Vehicel Defaulter Analysis

November 13, 2023

1 1.Data Preliminary Analysis:

Importing necessary packages

[1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn import metrics
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV

import warnings
warnings.filterwarnings('ignore')
%matplotlib inline

random_state=42
```

Data exploration

[2]:
```
df = pd.read_excel('D:\Data Analytics\Data␣
 ↪Capstones\Banking\Project2_Dataset\Dataset\data.xlsx')
print (df.shape)
df.head()
```

```
(233154, 41)
```

[2]:
```
   UniqueID  disbursed_amount  asset_cost    ltv  branch_id  supplier_id  \
0    420825             50578       58400  89.55         67        22807
1    417566             53278       61360  89.63         67        22807
2    539055             52378       60300  88.39         67        22807
3    529269             46349       61500  76.42         67        22807
4    563215             43594       78256  57.50         67        22744

   manufacturer_id  Current_pincode_ID Date.of.Birth Employment.Type  …  \
```

```
0              45                1441    1984-01-01        Salaried  …
1              45                1497    1985-08-24   Self employed  …
2              45                1495    1977-12-09   Self employed  …
3              45                1502    1988-06-01        Salaried  …
4              86                1499    1994-07-14   Self employed  …

  SEC.SANCTIONED.AMOUNT  SEC.DISBURSED.AMOUNT  PRIMARY.INSTAL.AMT  \
0                     0                     0                   0
1                     0                     0                   0
2                     0                     0                   0
3                     0                     0                   0
4                     0                     0                   0

   SEC.INSTAL.AMT  NEW.ACCTS.IN.LAST.SIX.MONTHS  \
0               0                             0
1               0                             0
2               0                             0
3               0                             0
4               0                             0

   DELINQUENT.ACCTS.IN.LAST.SIX.MONTHS  AVERAGE.ACCT.AGE  \
0                                    0         0yrs 0mon
1                                    0         0yrs 0mon
2                                    0         0yrs 0mon
3                                    0         0yrs 0mon
4                                    0         0yrs 0mon

   CREDIT.HISTORY.LENGTH  NO.OF_INQUIRIES  loan_default
0              0yrs 0mon                0             0
1              0yrs 0mon                0             0
2              0yrs 0mon                1             1
3              0yrs 0mon                0             0
4              0yrs 0mon                0             0

[5 rows x 41 columns]
```

[3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 233154 entries, 0 to 233153
Data columns (total 41 columns):
 #   Column                               Non-Null Count   Dtype
---  ------                               --------------   -----
 0   UniqueID                             233154 non-null  int64
 1   disbursed_amount                     233154 non-null  int64
 2   asset_cost                           233154 non-null  int64
 3   ltv                                  233154 non-null  float64
 4   branch_id                            233154 non-null  int64
```

```
 5   supplier_id                          233154 non-null  int64
 6   manufacturer_id                      233154 non-null  int64
 7   Current_pincode_ID                   233154 non-null  int64
 8   Date.of.Birth                        233154 non-null  datetime64[ns]
 9   Employment.Type                      225493 non-null  object
 10  DisbursalDate                        233154 non-null  datetime64[ns]
 11  State_ID                             233154 non-null  int64
 12  Employee_code_ID                     233154 non-null  int64
 13  MobileNo_Avl_Flag                    233154 non-null  int64
 14  Aadhar_flag                          233154 non-null  int64
 15  PAN_flag                             233154 non-null  int64
 16  VoterID_flag                         233154 non-null  int64
 17  Driving_flag                         233154 non-null  int64
 18  Passport_flag                        233154 non-null  int64
 19  PERFORM_CNS.SCORE                    233154 non-null  int64
 20  PERFORM_CNS.SCORE.DESCRIPTION        233154 non-null  object
 21  PRI.NO.OF.ACCTS                      233154 non-null  int64
 22  PRI.ACTIVE.ACCTS                     233154 non-null  int64
 23  PRI.OVERDUE.ACCTS                    233154 non-null  int64
 24  PRI.CURRENT.BALANCE                  233154 non-null  int64
 25  PRI.SANCTIONED.AMOUNT                233154 non-null  int64
 26  PRI.DISBURSED.AMOUNT                 233154 non-null  int64
 27  SEC.NO.OF.ACCTS                      233154 non-null  int64
 28  SEC.ACTIVE.ACCTS                     233154 non-null  int64
 29  SEC.OVERDUE.ACCTS                    233154 non-null  int64
 30  SEC.CURRENT.BALANCE                  233154 non-null  int64
 31  SEC.SANCTIONED.AMOUNT                233154 non-null  int64
 32  SEC.DISBURSED.AMOUNT                 233154 non-null  int64
 33  PRIMARY.INSTAL.AMT                   233154 non-null  int64
 34  SEC.INSTAL.AMT                       233154 non-null  int64
 35  NEW.ACCTS.IN.LAST.SIX.MONTHS         233154 non-null  int64
 36  DELINQUENT.ACCTS.IN.LAST.SIX.MONTHS  233154 non-null  int64
 37  AVERAGE.ACCT.AGE                     233154 non-null  object
 38  CREDIT.HISTORY.LENGTH                233154 non-null  object
 39  NO.OF_INQUIRIES                      233154 non-null  int64
 40  loan_default                         233154 non-null  int64
dtypes: datetime64[ns](2), float64(1), int64(34), object(4)
memory usage: 72.9+ MB
```

[4]:

```
# Inspecting the mean and standard deviation to see the scale of each features
df.describe()
```

[4]:

```
            UniqueID  disbursed_amount    asset_cost            ltv  \
count  233154.000000     233154.000000  2.331540e+05  233154.000000
mean   535917.573376      54356.993528  7.586507e+04      74.746530
std     68315.693711      12971.314171  1.894478e+04      11.456636
min    417428.000000      13320.000000  3.700000e+04      10.030000
```

```
25%    476786.250000     47145.000000  6.571700e+04      68.880000
50%    535978.500000     53803.000000  7.094600e+04      76.800000
75%    595039.750000     60413.000000  7.920175e+04      83.670000
max    671084.000000    990572.000000  1.628992e+06      95.000000

           branch_id    supplier_id  manufacturer_id  Current_pincode_ID  \
count  233154.000000  233154.000000    233154.000000       233154.000000
mean       72.936094   19638.635035        69.028054         3396.880247
std        69.834995    3491.949566        22.141304         2238.147502
min         1.000000   10524.000000        45.000000            1.000000
25%        14.000000   16535.000000        48.000000         1511.000000
50%        61.000000   20333.000000        86.000000         2970.000000
75%       130.000000   23000.000000        86.000000         5677.000000
max       261.000000   24803.000000       156.000000         7345.000000

            State_ID  Employee_code_ID  …  SEC.OVERDUE.ACCTS  \
count  233154.000000     233154.000000  …      233154.000000
mean        7.262243       1549.477148  …           0.007244
std         4.482230        975.261278  …           0.111079
min         1.000000          1.000000  …           0.000000
25%         4.000000        713.000000  …           0.000000
50%         6.000000       1451.000000  …           0.000000
75%        10.000000       2362.000000  …           0.000000
max        22.000000       3795.000000  …           8.000000

       SEC.CURRENT.BALANCE  SEC.SANCTIONED.AMOUNT  SEC.DISBURSED.AMOUNT  \
count         2.331540e+05           2.331540e+05          2.331540e+05
mean          5.427793e+03           7.295923e+03          7.179998e+03
std           1.702370e+05           1.831560e+05          1.825925e+05
min          -5.746470e+05           0.000000e+00          0.000000e+00
25%           0.000000e+00           0.000000e+00          0.000000e+00
50%           0.000000e+00           0.000000e+00          0.000000e+00
75%           0.000000e+00           0.000000e+00          0.000000e+00
max           3.603285e+07           3.000000e+07          3.000000e+07

       PRIMARY.INSTAL.AMT  SEC.INSTAL.AMT  NEW.ACCTS.IN.LAST.SIX.MONTHS  \
count        2.331540e+05    2.331540e+05                 233154.000000
mean         1.310548e+04    3.232684e+02                      0.381833
std          1.513679e+05    1.555369e+04                      0.955107
min          0.000000e+00    0.000000e+00                      0.000000
25%          0.000000e+00    0.000000e+00                      0.000000
50%          0.000000e+00    0.000000e+00                      0.000000
75%          1.999000e+03    0.000000e+00                      0.000000
max          2.564281e+07    4.170901e+06                     35.000000

       DELINQUENT.ACCTS.IN.LAST.SIX.MONTHS  NO.OF_INQUIRIES   loan_default
count                        233154.000000    233154.000000  233154.000000
```

```
mean                                  0.097481      0.206615      0.217071
std                                   0.384439      0.706498      0.412252
min                                   0.000000      0.000000      0.000000
25%                                   0.000000      0.000000      0.000000
50%                                   0.000000      0.000000      0.000000
75%                                   0.000000      0.000000      0.000000
max                                  20.000000     36.000000      1.000000

[8 rows x 35 columns]
```

[5]:

```python
# Checking for missing values
missing_values = df.isnull().sum()
print(missing_values)
```

```
UniqueID                                  0
disbursed_amount                          0
asset_cost                                0
ltv                                       0
branch_id                                 0
supplier_id                               0
manufacturer_id                           0
Current_pincode_ID                        0
Date.of.Birth                             0
Employment.Type                        7661
DisbursalDate                             0
State_ID                                  0
Employee_code_ID                          0
MobileNo_Avl_Flag                         0
Aadhar_flag                               0
PAN_flag                                  0
VoterID_flag                              0
Driving_flag                              0
Passport_flag                             0
PERFORM_CNS.SCORE                         0
PERFORM_CNS.SCORE.DESCRIPTION             0
PRI.NO.OF.ACCTS                           0
PRI.ACTIVE.ACCTS                          0
PRI.OVERDUE.ACCTS                         0
PRI.CURRENT.BALANCE                       0
PRI.SANCTIONED.AMOUNT                     0
PRI.DISBURSED.AMOUNT                      0
SEC.NO.OF.ACCTS                           0
SEC.ACTIVE.ACCTS                          0
SEC.OVERDUE.ACCTS                         0
SEC.CURRENT.BALANCE                       0
SEC.SANCTIONED.AMOUNT                     0
SEC.DISBURSED.AMOUNT                      0
PRIMARY.INSTAL.AMT                        0
```

```
SEC.INSTAL.AMT                         0
NEW.ACCTS.IN.LAST.SIX.MONTHS           0
DELINQUENT.ACCTS.IN.LAST.SIX.MONTHS    0
AVERAGE.ACCT.AGE                       0
CREDIT.HISTORY.LENGTH                  0
NO.OF_INQUIRIES                        0
loan_default                           0
dtype: int64
```

As we can see that, 'Employment.Type' has missing values so we will fill missing values by using mode method.

