Banking

August 27, 2024

[1]:
```python
# Import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix, classification_report
```

[2]:
```python
df = pd.read_excel('Dataset/data.xlsx')
```

0.1 1. Data Preliminary Analysis

0.1.1 1.1 Perform preliminary data inspection

[3]:
```python
print("Data Shape:", df.shape)
print("Data Info:")
df.info()
```

```
Data Shape: (233154, 41)
Data 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]:

```python
print("Missing Values:")
df.isnull().sum()
```

```
Missing Values:
```

[4]:

```
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
```

[5]:
```
# Filling missing values with new value - 'Unemployed'
df['Employment.Type'].fillna('Unemployed',inplace = True)
```

[6]:
```
df['Employment.Type'].value_counts()
```

[6]:
```
Self employed    127635
Salaried          97858
Unemployed         7661
Name: Employment.Type, dtype: int64
```

[7]:
```
df.isnull().sum()
```

[7]:
```
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
```

[8]:
```
print("Duplicates:", df.duplicated().sum())
```

```
Duplicates: 0
```

No Duplicates in the dataset!

0.1.2 1.2 Change variable names

[9]:
```
df.columns
```

[9]:
```
Index(['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'],
      dtype='object')
```

[10]:
```
# Replacing all '.' with '_' for the column names
df.columns = df.columns.str.replace('.','_')
```

```
C:\Users\USER\AppData\Local\Temp\ipykernel_16812\3670713857.py:2: FutureWarning:
The default value of regex will change from True to False in a future version.
In addition, single character regular expressions will *not* be treated as
literal strings when regex=True.
  df.columns = df.columns.str.replace('.','_')
```

[11]:
```
df.columns
```

[11]:
```
Index(['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'],
      dtype='object')
```

[12]:
```
# Also changing all columns names to lower case
df.columns = df.columns.str.lower()
df.columns
```

```
[12]: Index(['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'],
      dtype='object')
```

```
[13]: df.head()
```

```
[13]:    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]
```

0.2 2. Performing EDA

0.2.1 2.1 Statistical description of quantitative variables

[14]:
```
df.describe()
```

[14]:
```
            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]
```

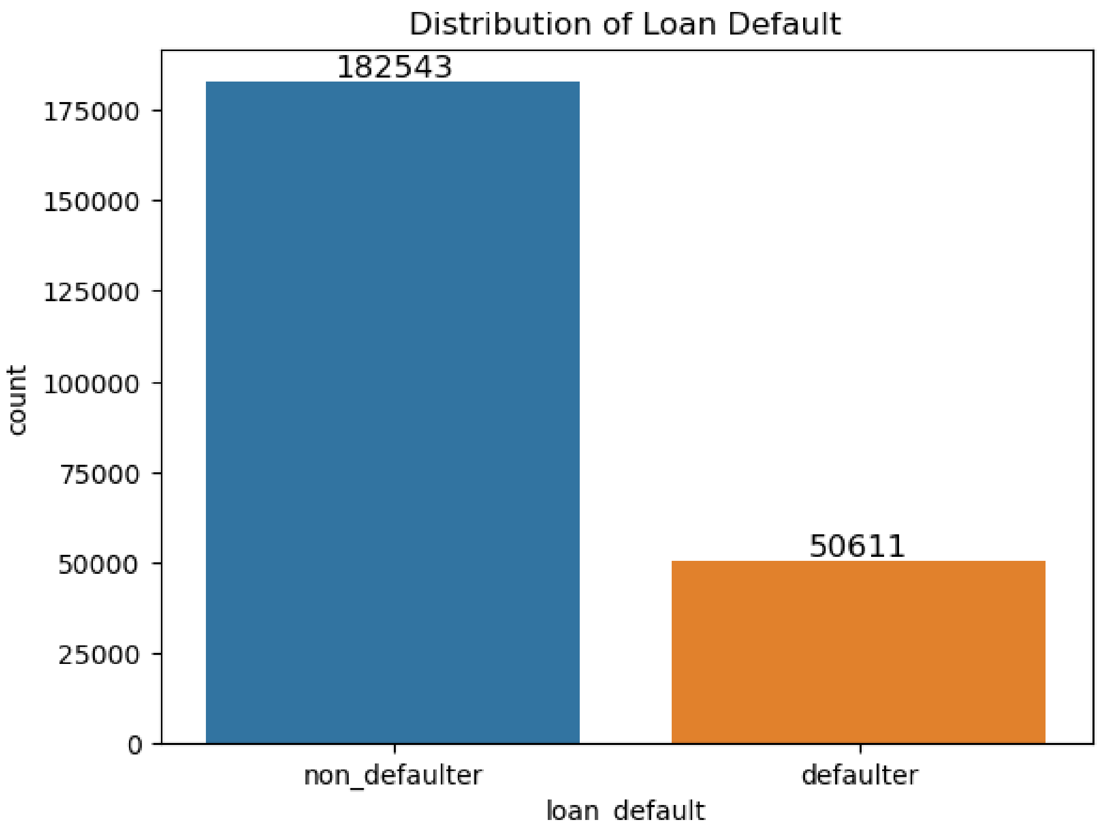
0.2.2 2.2 Distribution of the target variable

[15]:
```
df['loan_default'].unique()
```

[15]:
```
array([0, 1], dtype=int64)
```

[16]:
```
ax = sns.countplot(x='loan_default', data=df)
plt.title('Distribution of Loan Default')
plt.xticks(df['loan_default'].unique(), ['non_defaulter','defaulter'])

