Loan_Prediction

May 30, 2024

1 Objective : Loan Prediction

2 Exploratory Data Analysis (EDA) - Python

3 Insights - Patterns

4 Classification (Using the ML)

5 1. Load Python Modules

[56]:
```
#  Use Python's import statement to load modules
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

import warnings
warnings.filterwarnings('ignore', category=FutureWarning)

from tabulate import tabulate

from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import LabelEncoder

from scipy import stats
```

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

from sklearn.linear_model import LogisticRegression

from sklearn.naive_bayes import CategoricalNB
from sklearn.naive_bayes import GaussianNB

from sklearn.svm import SVC

from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier


from sklearn.ensemble import AdaBoostClassifier
from sklearn.tree import DecisionTreeClassifier

from sklearn.ensemble import GradientBoostingClassifier
from xgboost import XGBClassifier

from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from imblearn.over_sampling import SMOTE
```

6 2. Read the Dataset from CSV file - Using Pandas

[57]:
```
file_path=r"loan_train_dataset.csv"
loan_df=pd.read_csv(file_path)
loan_df
```

[57]:
```
      Loan_ID  Gender Married Dependents     Education Self_Employed  \
0    LP001002    Male      No          0      Graduate            No
1    LP001003    Male     Yes          1      Graduate            No
2    LP001005    Male     Yes          0      Graduate           Yes
3    LP001006    Male     Yes          0  Not Graduate            No
4    LP001008    Male      No          0      Graduate            No
..        …       …      …          …             …             …
609  LP002978  Female      No          0      Graduate            No
610  LP002979    Male     Yes         3+      Graduate            No
611  LP002983    Male     Yes          1      Graduate            No
612  LP002984    Male     Yes          2      Graduate            No
613  LP002990  Female      No          0      Graduate           Yes
```

```
     ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
0               5849                0.0         NaN             360.0
1               4583             1508.0       128.0             360.0
2               3000                0.0        66.0             360.0
3               2583             2358.0       120.0             360.0
4               6000                0.0       141.0             360.0
..               …                  …          …               …
609             2900                0.0        71.0             360.0
610             4106                0.0        40.0             180.0
611             8072              240.0       253.0             360.0
612             7583                0.0       187.0             360.0
613             4583                0.0       133.0             360.0

     Credit_History Property_Area Loan_Status
0               1.0         Urban           Y
1               1.0         Rural           N
2               1.0         Urban           Y
3               1.0         Urban           Y
4               1.0         Urban           Y
..              …             …          …
609             1.0         Rural           Y
610             1.0         Rural           Y
611             1.0         Urban           Y
612             1.0         Urban           Y
613             0.0     Semiurban           N

[614 rows x 13 columns]
```

6.0.1 2.1 Non-Significant columns - we need to drop here.

[58]:
```
#drop - sensitive - non imp columns for data analysis
print(loan_df["Loan_ID"].nunique())
loan_df.drop("Loan_ID",axis=1,inplace=True)
print(loan_df.columns)
```

```
614
Index(['Gender', 'Married', 'Dependents', 'Education', 'Self_Employed',
       'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
       'Loan_Amount_Term', 'Credit_History', 'Property_Area', 'Loan_Status'],
      dtype='object')
```

7 3. Basic Inspection on given dataset

[59]:
```
def basic_inspection_dataset(table):
    """Generates a basic inspection dataset from the given table."""

    print("top 5 rows - using head")
```

```python
    print(table.head())
    print()

    print("bottom 5 rows using tail")
    print(table.tail())
    print()

    print("numbers of samples and columns")
    print(table.shape)
    print()

    print("numbers of samples ")
    print(len(table))
    print()

    print("numbers of entries in the data frame")
    print(table.size)
    print()

    print("Columns Names")
    print(table.columns)
    print()

    print("Columns dtypes")
    print(table.dtypes)
    print()

    print("Dataframe info")
    print(table.info())
    print()

    print()
    print("check the missing value in each column")
    print(table.isnull().sum())

    print()
    print("check the missing value in each column")
    print(table.isna().sum())

    print()
    print("table summary ")
    print(table.describe())

basic_inspection_dataset(loan_df)
```

```
top 5 rows - using head
  Gender Married Dependents     Education Self_Employed  ApplicantIncome  \
0   Male      No          0      Graduate            No             5849
```

```
1   Male     Yes          1      Graduate            No             4583
2   Male     Yes          0      Graduate           Yes             3000
3   Male     Yes          0  Not Graduate            No             2583
4   Male      No          0      Graduate            No             6000

   CoapplicantIncome  LoanAmount  Loan_Amount_Term  Credit_History  \
0                0.0         NaN             360.0             1.0
1             1508.0       128.0             360.0             1.0
2                0.0        66.0             360.0             1.0
3             2358.0       120.0             360.0             1.0
4                0.0       141.0             360.0             1.0

  Property_Area Loan_Status
0         Urban           Y
1         Rural           N
2         Urban           Y
3         Urban           Y
4         Urban           Y

bottom 5 rows using tail
     Gender Married Dependents Education Self_Employed  ApplicantIncome  \
609  Female      No          0  Graduate            No             2900
610    Male     Yes         3+  Graduate            No             4106
611    Male     Yes          1  Graduate            No             8072
612    Male     Yes          2  Graduate            No             7583
613  Female      No          0  Graduate           Yes             4583

     CoapplicantIncome  LoanAmount  Loan_Amount_Term  Credit_History  \
609                0.0        71.0             360.0             1.0
610                0.0        40.0             180.0             1.0
611              240.0       253.0             360.0             1.0
612                0.0       187.0             360.0             1.0
613                0.0       133.0             360.0             0.0

    Property_Area Loan_Status
609         Rural           Y
610         Rural           Y
611         Urban           Y
612         Urban           Y
613     Semiurban           N

numbers of samples and columns
(614, 12)

numbers of samples
614

numbers of entries in the data frame
```

```
7368

Columns Names
Index(['Gender', 'Married', 'Dependents', 'Education', 'Self_Employed',
       'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
       'Loan_Amount_Term', 'Credit_History', 'Property_Area', 'Loan_Status'],
      dtype='object')

Columns dtypes
Gender                object
Married               object
Dependents            object
Education             object
Self_Employed         object
ApplicantIncome        int64
CoapplicantIncome    float64
LoanAmount           float64
Loan_Amount_Term     float64
Credit_History       float64
Property_Area         object
Loan_Status           object
dtype: object

Dataframe info
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Gender             601 non-null    object
 1   Married            611 non-null    object
 2   Dependents         599 non-null    object
 3   Education          614 non-null    object
 4   Self_Employed      582 non-null    object
 5   ApplicantIncome    614 non-null    int64
 6   CoapplicantIncome  614 non-null    float64
 7   LoanAmount         592 non-null    float64
 8   Loan_Amount_Term   600 non-null    float64
 9   Credit_History     564 non-null    float64
 10  Property_Area      614 non-null    object
 11  Loan_Status        614 non-null    object
dtypes: float64(4), int64(1), object(7)
memory usage: 57.7+ KB
None


check the missing value in each column
Gender               13
```

```
Married               3
Dependents           15
Education             0
Self_Employed        32
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount           22
Loan_Amount_Term     14
Credit_History       50
Property_Area         0
Loan_Status           0
dtype: int64

check the missing value in each column
Gender               13
Married               3
Dependents           15
Education             0
Self_Employed        32
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount           22
Loan_Amount_Term     14
Credit_History       50
Property_Area         0
Loan_Status           0
dtype: int64

table summary
       ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
count       614.000000         614.000000  592.000000         600.00000
mean       5403.459283        1621.245798  146.412162         342.00000
std        6109.041673        2926.248369   85.587325          65.12041
min         150.000000           0.000000    9.000000          12.00000
25%        2877.500000           0.000000  100.000000         360.00000
50%        3812.500000        1188.500000  128.000000         360.00000
75%        5795.000000        2297.250000  168.000000         360.00000
max       81000.000000       41667.000000  700.000000         480.00000

       Credit_History
count      564.000000
mean         0.842199
std          0.364878
min          0.000000
25%          1.000000
50%          1.000000
75%          1.000000
max          1.000000
```

[60]:
```python
# convertinh Credit_History column as categorical column - based on the␣
↪previous experiments
loan_df["Credit_History"]=loan_df["Credit_History"].map(lambda x: 'N' if x==0␣
↪else 'Y')
```

8 4. Handling Missing Values - Cat - Variables

[61]:
```python
def print_cat_values(cat_var):
    print("We are studying about varailbe/column/feature :", cat_var)
    print("categories:",loan_df[cat_var].unique())
    print("num of categories:",loan_df[cat_var].nunique())
    print("Value-counts:", loan_df[cat_var].value_counts())
```

[62]:
```python
cat_vars = loan_df.select_dtypes(include="object").columns
print(cat_vars) ### selct the missing values - cat -vars
cat_vars = ['Gender', 'Married', 'Dependents', 'Self_Employed','Credit_History']
```

```
Index(['Gender', 'Married', 'Dependents', 'Education', 'Self_Employed',
       'Credit_History', 'Property_Area', 'Loan_Status'],
      dtype='object')
```

[63]:
```python
for var in cat_vars:
    print_cat_values(var)
    print("=========================================")
    print()
```

```
We are studying about varailbe/column/feature : Gender
categories: ['Male' 'Female' nan]
num of categories: 2
Value-counts: Gender
Male      489
Female    112
Name: count, dtype: int64
=========================================

We are studying about varailbe/column/feature : Married
categories: ['No' 'Yes' nan]
num of categories: 2
Value-counts: Married
Yes    398
No     213
Name: count, dtype: int64
=========================================

We are studying about varailbe/column/feature : Dependents
categories: ['0' '1' '2' '3+' nan]
num of categories: 4
```

```
Value-counts: Dependents
0     345
1     102
2     101
3+     51
Name: count, dtype: int64
=========================================

We are studying about varailbe/column/feature : Self_Employed
categories: ['No' 'Yes' nan]
num of categories: 2
Value-counts: Self_Employed
No     500
Yes     82
Name: count, dtype: int64
=========================================

We are studying about varailbe/column/feature : Credit_History
categories: ['Y' 'N']
num of categories: 2
Value-counts: Credit_History
Y    525
N     89
Name: count, dtype: int64
=========================================
```

[64]:
```
for var in cat_vars:
    mode = loan_df[var].mode()[0]
    #print(mode)

    # fill the missing value with mode
    loan_df[var].fillna(mode,inplace=True)

# check for missing values - for confirmation
loan_df.isnull().sum()
```

[64]:
```
Gender                0
Married               0
Dependents            0
Education             0
Self_Employed         0
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount           22
Loan_Amount_Term     14
Credit_History        0
```

```
Property_Area        0
Loan_Status          0
dtype: int64
```

[65]:
```
# in dependents columns - replacing/filling with 3+ with 4
loan_df["Dependents"] = loan_df["Dependents"].map(lambda x : '4' if x=='3+'␣
↪else x)
```

[66]:
```
loan_df["Dependents"].value_counts()
```

[66]:
```
Dependents
0    360
1    102
2    101
4     51
Name: count, dtype: int64
```

[67]:
```
loan_df.dtypes
```

[67]:
```
Gender                object
Married               object
Dependents            object
Education             object
Self_Employed         object
ApplicantIncome        int64
CoapplicantIncome    float64
LoanAmount           float64
Loan_Amount_Term     float64
Credit_History        object
Property_Area         object
Loan_Status           object
dtype: object
```

9 5. Categorical- UniVariable - Analysis -Using Pipeline

[68]:
```
class BarPieChartTransformer(BaseEstimator, TransformerMixin):
    def __init__(self):
        pass

    def fit(self, X, y=None):
        return self

    def transform(self, X):
        df=X.copy()
        # get cat columns
        cat_cols = df.select_dtypes(include='object').columns
        for cat_name in cat_cols:
```

```
            value_counts = df[cat_name].value_counts().reset_index()
            # Rename the columns
            value_counts.columns = ['Class', 'Frequency']

            # Print the result as a table
            print(f"{cat_name} frequency table")
            print(tabulate(value_counts, headers='keys', tablefmt='pretty'))

            # Calculate relative frequency
            total_count = value_counts['Frequency'].sum()
            value_counts['Relative Frequency %'] =␣
↪round((value_counts['Frequency'] / total_count)*100,2)

            # Print the result as a table
            print(f"{cat_name} Relative frequency table")
            print(tabulate(value_counts, headers='keys', tablefmt='pretty'))

            # Extract the values and index from value counts
            value_counts = df[cat_name].value_counts()
            values = value_counts.values
            labels = value_counts.index

            fig, axs = plt.subplots(1, 2, figsize=(12, 6))  # 1 row, 2 columns
            # Create a bar graph
            axs[0].bar(labels, values)
            axs[0].set_title(f'Frequency of {cat_name}')
            axs[0].set_xlabel('Categories')  # Set x-label
            axs[0].set_ylabel('Count')       # Set y-label

            axs[1].pie(value_counts.values, labels=value_counts.index,␣
↪autopct='%1.1f%%', startangle=140)
            axs[1].set_title(f'Relative Frequency of {cat_name}')
            plt.tight_layout()
            # Show the plot
            plt.show()
```

[69]:

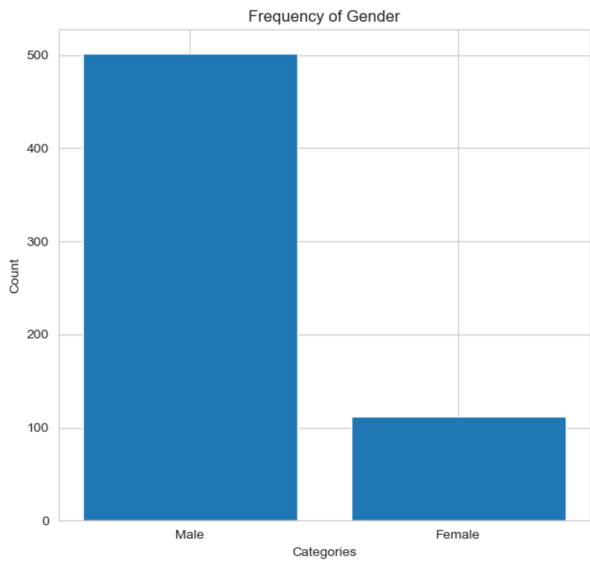
```
pipeline_cat_var = Pipeline([
    ('cat_univaraite_analysis', BarPieChartTransformer())
])