[6]:

```python
# Fill missing values in 'Employment.Type' with the mode (most frequent value)
mode_employment_type = df['Employment.Type'].mode()[0]  # Calculate the mode
df['Employment.Type'].fillna(mode_employment_type, inplace=True)  # Fill␣
 ↪missing values

# Verify that missing values have been filled
updated_missing_values = df.isnull().sum()
print("Updated Missing Values:")
print(updated_missing_values)
```

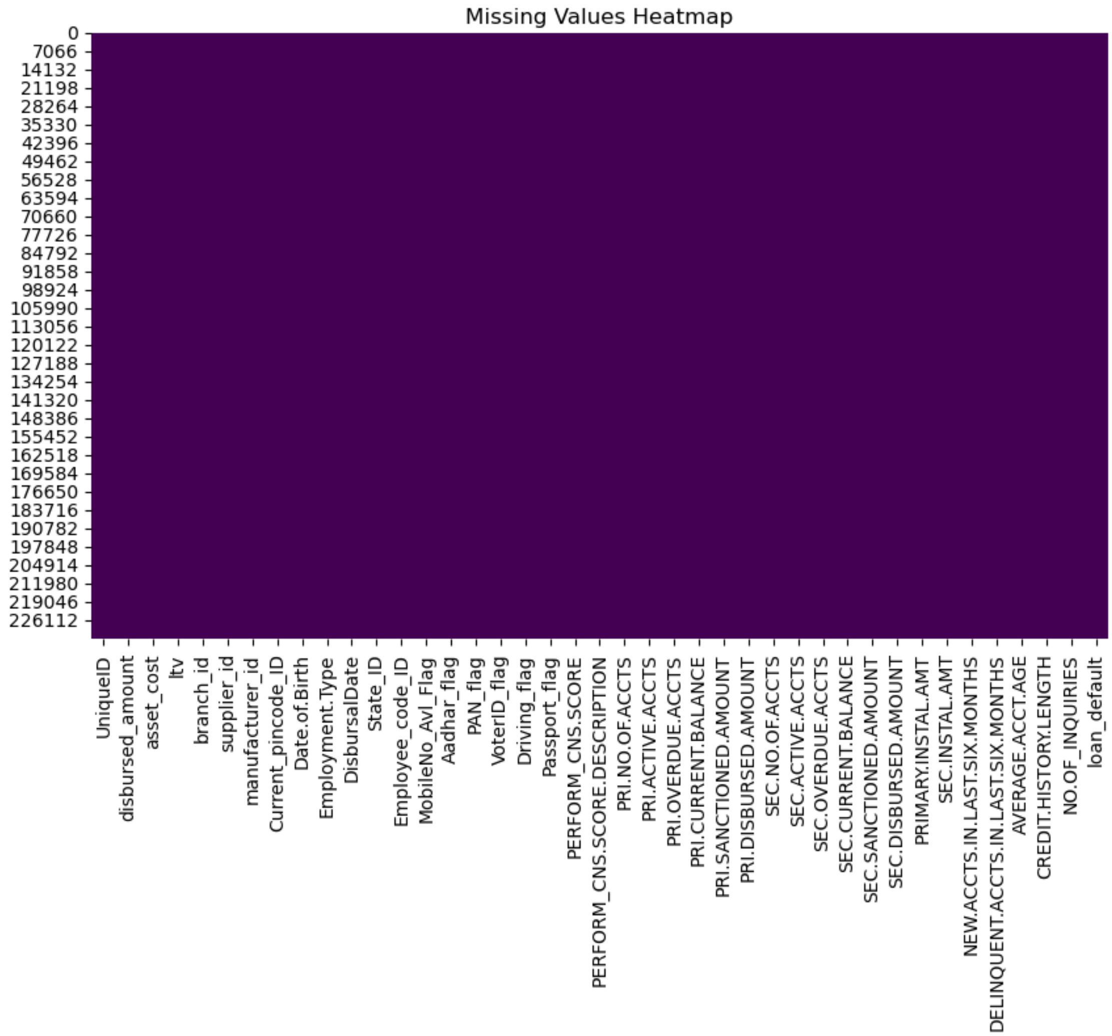
```
Updated Missing Values:
UniqueID                            0
disbursed_amount                    0
asset_cost                          0
ltv                                 0
branch_id                           0
supplier_id                         0
manufacturer_id                     0
Current_pincode_ID                  0
Date.of.Birth                       0
Employment.Type                     0
DisbursalDate                       0
State_ID                            0
Employee_code_ID                    0
MobileNo_Avl_Flag                   0
Aadhar_flag                         0
PAN_flag                            0
VoterID_flag                        0
Driving_flag                        0
Passport_flag                       0
PERFORM_CNS.SCORE                   0
PERFORM_CNS.SCORE.DESCRIPTION       0
PRI.NO.OF.ACCTS                     0
PRI.ACTIVE.ACCTS                    0
PRI.OVERDUE.ACCTS                   0
PRI.CURRENT.BALANCE                 0
```

```
PRI.SANCTIONED.AMOUNT                  0
PRI.DISBURSED.AMOUNT                   0
SEC.NO.OF.ACCTS                        0
SEC.ACTIVE.ACCTS                       0
SEC.OVERDUE.ACCTS                      0
SEC.CURRENT.BALANCE                    0
SEC.SANCTIONED.AMOUNT                  0
SEC.DISBURSED.AMOUNT                   0
PRIMARY.INSTAL.AMT                     0
SEC.INSTAL.AMT                         0
NEW.ACCTS.IN.LAST.SIX.MONTHS           0
DELINQUENT.ACCTS.IN.LAST.SIX.MONTHS    0
AVERAGE.ACCT.AGE                       0
CREDIT.HISTORY.LENGTH                  0
NO.OF_INQUIRIES                        0
loan_default                           0
dtype: int64
```

[7]:
```python
# Checkong for duplicates
duplicate_rows = df[df.duplicated()]
print("Duplicate rows:")
print(duplicate_rows)
```

```
Duplicate rows:
Empty DataFrame
Columns: [UniqueID, disbursed_amount, asset_cost, ltv, branch_id, supplier_id,
manufacturer_id, Current_pincode_ID, Date.of.Birth, Employment.Type,
DisbursalDate, State_ID, Employee_code_ID, MobileNo_Avl_Flag, Aadhar_flag,
PAN_flag, VoterID_flag, Driving_flag, Passport_flag, PERFORM_CNS.SCORE,
PERFORM_CNS.SCORE.DESCRIPTION, PRI.NO.OF.ACCTS, PRI.ACTIVE.ACCTS,
PRI.OVERDUE.ACCTS, PRI.CURRENT.BALANCE, PRI.SANCTIONED.AMOUNT,
PRI.DISBURSED.AMOUNT, SEC.NO.OF.ACCTS, SEC.ACTIVE.ACCTS, SEC.OVERDUE.ACCTS,
SEC.CURRENT.BALANCE, SEC.SANCTIONED.AMOUNT, SEC.DISBURSED.AMOUNT,
PRIMARY.INSTAL.AMT, SEC.INSTAL.AMT, NEW.ACCTS.IN.LAST.SIX.MONTHS,
DELINQUENT.ACCTS.IN.LAST.SIX.MONTHS, AVERAGE.ACCT.AGE, CREDIT.HISTORY.LENGTH,
NO.OF_INQUIRIES, loan_default]
Index: []

[0 rows x 41 columns]
```

[8]:
```python
# Visualize missing values using a heatmap
plt.figure(figsize=(10, 6))
sns.heatmap(df.isnull(), cmap='viridis', cbar=False)
plt.title('Missing Values Heatmap')
plt.show()
```



Seperating numerical and categorical features

[9]:
```python
# List of columns with numerical features
numerical_feature_columns = list(df._get_numeric_data().columns)
numerical_feature_columns
```

[9]:
```
['UniqueID',
 'disbursed_amount',
 'asset_cost',
 'ltv',
 'branch_id',
 'supplier_id',
 'manufacturer_id',
 'Current_pincode_ID',
 'State_ID',
```

```
 'Employee_code_ID',
 'MobileNo_Avl_Flag',
 'Aadhar_flag',
 'PAN_flag',
 'VoterID_flag',
 'Driving_flag',
 'Passport_flag',
 'PERFORM_CNS.SCORE',
 'PRI.NO.OF.ACCTS',
 'PRI.ACTIVE.ACCTS',
 'PRI.OVERDUE.ACCTS',
 'PRI.CURRENT.BALANCE',
 'PRI.SANCTIONED.AMOUNT',
 'PRI.DISBURSED.AMOUNT',
 'SEC.NO.OF.ACCTS',
 'SEC.ACTIVE.ACCTS',
 'SEC.OVERDUE.ACCTS',
 'SEC.CURRENT.BALANCE',
 'SEC.SANCTIONED.AMOUNT',
 'SEC.DISBURSED.AMOUNT',
 'PRIMARY.INSTAL.AMT',
 'SEC.INSTAL.AMT',
 'NEW.ACCTS.IN.LAST.SIX.MONTHS',
 'DELINQUENT.ACCTS.IN.LAST.SIX.MONTHS',
 'NO.OF_INQUIRIES',
 'loan_default']
```

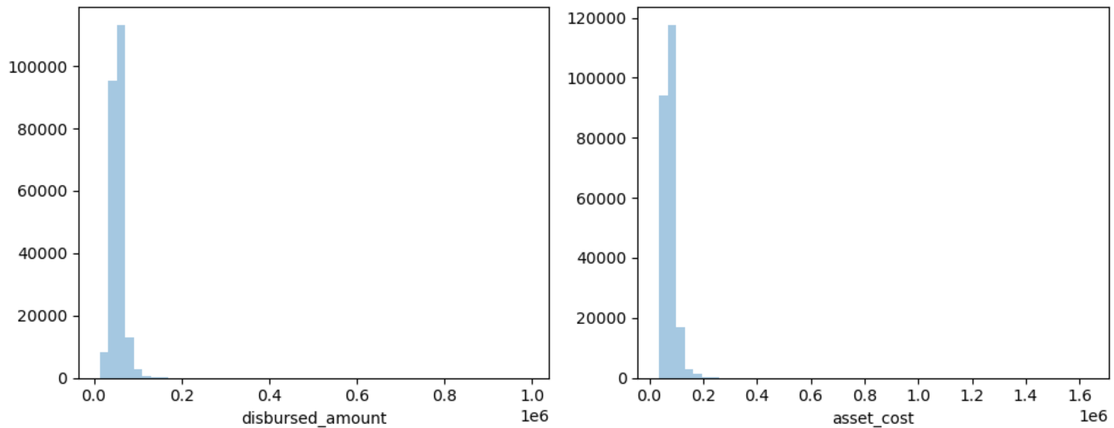
[10]:
```
# List of columns with categorical features
categorical_feature_columns = list(set(df.columns) -␣
 ↪set(numerical_feature_columns))
categorical_feature_columns
```

