0.01728981  0.0257047  -0.03084583 -0.01627224 -0.08373777
  0.05270426 -0.09142139  0.03041964  0.07187084  0.03306828  0.0128929
 -0.00411583 -0.0268525   0.10555545 -0.01875671 -0.00899999 -0.00320147
 -0.0128225  -0.00802002 -0.00576583  0.01943511 -0.04694407 -0.01563138
  0.03335741 -0.06598826 -0.06469446 -0.10865736]
```

Input:

```
# Calculate residuals for the training set

residual_train = y_train.values - y_pred_train

# Calculate and display the mean of the residuals

mean_residual_train = residual_train.mean()

print("Mean Residuals for Training Set:", mean_residual_train)
```

Output:

```
Mean Residuals for Training Set: 1.4419021532319221e-16
```

Input:

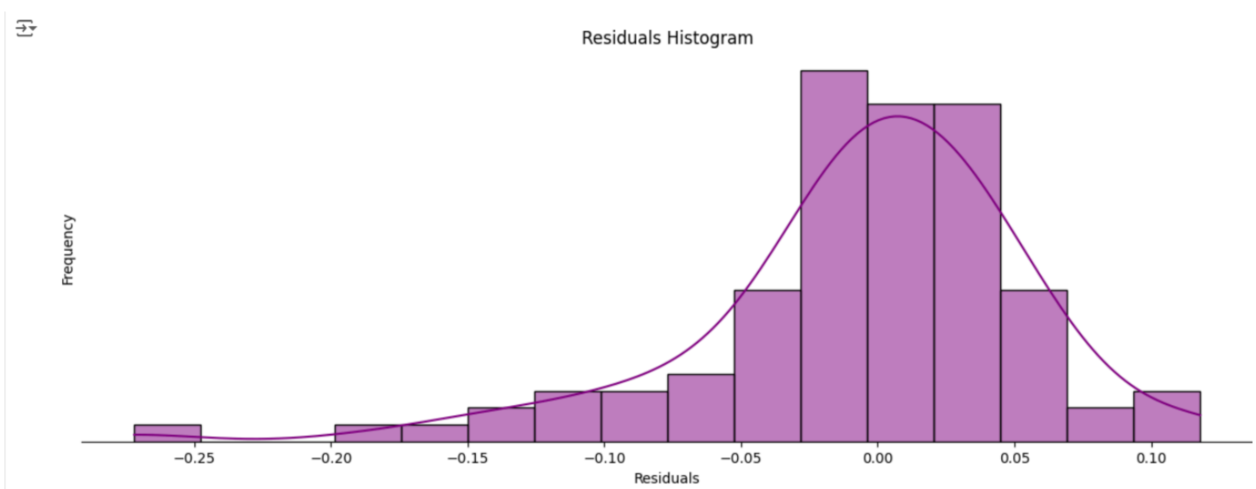
```
# Calculate residuals for the testing set

residual_test = y_test.values - y_pred_test

# Calculate and display the mean of the residuals for the testing
set

mean_residual_test = residual_test.mean()

print("Mean Residuals for Testing Set:", mean_residual_test)
```

Output:

```
Mean Residuals for Testing Set: -0.005453623717661251
```

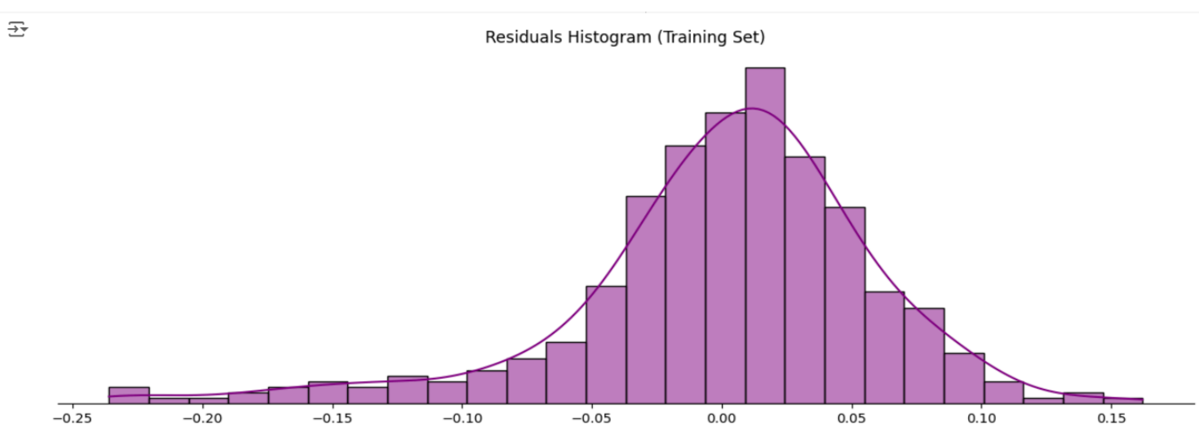
Input:

```
# Set the figure size

plt.figure(figsize=(15, 5))

# Plot the histogram of residuals with a Kernel Density Estimate
(KDE)

sns.histplot(residual, kde=True, color='purple')

# Add titles and labels

plt.title('Residuals Histogram')

plt.xlabel('Residuals')

plt.ylabel('Frequency')

# Remove the left spine and hide y-ticks for a cleaner look

sns.despine(left=True)

plt.yticks([])  # Hides y-ticks

# Show the plot

plt.show()
```



Input:

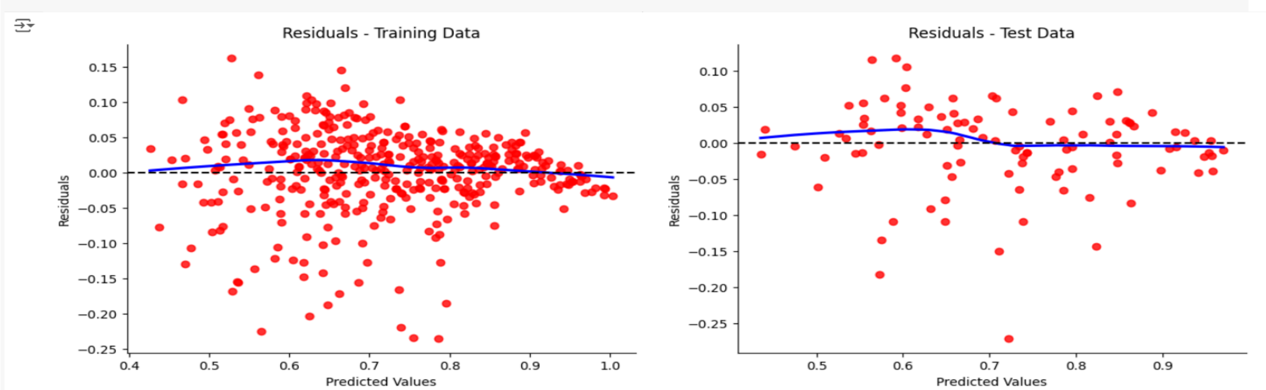
```
# Set the figure size

plt.figure(figsize=(15, 5))

# Plot the histogram of training residuals with a Kernel Density Estimate
(KDE)

sns.histplot(residual_train, kde=True, color='r')  # Color set to red

# Add a title to the plot

plt.title('Residuals Histogram (Training Set)')

# Remove the left spine for a cleaner look

sns.despine(left=True)

# Hide the y-axis label and ticks

plt.ylabel("")

plt.yticks([])

# Show the plot

plt.show()
```



Insight: **The mean of the residuals is close to zero, indicating that our model is unbiased in its predictions**

Assumption of Linearity:

```
# Set the figure size
plt.figure(figsize=(15, 5))
# First subplot: Residuals for training data
plt.subplot(121)
plt.title('Residuals - Training Data')  # Title for the training residuals plot
sns.regplot(x=y_pred_train, y=residual_train, lowess=True, color='r', line_kws={'color': 'blue'})  # Scatter plot with LOWESS line
plt.axhline(y=0, color='k', linestyle='--')  # Horizontal line at y=0 for reference
plt.xlabel('Predicted Values')  # X-axis label
plt.ylabel('Residuals')  # Y-axis label