# Fit and transform your data using the pipeline
processed_data = pipeline_cat_var.fit_transform(loan_df)
```

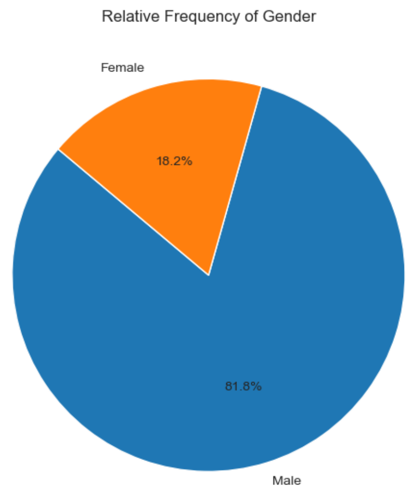
```
Gender frequency table
+---+--------+-----------+
|   | Class  | Frequency |
```

0	Male	502
1	Female	112

Gender Relative frequency table

	Class	Frequency	Relative Frequency %
0	Male	502	81.76
1	Female	112	18.24



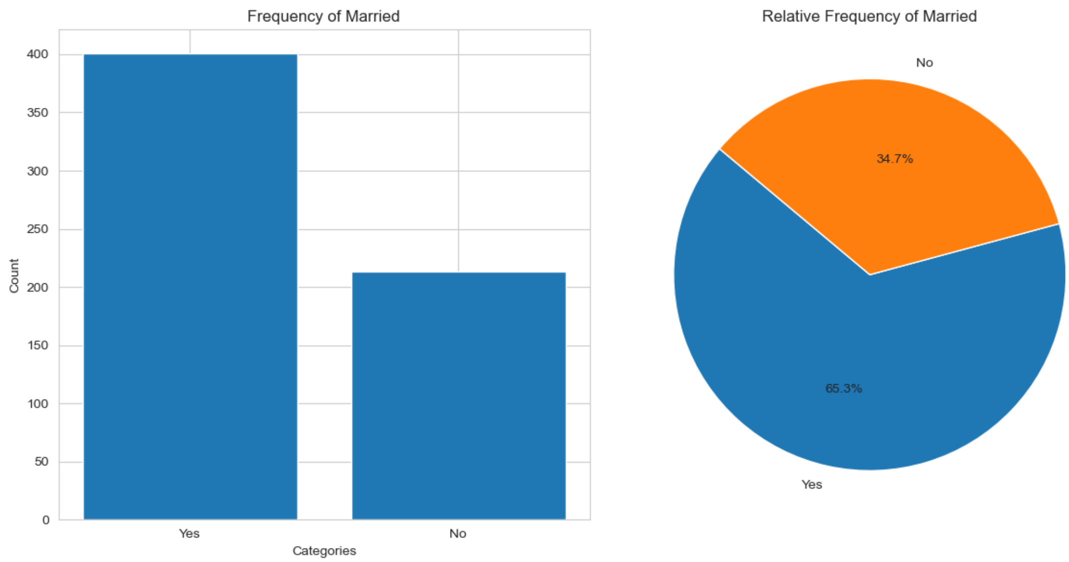


Married frequency table

	Class	Frequency
0	Yes	401
1	No	213

Married Relative frequency table

	Class	Frequency	Relative Frequency %
0	Yes	401	65.31
1	No	213	34.69

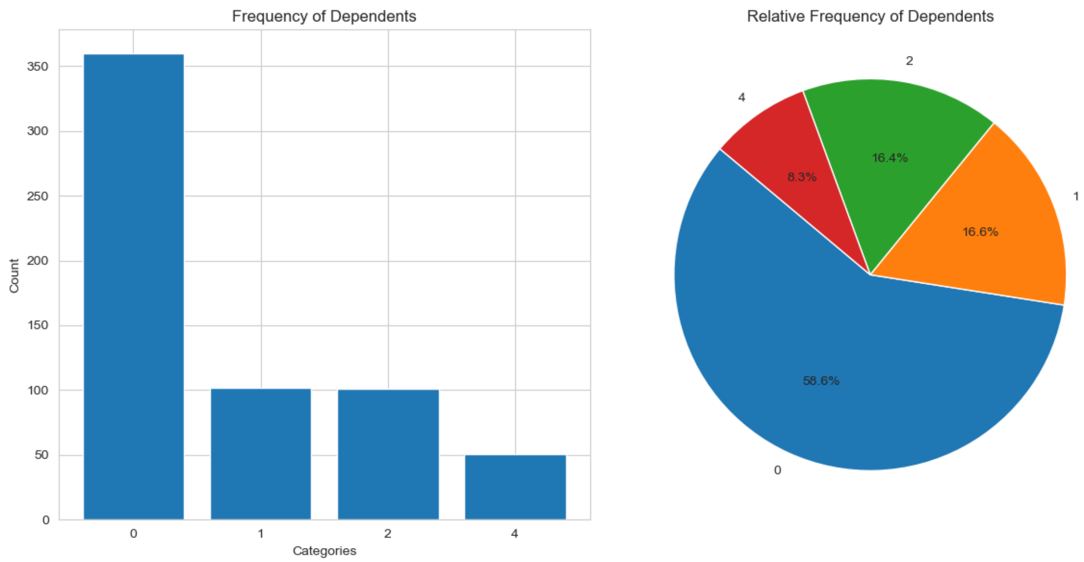


Dependents frequency table

	Class	Frequency
0	0	360
1	1	102
2	2	101
3	4	51

Dependents Relative frequency table

	Class	Frequency	Relative Frequency %
0	0	360	58.63
1	1	102	16.61
2	2	101	16.45
3	4	51	8.31

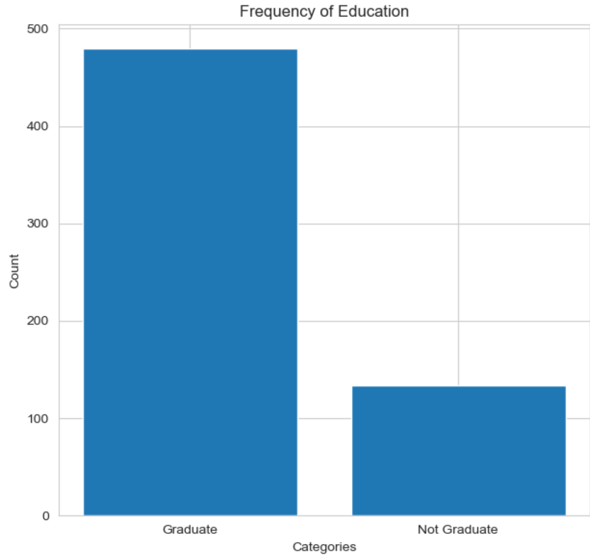


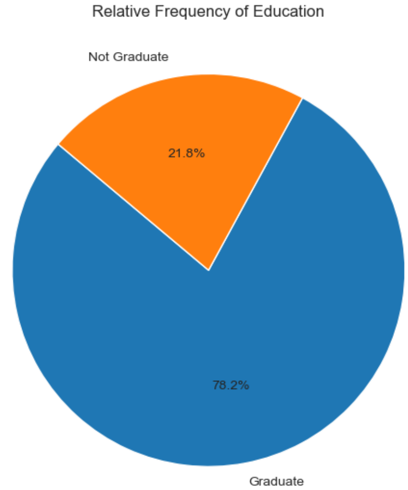
Education frequency table

	Class	Frequency
0	Graduate	480
1	Not Graduate	134

Education Relative frequency table

	Class	Frequency	Relative Frequency %
0	Graduate	480	78.18
1	Not Graduate	134	21.82



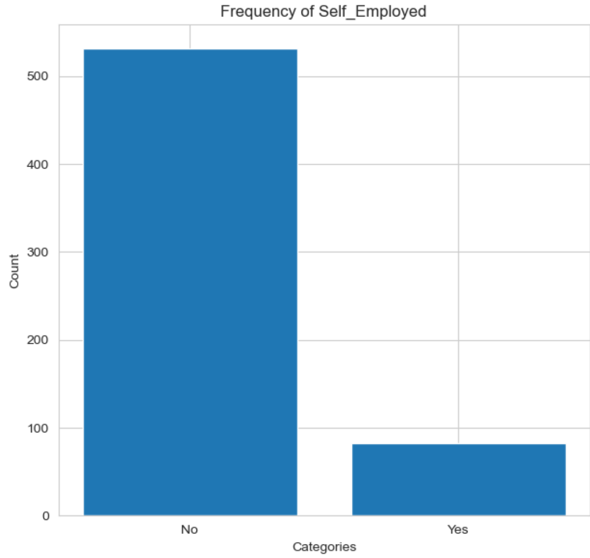


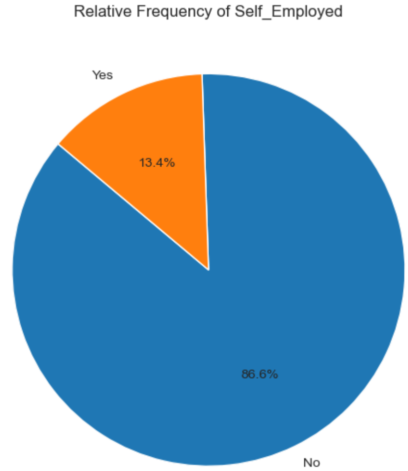
Self_Employed frequency table

	Class	Frequency
0	No	532
1	Yes	82

Self_Employed Relative frequency table

	Class	Frequency	Relative Frequency %
0	No	532	86.64
1	Yes	82	13.36



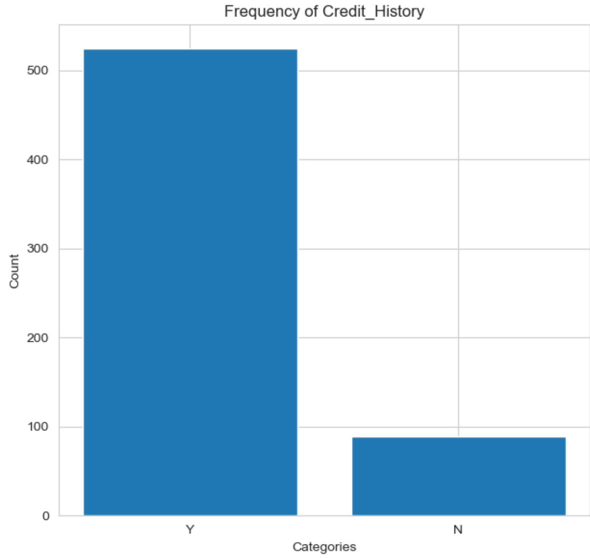


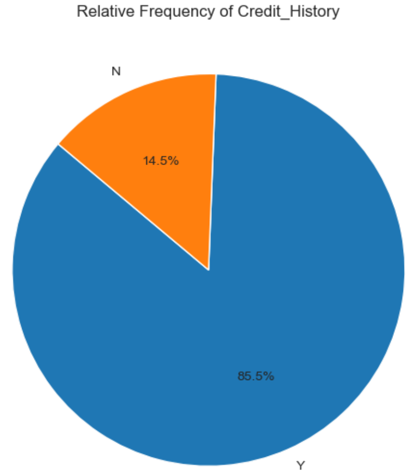
Credit_History frequency table

	Class	Frequency
0	Y	525
1	N	89

Credit_History Relative frequency table

	Class	Frequency	Relative Frequency %
0	Y	525	85.5
1	N	89	14.5



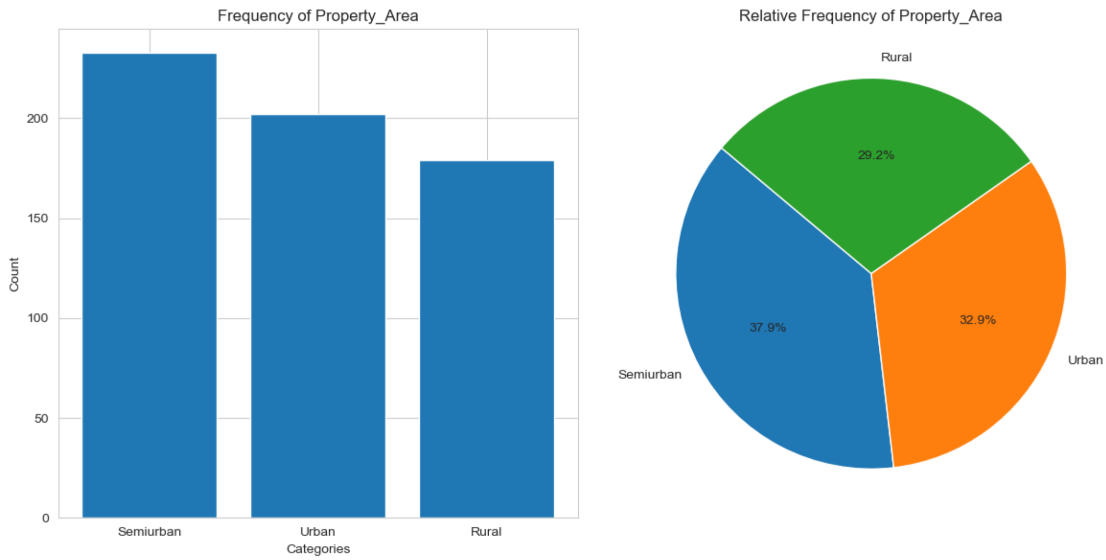


Property_Area frequency table

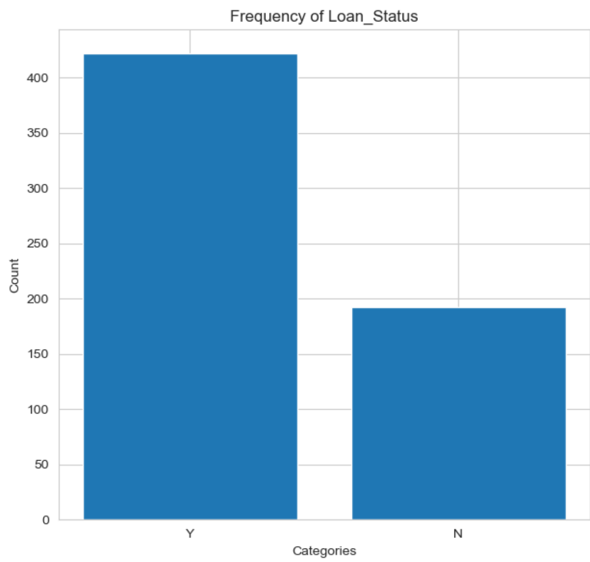
	Class	Frequency
0	Semiurban	233
1	Urban	202
2	Rural	179

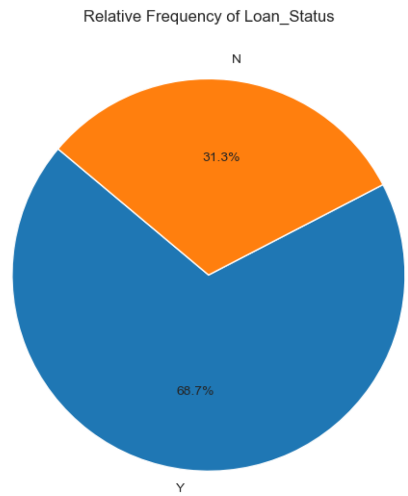
Property_Area Relative frequency table

	Class	Frequency	Relative Frequency %
0	Semiurban	233	37.95
1	Urban	202	32.9
2	Rural	179	29.15




```
Loan_Status frequency table
+---+-------+-----------+
|   | Class | Frequency |
+---+-------+-----------+
| 0 |   Y   |    422    |
| 1 |   N   |    192    |
+---+-------+-----------+
Loan_Status Relative frequency table
+---+-------+-----------+----------------------+
|   | Class | Frequency | Relative Frequency % |
+---+-------+-----------+----------------------+
| 0 |   Y   |    422    |        68.73         |
| 1 |   N   |    192    |        31.27         |
+---+-------+-----------+----------------------+
```





10 6. Handling Missing Values in Numerical Columns

[70]:
```
loan_df.isnull().sum()
```

[70]:
```
Gender                0
Married               0
Dependents            0
Education             0
Self_Employed         0
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount           22
Loan_Amount_Term     14
Credit_History        0
Property_Area         0
Loan_Status           0
dtype: int64
```

[71]:
```
loan_df.describe()
```

[71]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term
count	614.000000	614.000000	592.000000	600.00000
mean	5403.459283	1621.245798	146.412162	342.00000
std	6109.041673	2926.248369	85.587325	65.12041
min	150.000000	0.000000	9.000000	12.00000
25%	2877.500000	0.000000	100.000000	360.00000
50%	3812.500000	1188.500000	128.000000	360.00000

```
75%       5795.000000       2297.250000  168.000000         360.00000
max      81000.000000      41667.000000  700.000000         480.00000
```

[72]:
```
global_loan_amount_term_mode = loan_df['Loan_Amount_Term'].mode()[0]
loan_df['Loan_Amount_Term'].fillna(global_loan_amount_term_mode,inplace=True)
```

[73]:
```
global_loan_amount_mean = 0
for var in ["LoanAmount"]:
    mean = loan_df[var].mean()
    global_loan_amount_mean = mean
    #print(median)