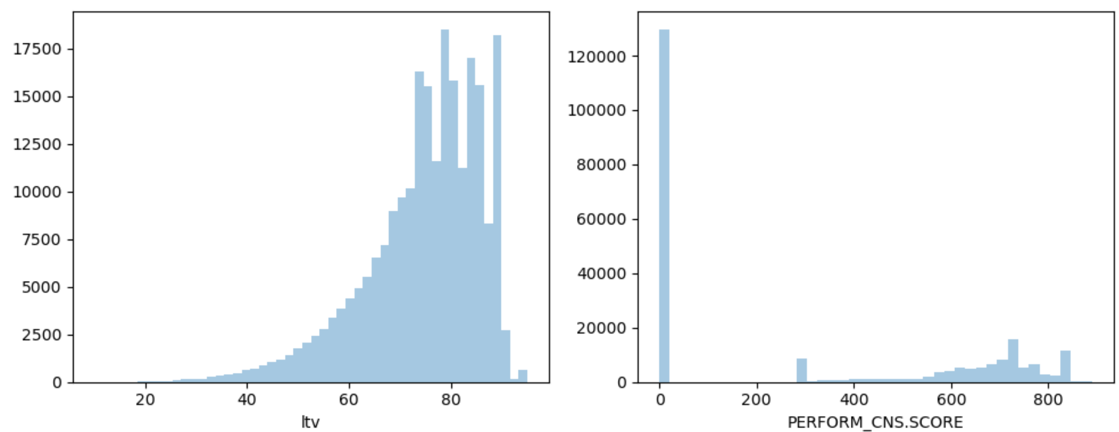
[10]:
```
['Date.of.Birth',
 'AVERAGE.ACCT.AGE',
 'PERFORM_CNS.SCORE.DESCRIPTION',
 'DisbursalDate',
 'CREDIT.HISTORY.LENGTH',
 'Employment.Type']
```

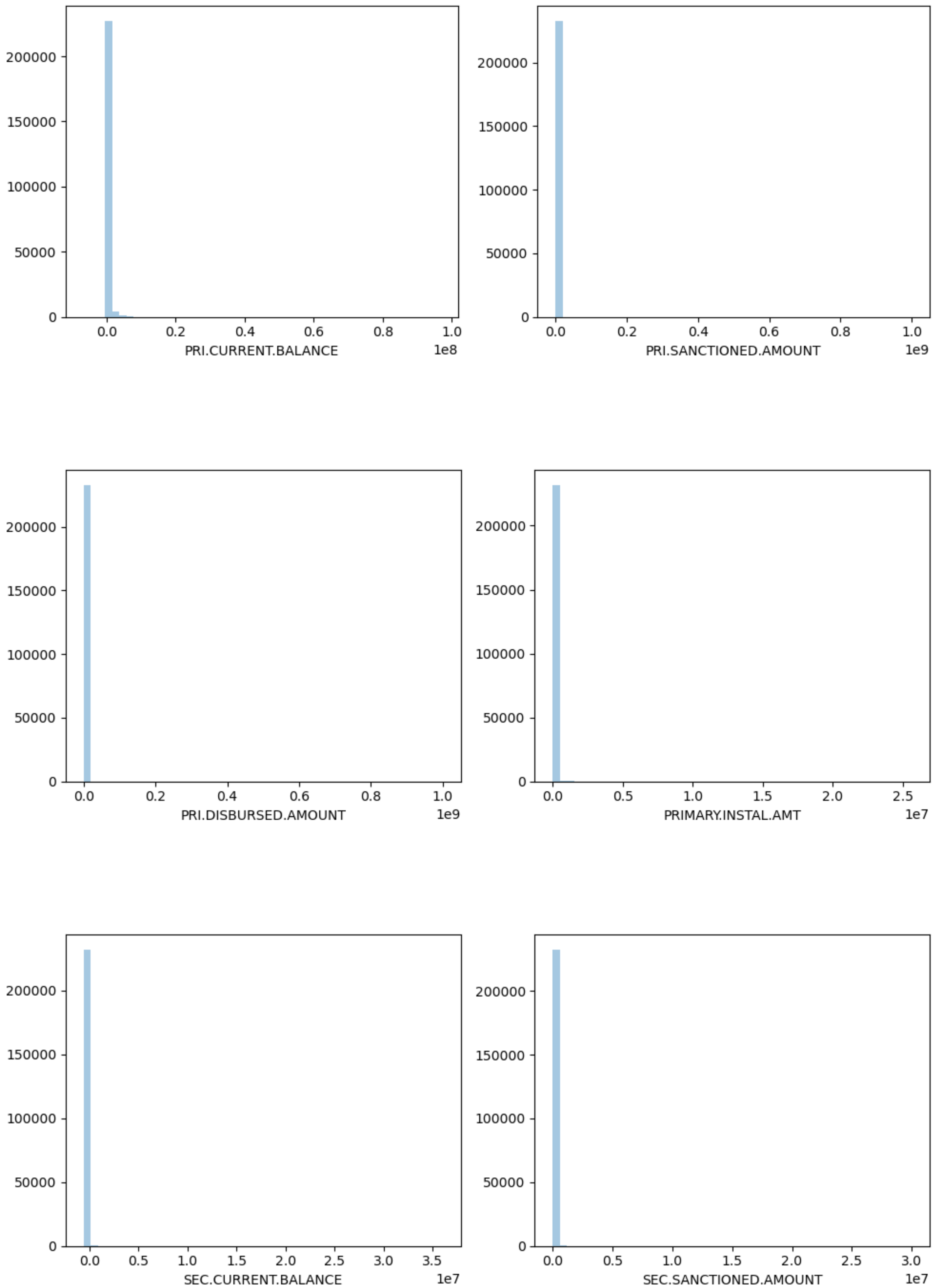
Let's plot the histogram of below features to see its distribution

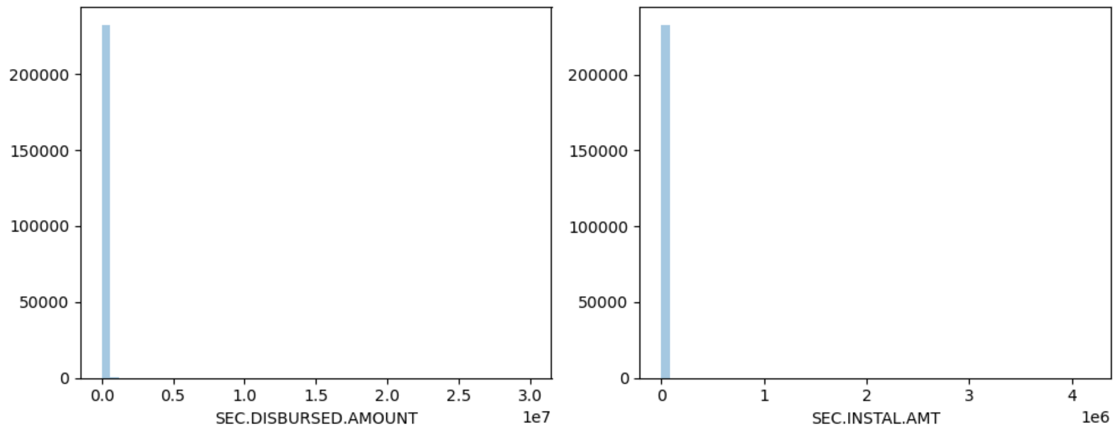
[11]:
```
# Let's plot the histogram of below features to see its distribution
num_columns = ['disbursed_amount','asset_cost','ltv','PERFORM_CNS.SCORE','PRI.
 ↪CURRENT.BALANCE','PRI.SANCTIONED.AMOUNT',
            'PRI.DISBURSED.AMOUNT','PRIMARY.INSTAL.AMT','SEC.CURRENT.
 ↪BALANCE','SEC.SANCTIONED.AMOUNT','SEC.DISBURSED.AMOUNT',
            'SEC.INSTAL.AMT']
```

```
for i in range(0, len(num_columns), 2):
    plt.figure(figsize=(10,4))
    plt.subplot(121)
    sns.distplot(df[num_columns[i]], kde=False)
    plt.subplot(122)
    sns.distplot(df[num_columns[i+1]], kde=False)
    plt.tight_layout()
    plt.show()
```






PRI.CURRENT.BALANCE
1e8
PRI.SANCTIONED.AMOUNT
1e9
PRI.DISBURSED.AMOUNT
1e9
PRIMARY.INSTAL.AMT
1e7
SEC.CURRENT.BALANCE
1e7
SEC.SANCTIONED.AMOUNT
1e7



Checking categorical data

[12]:
```
df[categorical_feature_columns].head()
```

[12]:
```
  Date.of.Birth AVERAGE.ACCT.AGE PERFORM_CNS.SCORE.DESCRIPTION DisbursalDate  \
0    1984-01-01        0yrs 0mon    No Bureau History Available    2018-08-03
1    1985-08-24        0yrs 0mon    No Bureau History Available    2018-08-01
2    1977-12-09        0yrs 0mon    No Bureau History Available    2018-09-26
3    1988-06-01        0yrs 0mon    No Bureau History Available    2018-09-23
4    1994-07-14        0yrs 0mon    No Bureau History Available    2018-10-08

  CREDIT.HISTORY.LENGTH Employment.Type
0             0yrs 0mon        Salaried
1             0yrs 0mon   Self employed
2             0yrs 0mon   Self employed
3             0yrs 0mon        Salaried
4             0yrs 0mon   Self employed
```

Two features 'AVERAGE.ACCT.AGE' and 'CREDIT.HISTORY.LENGTH' need to convert in terms of years.

[13]:
```
df['AVERAGE.ACCT.AGE'] = df['AVERAGE.ACCT.AGE'].str.replace('yrs ','.
 ↪',regex=False)
df['AVERAGE.ACCT.AGE'] = df['AVERAGE.ACCT.AGE'].str.
 ↪replace('mon','',regex=False).astype(float)
df['CREDIT.HISTORY.LENGTH'] = df['CREDIT.HISTORY.LENGTH'].str.replace('yrs ','.
 ↪',regex=False)
df['CREDIT.HISTORY.LENGTH'] = df['CREDIT.HISTORY.LENGTH'].str.
 ↪replace('mon','',regex=False).astype(float)
df[categorical_feature_columns].head()
```

[13]:
```
  Date.of.Birth  AVERAGE.ACCT.AGE PERFORM_CNS.SCORE.DESCRIPTION DisbursalDate  \
0    1984-01-01               0.0    No Bureau History Available    2018-08-03
1    1985-08-24               0.0    No Bureau History Available    2018-08-01
2    1977-12-09               0.0    No Bureau History Available    2018-09-26
3    1988-06-01               0.0    No Bureau History Available    2018-09-23
4    1994-07-14               0.0    No Bureau History Available    2018-10-08

   CREDIT.HISTORY.LENGTH Employment.Type
0                    0.0        Salaried
1                    0.0   Self employed
2                    0.0   Self employed
3                    0.0        Salaried
4                    0.0   Self employed
```

[14]:
```python
# Count the each category values from feature
df['Employment.Type'].value_counts()
```

[14]:
```
Self employed    135296
Salaried          97858
Name: Employment.Type, dtype: int64
```

[15]:
```python
# Encode the values in terms of 0 and 1
df['Employment.Type'].replace({'Salaried': 0, 'Self employed': 1}, inplace=True)
```

[16]:
```python
# Dropping unecessary features
df.drop(['Date.of.Birth','DisbursalDate','PERFORM_CNS.SCORE.DESCRIPTION'], axis␣
 ↪= 1, inplace=True)
```

[17]:
```python
# Now let's check if null values present in data
df.isnull().sum().sum()
```