# Add the counts on top of the bars
for p in ax.patches:
```

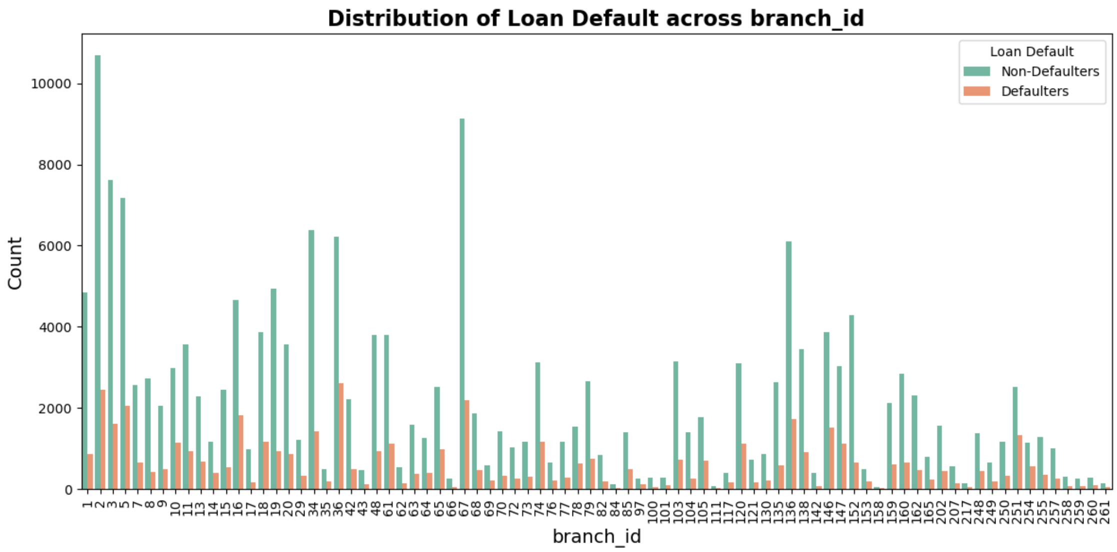
```
    ax.annotate(f'{int(p.get_height())}', (p.get_x() + p.get_width() / 2., p.
↪get_height()),
                ha = 'center', va = 'center', fontsize=12, color='black',␣
↪xytext=(0, 5),
                textcoords='offset points')
plt.show()
```

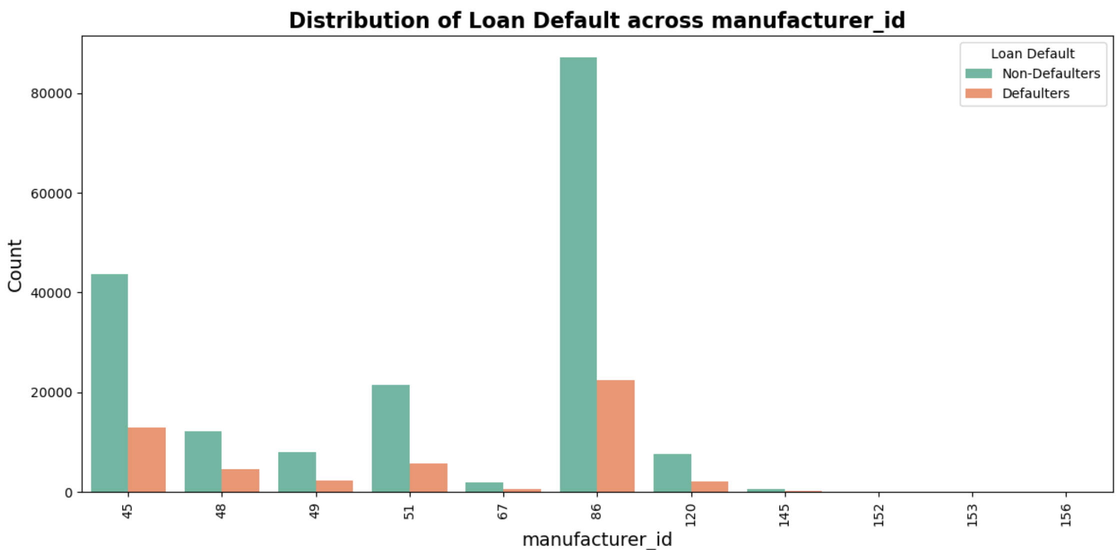


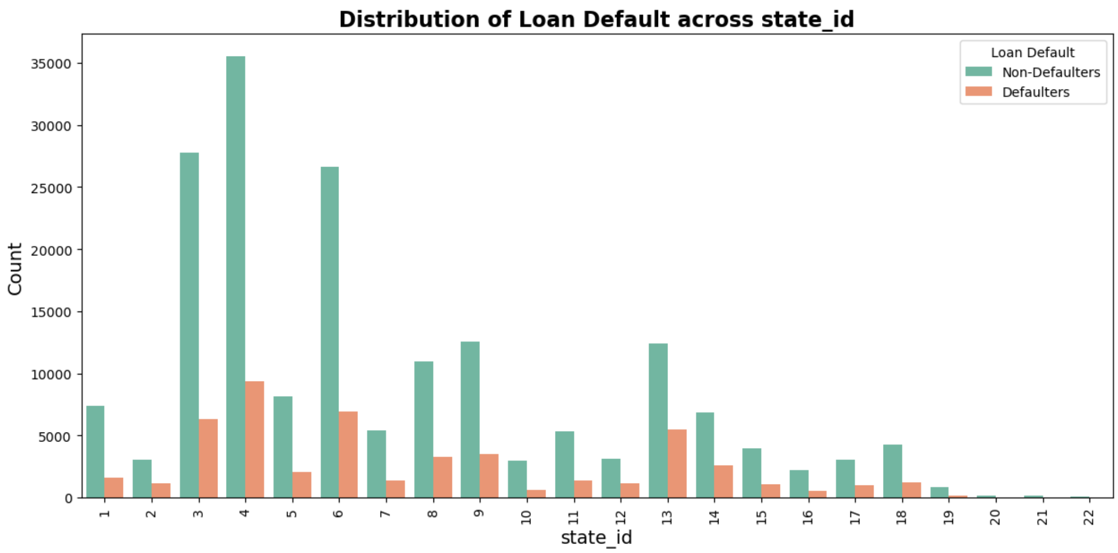
0.2.3 2.3 Distribution of the target variable across various categories

[17]:
```
categories = ['branch_id', 'manufacturer_id', 'state_id']

for cat in categories:
    plt.figure(figsize=(12, 6))  # Adjust figure size to provide more space
    sns.countplot(x=cat, hue='loan_default', data=df, palette='Set2')
    plt.title(f'Distribution of Loan Default across {cat}', fontsize=16,␣
↪fontweight='bold')
    plt.xticks(rotation=90)  # Rotate labels to 90 degrees for better␣
↪readability
    plt.xlabel(cat, fontsize=14)
    plt.ylabel('Count', fontsize=14)
```

```
    plt.legend(title='Loan Default', labels=['Non-Defaulters', 'Defaulters'], loc='upper right')
    plt.tight_layout()  # Adjust layout to prevent clipping of labels
    plt.show()
```



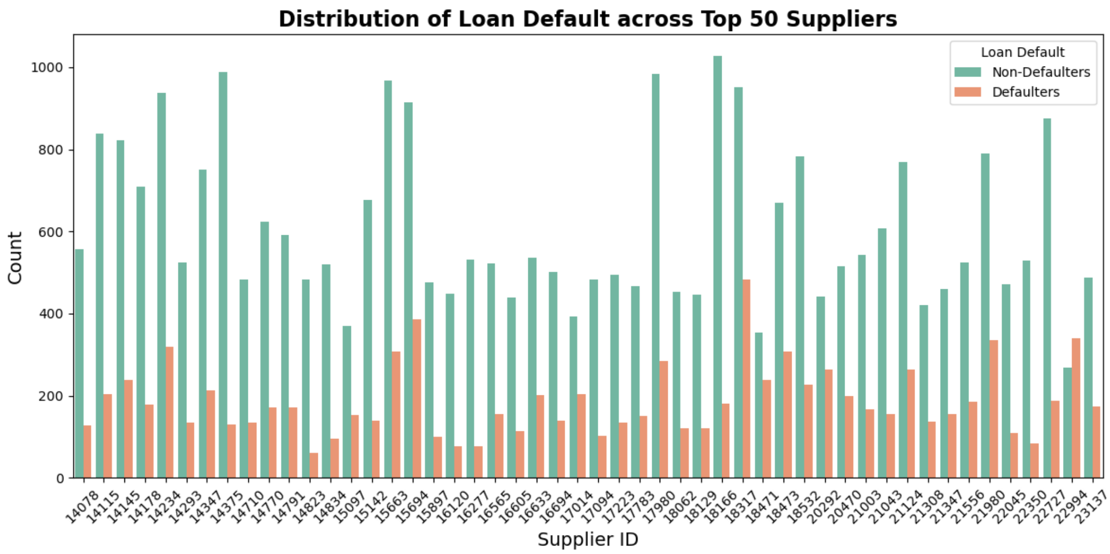




[18]:
```
# Supplier Id is having so many values to be listed in the x axis
df['supplier_id'].nunique()
```

[18]: 2953

[19]:
```
# Set the number of top suppliers to visualize
top_n = 50