    # fill the missing value with mode
    loan_df[var].fillna(global_loan_amount_mean,inplace=True)

# check for missing values - for confirmation
loan_df.isnull().sum()
```

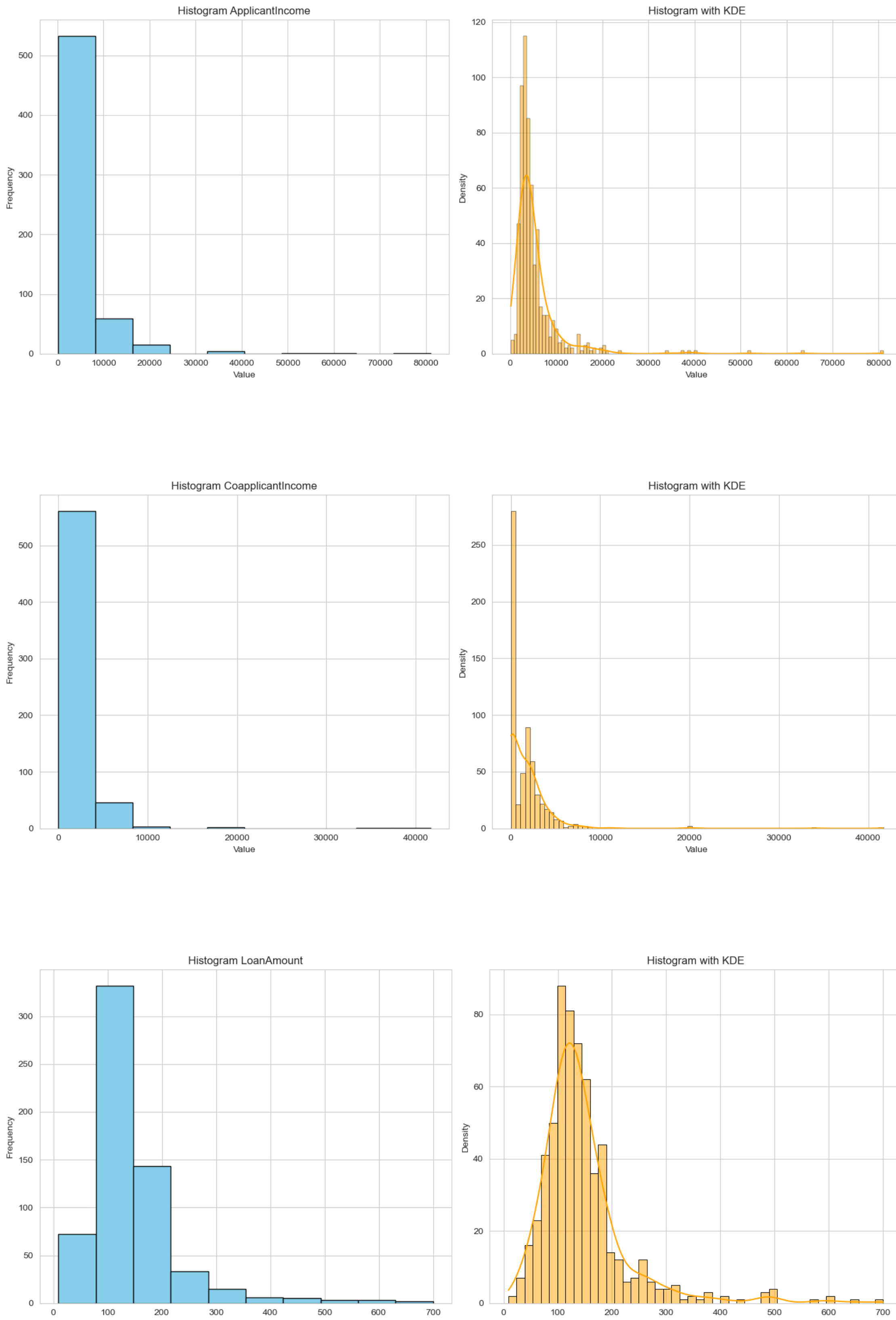
[73]:
```
Gender               0
Married              0
Dependents           0
Education            0
Self_Employed        0
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount           0
Loan_Amount_Term     0
Credit_History       0
Property_Area        0
Loan_Status          0
dtype: int64
```

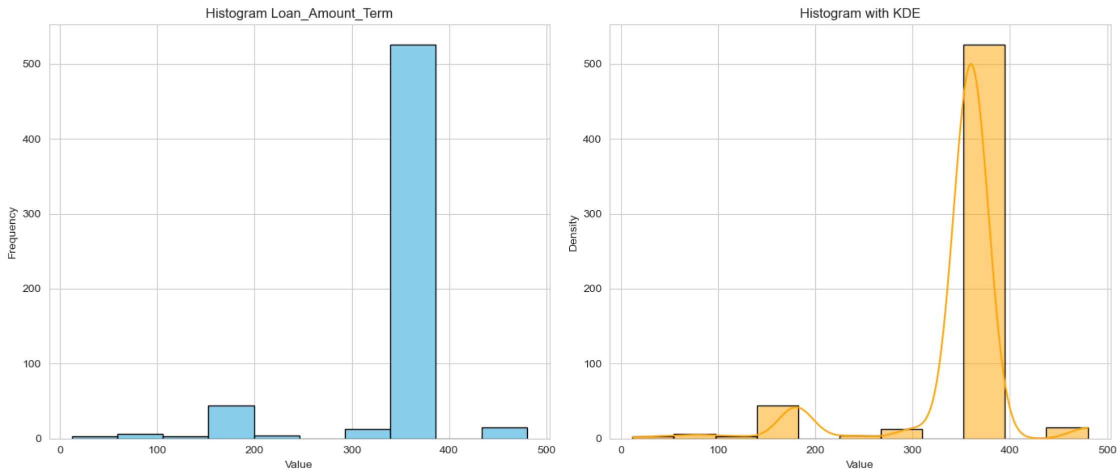
11 7. Numerical - UniVariable - Analysis - Using -Pipeline

[74]:
```
class HistBoxChartTransformer(BaseEstimator, TransformerMixin):
    def __init__(self):
        pass

    def fit(self, X, y=None):
        return self

    def transform(self, X):
        df=X.copy()
        # getting num cols
        num_cols = df.select_dtypes(exclude='object').columns
        for con_var in num_cols:
```

```
        # Create a figure and axes object
        fig, axes = plt.subplots(1, 2, figsize=(14, 6))

        # Plot histogram without KDE on the left
        axes[0].hist(df[con_var],  color='skyblue', edgecolor='black')
        axes[0].set_xlabel('Value')
        axes[0].set_ylabel('Frequency')
        axes[0].set_title(f'Histogram {con_var}')

        # Plot histogram with KDE on the right
        sns.histplot(data=df, x=con_var, kde=True, color='orange',␣
↪edgecolor='black', ax=axes[1])
        axes[1].set_xlabel('Value')
        axes[1].set_ylabel('Density')
        axes[1].set_title('Histogram with KDE')

        # Adjust layout
        plt.tight_layout()

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

[75]:
```
pipeline_num_var = Pipeline([
    ('num_uni_variate_analysis', HistBoxChartTransformer())
])

loan_num_df =␣
↪loan_df[["ApplicantIncome","CoapplicantIncome","LoanAmount","Loan_Amount_Term"]].
↪copy()
# Fit and transform your data using the pipeline
processed_data = pipeline_num_var.fit_transform(loan_num_df)
```


Histogram ApplicantIncome
Frequency
Value
Histogram with KDE
Density
Value
Histogram CoapplicantIncome
Frequency
Value
Histogram with KDE
Density
Value
Histogram LoanAmount
Frequency
Value
Histogram with KDE
Density
Value



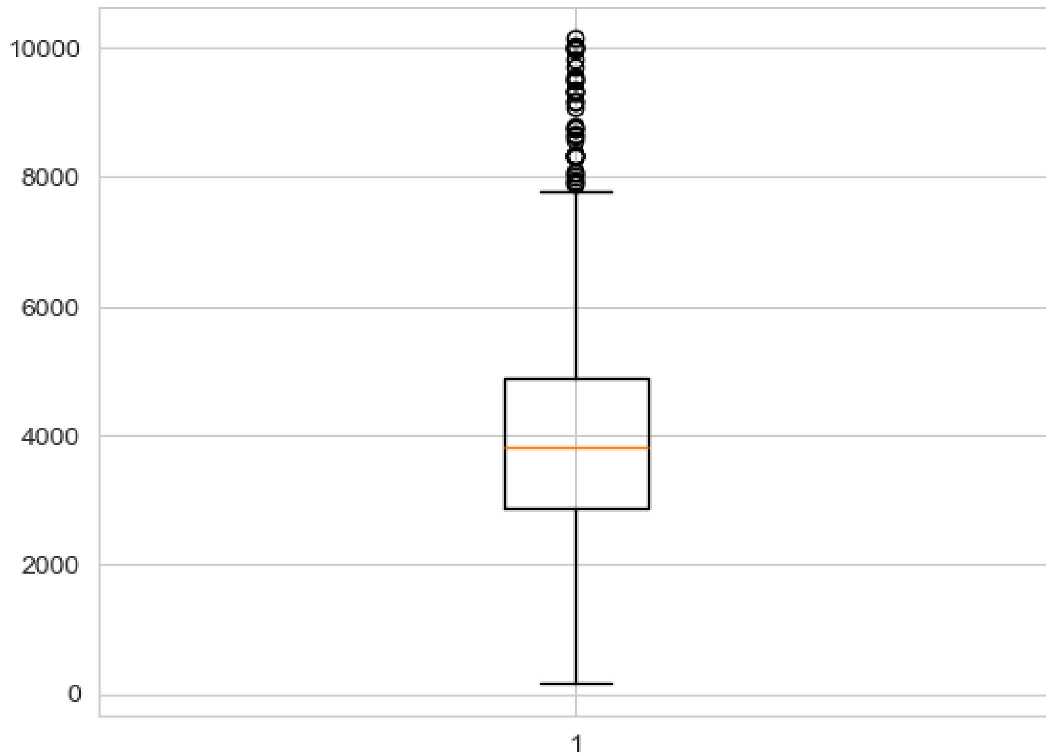
12 8. Numerical - Variables -Outliers Analysis

[76]:
```
def find_outliers_fill_with_median(con_var):
    """find outliers and remove the outliers from the dataset for given var ␣
 ↪feature"""
    print(f"outliers filling for {con_var}")
    q1 = loan_df[con_var].quantile(0.25)
    q3 = loan_df[con_var].quantile(0.75)
    iqr = q3 - q1
    lower_fence = q1 - (1.5*iqr)
    higher_fence = q3 + (1.5*iqr)

    cond1 = loan_df[con_var] < lower_fence
    cond2 = loan_df[con_var] > higher_fence


    con = cond1 |  cond2
    val = loan_df[con_var].median()
    loan_df[con_var]=np.where(con, val,loan_df[con_var])
    plt.boxplot(loan_df[con_var])
    plt.show()
```

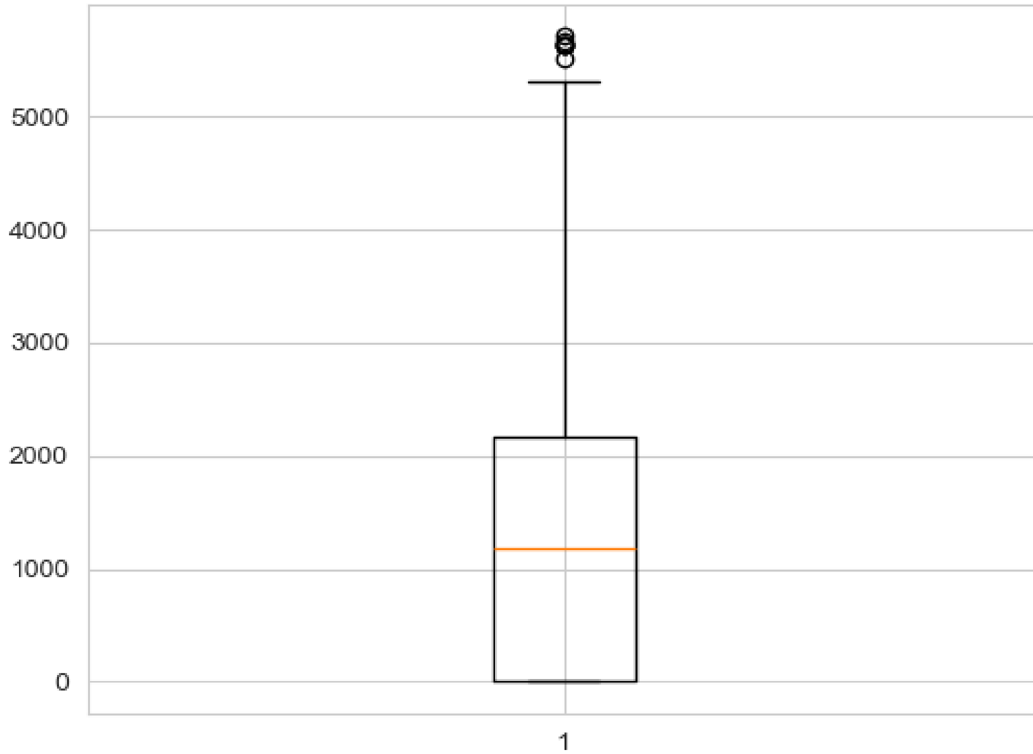
[77]:
```
loan_num_df = loan_df[["ApplicantIncome","CoapplicantIncome","LoanAmount"]].
 ↪copy()
con_vars = loan_num_df.select_dtypes(exclude="object").columns
print(con_vars)
for var in con_vars:
    find_outliers_fill_with_median(var)
```

```python
    print("========================================================")
```

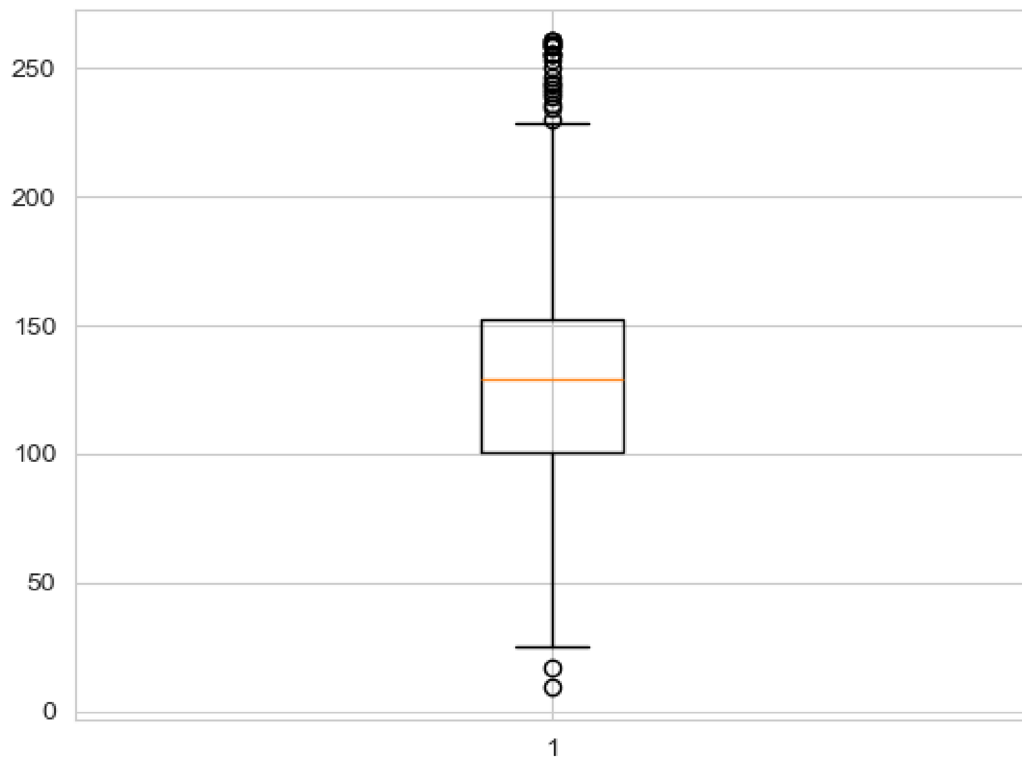
```
Index(['ApplicantIncome', 'CoapplicantIncome', 'LoanAmount'], dtype='object')
outliers filling for ApplicantIncome
```




```
========================================================
outliers filling for CoapplicantIncome
```




```
========================================================
outliers filling for LoanAmount
```