[17]:
```
0
```

[18]:
```python
# Size of the data
df.shape
```

[18]:
```
(233154, 38)
```

[19]:
```python
# Identify unique values in each features
df.nunique()
```

[19]:
```
UniqueID                               233154
disbursed_amount                        24565
asset_cost                              46252
ltv                                      6579
branch_id                                  82
supplier_id                              2953
manufacturer_id                            11
```

```
Current_pincode_ID                       6698
Employment.Type                             2
State_ID                                   22
Employee_code_ID                         3270
MobileNo_Avl_Flag                           1
Aadhar_flag                                 2
PAN_flag                                    2
VoterID_flag                                2
Driving_flag                                2
Passport_flag                               2
PERFORM_CNS.SCORE                         573
PRI.NO.OF.ACCTS                           108
PRI.ACTIVE.ACCTS                           40
PRI.OVERDUE.ACCTS                          22
PRI.CURRENT.BALANCE                     71341
PRI.SANCTIONED.AMOUNT                   44390
PRI.DISBURSED.AMOUNT                    47909
SEC.NO.OF.ACCTS                            37
SEC.ACTIVE.ACCTS                           23
SEC.OVERDUE.ACCTS                           9
SEC.CURRENT.BALANCE                      3246
SEC.SANCTIONED.AMOUNT                    2223
SEC.DISBURSED.AMOUNT                     2553
PRIMARY.INSTAL.AMT                      28067
SEC.INSTAL.AMT                           1918
NEW.ACCTS.IN.LAST.SIX.MONTHS               26
DELINQUENT.ACCTS.IN.LAST.SIX.MONTHS        14
AVERAGE.ACCT.AGE                          178
CREDIT.HISTORY.LENGTH                     272
NO.OF_INQUIRIES                            25
loan_default                                2
dtype: int64
```

Calculate correlation matrix to inspect correlation among features:

[20]:
```
corr_max = df.corr()  #create correlation matrix
threshold = 0.5
corr_var_list = []
cols = df.columns.tolist()

for i in range(1, len(cols)):
    for j in range(i):
        if((abs(corr_max.iloc[i,j]) > threshold) & (abs(corr_max.iloc[i,j]) <␣
 ↪1)):
            corr_var_list.append([corr_max.iloc[i,j], i, j])

# Sort the list showing higher ones first
```

```
sort_corr_list = sorted(corr_var_list, key=lambda x:abs(x[0]))

#Print correlations and column names
for corr_value, i, j in sort_corr_list:
    print (f"{cols[i]} and {cols[j]} = {round(corr_value, 2)}")
```

```
CREDIT.HISTORY.LENGTH and PRI.ACTIVE.ACCTS = 0.5
SEC.OVERDUE.ACCTS and SEC.NO.OF.ACCTS = 0.51
SEC.OVERDUE.ACCTS and SEC.ACTIVE.ACCTS = 0.53
NEW.ACCTS.IN.LAST.SIX.MONTHS and PRI.NO.OF.ACCTS = 0.54
NEW.ACCTS.IN.LAST.SIX.MONTHS and PRI.ACTIVE.ACCTS = 0.7
asset_cost and disbursed_amount = 0.75
PRI.ACTIVE.ACCTS and PRI.NO.OF.ACCTS = 0.75
CREDIT.HISTORY.LENGTH and AVERAGE.ACCT.AGE = 0.82
SEC.ACTIVE.ACCTS and SEC.NO.OF.ACCTS = 0.83
VoterID_flag and Aadhar_flag = -0.87
SEC.SANCTIONED.AMOUNT and SEC.CURRENT.BALANCE = 0.93
SEC.DISBURSED.AMOUNT and SEC.CURRENT.BALANCE = 0.93
PRI.DISBURSED.AMOUNT and PRI.SANCTIONED.AMOUNT = 1.0
SEC.DISBURSED.AMOUNT and SEC.SANCTIONED.AMOUNT = 1.0
```

2 2.Performing EDA:

Statistical description of quantitative data variables

[21]:
```
quantitative_stats = df.describe()
print("Statistical Description of Quantitative Data Variables:")
print(quantitative_stats)
```

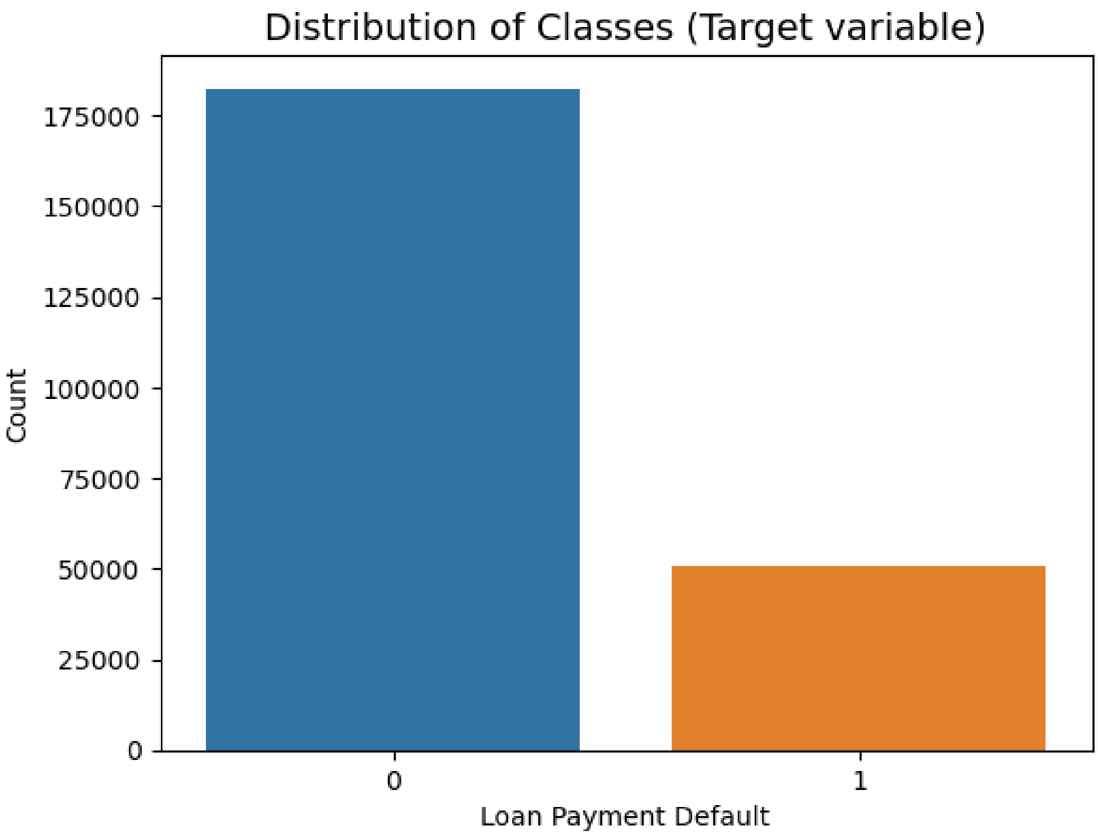
```
Statistical Description of Quantitative Data Variables:
            UniqueID  disbursed_amount    asset_cost            ltv  \
count  233154.000000     233154.000000  2.331540e+05  233154.000000
mean   535917.573376      54356.993528  7.586507e+04      74.746530
std     68315.693711      12971.314171  1.894478e+04      11.456636
min    417428.000000      13320.000000  3.700000e+04      10.030000
25%    476786.250000      47145.000000  6.571700e+04      68.880000
50%    535978.500000      53803.000000  7.094600e+04      76.800000
75%    595039.750000      60413.000000  7.920175e+04      83.670000
max    671084.000000     990572.000000  1.628992e+06      95.000000

           branch_id    supplier_id  manufacturer_id  Current_pincode_ID  \
count  233154.000000  233154.000000    233154.000000       233154.000000
mean       72.936094   19638.635035        69.028054         3396.880247
std        69.834995    3491.949566        22.141304         2238.147502
min         1.000000   10524.000000        45.000000            1.000000
25%        14.000000   16535.000000        48.000000         1511.000000
50%        61.000000   20333.000000        86.000000         2970.000000
75%       130.000000   23000.000000        86.000000         5677.000000
```

```
max        261.000000   24803.000000        156.000000          7345.000000

       Employment.Type       State_ID  …  SEC.SANCTIONED.AMOUNT  \
count    233154.000000  233154.000000  …           2.331540e+05
mean          0.580286       7.262243  …           7.295923e+03
std           0.493513       4.482230  …           1.831560e+05
min           0.000000       1.000000  …           0.000000e+00
25%           0.000000       4.000000  …           0.000000e+00
50%           1.000000       6.000000  …           0.000000e+00
75%           1.000000      10.000000  …           0.000000e+00
max           1.000000      22.000000  …           3.000000e+07

       SEC.DISBURSED.AMOUNT  PRIMARY.INSTAL.AMT  SEC.INSTAL.AMT  \
count          2.331540e+05        2.331540e+05    2.331540e+05
mean           7.179998e+03        1.310548e+04    3.232684e+02
std            1.825925e+05        1.513679e+05    1.555369e+04
min            0.000000e+00        0.000000e+00    0.000000e+00
25%            0.000000e+00        0.000000e+00    0.000000e+00
50%            0.000000e+00        0.000000e+00    0.000000e+00
75%            0.000000e+00        1.999000e+03    0.000000e+00
max            3.000000e+07        2.564281e+07    4.170901e+06

       NEW.ACCTS.IN.LAST.SIX.MONTHS  DELINQUENT.ACCTS.IN.LAST.SIX.MONTHS  \
count                 233154.000000                        233154.000000
mean                       0.381833                             0.097481
std                        0.955107                             0.384439
min                        0.000000                             0.000000
25%                        0.000000                             0.000000
50%                        0.000000                             0.000000
75%                        0.000000                             0.000000
max                       35.000000                            20.000000

       AVERAGE.ACCT.AGE  CREDIT.HISTORY.LENGTH  NO.OF_INQUIRIES   loan_default
count     233154.000000          233154.000000    233154.000000  233154.000000
mean           0.715615               1.327379         0.206615       0.217071
std            1.252152               2.367571         0.706498       0.412252
min            0.000000               0.000000         0.000000       0.000000
25%            0.000000               0.000000         0.000000       0.000000
50%            0.000000               0.000000         0.000000       0.000000
75%            1.100000               2.000000         0.000000       0.000000
max           30.900000              39.000000        36.000000       1.000000

[8 rows x 38 columns]
```

Target variable distribution

[22]:
```python
import seaborn as sns
import matplotlib.pyplot as plt
```

```
sns.countplot(x='loan_default', data=df)

# Set plot labels and title
plt.xlabel('Loan Payment Default')
plt.ylabel('Count')
plt.title('Distribution of Classes (Target variable)', fontsize=14)

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



Here we clearly see the imbalance between two classes. We need to resolve class imbalance by oversampling class 1.

[23]:
```
# Over sampling to resolve imbalance
df = df.sample(frac=1)
loan_default_1 = df.loc[df['loan_default'] == 1]
loan_default_0 = df.loc[df['loan_default'] == 0]
```

```
normal_distributed_df = pd.concat([loan_default_1, loan_default_1,
 ↪loan_default_1, loan_default_0])