# Identify the top N suppliers by frequency
top_suppliers = df['supplier_id'].value_counts().nlargest(top_n).index

# Filter the dataset to include only rows with the top N suppliers
filtered_df = df[df['supplier_id'].isin(top_suppliers)]

# Plot the distribution of loan default for the top N suppliers
plt.figure(figsize=(12, 6))
sns.countplot(x='supplier_id', hue='loan_default', data=filtered_df,␣
 ↪palette='Set2')
plt.title(f'Distribution of Loan Default across Top {top_n} Suppliers',␣
 ↪fontsize=16, fontweight='bold')
plt.xlabel('Supplier ID', fontsize=14)
plt.ylabel('Count', fontsize=14)
plt.xticks(rotation=45)  # Rotate the x-axis labels for better readability
plt.legend(title='Loan Default', labels=['Non-Defaulters', 'Defaulters'],␣
 ↪loc='upper right')
plt.tight_layout()  # Adjust layout to prevent clipping of labels
plt.show()
```



0.2.4 2.4 Employment types and pie chart for defaulters and non-defaulters

[20]:
```python
df['employment_type'].value_counts()
```

[20]:
```
Self employed    127635
Salaried          97858
Unemployed         7661
Name: employment_type, dtype: int64
```

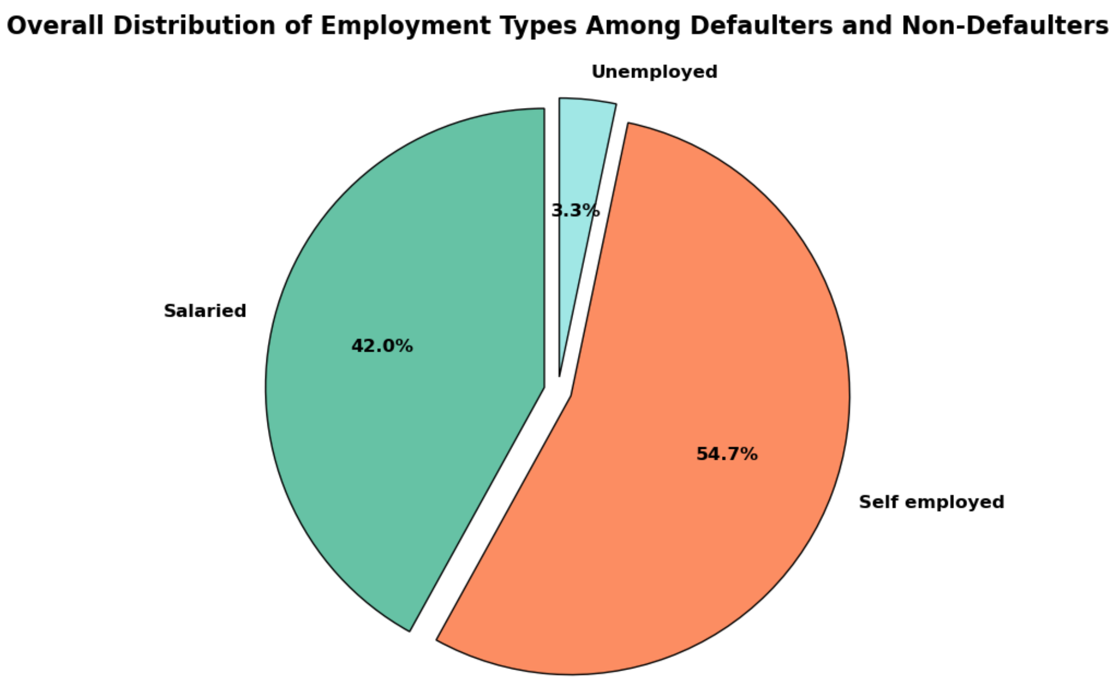
we have already removed the null values and replaced it with “Unemployed”

[21]:
```python
# Group by 'employment_type' and 'loan_default' and calculate sizes
employment_pie = df.groupby(['employment_type', 'loan_default']).size().unstack().fillna(0)
employment_pie
```

[21]:
```
loan_default         0      1
employment_type
Salaried         77948  19910
Self employed    98578  29057
Unemployed        6017   1644
```

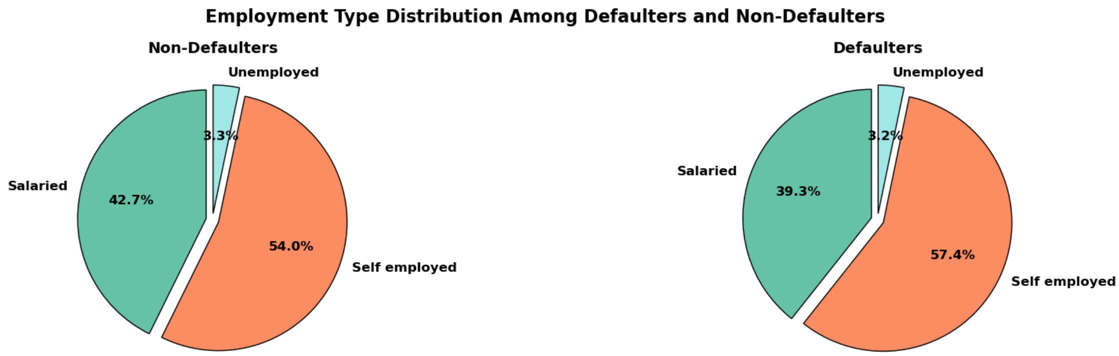
[22]:
```python
# Sum the defaulters and non-defaulters across employment types
employment_type_totals = employment_pie.sum(axis=1)

# Plot a pie chart for the overall distribution of defaulters and non-defaulters by employment type
plt.figure(figsize=(8, 8))
employment_type_totals.plot.pie(
```

```
    autopct='%.1f%%',
    colors=['#66c2a5', '#fc8d62', '#a0e7e5'],
    startangle=90,
    labels=employment_type_totals.index,
    explode=[0.05] * len(employment_type_totals.index),
    wedgeprops={'edgecolor': 'black'},
    textprops={'fontsize': 12, 'weight': 'bold'}
)
plt.title('Overall Distribution of Employment Types Among Defaulters and␣
 ↪Non-Defaulters', fontsize=16, fontweight='bold')
plt.ylabel('')  # Remove the y-label for a cleaner look
plt.tight_layout()  # Ensure the layout is tight and well-organized
plt.show()
```



[23]:
```
# Define colors for the pie charts
colors = ['#66c2a5', '#fc8d62', '#a0e7e5']