==

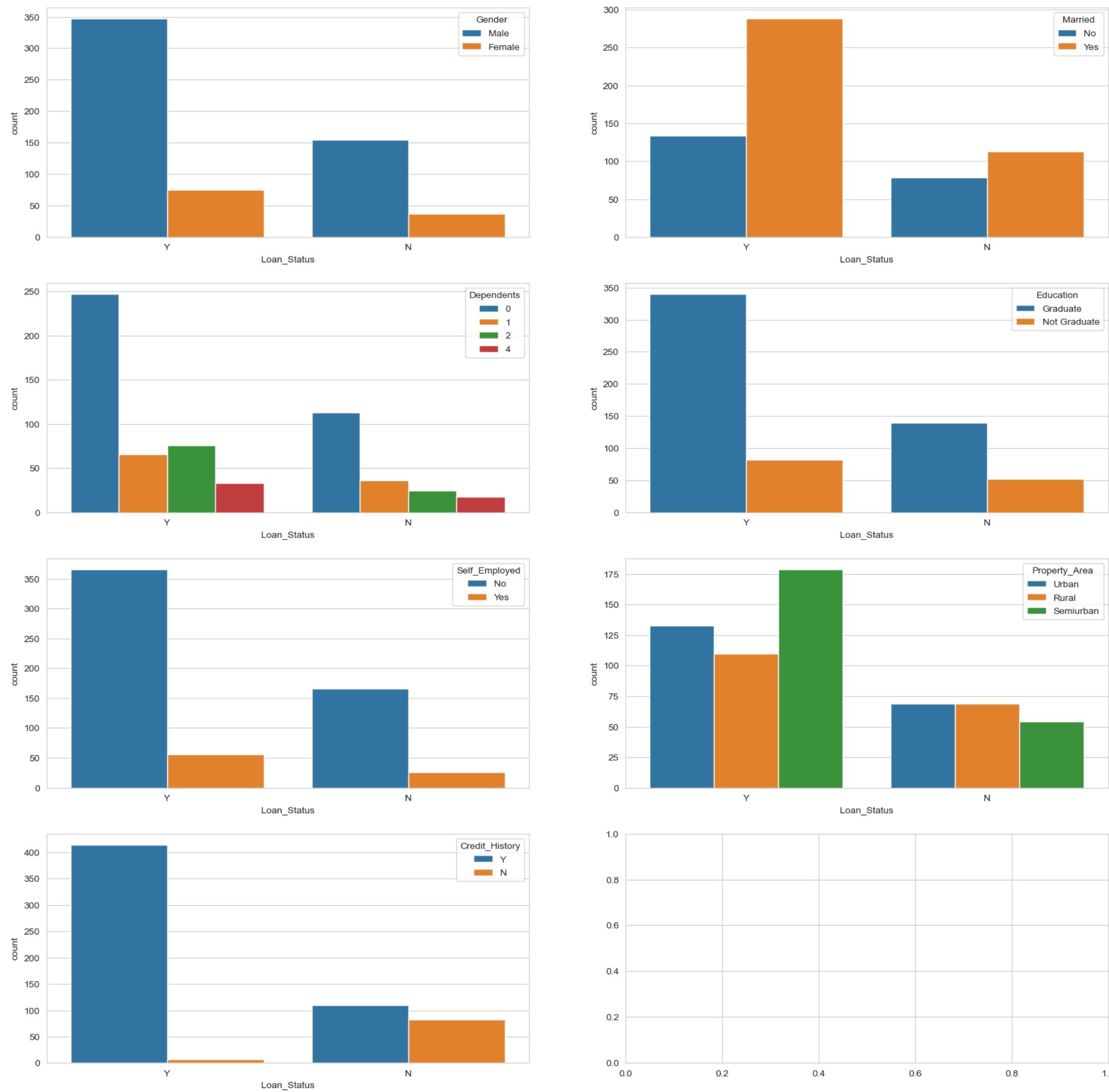
13 9. Bi Variate Analysis

13.0.1 9.1 Cat Vs Cat

[78]:
```
cat_vars = loan_df.select_dtypes(include="object").columns
print(cat_vars)
cat_vars = ['Gender', 'Married', 'Dependents', 'Education', 'Self_Employed',␣
 ↪'Property_Area','Credit_History']
```

```
Index(['Gender', 'Married', 'Dependents', 'Education', 'Self_Employed',
       'Credit_History', 'Property_Area', 'Loan_Status'],
      dtype='object')
```

[79]:
```
## Cat Vs Cat
fig,ax = plt.subplots(4,2,figsize=(20,20))
for axi,x in zip(ax.flat,cat_vars):
    sns.countplot(x=loan_df.Loan_Status,hue=loan_df[x],ax=axi)
```



13.0.2 9.2 Cat Vs Num

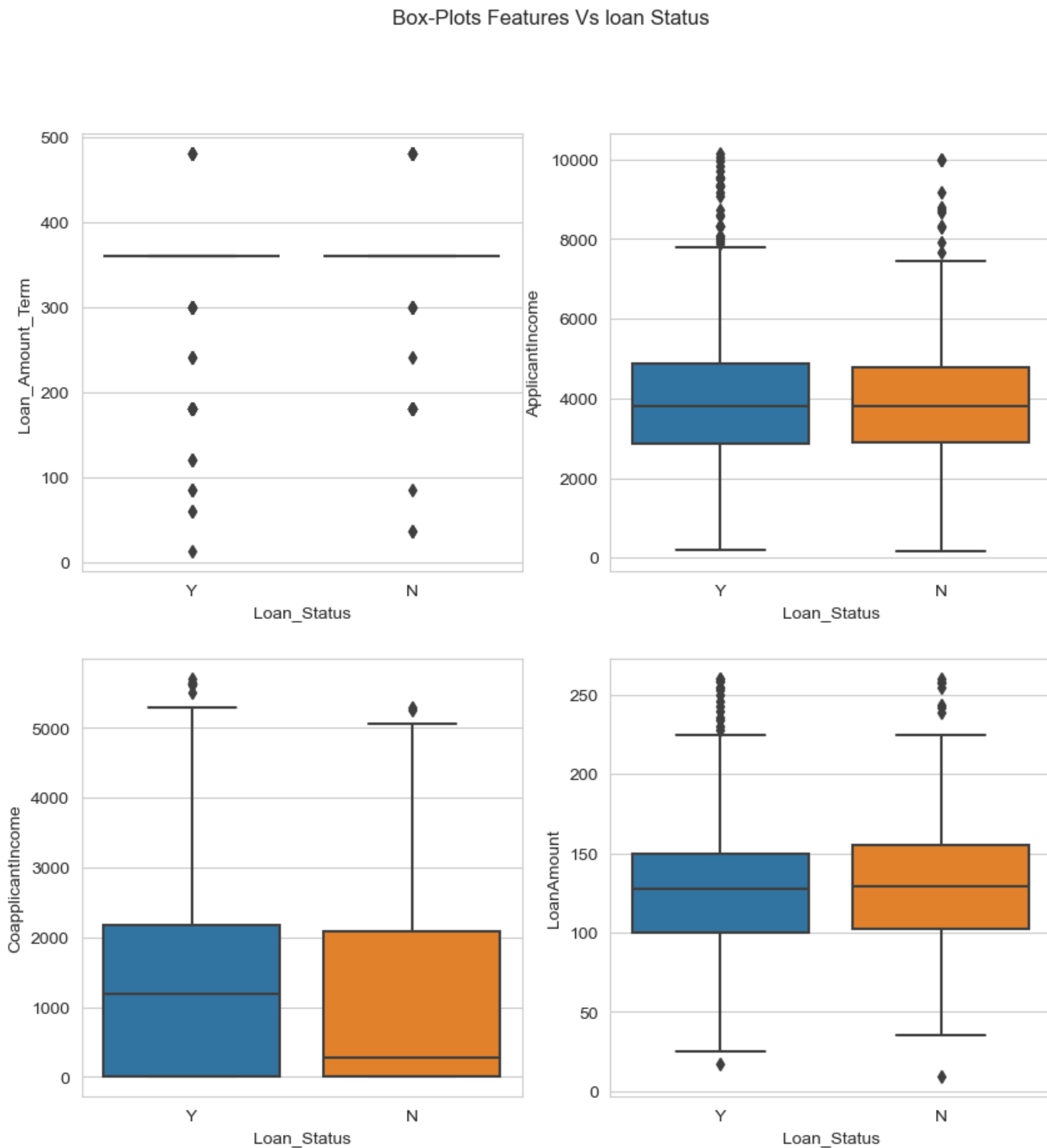
[80]:
```python
## Cat Vs Num
loan_df.select_dtypes(exclude="object").columns
```

[80]:
```
Index(['ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
       'Loan_Amount_Term'],
      dtype='object')
```

[81]:
```python
output_var='Loan_Status'
```

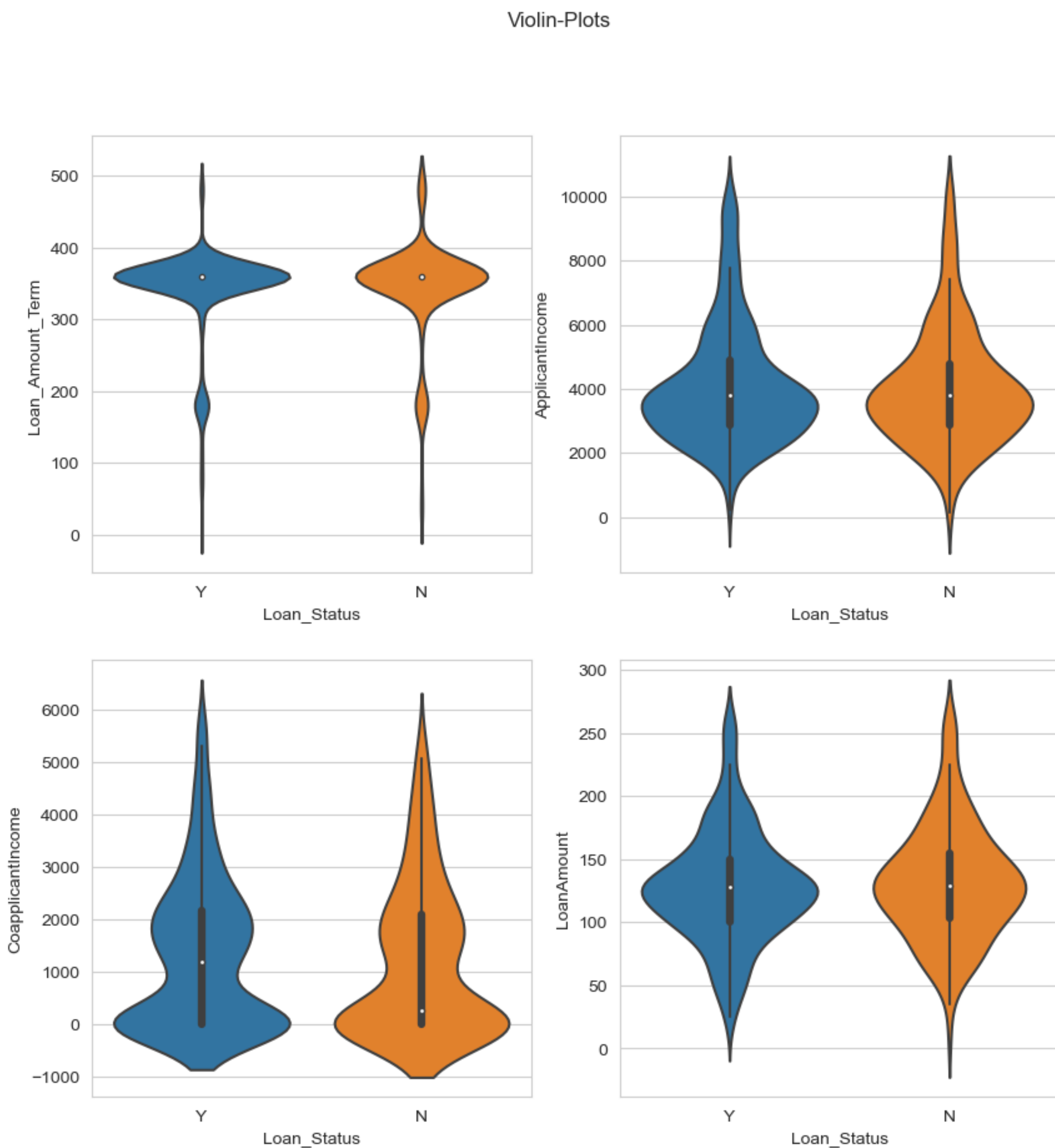
[82]:
```python
sns.set_style("whitegrid")
fig, axes = plt.subplots(2, 2, figsize=(10, 10))
```

```
fig.suptitle('Box-Plots Features Vs loan Status')
sns.boxplot(ax=axes[0, 0], x=output_var, y='Loan_Amount_Term', data=loan_df)
sns.boxplot(ax=axes[0, 1], x=output_var, y='ApplicantIncome', data=loan_df)
sns.boxplot(ax=axes[1, 0], x=output_var, y='CoapplicantIncome', data=loan_df)
sns.boxplot(ax=axes[1, 1], x=output_var, y='LoanAmount', data=loan_df)
plt.show()
```