# Shuffle dataframe rows
new_df = normal_distributed_df.sample(frac=1, random_state=42)
new_df.head()
```

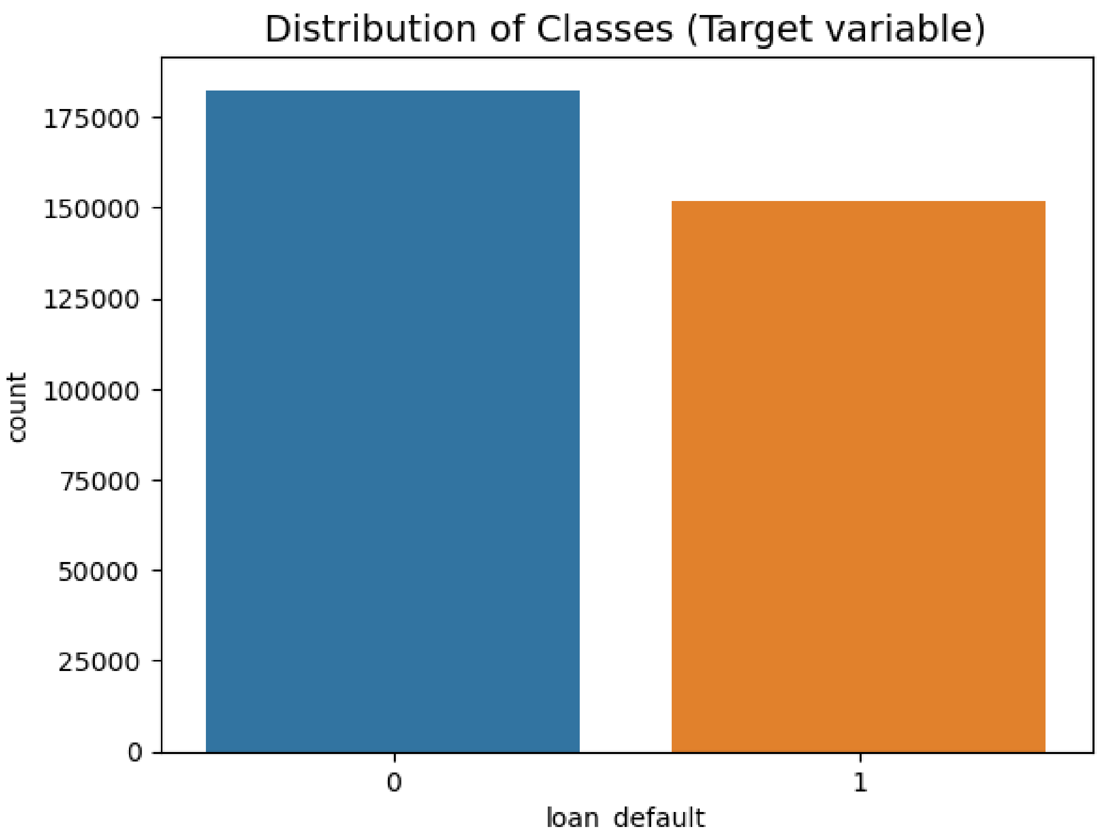
[23]:

```
        UniqueID  disbursed_amount  asset_cost    ltv  branch_id  supplier_id  \
9855      484931             71365       85000  84.99          2        15097
160004    436323             54499       75887  73.12        136        15523
100489    586447             50003       70634  72.20         14        24004
222841    532227             58013       76902  78.02         36        23901
210758    588229             66002       92574  74.53         78        18404

        manufacturer_id  Current_pincode_ID  Employment.Type  State_ID  …  \
9855                 86                2389                0         4  …
160004               86                3693                0         8  …
100489               86                 820                1        15  …
222841               86                6553                1        13  …
210758               86                2067                0         4  …

        SEC.SANCTIONED.AMOUNT  SEC.DISBURSED.AMOUNT  PRIMARY.INSTAL.AMT  \
9855                        0                     0                   0
160004                      0                     0                   0
100489                      0                     0                   0
222841                      0                     0                1700
210758                      0                     0                4034

        SEC.INSTAL.AMT  NEW.ACCTS.IN.LAST.SIX.MONTHS  \
9855                 0                             0
160004               0                             0
100489               0                             0
222841               0                             1
210758               0                             1

        DELINQUENT.ACCTS.IN.LAST.SIX.MONTHS  AVERAGE.ACCT.AGE  \
9855                                      0               0.0
160004                                    0               0.4
100489                                    0               0.0
222841                                    0               0.2
210758                                    1               2.4

        CREDIT.HISTORY.LENGTH  NO.OF_INQUIRIES  loan_default
9855                      0.0                0             0
160004                    0.5                0             0
100489                    0.0                1             1
222841                    0.2                1             1
```

```
210758                          4.1                  2             0

[5 rows x 38 columns]
```

[24]:
```
print('Distribution of the payment_default in the dataset')
print(new_df['loan_default'].value_counts()/len(new_df))

sns.countplot(x='loan_default', data=new_df)
plt.title('Distribution of Classes (Target variable)', fontsize=14)
plt.show()
```

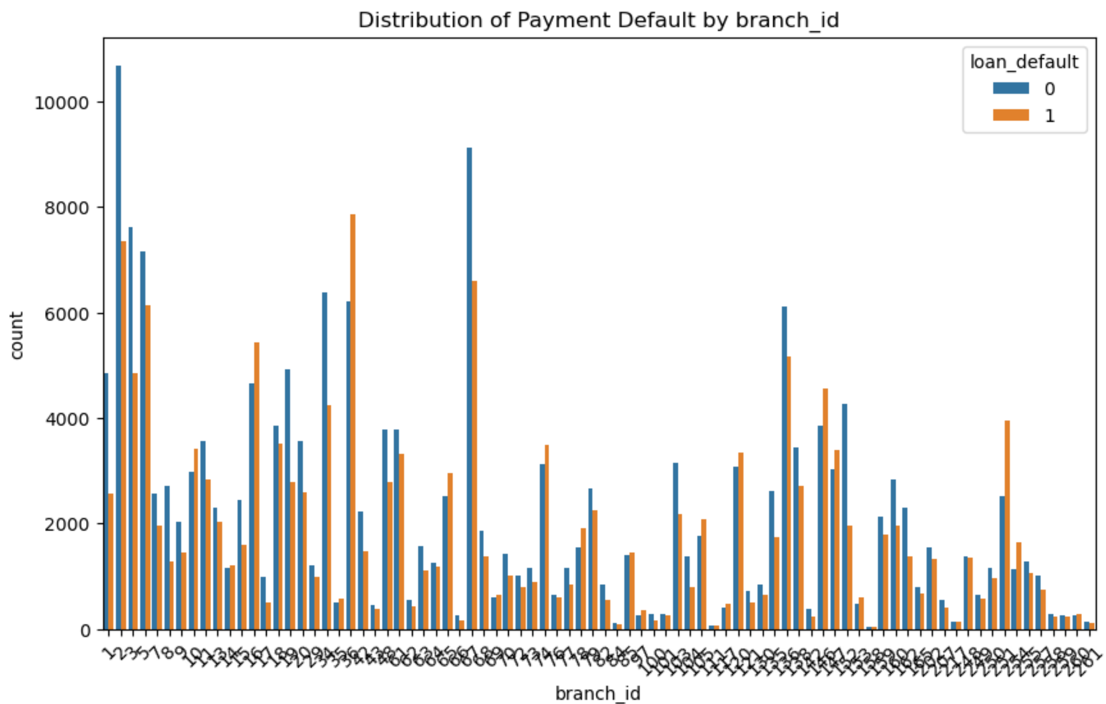
```
Distribution of the payment_default in the dataset
0    0.545921
1    0.454079
Name: loan_default, dtype: float64
```

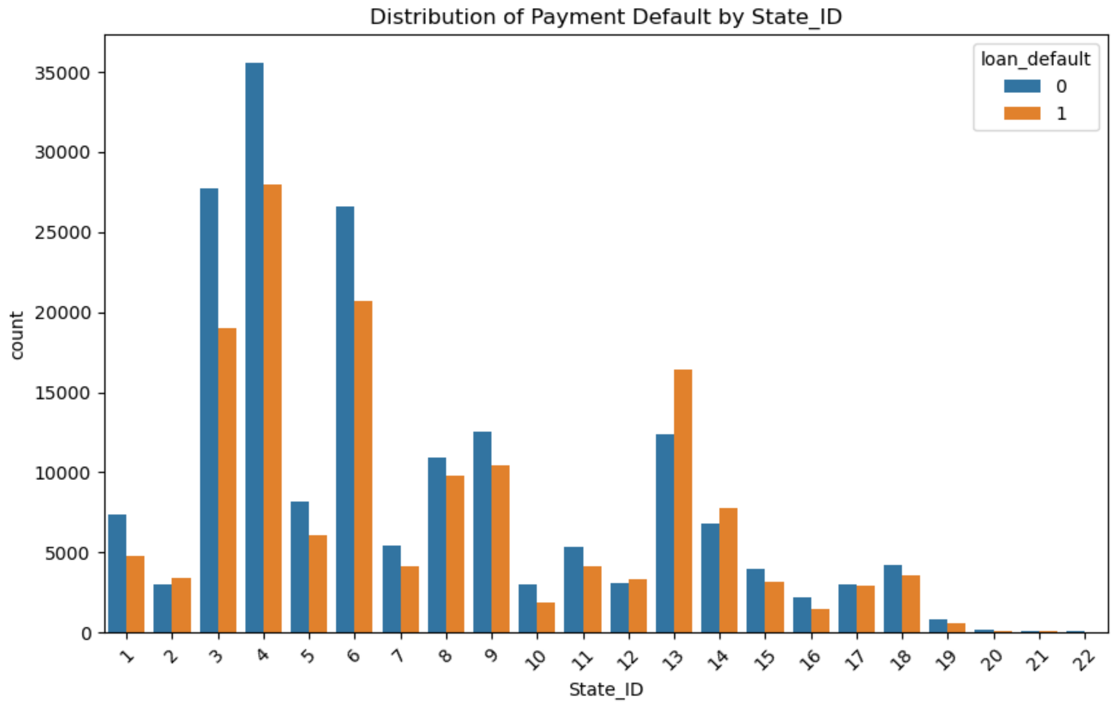


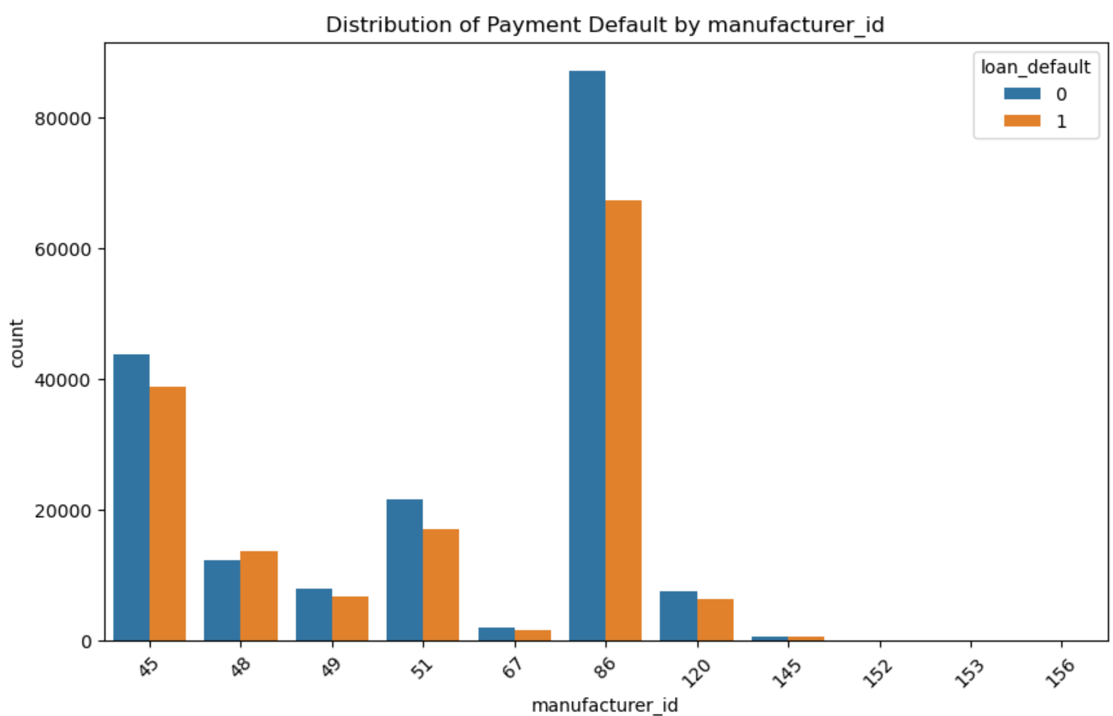
[25]:
```
# Size of dataset after over sampling
new_df.shape
```

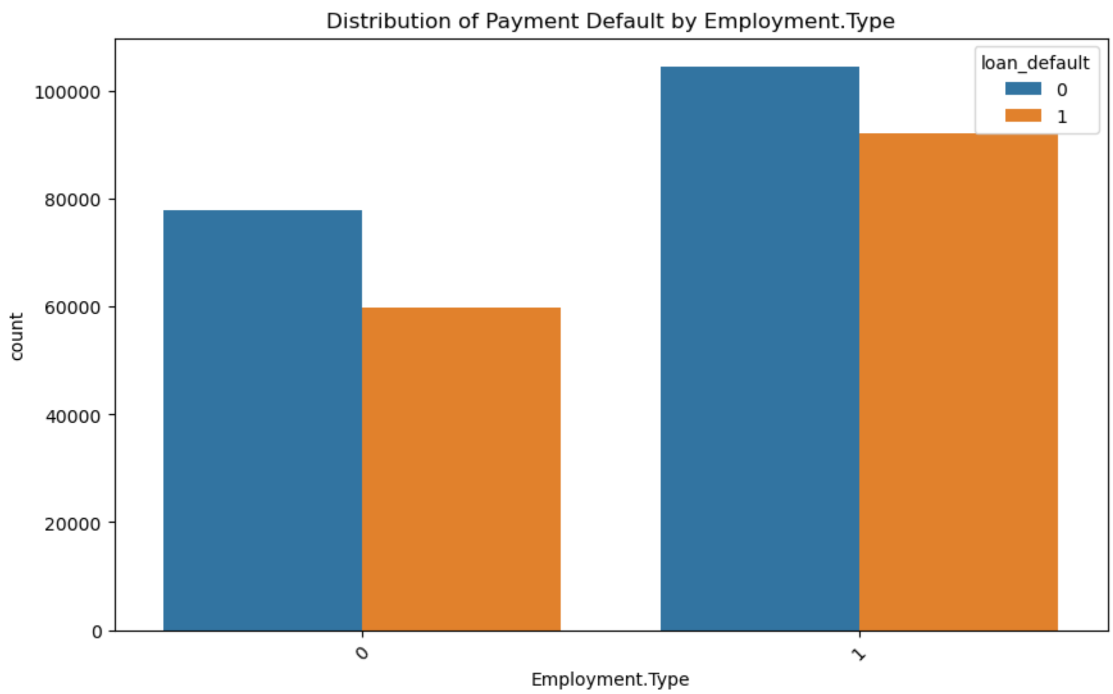
[25]: (334376, 38)

[26]:
```python
import seaborn as sns
import matplotlib.pyplot as plt