# Plot pie charts for defaulters and non-defaulters
fig, axes = plt.subplots(1, 2, figsize=(18, 5))

# Plot for non-defaulters
employment_pie[0].plot.pie(
    ax=axes[0],
```

```
    autopct='%.1f%%',
    colors=colors,
    startangle=90,
    labels=employment_pie.index,
    explode=[0.05] * len(employment_pie.index),
    wedgeprops={'edgecolor': 'black'},
    textprops={'fontsize': 12, 'weight': 'bold'}
)
axes[0].set_title('Non-Defaulters', fontsize=14, fontweight='bold')
axes[0].set_ylabel('')  # Remove the y-label for a cleaner look

# Plot for defaulters
employment_pie[1].plot.pie(
    ax=axes[1],
    autopct='%.1f%%',
    colors=colors,
    startangle=90,
    labels=employment_pie.index,
    explode=[0.05] * len(employment_pie.index),
    wedgeprops={'edgecolor': 'black'},
    textprops={'fontsize': 12, 'weight': 'bold'}
)
axes[1].set_title('Defaulters', fontsize=14, fontweight='bold')
axes[1].set_ylabel('')  # Remove the y-label for a cleaner look

# Add a central title for the figure
plt.suptitle('Employment Type Distribution Among Defaulters and␣
 ↪Non-Defaulters', fontsize=16, fontweight='bold')

# Ensure tight layout for the plots
plt.tight_layout()

# Adjust the space between the plots and the central title
plt.subplots_adjust(top=0.85)

# Display the pie charts
plt.show()
```

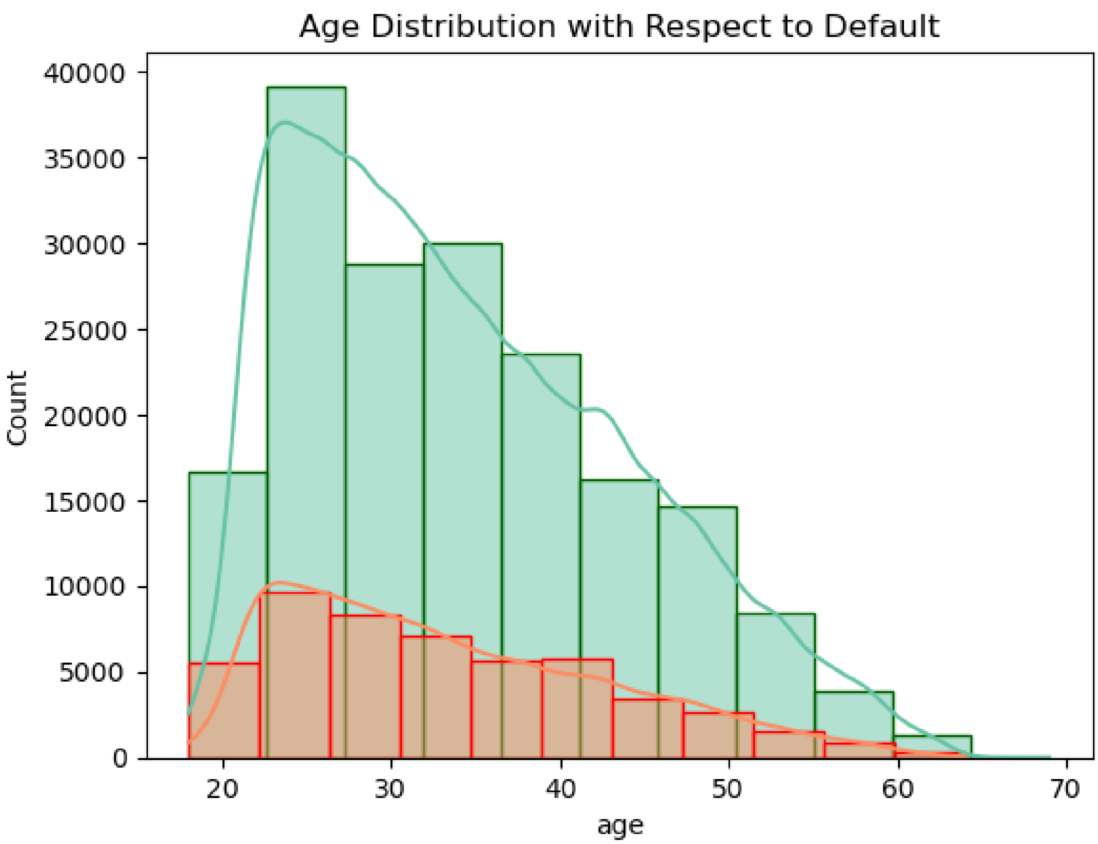


0.2.5 2.5 Age distribution with respect to defaulters

[24]:
```
df['disbursaldate']
```

[24]:
```
0        2018-08-03
1        2018-08-01
2        2018-09-26
3        2018-09-23
4        2018-10-08
            ...
233149   2018-10-06
233150   2018-10-31
233151   2018-10-23
233152   2018-08-17
233153   2018-09-28
Name: disbursaldate, Length: 233154, dtype: datetime64[ns]
```

[25]:
```
df['age'] = df['disbursaldate'].dt.year - df['date_of_birth'].dt.year
sns.histplot(x ='age',data = df[df['loan_default']==0] ,bins = 11,kde␣
↪=True,color = '#66c2a5',
             label = 'NON-defaulter'.upper(),edgecolor = 'darkgreen')
sns.histplot(x ='age',data = df[df['loan_default']==1] ,bins = 11,kde␣
↪=True,color = '#fc8d62',
             label = 'defaulter'.upper(),edgecolor = 'red')
plt.title('Age Distribution with Respect to Default')
plt.show()
```



0.2.6 2.6 What type of ID is presented by most of the customers as proofs?

[26]:
```
df.columns
```

[26]:
```
Index(['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', 'age'],
      dtype='object')
```

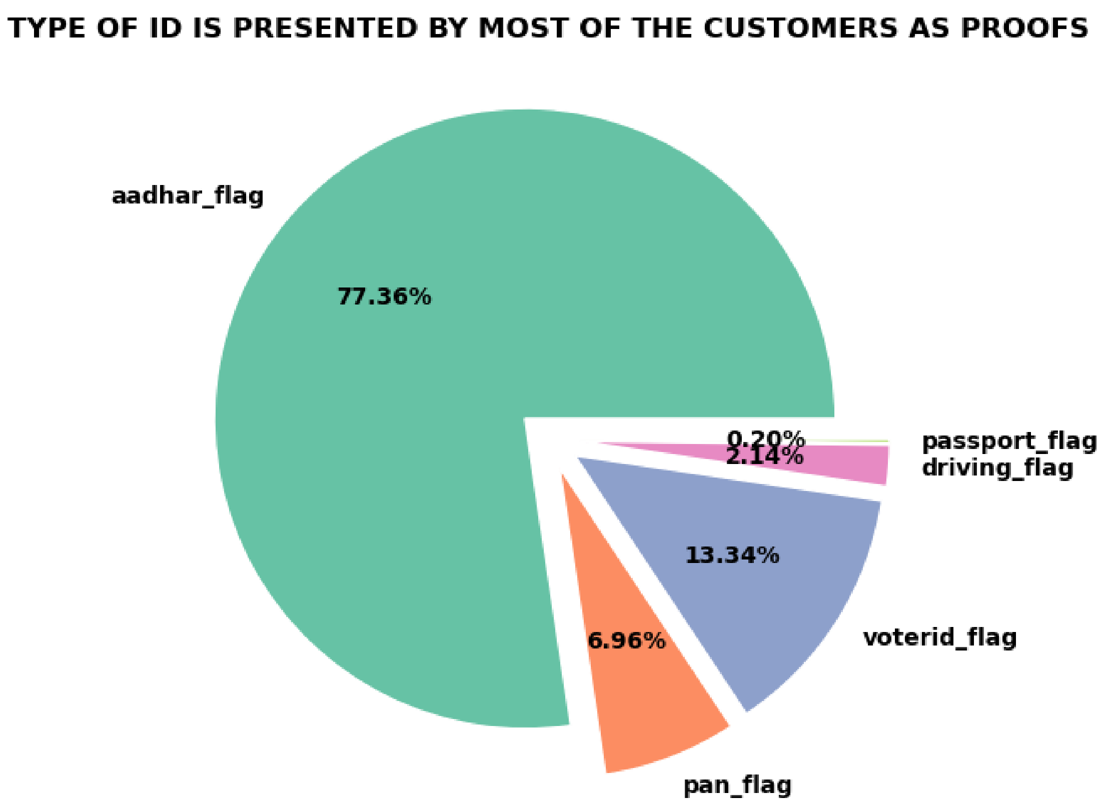
[27]:
```
id_flags = ['aadhar_flag', 'pan_flag', 'voterid_flag', 'driving_flag',␣
↪'passport_flag']
id_flags_summary = df[id_flags].sum()
print("Most common ID types presented:")
id_flags_count = pd.DataFrame({'ID': id_flags_summary.index,'CNT':
↪id_flags_summary.values})
id_flags_count
```