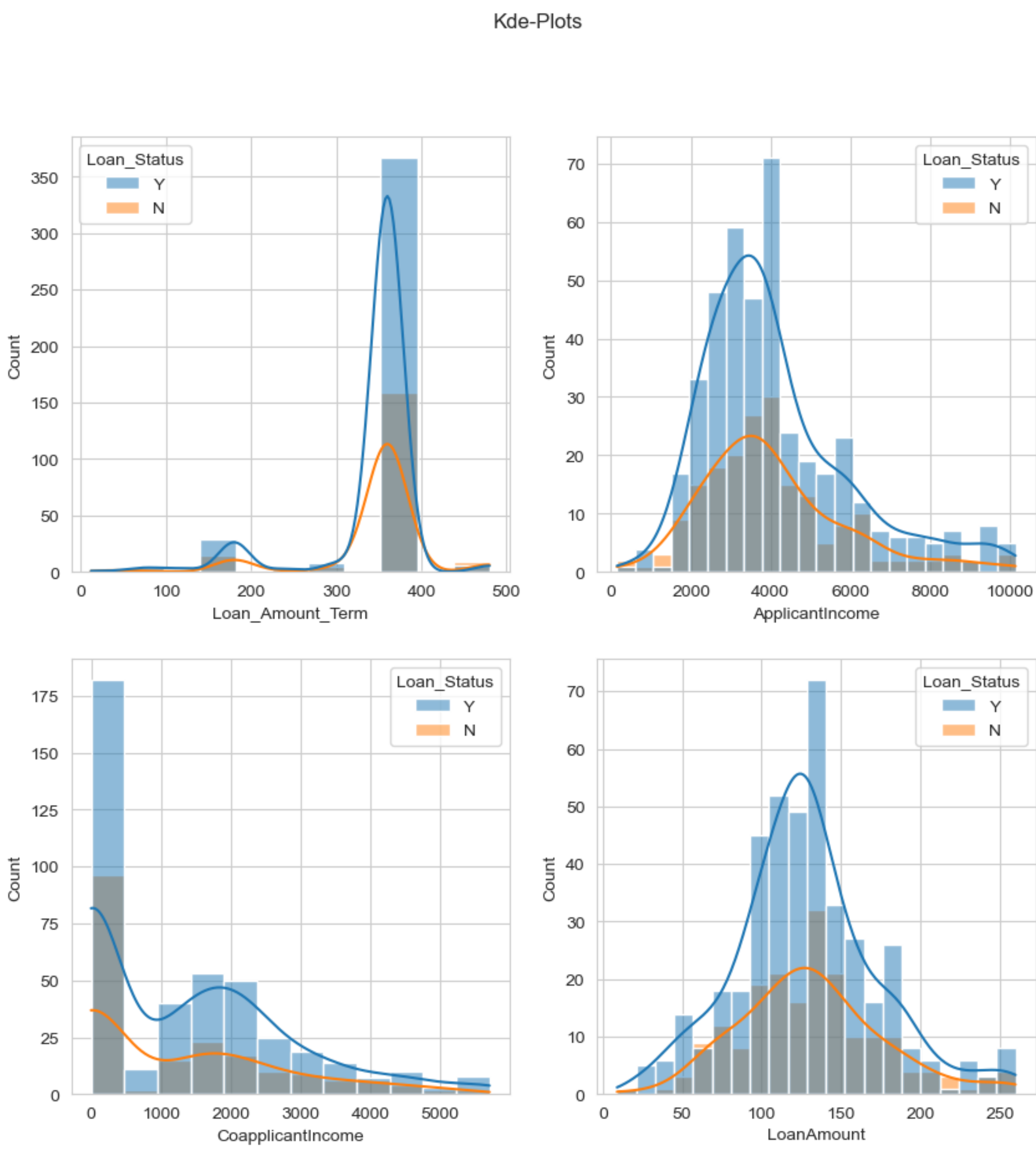
[83]:
```
sns.set_style("whitegrid")
fig, axes = plt.subplots(2, 2, figsize=(10, 10))
fig.suptitle('Violin-Plots')
```

```
sns.violinplot(ax=axes[0, 0], x=output_var, y='Loan_Amount_Term', data=loan_df)
sns.violinplot(ax=axes[0, 1], x=output_var, y='ApplicantIncome', data=loan_df)
sns.violinplot(ax=axes[1, 0], x=output_var, y='CoapplicantIncome', data=loan_df)
sns.violinplot(ax=axes[1, 1], x=output_var, y='LoanAmount', data=loan_df)
plt.show()
```



[84]:
```
sns.set_style("whitegrid")
fig, axes = plt.subplots(2, 2, figsize=(10, 10))
fig.suptitle('Kde-Plots')
```

```
sns.histplot(ax=axes[0, 0], hue=output_var, x='Loan_Amount_Term',␣
 ↪data=loan_df,kde=True)
sns.histplot(ax=axes[0, 1], hue=output_var, x='ApplicantIncome',␣
 ↪data=loan_df,kde=True)
sns.histplot(ax=axes[1, 0], hue=output_var, x='CoapplicantIncome',␣
 ↪data=loan_df,kde=True)
sns.histplot(ax=axes[1, 1], hue=output_var, x='LoanAmount',␣
 ↪data=loan_df,kde=True)
plt.show()
```



13.1 9.3 Num Vs Num

[85]:
```
loan_df.select_dtypes(exclude="object").columns
```

[85]:
```
Index(['ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
       'Loan_Amount_Term'],
      dtype='object')
```

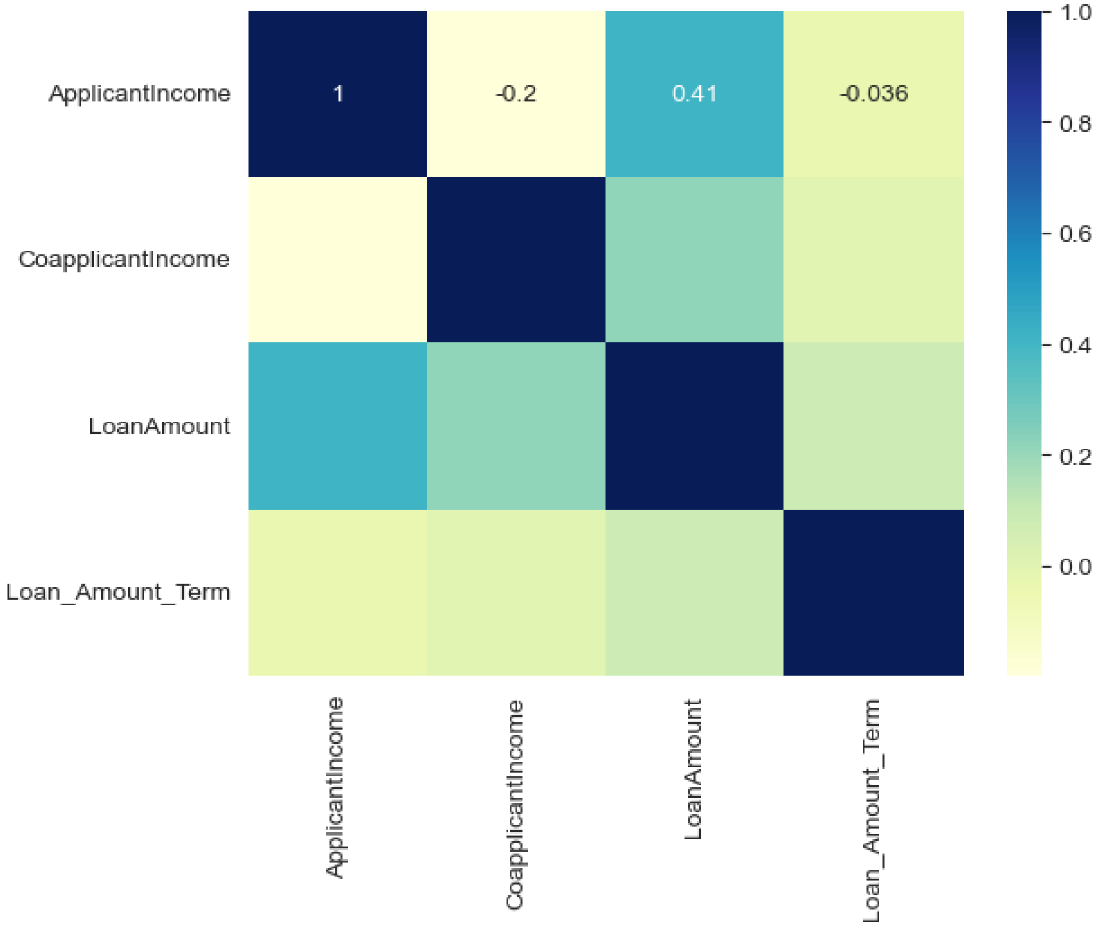
[86]:
```
# Selecting only numerical columns
numerical_columns = loan_df.select_dtypes(exclude="object").columns

# Creating unique scatter plots
num_cols_count = len(numerical_columns)
num_plots = num_cols_count * (num_cols_count - 1) // 2

# Setting up subplots
fig, axes = plt.subplots(num_plots // 2, 2, figsize=(15, 15))

plot_index = 0
for i in range(num_cols_count):
    for j in range(i+1, num_cols_count):
        row = plot_index // 2
        col = plot_index % 2

        # Scatter plot
        sns.scatterplot(x=numerical_columns[i], y=numerical_columns[j],␣
 ↪hue=output_var,data=loan_df, ax=axes[row, col])
        axes[row, col].set_title(f'{numerical_columns[i]} vs␣
 ↪{numerical_columns[j]}')

        plot_index += 1

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

13.1.1 9.4 Correaltion Numerical Columns

[87]:
```
print(loan_df.corr(numeric_only=True))
sns.heatmap(loan_df.corr(numeric_only=True), cmap="YlGnBu", annot=True)
plt.show()
```

```
                   ApplicantIncome  CoapplicantIncome  LoanAmount  \
ApplicantIncome           1.000000          -0.198660    0.409769
CoapplicantIncome        -0.198660           1.000000    0.217976
LoanAmount                0.409769           0.217976    1.000000
Loan_Amount_Term         -0.035532          -0.005549    0.077932

                   Loan_Amount_Term
```

```
ApplicantIncome         -0.035532
CoapplicantIncome       -0.005549
LoanAmount               0.077932
Loan_Amount_Term         1.000000
```



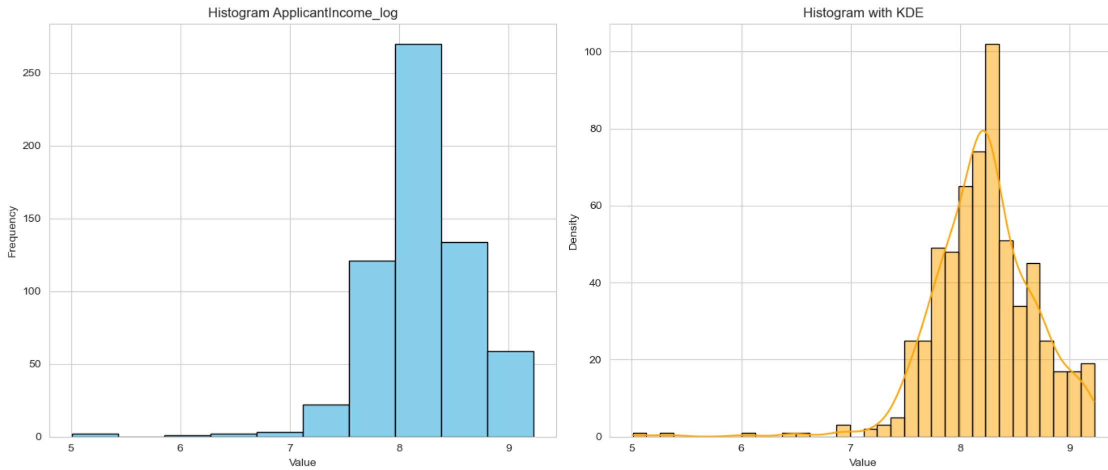
14 10. Data Transformation

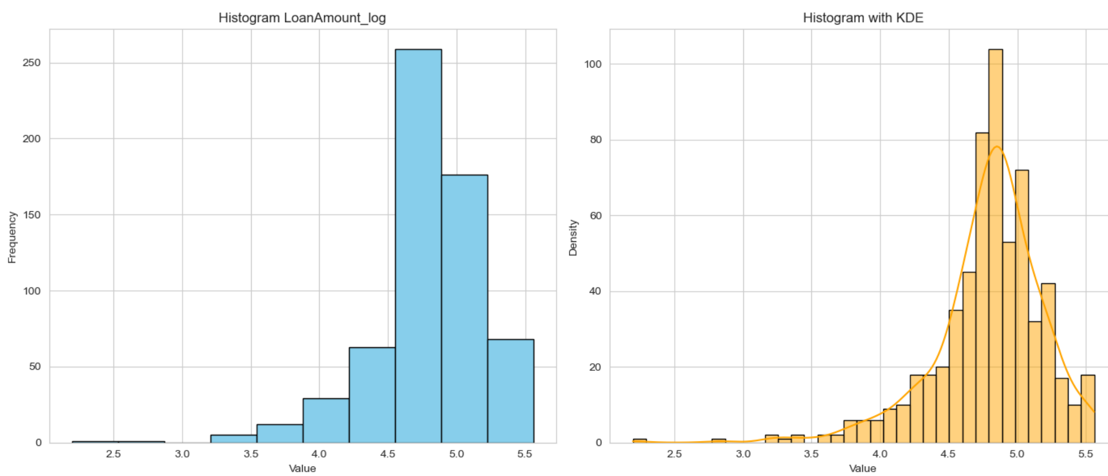
[88]:
```
num_cols = ['ApplicantIncome', 'CoapplicantIncome', 'LoanAmount']
```

[89]:
```
loan_df["ApplicantIncome_log"]=np.log(loan_df["ApplicantIncome"])
loan_df["CoapplicantIncome_log"]=np.log(loan_df["CoapplicantIncome"])
loan_df["LoanAmount_log"]=np.log(loan_df["LoanAmount"])

loan_num_df = loan_df[['ApplicantIncome_log',  'LoanAmount_log']].copy()
# Fit and transform your data using the pipeline
processed_data = pipeline_num_var.fit_transform(loan_num_df)
```

```
C:\Users\srishanm\AppData\Local\anaconda3\Lib\site-
```

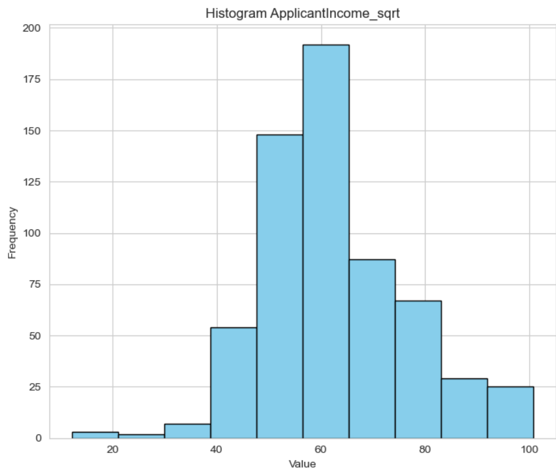
```
packages\pandas\core\arraylike.py:396: RuntimeWarning: divide by zero
encountered in log
  result = getattr(ufunc, method)(*inputs, **kwargs)
```

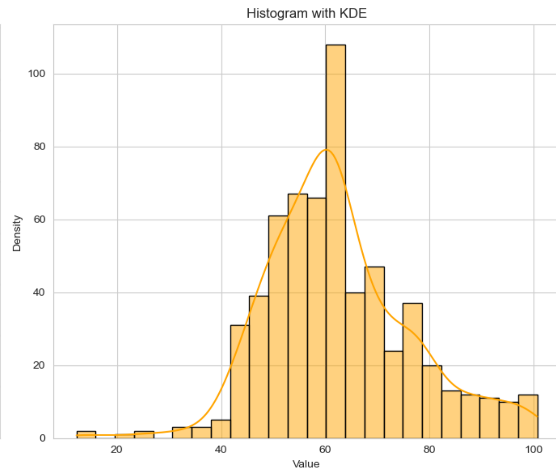


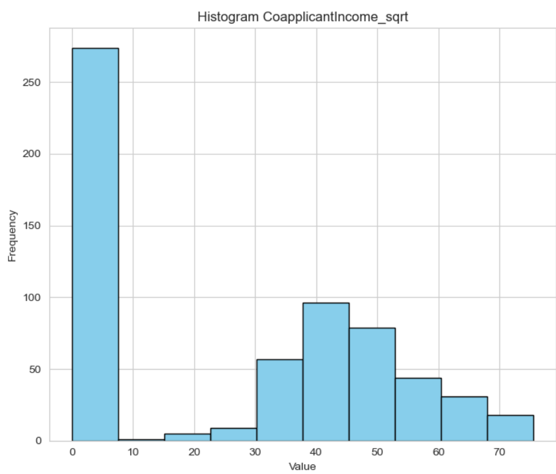


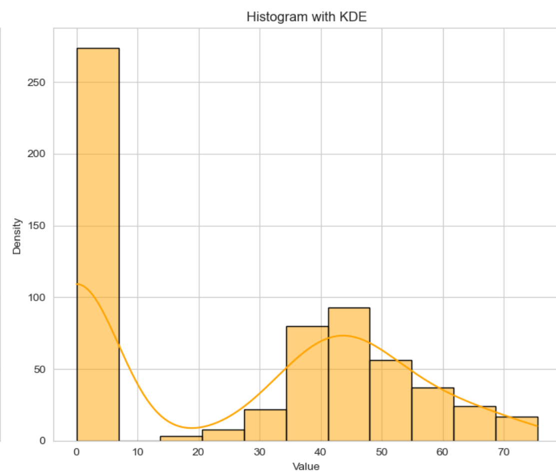
[90]:

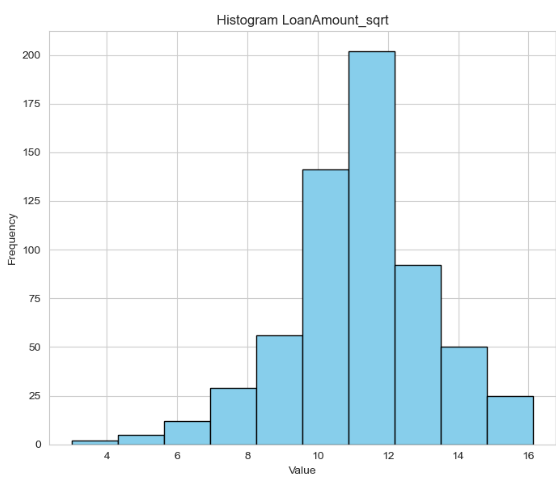
```python
loan_df["ApplicantIncome_sqrt"]=np.sqrt(loan_df["ApplicantIncome"])
loan_df["CoapplicantIncome_sqrt"]=np.sqrt(loan_df["CoapplicantIncome"])
loan_df["LoanAmount_sqrt"]=np.sqrt(loan_df["LoanAmount"])