categorical_features = ['branch_id', 'State_ID', 'manufacturer_id', 'Employment.
 ↪Type']
for feature in categorical_features:
    plt.figure(figsize=(10, 6))
    sns.countplot(x=feature, hue='loan_default', data=new_df)
    plt.title(f'Distribution of Payment Default by {feature}')
    plt.xlabel(feature)
    plt.xticks(rotation=45)
    plt.show()
```



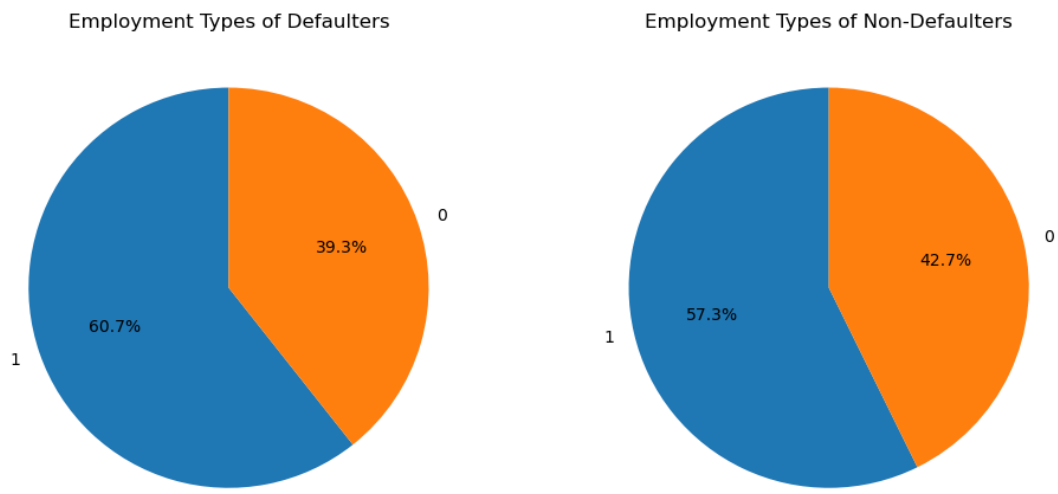

Distribution of Payment Default by State_ID
loan_default
0
1
count
35000
30000
25000
20000
15000
10000
5000
0
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
State_ID


Distribution of Payment Default by manufacturer_id
loan_default
0
1
count
80000
60000
40000
20000
0
45
48
49
51
67
86
120
145
152
153
156
manufacturer_id



[27]:
```
import pandas as pd
import matplotlib.pyplot as plt

# Step 1: Determine unique employment types
employment_types = new_df['Employment.Type'].unique()

# Step 2: Create subsets for defaulters and non-defaulters
defaulter_subset = new_df[new_df['loan_default'] == 1]
non_defaulter_subset = new_df[new_df['loan_default'] == 0]

# Step 3: Count occurrences of employment types in both subsets
defaulter_counts = defaulter_subset['Employment.Type'].value_counts()
non_defaulter_counts = non_defaulter_subset['Employment.Type'].value_counts()

# Step 4: Create pie charts
fig, axes = plt.subplots(1, 2, figsize=(12, 6))

# Pie chart for defaulters
axes[0].pie(defaulter_counts, labels=defaulter_counts.index, autopct='%1.1f%%',␣
↪startangle=90)
axes[0].set_title('Employment Types of Defaulters')

# Pie chart for non-defaulters
```

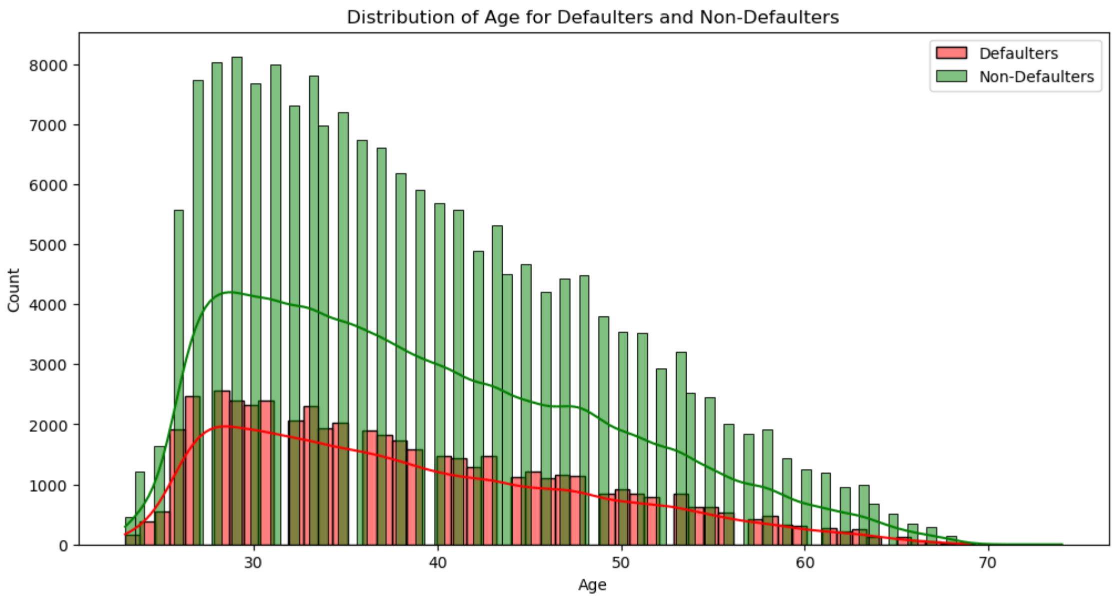
```
axes[1].pie(non_defaulter_counts, labels=non_defaulter_counts.index,␣
 ↪autopct='%1.1f%%', startangle=90)
axes[1].set_title('Employment Types of Non-Defaulters')