```
Most common ID types presented:
```

[27]:

	ID	CNT
0	aadhar_flag	195924
1	pan_flag	17621
2	voterid_flag	33794
3	driving_flag	5419
4	passport_flag	496

[28]:
```
plt.figure(figsize =(8,6))
plt.pie(x = 'CNT',data = id_flags_count,
        autopct = "%1.2f%%",
        shadow = False,
        explode = [0.1]*len(id_flags_count['ID'].values),
        colors = ['#66c2a5', '#fc8d62', '#8da0cb', '#e78ac3', '#a6d854'],
       labels = id_flags_count['ID'].values,
       startangle = 0,
       textprops = {'fontweight':'bold'},
       wedgeprops = {'linewidth':1,
                    'edgecolor':'w'})

plt.title("type of ID is presented by most of the customers as proofs".
↪upper(),weight = 'bold')
plt.show()
```



0.3 3. Performing EDA and Modeling

0.3.1 3.1 Study the credit bureau score distribution

[29]:
```
df['perform_cns_score_description'].unique()
```

[29]:
```
array(['No Bureau History Available', 'A-Very Low Risk',
       'B-Very Low Risk', 'C-Very Low Risk', 'D-Very Low Risk',
       'E-Low Risk', 'F-Low Risk', 'G-Low Risk', 'H-Medium Risk',
       'I-Medium Risk', 'J-High Risk', 'K-High Risk', 'L-Very High Risk',
       'M-Very High Risk',
       'Not Scored: No Updates available in last 36 months',
       'Not Scored: Not Enough Info available on the customer',
       'Not Scored: No Activity seen on the customer (Inactive)',
       'Not Scored: Sufficient History Not Available',
       'Not Scored: Only a Guarantor',
       'Not Scored: More than 50 active Accounts found'], dtype=object)
```

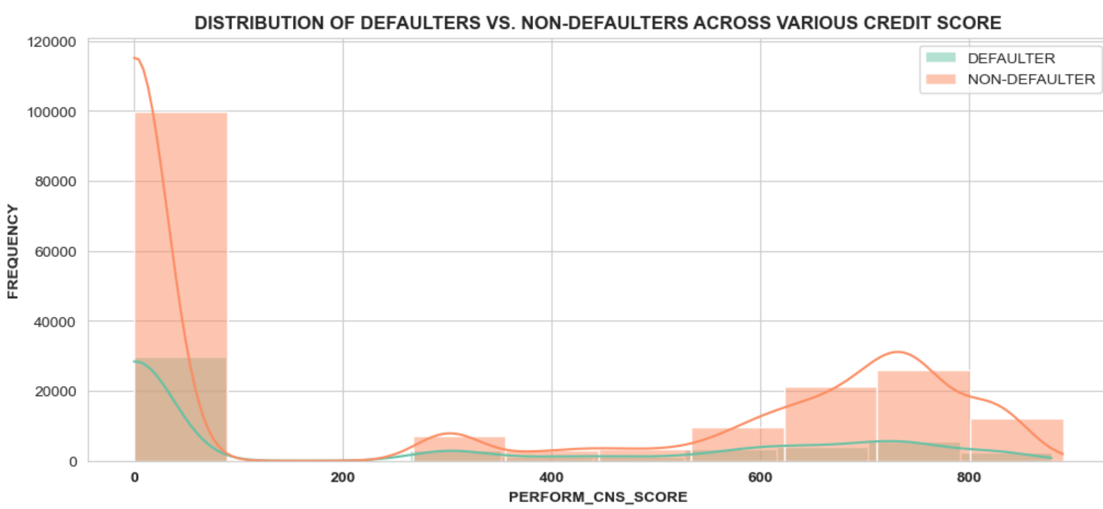
[30]:
```
df['perform_cns_score'].describe()
```

[30]:

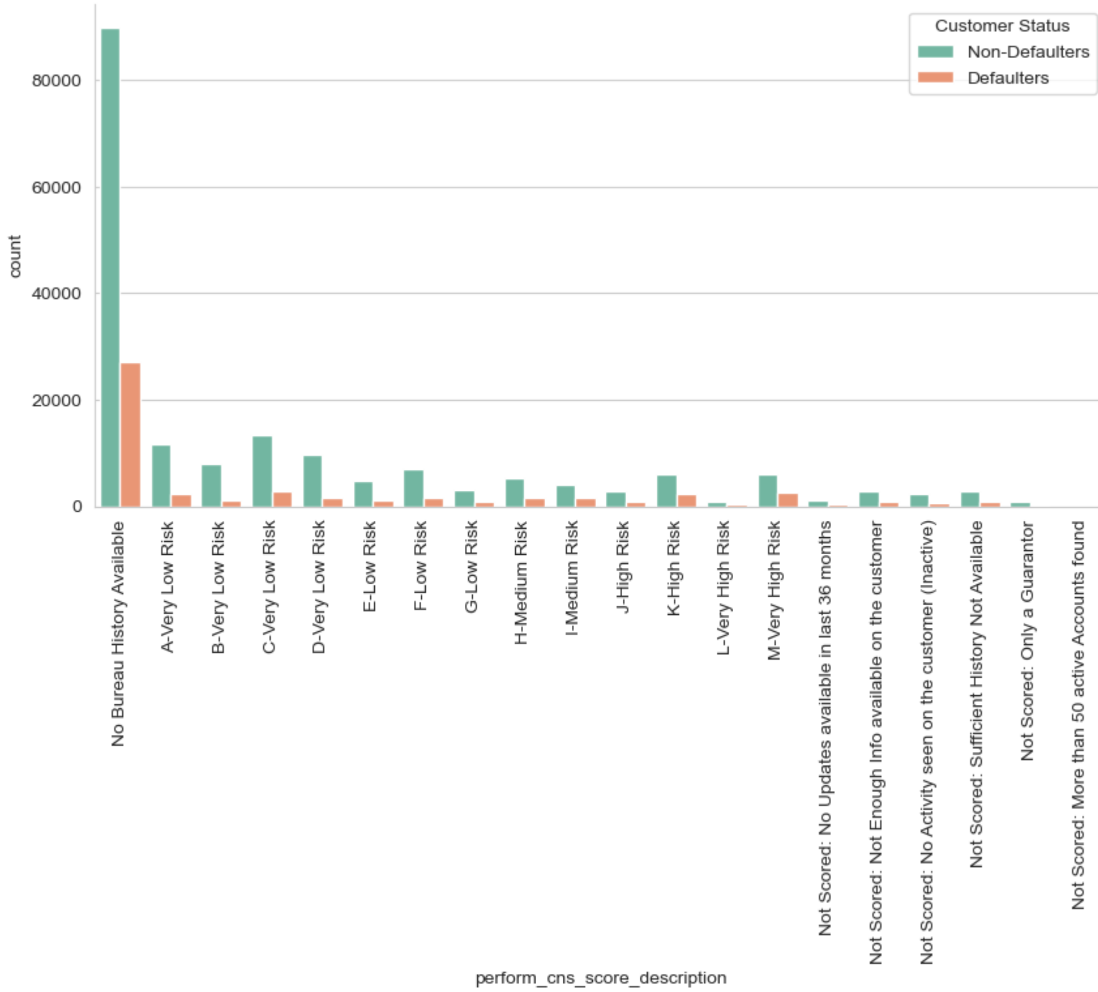
```
count    233154.000000
mean        289.462994
std         338.374779
min           0.000000
25%           0.000000
50%           0.000000
75%         678.000000
max         890.000000
Name: perform_cns_score, dtype: float64
```

[31]:

```
plt.figure(figsize = (12,5))
sns.set_style('whitegrid')


sns.histplot(x ='perform_cns_score',data = df[df['loan_default']==1],bins =␣
↪10,color = '#66c2a5',kde = True,label = 'DEFAULTER')
sns.histplot(x ='perform_cns_score',data = df[df['loan_default']==0],bins =␣
↪10,color = '#fc8d62',kde = True,label = 'NON-DEFAULTER')


plt.xlabel('perform_cns_score'.upper(),weight = 'bold')
plt.ylabel('frequency'.upper(),weight='bold')
plt.xticks(weight ='bold')
plt.xticks(weight ='bold')
plt.title('distribution of defaulters vs. non-defaulters across various credit␣
↪score'.upper(),weight = 'bold')
plt.legend(loc = 'best')


plt.show()
```



[32]:
```
plt.figure(figsize = (10,5))
sns.countplot(x = df['perform_cns_score_description'],hue = 'loan_default',data␣
 ↪= df,palette = 'Set2')

# Update legend labels
plt.legend(title='Customer Status', labels=['Non-Defaulters', 'Defaulters'])
plt.xticks(rotation = 90)
sns.despine()
plt.show()
```

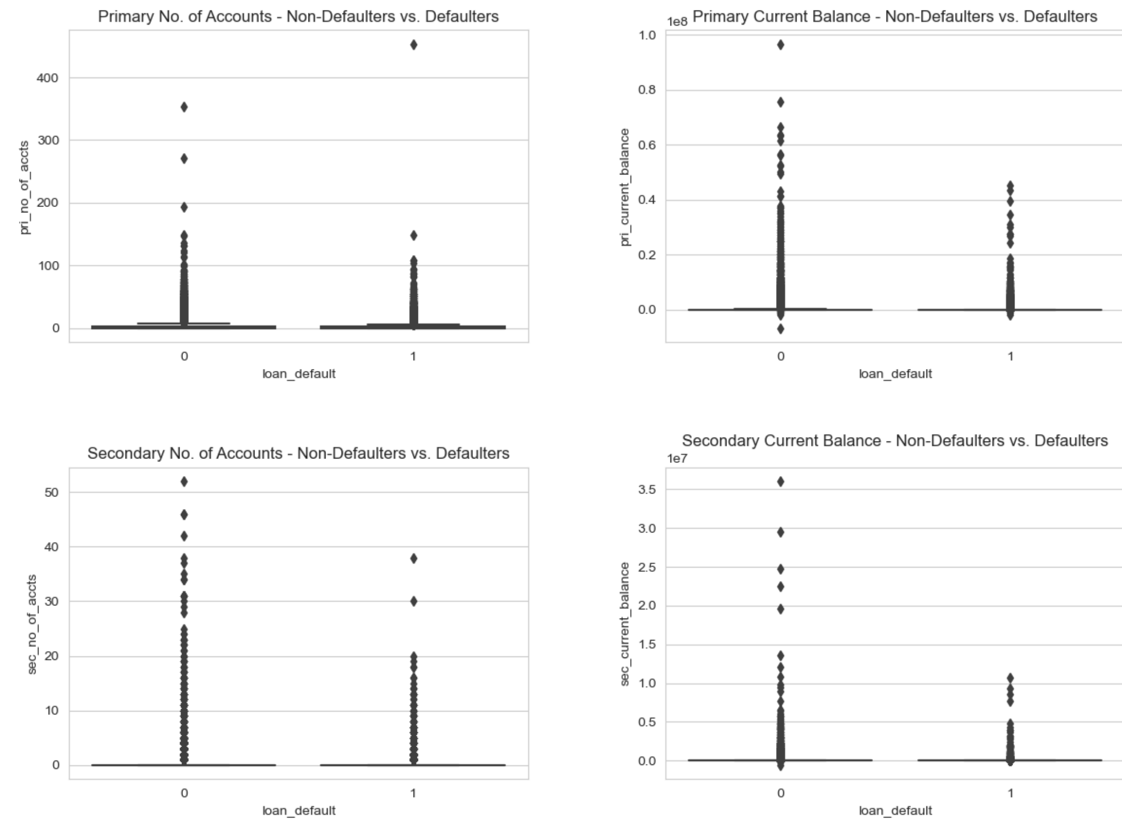


0.3.2 3.2 Primary and secondary account details

[33]:
```
df[['pri_no_of_accts', 'sec_no_of_accts', 'loan_default']].
 ↪groupby('loan_default').describe()
```

[33]:
```
                pri_no_of_accts                                                 \
                          count      mean       std  min  25%  50%  75%    max
loan_default
0                      182543.0  2.538038  5.261142  0.0  0.0  1.0  3.0  354.0
1                       50611.0  2.089328  5.040134  0.0  0.0  0.0  2.0  453.0