loan_num_df = loan_df[['ApplicantIncome_sqrt', 'CoapplicantIncome_sqrt', 'LoanAmount_sqrt']].copy()
# Fit and transform your data using the pipeline
processed_data = pipeline_num_var.fit_transform(loan_num_df)
```

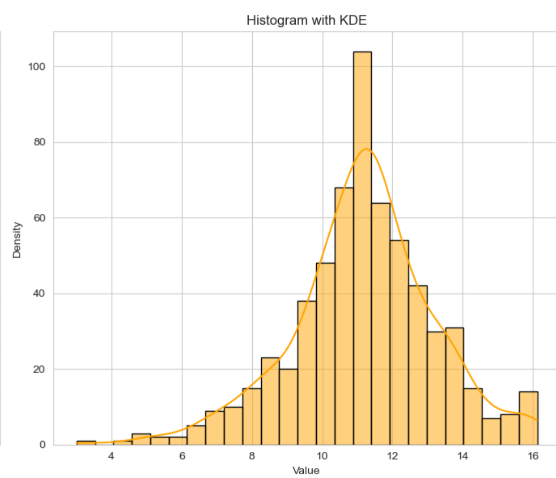

Histogram ApplicantIncome_sqrt
Frequency
0
25
50
75
100
125
150
175
200
20
40
60
80
100
Value


Histogram with KDE
Density
0
20
40
60
80
100
20
40
60
80
100
Value


Histogram CoapplicantIncome_sqrt
Frequency
0
50
100
150
200
250
0
10
20
30
40
50
60
70
Value


Histogram with KDE
Density
0
50
100
150
200
250
0
10
20
30
40
50
60
70
Value


Histogram LoanAmount_sqrt
Frequency
0
25
50
75
100
125
150
175
200
4
6
8
10
12
14
16
Value


Histogram with KDE
Density
0
20
40
60
80
100
4
6
8
10
12
14
16
Value

15 11. Standization - Normalization

[91]:
```
scaler = StandardScaler()

# Fit and transform the scaler on the selected columns
scaled_columns = scaler.fit_transform(loan_df[['ApplicantIncome_sqrt',␣
↪'CoapplicantIncome_sqrt', 'LoanAmount_sqrt']])

# Replace the original columns with the scaled columns
loan_df[['ApplicantIncome_sqrt_stand',␣
↪'CoapplicantIncome_sqrt_stand','LoanAmount_sqrt_stand']] = scaled_columns

print(loan_df)
```

```
     Gender Married Dependents     Education Self_Employed  ApplicantIncome  \
0      Male      No          0      Graduate            No           5849.0
1      Male     Yes          1      Graduate            No           4583.0
2      Male     Yes          0      Graduate           Yes           3000.0
3      Male     Yes          0  Not Graduate            No           2583.0
4      Male      No          0      Graduate            No           6000.0
..      …       …          …             …            …              …
609  Female      No          0      Graduate            No           2900.0
610    Male     Yes          4      Graduate            No           4106.0
611    Male     Yes          1      Graduate            No           8072.0
612    Male     Yes          2      Graduate            No           7583.0
613  Female      No          0      Graduate           Yes           4583.0

     CoapplicantIncome  LoanAmount  Loan_Amount_Term Credit_History  …   \
0                  0.0  146.412162             360.0              Y  …
1               1508.0  128.000000             360.0              Y  …
2                  0.0   66.000000             360.0              Y  …
3               2358.0  120.000000             360.0              Y  …
4                  0.0  141.000000             360.0              Y  …
..                 …           …               …            …   …
609                0.0   71.000000             360.0              Y  …
610                0.0   40.000000             180.0              Y  …
611              240.0  253.000000             360.0              Y  …
612                0.0  187.000000             360.0              Y  …
613                0.0  133.000000             360.0              N  …

    Loan_Status ApplicantIncome_log  CoapplicantIncome_log  LoanAmount_log  \
0             Y            8.674026                   -inf        4.986426
1             N            8.430109               7.318540        4.852030
2             Y            8.006368                   -inf        4.189655
3             Y            7.856707               7.765569        4.787492
```

```
4           Y          8.699515               -inf        4.948760
..          …             …                  …             …
609         Y          7.972466               -inf        4.262680
610         Y          8.320205               -inf        3.688879
611         Y          8.996157           5.480639        5.533389
612         Y          8.933664               -inf        5.231109
613         N          8.430109               -inf        4.890349

     ApplicantIncome_sqrt  CoapplicantIncome_sqrt  LoanAmount_sqrt  \
0               76.478755                0.000000        12.100089
1               67.697858               38.832976        11.313708
2               54.772256                0.000000         8.124038
3               50.823223               48.559242        10.954451
4               77.459667                0.000000        11.874342
..                    …                       …                 …
609             53.851648                0.000000         8.426150
610             64.078077                0.000000         6.324555
611             89.844310               15.491933        15.905974
612             87.080423                0.000000        13.674794
613             67.697858                0.000000        11.532563

     ApplicantIncome_sqrt_stand  CoapplicantIncome_sqrt_stand  \
0                      1.005715                     -1.043770
1                      0.374031                      0.521418
2                     -0.555816                     -1.043770
3                     -0.839903                      0.913442
4                      1.076280                     -1.043770
..                          …                            …
609                   -0.622043                     -1.043770
610                    0.113630                     -1.043770
611                    1.967212                     -0.419358
612                    1.768382                     -1.043770
613                    0.374031                     -1.043770

     LoanAmount_sqrt_stand
0                 0.451125
1                 0.064755
2                -1.502418
3                -0.111758
4                 0.340209
..                     …
609              -1.353982
610              -2.386553
611               2.321061
612               1.224821
613               0.172284

[614 rows x 21 columns]
```

16 12. Convert Cat - to - Numerical Columns

[92]:
```
le = LabelEncoder()
loan_df["Loan_Status"]=le.fit_transform(loan_df["Loan_Status"])
```

17 13. SMOTE for Balancing Data

[93]:
```
Y=loan_df["Loan_Status"]
X=loan_df[[ 'Married', ␣
 ↪'Education','Property_Area','Credit_History','ApplicantIncome_sqrt_stand',␣
 ↪'CoapplicantIncome_sqrt_stand','LoanAmount_sqrt_stand']]
print(len(Y),len(X))
X=pd.get_dummies(X,dtype='int',drop_first=False)
```

```
614 614
```

[94]:
```
X, Y = SMOTE().fit_resample(X, Y)
```

[95]:
```
print(X.columns)
print(len(Y),len(X))
```

```
Index(['ApplicantIncome_sqrt_stand', 'CoapplicantIncome_sqrt_stand',
       'LoanAmount_sqrt_stand', 'Married_No', 'Married_Yes',
       'Education_Graduate', 'Education_Not Graduate', 'Property_Area_Rural',
       'Property_Area_Semiurban', 'Property_Area_Urban', 'Credit_History_N',
       'Credit_History_Y'],
      dtype='object')
844 844
```

[96]:
```
Y.value_counts()
```

[96]:
```
Loan_Status
1    422
0    422
Name: count, dtype: int64
```

18 ML Models

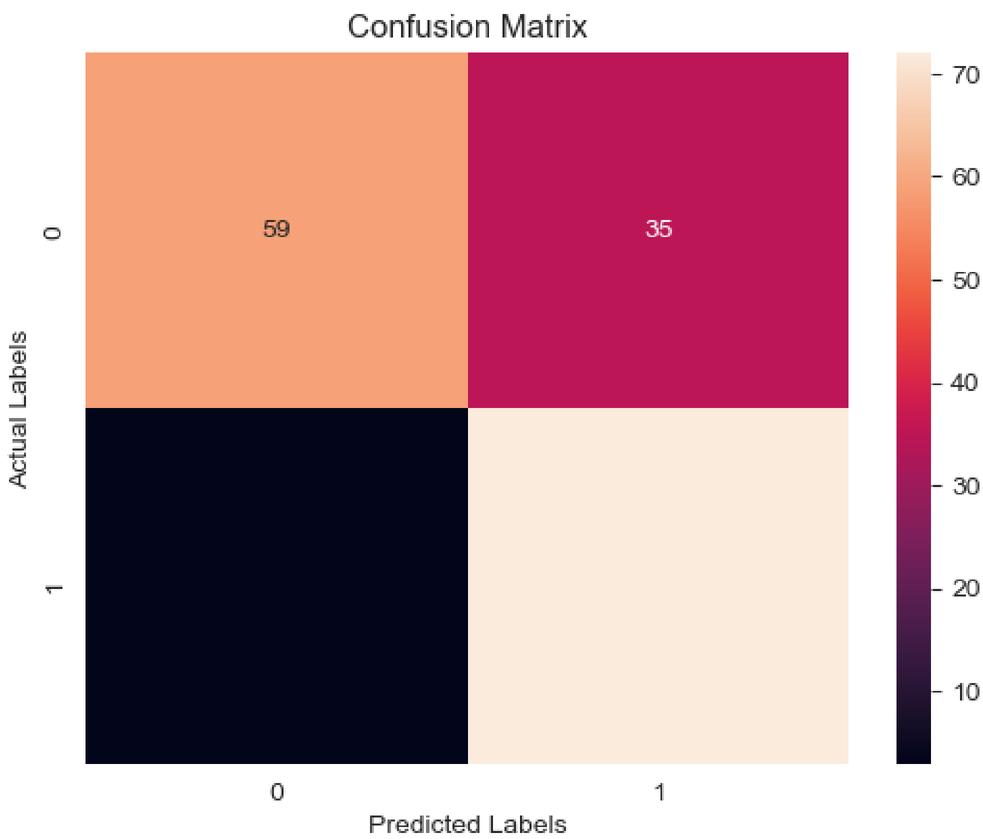
[97]:
```
X_train, X_test, Y_train, Y_test = train_test_split(X,Y,test_size=0.
 ↪2,random_state = 42)
```

[98]:
```
def draw_heatmap(conf_matrix):
    sns.heatmap(conf_matrix, annot=True)
    plt.xlabel('Predicted Labels')
    plt.ylabel('Actual Labels')
    plt.title('Confusion Matrix')
    plt.show()
```

18.1 Logistic Regression

[99]:
```
lg_model = LogisticRegression(solver='saga', max_iter=500, random_state=42)
lg_model.fit(X_train, Y_train)

print("Model - Logistic Regression")
score = lg_model.score(X_train, Y_train)
print('accuracy train score overall :', score)
score = lg_model.score(X_test, Y_test)
print('accuracy test score overall :', score)

y_pred = lg_model.predict(X_test)
print(classification_report(Y_test, y_pred))
print(confusion_matrix(Y_test, y_pred))
conf_matrix = confusion_matrix(Y_test, y_pred)
draw_heatmap(conf_matrix)
```

```
Model - Logistic Regression
accuracy train score overall : 0.7777777777777778
accuracy test score overall : 0.7751479289940828
              precision    recall  f1-score   support

           0       0.95      0.63      0.76        94
           1       0.67      0.96      0.79        75

    accuracy                           0.78       169
   macro avg       0.81      0.79      0.77       169
weighted avg       0.83      0.78      0.77       169

[[59 35]
 [ 3 72]]
```

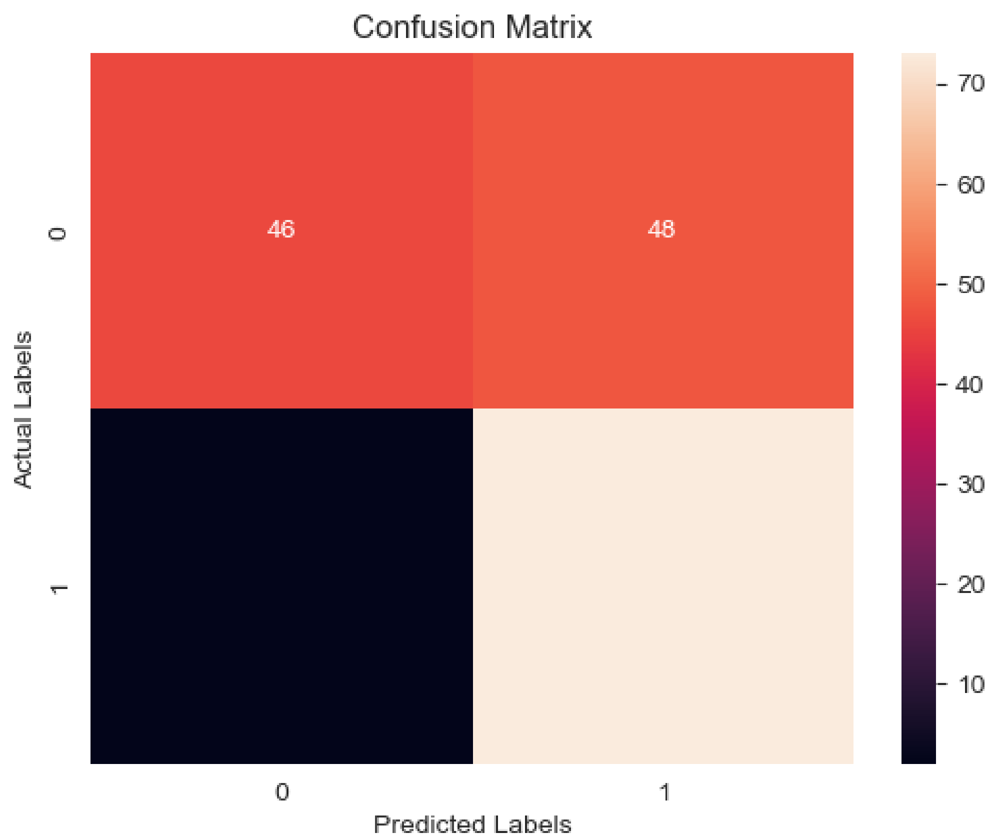


18.2 GaussianNB

[100]:
```
from sklearn.naive_bayes import GaussianNB, CategoricalNB
gnb_model = GaussianNB()
gnb_model.fit(X_train,Y_train)

print("Model-GaussianNB")
print("train score",gnb_model.score(X_train,Y_train))
print("test score",gnb_model.score(X_test,Y_test))

y_pred = gnb_model.predict(X_test)
print(classification_report(Y_test, y_pred))
print(confusion_matrix(Y_test, y_pred))
conf_matrix = confusion_matrix(Y_test, y_pred)
draw_heatmap(conf_matrix)
```