plt.show()
```



[28]:

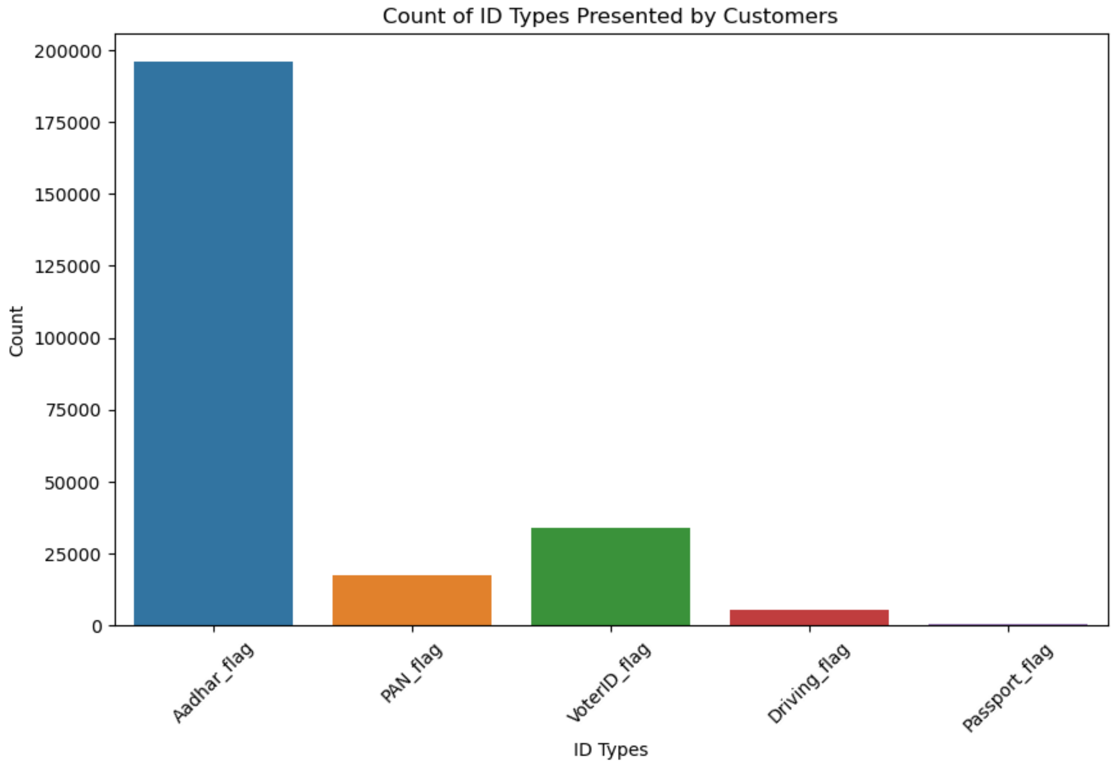
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

df = pd.read_excel('D:\Data Analytics\Data␣
 ↪Capstones\Banking\Project2_Dataset\Dataset\data.xlsx')

# Step 1: Calculate the age of each customer
df['date_of_birth'] = pd.to_datetime(df['Date.of.Birth'])  # Convert to datetime
current_year = pd.to_datetime('now').year  # Get the current year
df['age'] = current_year - df['Date.of.Birth'].dt.year

# Step 2: Create subsets for defaulters and non-defaulters
defaulter_subset = df[df['loan_default'] == 1]
non_defaulter_subset = df[df['loan_default'] == 0]

# Step 3: Plot histograms or density plots to visualize age distribution
plt.figure(figsize=(12, 6))
sns.histplot(defaulter_subset['age'], kde=True, label='Defaulters', color='red')
sns.histplot(non_defaulter_subset['age'], kde=True, label='Non-Defaulters',␣
 ↪color='green')
plt.title('Distribution of Age for Defaulters and Non-Defaulters')
```

```
plt.xlabel('Age')
plt.legend()
plt.show()
```



[29]:

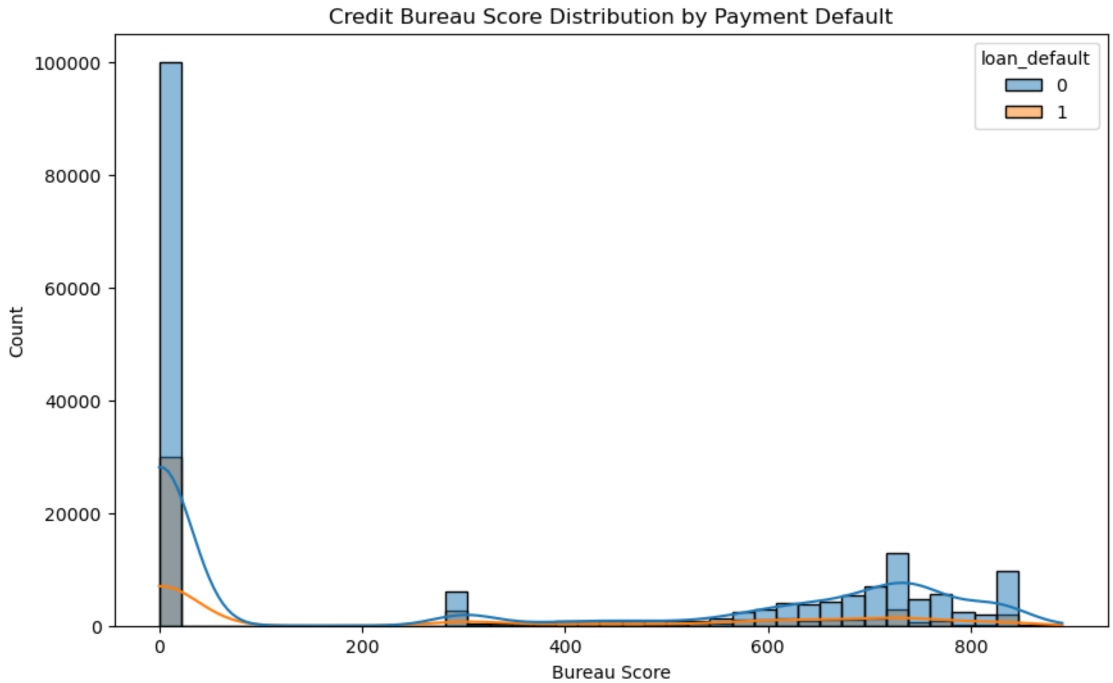
```
import matplotlib.pyplot as plt
import seaborn as sns

id_columns = ['Aadhar_flag', 'PAN_flag', 'VoterID_flag', 'Driving_flag',␣
 ↪'Passport_flag']

# Calculate the count of each ID type
id_counts = df[id_columns].sum()

# Create a bar plot to show the count of each ID type
plt.figure(figsize=(10, 6))
sns.barplot(x=id_counts.index, y=id_counts.values)
plt.title('Count of ID Types Presented by Customers')
plt.xlabel('ID Types')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.show()

# Find the ID type presented by most customers
most_presented_id = id_counts.idxmax()
print(f"The most presented ID type is: {most_presented_id}")
```




```
The most presented ID type is: Aadhar_flag
```

3 3. Performing EDA and Modeling:

[30]:
```
# 1.Study the credit bureau score distribution. How is the distribution for␣
↪defaulters vs. non-defaulters? Explore in detail.

import matplotlib.pyplot as plt
import seaborn as sns

# Plot distribution of bureau scores for defaulters and non-defaulters
plt.figure(figsize=(10, 6))
sns.histplot(data=df, x='PERFORM_CNS.SCORE', hue='loan_default', kde=True)
plt.title('Credit Bureau Score Distribution by Payment Default')
plt.xlabel('Bureau Score')
plt.show()
```

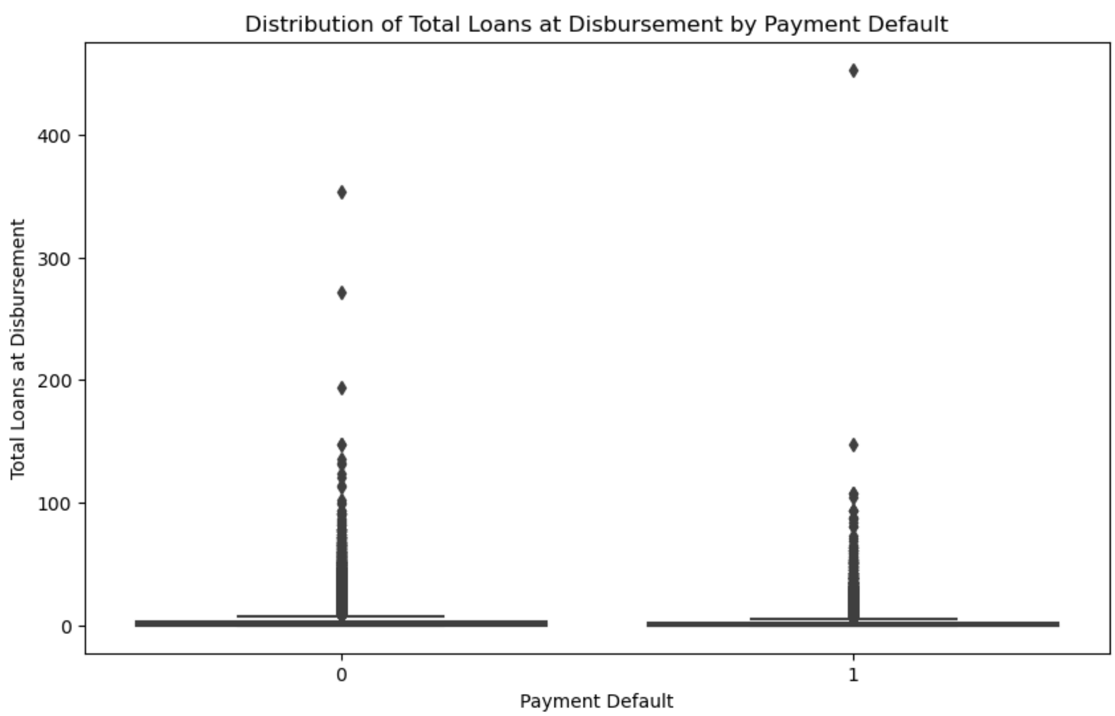


[31]:
```
# 2.Calculate summary statistics for primary and secondary accounts by payment␣
↪default
primary_loan_default = new_df[new_df['loan_default'] == 1]['PRI.NO.OF.ACCTS'].
↪describe()
primary_loan_non_default = new_df[new_df['loan_default'] == 0]['PRI.NO.OF.
↪ACCTS'].describe()

print("Summary Statistics for Defaulters - Primary Loans:")
print(primary_loan_default)

print("\nSummary Statistics for Non-Defaulters - Primary Loans:")
print(primary_loan_non_default)
```

```
Summary Statistics for Defaulters - Primary Loans:
count    151833.000000
mean          2.089328
std           5.040100
min           0.000000
25%           0.000000
50%           0.000000
75%           2.000000
max         453.000000
Name: PRI.NO.OF.ACCTS, dtype: float64

Summary Statistics for Non-Defaulters - Primary Loans:
```

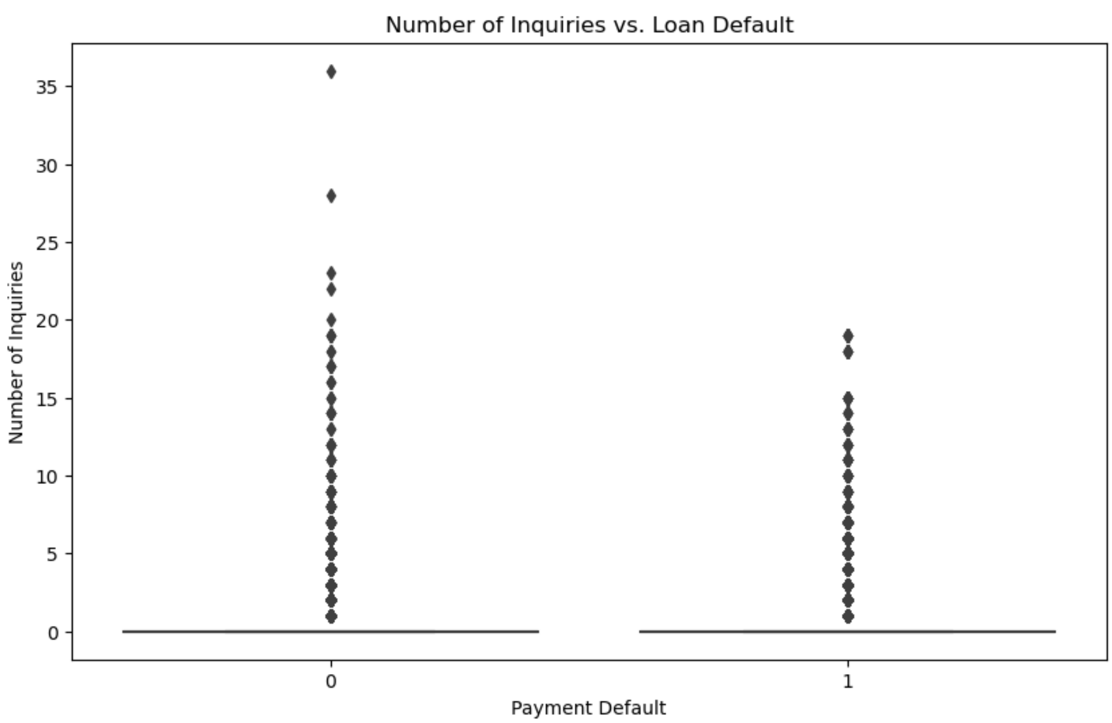
```
count    182543.000000
mean          2.538038
std           5.261142
min           0.000000
25%           0.000000
50%           1.000000
75%           3.000000
max         354.000000
Name: PRI.NO.OF.ACCTS, dtype: float64
```