# Second subplot: Residuals for test data
plt.subplot(122)
plt.title('Residuals - Test Data')  # Title for the test residuals plot
sns.regplot(x=y_pred_test, y=residual, lowess=True, color='r', line_kws={'color': 'blue'})  # Scatter plot with LOWESS line
plt.axhline(y=0, color='k', linestyle='--')  # Horizontal line at y=0 for reference
plt.xlabel('Predicted Values')  # X-axis label
plt.ylabel('Residuals')  # Y-axis label
# Remove spines for cleaner look
sns.despine()
# Show the plots
plt.show()
```



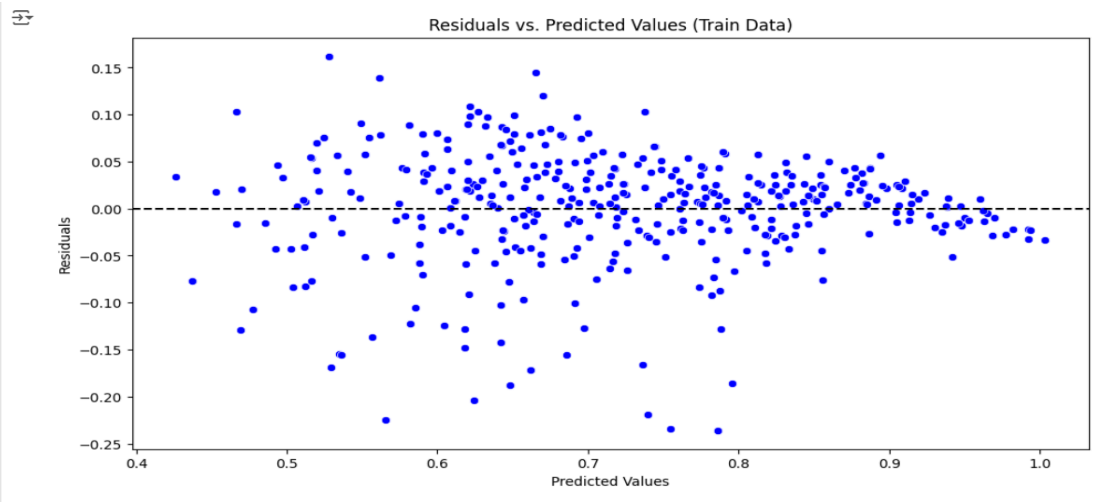
Insights: **From the Joint plot & pairplot in the graphical analysis, we can say that there is a linear relationship between dependent variable and independent variables.**

No Heteroskedasticity:

Input:

```
plt.figure(figsize=(12, 6))

# Residuals vs. Predicted Values Plot

sns.scatterplot(x=y_pred_train, y=residual_train, color='blue')

plt.axhline(y=0, color='k', linestyle='--')  # Horizontal line at
y=0

plt.title('Residuals vs. Predicted Values (Train Data)')

plt.xlabel('Predicted Values')

plt.ylabel('Residuals')

plt.show()
```

Output:



Insights: **While the plot suggests that there is no heteroscedasticity present in the errors and predicted values, let's conduct further tests to confirm this observation more precisely.**

4. **Model performance evaluation.**

Breusch-Pagan test for Homoscedasticity:

Input:

```
import statsmodels.api as sm

from statsmodels.stats.diagnostic import het_breuschpagan

# Assuming you have already fitted your OLS model

new_x_train = sm.add_constant(x_train)  # Add constant to the model

model = sm.OLS(y_train, new_x_train).fit()  # Fit the model

# Perform the Breusch-Pagan test

bp_test = het_breuschpagan(model.resid, model.model.exog)

# Results of the test

bp_lm = bp_test[0]  # Lagrange multiplier statistic

bp_pvalue = bp_test[1]  # p-value

if bp_pvalue < 0.05:

    print("Reject the null hypothesis: Heteroscedasticity exists.")

else:

    print("Fail to reject the null hypothesis: No evidence of
heteroscedasticity.")

print(f'Breusch-Pagan Test statistic: {bp_lm:.4f}, p-value:
{bp_pvalue:.4f}')
```

Output:

```
Reject the null hypothesis: Heteroscedasticity exists.
Breusch-Pagan Test statistic: 25.1559, p-value: 0.0007
```

Hypothesis:

- Null Hypothesis (H0): Homoscedasticity is present in the residuals.
- Alternate Hypothesis (Ha): Heteroscedasticity is present in the residuals.
- Alpha (α): 0.05

Scatterplot Analysis:

- We created scatterplots of residuals against each independent variable to visually inspect for homoscedasticity.
- Observation: Since we do not observe any significant change in the spread of residuals with respect to changes in the independent variables, the visual inspection suggests that homoscedasticity is met.

Statistical Test for Heteroscedasticity:

- **After performing the statistical test:**
    - P-value: The p-value obtained is significantly lower than the alpha value (0.05).
    - Conclusion: Since the p-value is lower than the significance threshold, we reject the null hypothesis.

Insight:

- **Conclusion: The rejection of the null hypothesis suggests that there is evidence of heteroscedasticity in the residuals. This means that the variance of the residuals is not constant across all levels of the independent variables.**
- **Impact: The violation of the homoscedasticity assumption may affect the validity of the linear regression model's results, potentially leading to biased estimates.**

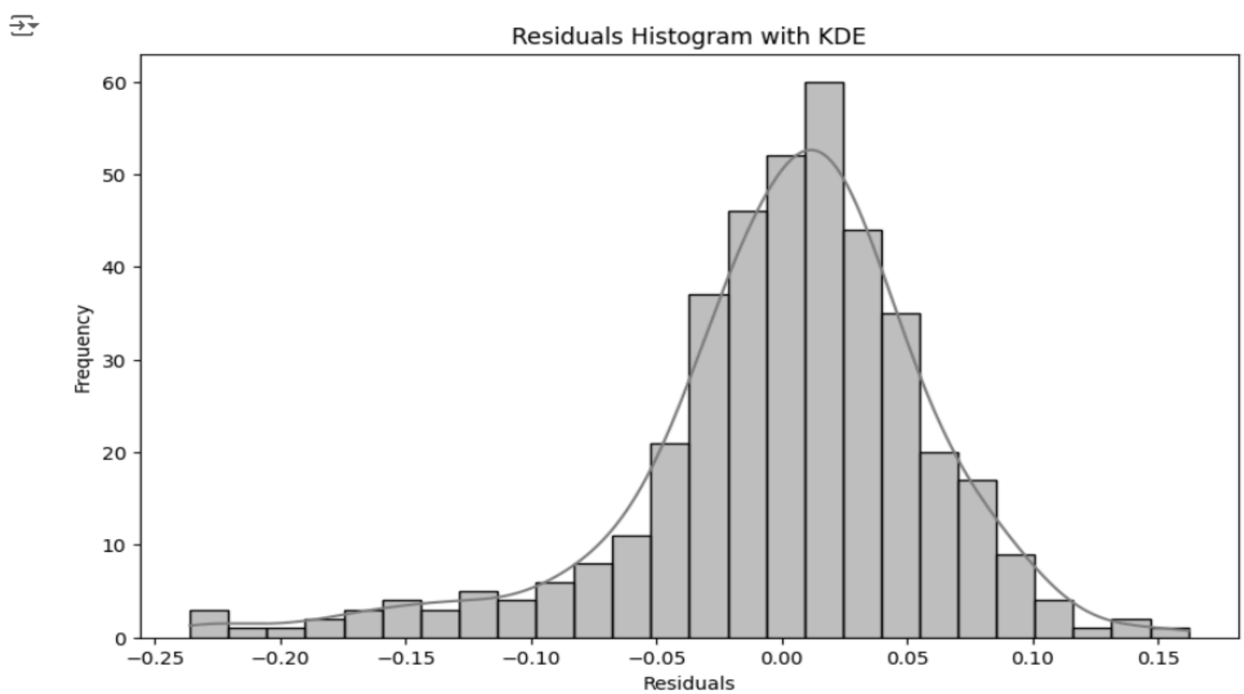
Normality of Residuals:

- If the mean of residuals is significantly non-zero, then the model is overestimating or underestimating the observed values.
- If the mean of residuals is close to zero then on average predictions made by linear regression model are accurate, within the equal
- balance of overestimating and underestimating. This is the desired characteristic for a well-fitted regression model.

Input:

```
import seaborn as sns
import matplotlib.pyplot as plt

# Assuming residual_train or residual is the residuals array
plt.figure(figsize=(10, 6))
sns.histplot(residual_train, kde=True, color='grey')
plt.title('Residuals Histogram with KDE')
plt.xlabel('Residuals')
plt.ylabel('Frequency')
plt.show()
```

Output:



Anderson-Darling Test for Normality:

Input:

```
from scipy.stats import anderson

# Anderson-Darling Test for normality
ad_test = anderson(residual_train, dist='norm')

# Output the test statistic
print('Anderson-Darling Test Statistic: %.4f' % ad_test.statistic)

# Critical values at different significance levels
for i, critical_value in enumerate(ad_test.critical_values):
    significance_level = ad_test.significance_level[i]
    print(f"Critical value at {significance_level}%:
{critical_value}")