```
Model-GaussianNB
train score 0.7303703703703703
test score 0.7041420118343196
              precision    recall  f1-score   support
```

```
              0       0.96      0.49      0.65        94
              1       0.60      0.97      0.74        75

       accuracy                           0.70       169
      macro avg       0.78      0.73      0.70       169
   weighted avg       0.80      0.70      0.69       169

[[46 48]
 [ 2 73]]
```

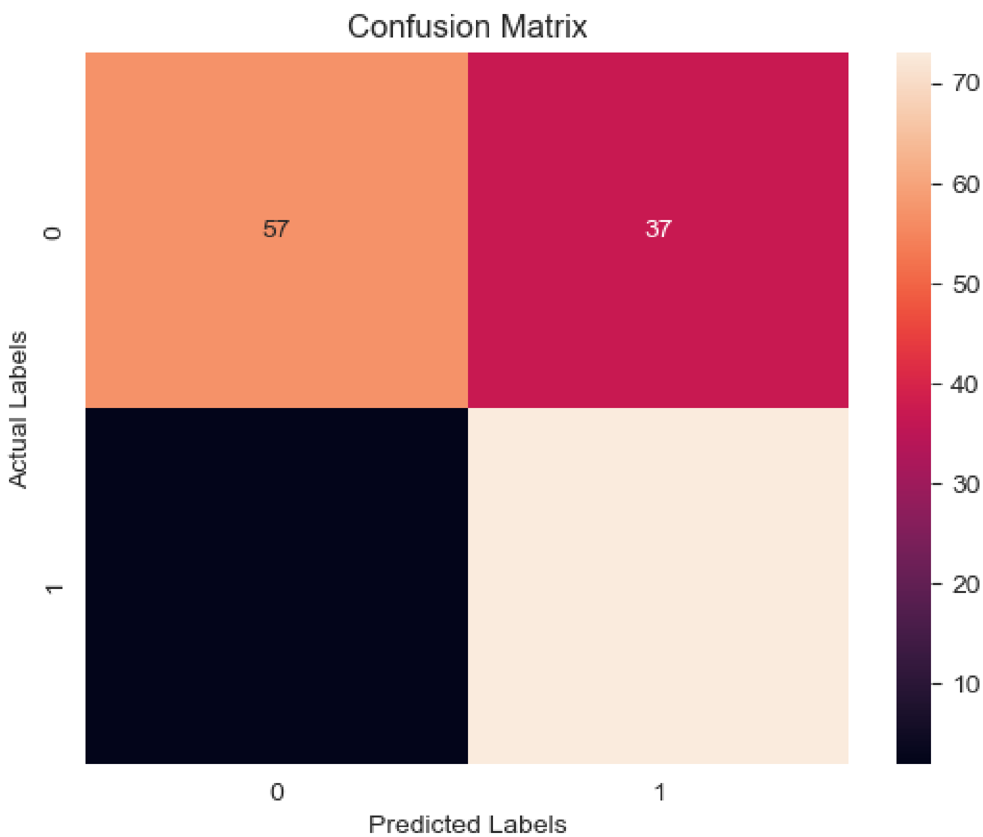


19 Suport Vector Machine - Classifier

[101]:
```python
from sklearn.svm import SVC
# Initialize the SVM classifier
svm_linear_classifier = SVC(kernel='linear', random_state=42)

# Train the SVM classifier
svm_linear_classifier.fit(X_train, Y_train)
print("model-Suport Vector Machine - kernel - linear -Classifier")
```

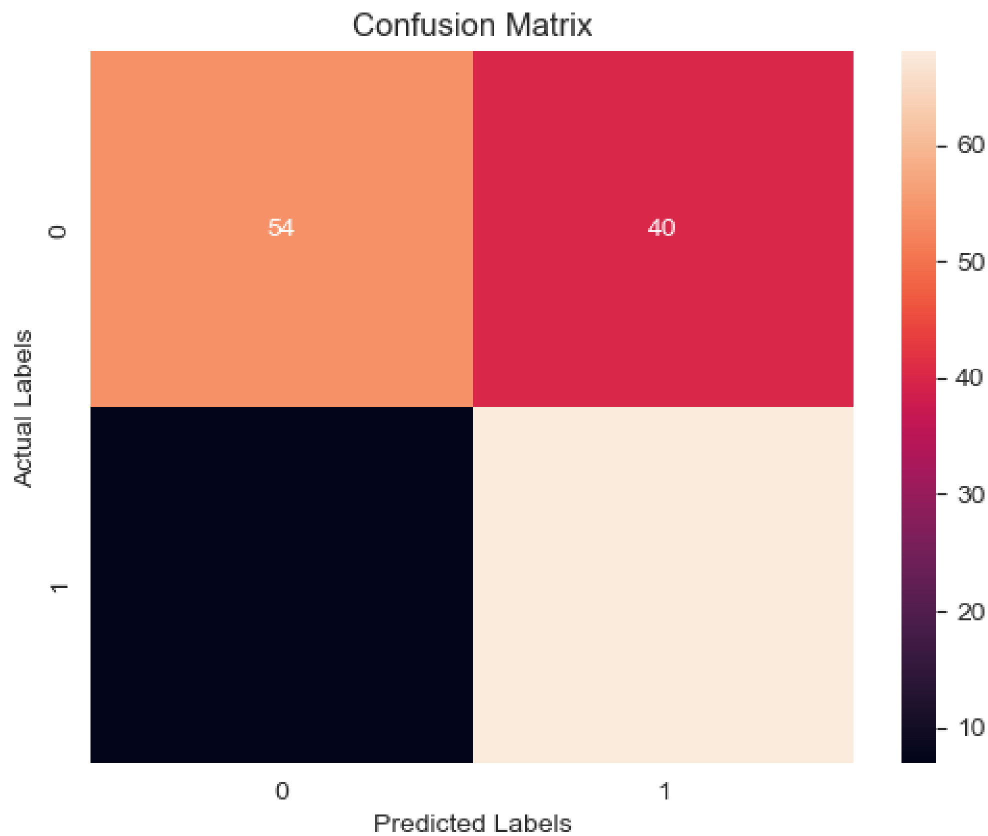
```python
y_pred = svm_linear_classifier.predict(X_train)
# Calculate the accuracy of the model
accuracy = accuracy_score(Y_train, y_pred)
print("Train Accuracy:", accuracy)

# Predict the classes for test set
y_pred = svm_linear_classifier.predict(X_test)
# Calculate the accuracy of the model
accuracy = accuracy_score(Y_test, y_pred)
print("Test Accuracy:", accuracy)

print(classification_report(Y_test, y_pred))
print(confusion_matrix(Y_test, y_pred))
conf_matrix = confusion_matrix(Y_test, y_pred)
draw_heatmap(conf_matrix)
```

```
model-Suport Vector Machine - kernel - linear -Classifier
Train Accuracy: 0.7807407407407407
Test Accuracy: 0.7692307692307693
              precision    recall  f1-score   support

           0       0.97      0.61      0.75        94
           1       0.66      0.97      0.79        75

    accuracy                           0.77       169
   macro avg       0.81      0.79      0.77       169
weighted avg       0.83      0.77      0.76       169

[[57 37]
 [ 2 73]]
```



[102]:
```
svm_rbf_classifier = SVC(kernel='rbf', random_state=42)

# Train the SVM classifier
svm_rbf_classifier.fit(X_train, Y_train)
print("model-Suport Vector Machine - Kernel -rbf - Classifier")
y_pred = svm_rbf_classifier.predict(X_train)
# Calculate the accuracy of the model
accuracy = accuracy_score(Y_train, y_pred)
print("Train Accuracy:", accuracy)

# Predict the classes for test set
y_pred = svm_rbf_classifier.predict(X_test)
# Calculate the accuracy of the model
accuracy = accuracy_score(Y_test, y_pred)
print("Test Accuracy:", accuracy)

print(classification_report(Y_test, y_pred))
print(confusion_matrix(Y_test, y_pred))
conf_matrix = confusion_matrix(Y_test, y_pred)
draw_heatmap(conf_matrix)
```

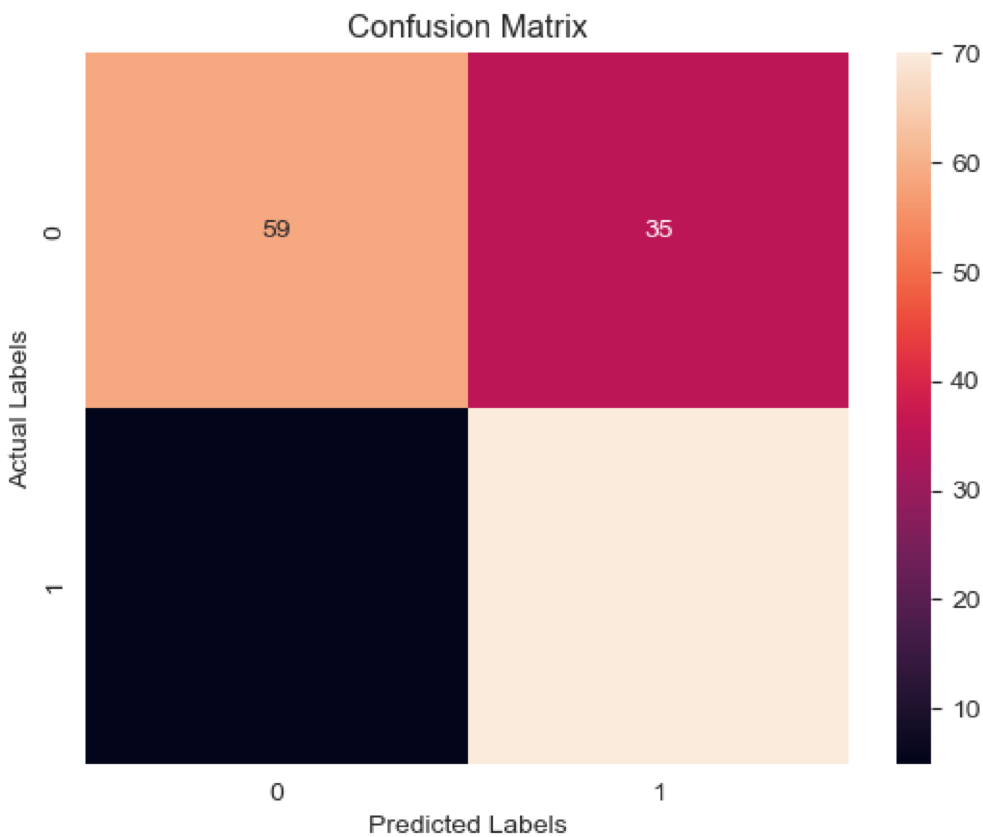
```
model-Suport Vector Machine - Kernel -rbf - Classifier
Train Accuracy: 0.7896296296296297
Test Accuracy: 0.7218934911242604
              precision    recall  f1-score   support

           0       0.89      0.57      0.70        94
           1       0.63      0.91      0.74        75

    accuracy                           0.72       169
   macro avg       0.76      0.74      0.72       169
weighted avg       0.77      0.72      0.72       169

[[54 40]
 [ 7 68]]
```



[103]:
```python
svm_poly_classifier = SVC(kernel='poly', random_state=42)

# Train the SVM classifier
svm_poly_classifier.fit(X_train, Y_train)
print("model-Suport Vector Machine - Kernel -poly - Classifier")
```

```python
y_pred = svm_poly_classifier.predict(X_train)
# Calculate the accuracy of the model
accuracy = accuracy_score(Y_train, y_pred)
print("Train Accuracy:", accuracy)

# Predict the classes for test set
y_pred = svm_poly_classifier.predict(X_test)

# Calculate the accuracy of the model
accuracy = accuracy_score(Y_test, y_pred)
print("Test Accuracy:", accuracy)

print(classification_report(Y_test, y_pred))
print(confusion_matrix(Y_test, y_pred))
conf_matrix = confusion_matrix(Y_test, y_pred)
draw_heatmap(conf_matrix)
```

```
model-Suport Vector Machine - Kernel -poly - Classifier
Train Accuracy: 0.802962962962963
Test Accuracy: 0.7633136094674556
              precision    recall  f1-score   support

           0       0.92      0.63      0.75        94
           1       0.67      0.93      0.78        75

    accuracy                           0.76       169
   macro avg       0.79      0.78      0.76       169
weighted avg       0.81      0.76      0.76       169

[[59 35]
 [ 5 70]]
```

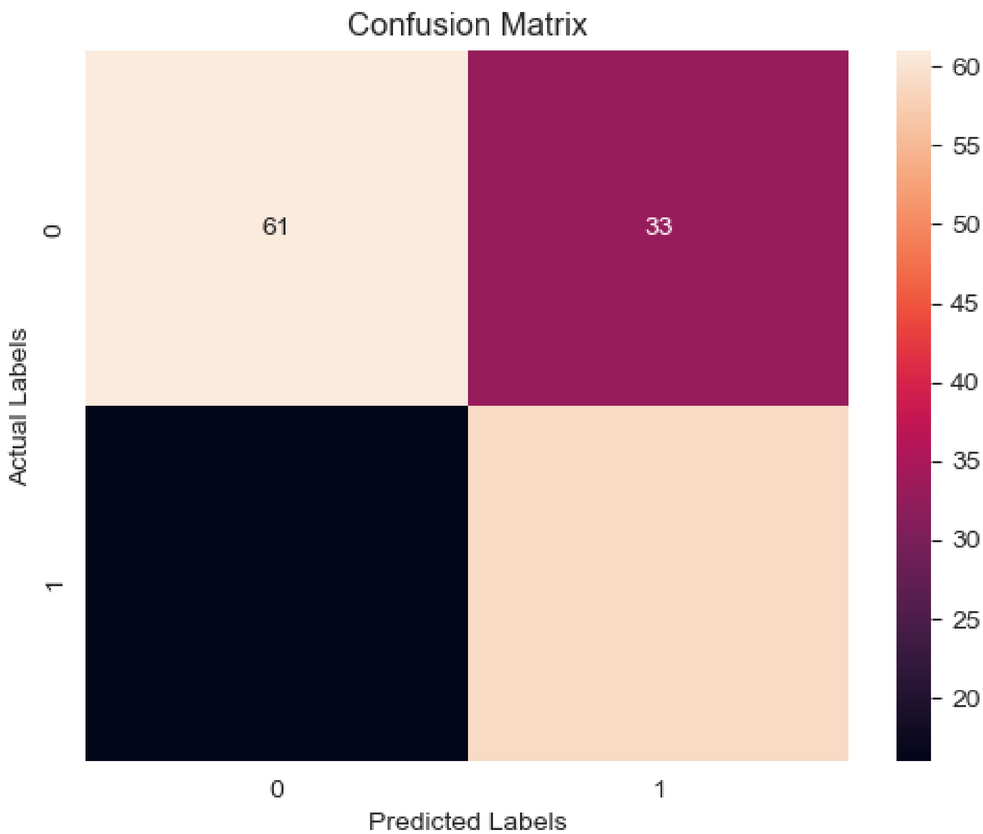


19.1 Decision Tree

[104]:
```
dt_clf = DecisionTreeClassifier(max_leaf_nodes=20,random_state=42)
dt_clf.fit(X_train, Y_train)
print("Model-Decion Tree")

accuracy=dt_clf.score(X_train, Y_train)
print(f"train score: {accuracy}")

accuracy=dt_clf.score(X_test, Y_test)
print(f"test score: {accuracy}")

y_pred=dt_clf.predict(X_test)
print(classification_report(Y_test, y_pred))
print(confusion_matrix(Y_test, y_pred))
conf_matrix = confusion_matrix(Y_test, y_pred)
draw_heatmap(conf_matrix)
```