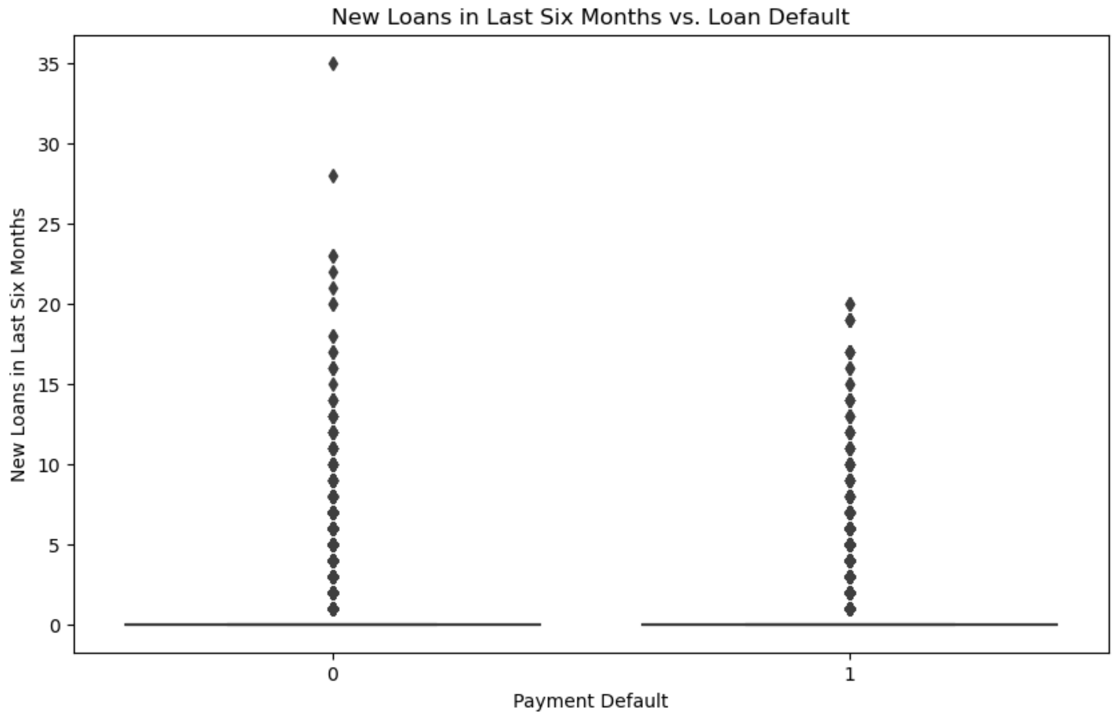
[32]:
```
import seaborn as sns
import matplotlib.pyplot as plt

# Box plot to compare primary loan details for defaulters and non-defaulters
plt.figure(figsize=(10, 6))
sns.boxplot(x='loan_default', y='PRI.NO.OF.ACCTS', data=df)
plt.title('Distribution of Total Loans at Disbursement by Payment Default')
plt.xlabel('Payment Default')
plt.ylabel('Total Loans at Disbursement')
plt.show()
```

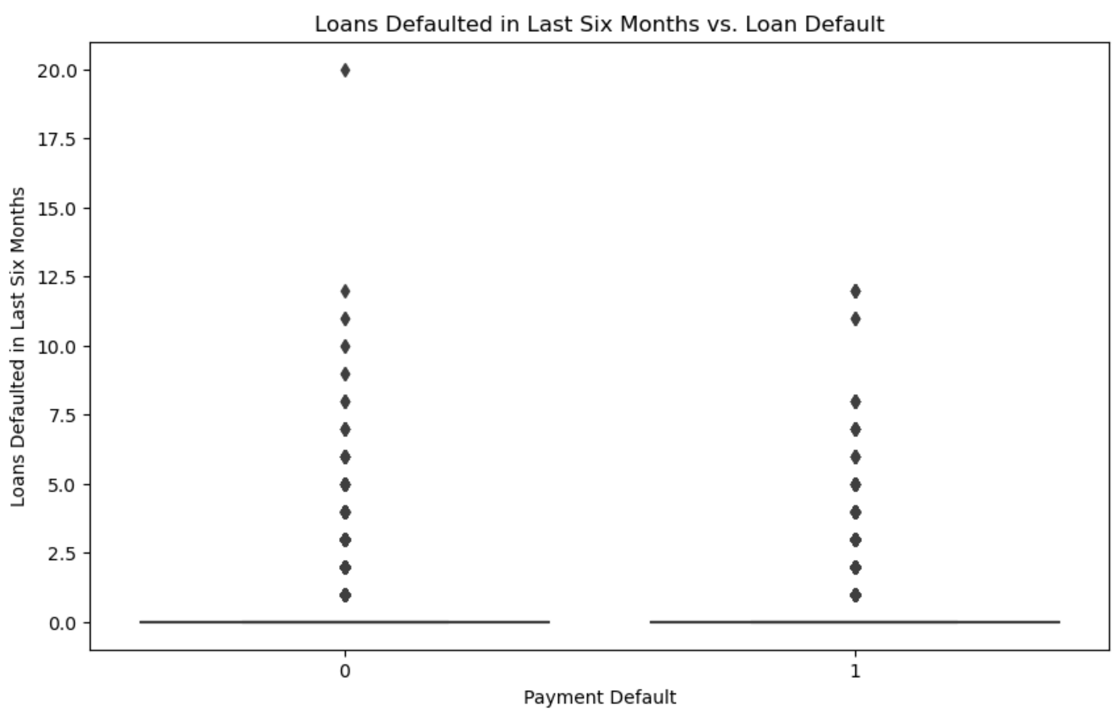


[33]:
```
import matplotlib.pyplot as plt
import seaborn as sns
```

```python
# Number of Inquiries
plt.figure(figsize=(10, 6))
sns.boxplot(x='loan_default', y='NO.OF_INQUIRIES', data=new_df)
plt.title('Number of Inquiries vs. Loan Default')
plt.xlabel('Payment Default')
plt.ylabel('Number of Inquiries')
plt.show()

# Credit History - New Loans in Last Six Months
plt.figure(figsize=(10, 6))
sns.boxplot(x='loan_default', y='NEW.ACCTS.IN.LAST.SIX.MONTHS', data=new_df)
plt.title('New Loans in Last Six Months vs. Loan Default')
plt.xlabel('Payment Default')
plt.ylabel('New Loans in Last Six Months')
plt.show()

# Credit History - Loans Defaulted in Last Six Months
plt.figure(figsize=(10, 6))
sns.boxplot(x='loan_default', y='DELINQUENT.ACCTS.IN.LAST.SIX.MONTHS', 
 ↪data=new_df)
plt.title('Loans Defaulted in Last Six Months vs. Loan Default')
plt.xlabel('Payment Default')
plt.ylabel('Loans Defaulted in Last Six Months')
plt.show()
```







Performing logistic regression model

[34]:
```
# Seperate features and target variable
X = new_df.drop('loan_default', axis=1)
y = new_df['loan_default'].copy()
```

[35]:
```
# Split train and test data with 70:30 ratio
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3,␣
 ↪random_state = random_state)
print("X_train size: ", X_train.shape)
print("X_test size: ", X_test.shape)
```

```
X_train size:  (234063, 37)
X_test size:  (100313, 37)
```

4 Build and evaluate models

Define evaluation function which calculates following metrics:

Confusion matrix Accuracy score Precision Recall F1 score ROC AUC score.

[36]:
```
def evaluate_model(y_test, y_pred):
    print("Confusion Matrix: \n", metrics.confusion_matrix(y_test, y_pred))
    print("Accuracy: ",metrics.accuracy_score(y_test, y_pred))
    print("Precision: ",metrics.precision_score(y_test, y_pred))
    print("Recall: ",metrics.recall_score(y_test, y_pred))
    print("f1 score: ",metrics.f1_score(y_test, y_pred))
    print("roc_auc_score: ",metrics.roc_auc_score(y_test, y_pred))
```

[37]:
```
# Scaling data before model training and testing
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

5 1. Logistic Regression

[38]:
```
#Find best parameters using grid search
params = {'C':[0.1, 0.5, 1, 5]}

lr = LogisticRegression()
grid = GridSearchCV(estimator=lr, param_grid=params)
grid.fit(X_train, y_train)
y_pred = grid.predict(X_test)
evaluate_model(y_test, y_pred)
```

```
Confusion Matrix:
 [[39389 15524]
 [24924 20476]]
Accuracy:  0.5967820721142822
Precision:  0.5687777777777778
```

```
Recall:  0.4510132158590308
f1 score:  0.5030958230958231
roc_auc_score:  0.5841557438354029
```

6 2. Decision Trees

[39]:
```python
params = {'criterion':['gini','entropy'], 'max_depth': [2,3,4,5]}
dt = DecisionTreeClassifier()
dt_clf =
evaluate_model(y_test, y_pred)GridSearchCV(dt, params)
dt_clf.fit(X_train, y_train)
y_pred = dt_clf.predict(X_test)
```

```
Confusion Matrix:
 [[36664 18249]
 [22701 22699]]
Accuracy:  0.5917777356872987
Precision:  0.554337208166455
Recall:  0.49997797356828194
f1 score:  0.5257562421827953
roc_auc_score:  0.5838261473836347
```

7 3. Random Forest

[40]:
```python
rf = RandomForestClassifier(n_estimators=250, random_state=random_state)
rf.fit(X_train,y_train)
y_pred = rf.predict(X_test)
evaluate_model(y_test, y_pred)
```

```
Confusion Matrix:
 [[49521  5392]
 [ 3342 42058]]
Accuracy:  0.912932521208617
Precision:  0.8863645943097997
Recall:  0.9263876651982379
f1 score:  0.9059343026386645
roc_auc_score:  0.914097990084596
```

8 Conclusion

In this classification problem, it is clear the Random Forest Classifier outperformes Logistic Regression and Decision Trees models.