# Interpretation based on comparison
for i, critical_value in enumerate(ad_test.critical_values):
    if ad_test.statistic > critical_value:
        print(f"At {ad_test.significance_level[i]}% significance
level, we reject the null hypothesis of normality.")
    else:
        print(f"At {ad_test.significance_level[i]}% significance
level, we fail to reject the null hypothesis of normality.")
```

Output:

```
Anderson-Darling Test Statistic: 7.3573
Critical value at 15.0%: 0.57
Critical value at 10.0%: 0.65
Critical value at 5.0%: 0.779
Critical value at 2.5%: 0.909
Critical value at 1.0%: 1.081
At 15.0% significance level, we reject the null hypothesis of normality.
At 10.0% significance level, we reject the null hypothesis of normality.
At 5.0% significance level, we reject the null hypothesis of normality.
At 2.5% significance level, we reject the null hypothesis of normality.
At 1.0% significance level, we reject the null hypothesis of normality.
```

Insights:

- At all significance levels (15%, 10%, 5%, 2.5%, and 1%), the test statistic (7.3573) exceeds the respective critical values.
- Therefore, **we reject the null hypothesis of normality** at all these significance levels.
- The rejection of the null hypothesis indicates that the residuals do not follow a normal distribution. This violation of the normality assumption may impact the validity of the linear regression model, particularly when it comes to inference and hypothesis testing.

Lasso and Ridge Regression - L1 & L2 Regularization:

```
from sklearn.linear_model import Lasso

# Initialize the Lasso model with alpha = 0.45

model_lasso = Lasso(alpha=0.45)

# Fit the model on the training data

model_lasso.fit(x_train, y_train)

# Retrieve the coefficients and intercept

lasso_weights = pd.DataFrame(model_lasso.coef_.reshape(1,-1),
columns=x_train.columns)

lasso_weights["Intercept"] = model_lasso.intercept_

# Display the weights

lasso_weights
```

Output:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Intercept
0	0.006765	0.0	0.0	0.0	0.0	0.0	0.0	-1.418501

Input:

```
from sklearn.linear_model import Ridge

# Initialize the Ridge model

model_ridge = Ridge()

# Fit the model to the training data

model_ridge.fit(x_train, y_train)

# Retrieve the coefficients and intercept

ridge_weights = pd.DataFrame(model_ridge.coef_.reshape(1,-1), columns=x_train.columns)

ridge_weights["Intercept"] = model_ridge.intercept_

# Display the weights

ridge_weights
```

Output:

	GRE Score	TOEFL Score	University Rating	SOP	LOR	CGPA	Research	Intercept
0	0.002521	0.003073	0.002767	0.002164	0.017478	0.109079	0.023679	-1.430098

Input:

```python
# Generate predictions for the Ridge model

y_pred_train_ridge = model_ridge.predict(x_train)

y_pred_test_ridge = model_ridge.predict(x_test)

# Generate predictions for the Lasso model

y_pred_train_lasso = model_lasso.predict(x_train)

y_pred_test_lasso = model_lasso.predict(x_test)
```

```python
print("Ridge Model:")
model_evaluation(y_train.values, y_pred_train_ridge, model_ridge)
print("\nLasso Model:")
model_evaluation(y_train.values, y_pred_train_lasso, model_lasso)
```

Output:

```
Ridge Model:
MSE: 0.0
MAE: 0.04
RMSE: 0.06
R2 Score: 0.82
Adjusted R2: 0.82

Lasso Model:
MSE: 0.01
MAE: 0.07
RMSE: 0.09
R2 Score: 0.59
Adjusted R2: 0.58
```

5. Actionable Insights & Recommendations.

Insights:

- **CGPA stands out as the most influential feature in predicting admission chances.**
- **GRE and TOEFL scores also play a significant role in the model's predictions.**
- **A thorough multicollinearity check was conducted, and the VIF scores for all features were found to be consistently below 5, indicating minimal multicollinearity among predictors.**
- **Although the model does not show signs of high multicollinearity, the Anderson-Darling test revealed that the residuals do not follow a normal distribution, violating the normality assumption.**
- **The scatterplot of residuals against predicted values indicates the presence of heteroscedasticity, suggesting that the variance of residuals is not constant across different levels of the independent variables.**

Recommendations:

- **Students should prioritize improving GRE scores, CGPA, and Letters of Recommendation (LOR) to maximize their chances of admission.**
- **In addition to academic metrics, applicants could benefit from showcasing extracurricular achievements, personal statements, and other diversity factors.**
- **To enhance the predictive model, additional features such as work experience, internships, or extracurricular activities could be considered for inclusion.**