```
Model-Decion Tree
train score: 0.8311111111111111
test score: 0.7100591715976331
```

```
              precision    recall  f1-score   support

           0       0.79      0.65      0.71        94
           1       0.64      0.79      0.71        75

    accuracy                           0.71       169
   macro avg       0.72      0.72      0.71       169
weighted avg       0.73      0.71      0.71       169

[[61 33]
 [16 59]]
```

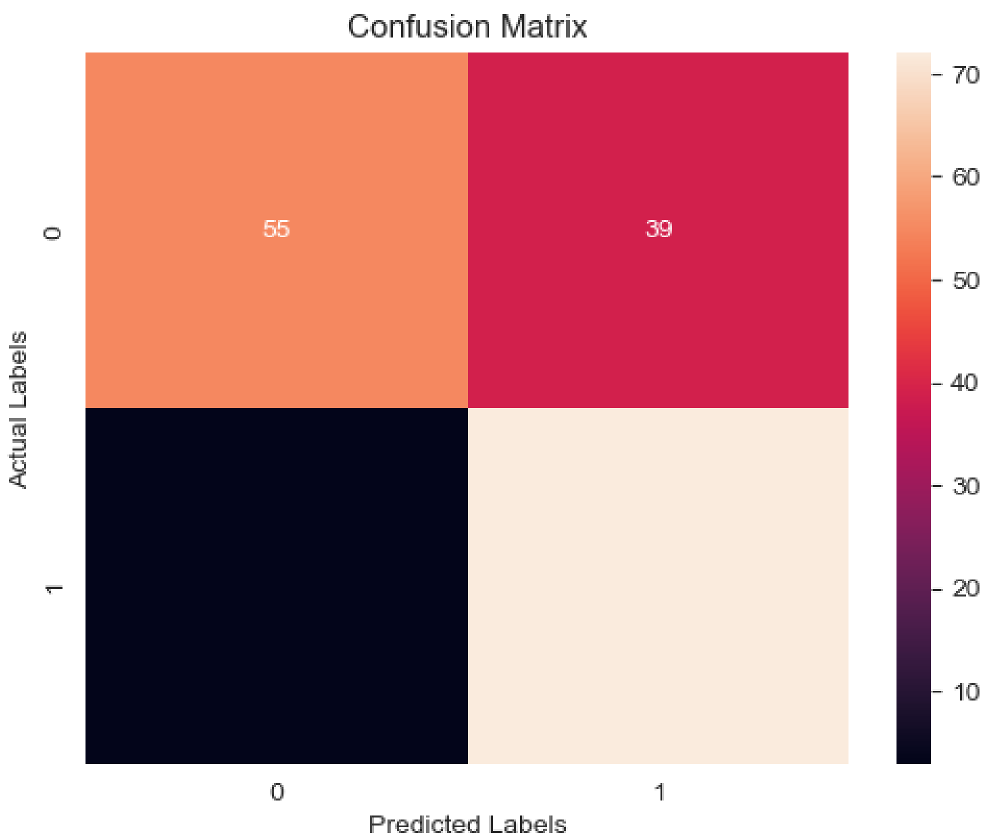


19.2 Radom Forest

[105]:
```
rf_clf= RandomForestClassifier(n_estimators = 1000, random_state = 42,␣
  ↪max_leaf_nodes=20)
rf_clf.fit(X_train, Y_train)
print("Model- Random Forest Tree")

accuracy=rf_clf.score(X_train, Y_train)
```

```python
print(f"train score: {accuracy}")

accuracy=rf_clf.score(X_test, Y_test)
print(f"test score: {accuracy}")

y_pred=rf_clf.predict(X_test)
print(classification_report(Y_test, y_pred))
print(confusion_matrix(Y_test, y_pred))
conf_matrix = confusion_matrix(Y_test, y_pred)
draw_heatmap(conf_matrix)
```

```
Model- Random Forest Tree
train score: 0.8577777777777778
test score: 0.7514792899408284
              precision    recall  f1-score   support

           0       0.95      0.59      0.72        94
           1       0.65      0.96      0.77        75

    accuracy                           0.75       169
   macro avg       0.80      0.77      0.75       169
weighted avg       0.82      0.75      0.75       169

[[55 39]
 [ 3 72]]
```

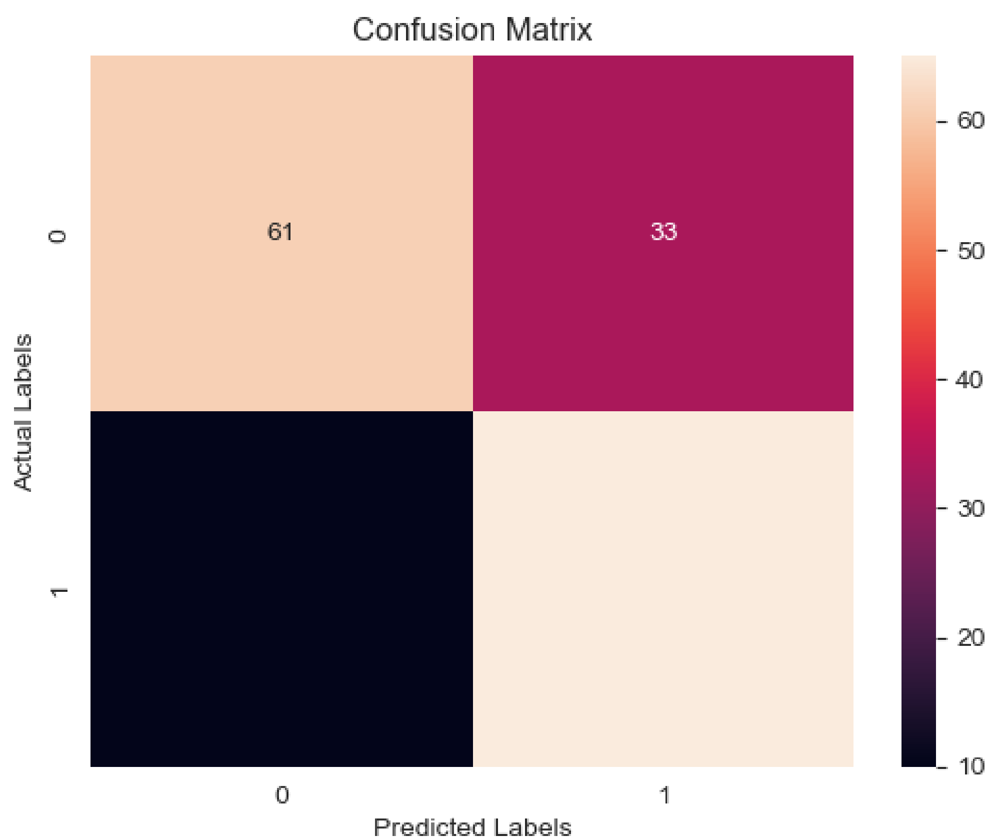


19.3 AdaBoost

[106]:
```
base_classifier = DecisionTreeClassifier(max_depth=1)
adaboost_clf = AdaBoostClassifier( n_estimators=50, random_state=42)

# Train the AdaBoost classifier
adaboost_clf.fit(X_train, Y_train)

print("Model-AdaBoost")
print("train score",adaboost_clf.score(X_train, Y_train))

# Predict on the test set
y_pred = adaboost_clf.predict(X_test)

# Calculate accuracy
accuracy = accuracy_score(Y_test, y_pred)
print(f"test score: {accuracy}")

print(classification_report(Y_test, y_pred))
print(confusion_matrix(Y_test, y_pred))
```

```
conf_matrix = confusion_matrix(Y_test, y_pred)
draw_heatmap(conf_matrix)
```

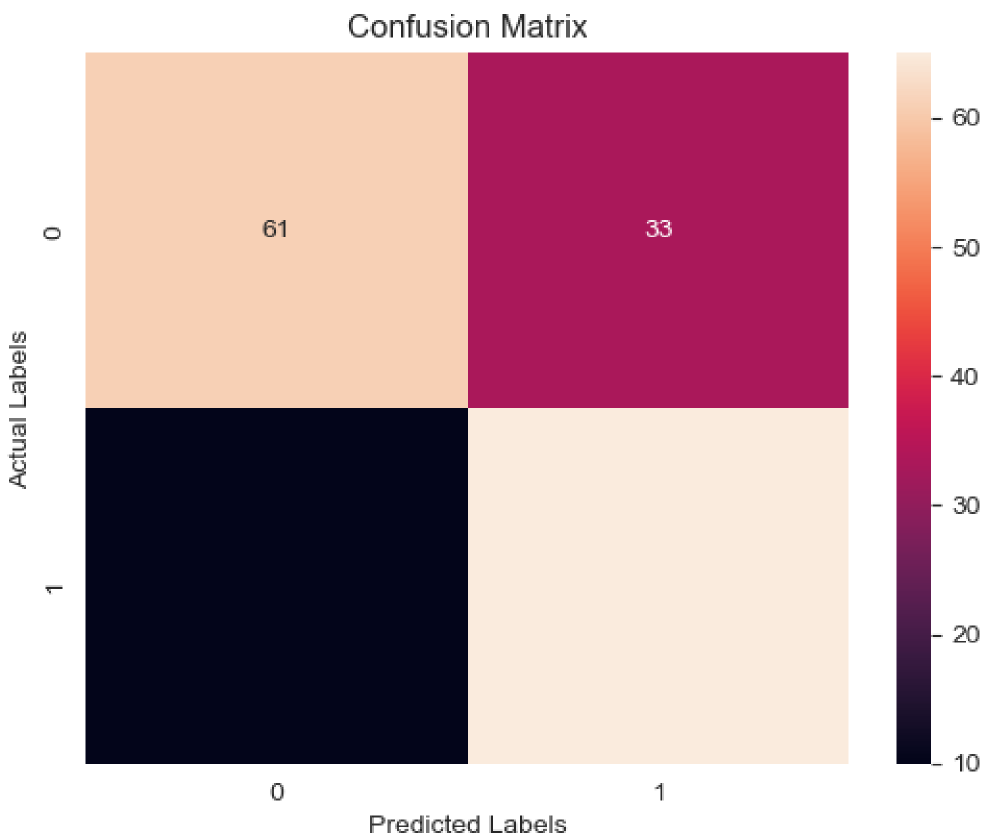
```
Model-AdaBoost
train score 0.8088888888888889
test score: 0.7455621301775148
              precision    recall  f1-score   support

           0       0.86      0.65      0.74        94
           1       0.66      0.87      0.75        75

    accuracy                           0.75       169
   macro avg       0.76      0.76      0.75       169
weighted avg       0.77      0.75      0.74       169

[[61 33]
 [10 65]]
```



19.4 GradientBoostingClassifier

[107]:
```
gdb_clf = GradientBoostingClassifier(n_estimators=20, learning_rate=0.1,␣
    ↪max_depth=1, random_state=42)
gdb_clf.fit(X_train, Y_train)
print("model-Gradient Boosting Classifier")

accuracy = gdb_clf.score(X_train, Y_train)
print("Train Accuracy:", accuracy)

accuracy = gdb_clf.score(X_test, Y_test)
print("Test Accuracy:", accuracy)

print(classification_report(Y_test, y_pred))
print(confusion_matrix(Y_test, y_pred))
conf_matrix = confusion_matrix(Y_test, y_pred)
draw_heatmap(conf_matrix)
```

```
model-Gradient Boosting Classifier
Train Accuracy: 0.7303703703703703
Test Accuracy: 0.7041420118343196
              precision    recall  f1-score   support

           0       0.86      0.65      0.74        94
           1       0.66      0.87      0.75        75

    accuracy                           0.75       169
   macro avg       0.76      0.76      0.75       169
weighted avg       0.77      0.75      0.74       169

[[61 33]
 [10 65]]
```

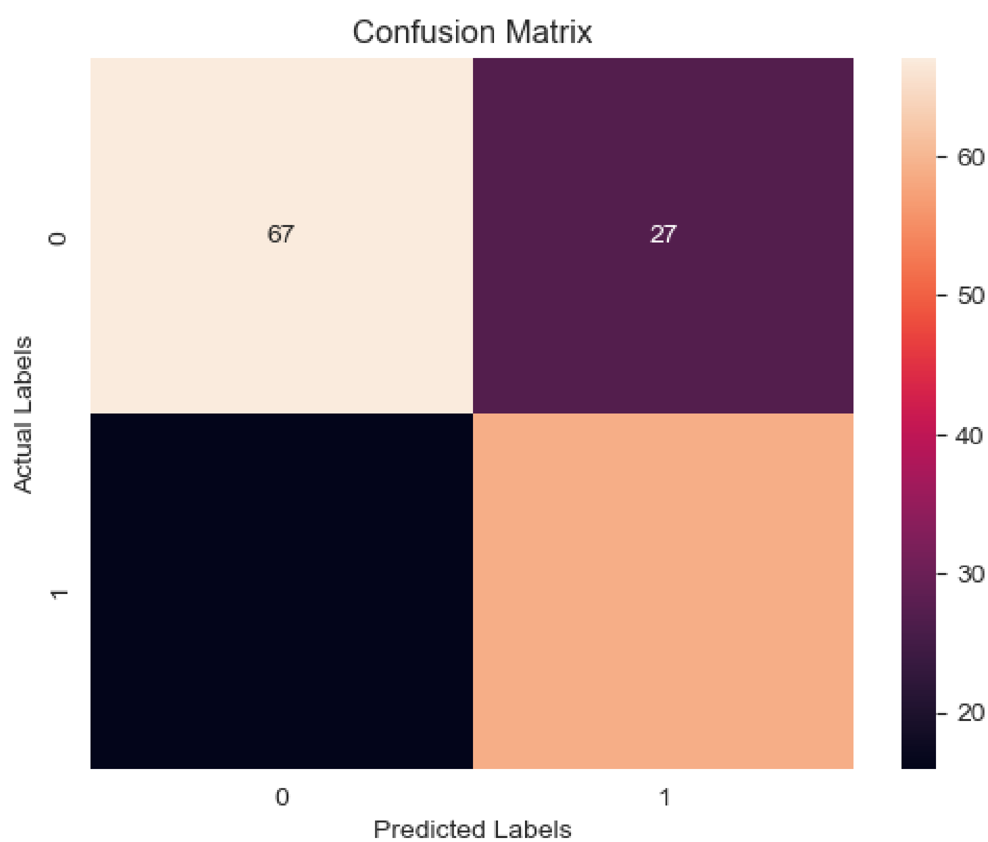


19.5 XGBClassifier

[108]:
```
from xgboost import XGBClassifier
xgmodel = XGBClassifier()
xgmodel.fit(X_train, Y_train)


print("model- XGB Classifier")
# Make predictions on the test set
y_pred = xgmodel.predict(X_train)
accuracy = accuracy_score(Y_train, y_pred)
print("Test Accuracy:", accuracy)
# Evaluate the model

# Make predictions on the test set
y_pred = xgmodel.predict(X_test)
accuracy = accuracy_score(Y_test, y_pred)
print("Test Accuracy:", accuracy)

print(classification_report(Y_test, y_pred))
```

```
print(confusion_matrix(Y_test, y_pred))
conf_matrix = confusion_matrix(Y_test, y_pred)
draw_heatmap(conf_matrix)
```

```
model- XGB Classifier
Test Accuracy: 0.9955555555555555
Test Accuracy: 0.7455621301775148
              precision    recall  f1-score   support

           0       0.81      0.71      0.76        94
           1       0.69      0.79      0.73        75

    accuracy                           0.75       169
   macro avg       0.75      0.75      0.74       169
weighted avg       0.75      0.75      0.75       169

[[67 27]
 [16 59]]
```



Observations 1. Did the EDA 2. Developed Models on Given dataset