                sec_no_of_accts
                          count      mean       std  min  25%  50%  75%   max
loan_default
0                      182543.0  0.061848  0.651657  0.0  0.0  0.0  0.0  52.0
1                       50611.0  0.049100  0.527358  0.0  0.0  0.0  0.0  38.0
```

[34]:
```
# Set figure size and layout for all box plots
fig, axes = plt.subplots(2, 2, figsize=(14, 10))
plt.subplots_adjust(wspace=0.3, hspace=0.4)  # Adjust spacing between plots

# Box plot for Primary No. of Accounts
sns.boxplot(ax=axes[0, 0], x='loan_default', y='pri_no_of_accts', data=df)
axes[0, 0].set_title('Primary No. of Accounts - Non-Defaulters vs. Defaulters')

# Box plot for Primary Current Balance
sns.boxplot(ax=axes[0, 1], x='loan_default', y='pri_current_balance', data=df)
axes[0, 1].set_title('Primary Current Balance - Non-Defaulters vs. Defaulters')

# Box plot for Secondary No. of Accounts
sns.boxplot(ax=axes[1, 0], x='loan_default', y='sec_no_of_accts', data=df)
axes[1, 0].set_title('Secondary No. of Accounts - Non-Defaulters vs.␣
 ↪Defaulters')

# Box plot for Secondary Current Balance
sns.boxplot(ax=axes[1, 1], x='loan_default', y='sec_current_balance', data=df)
axes[1, 1].set_title('Secondary Current Balance - Non-Defaulters vs.␣
 ↪Defaulters')

# Display all plots
plt.show()
```



0.3.3 Analysis Summary

Primary Number of Accounts: Defaulters typically maintain a higher number of primary accounts compared to non-defaulters.

Primary Current Balance: Defaulters generally exhibit a lower primary current balance than non-defaulters.

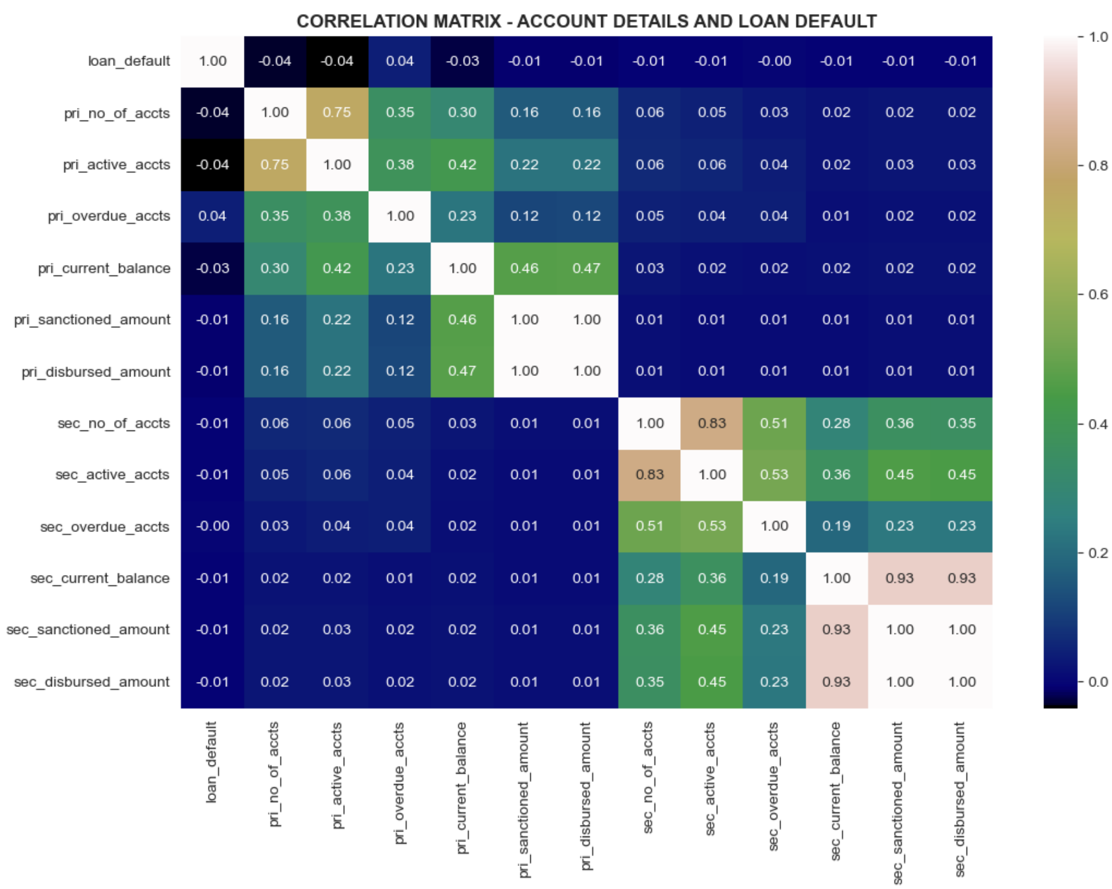
Secondary Number of Accounts: Reflecting the pattern observed in primary accounts, defaulters usually have a greater number of secondary accounts than non-defaulters.

Secondary Current Balance: Defaulters often hold a lower secondary current balance compared to non-defaulters.

Conclusion: The analysis indicates that defaulters are characterised by a higher number of accounts and a lower balance across both primary and secondary accounts compared to non-defaulters. These insights can be valuable for financial institutions in evaluating loan default risk. However, it is crucial to remember that correlation does not imply causation. These factors should be integrated into a comprehensive risk assessment strategy rather than being used in isolation.

[35]:
```
primary_cols = ['pri_no_of_accts', 'pri_active_accts', 'pri_overdue_accts',␣
↪'pri_current_balance', 'pri_sanctioned_amount', 'pri_disbursed_amount']
```

```
secondary_cols = ['sec_no_of_accts', 'sec_active_accts', 'sec_overdue_accts', 'sec_current_balance', 'sec_sanctioned_amount', 'sec_disbursed_amount']

account_details = df[['loan_default'] + primary_cols + secondary_cols]
correlation_matrix = account_details.corr()

# Heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='gist_earth', fmt='.2f')
plt.title('Correlation Matrix - Account Details and Loan Default'.upper(),weight = 'bold')
plt.show()
```



0.3.4 Correlation Analysis Summary

Primary Overdue Accounts (pri_overdue_accts): There is a small positive correlation between the number of primary overdue accounts and loan default. This indicates that customers with a higher number of primary overdue accounts are likely to default on their loans.

Secondary Overdue Accounts (sec_overdue_accts): Secondary overdue accounts also exhibit a minute positive correlation with loan default, similar to primary overdue accounts. This suggests that customers with more secondary overdue accounts maybe prone to defaulting.

Primary Number of Accounts (pri_no_of_accts), Primary Active Accounts (pri_active_accts), and Related Variables: These variables demonstrate a weak negative correlation with loan default. This implies that as the values for these variables increase, the likelihood of loan default may slightly decrease. However, the correlations are weak, indicating that these variables are not strong predictors of loan default.

0.3.5 3.3 Difference between sanctioned and disbursed amount

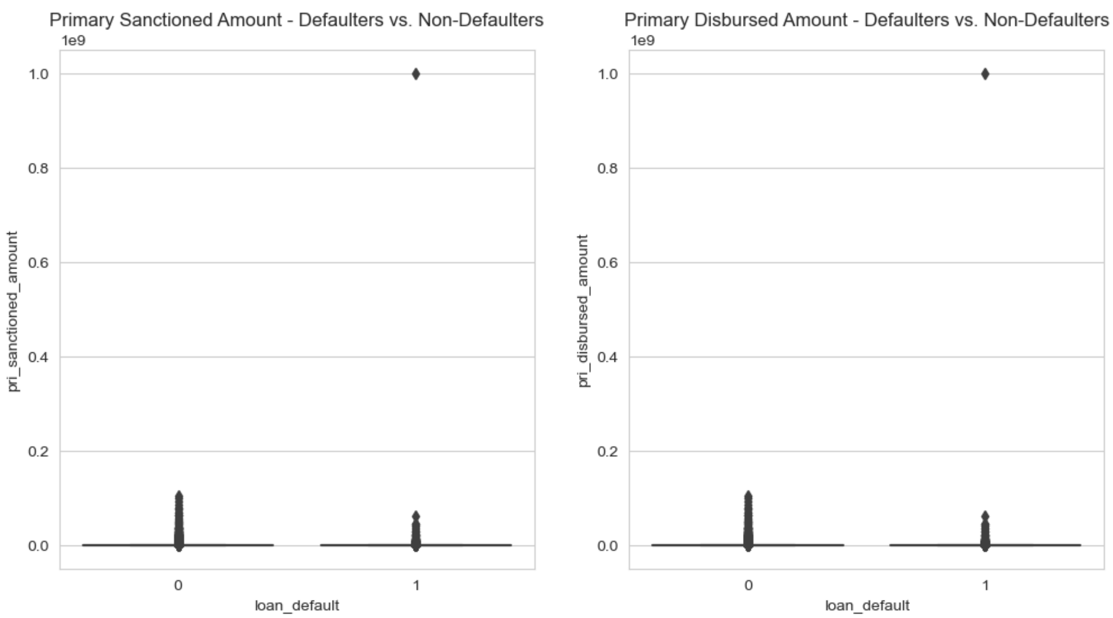
[36]:
```
pri_col = ['pri_sanctioned_amount','pri_disbursed_amount']
sec_col = ['sec_sanctioned_amount','sec_disbursed_amount']
```

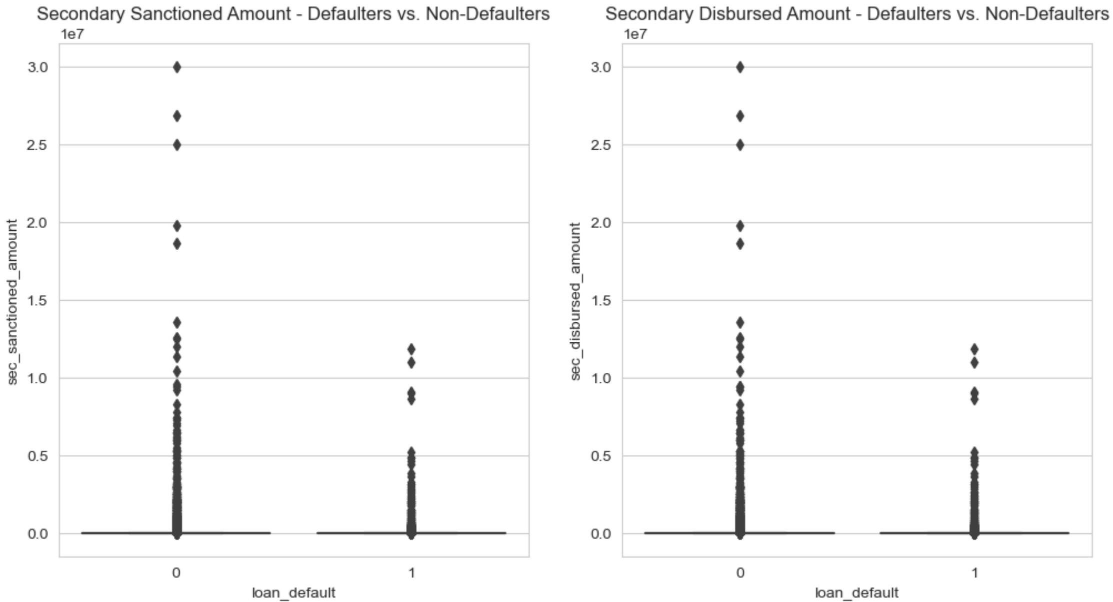
[37]:
```
# Calculate descriptive statistics for primary loans
primary_stats = df[['pri_sanctioned_amount', 'pri_disbursed_amount']].describe()
print('Primary Statistics\n', primary_stats)
# Calculate descriptive statistics for secondary loans
secondary_stats = df[['sec_sanctioned_amount', 'sec_disbursed_amount']].
 ↪describe()
print('\nSecondary Statistics\n', secondary_stats)
```

```
Primary Statistics
        pri_sanctioned_amount  pri_disbursed_amount
count           2.331540e+05          2.331540e+05
mean            2.185039e+05          2.180659e+05
std             2.374794e+06          2.377744e+06
min             0.000000e+00          0.000000e+00
25%             0.000000e+00          0.000000e+00
50%             0.000000e+00          0.000000e+00
75%             6.250000e+04          6.080000e+04
max             1.000000e+09          1.000000e+09

Secondary Statistics
        sec_sanctioned_amount  sec_disbursed_amount
count           2.331540e+05          2.331540e+05
mean            7.295923e+03          7.179998e+03
std             1.831560e+05          1.825925e+05
min             0.000000e+00          0.000000e+00
25%             0.000000e+00          0.000000e+00
50%             0.000000e+00          0.000000e+00
75%             0.000000e+00          0.000000e+00
max             3.000000e+07          3.000000e+07
```

[38]:
```
# Box plots for primary loan amounts
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
sns.boxplot(data=df, y='pri_sanctioned_amount', x='loan_default')
```

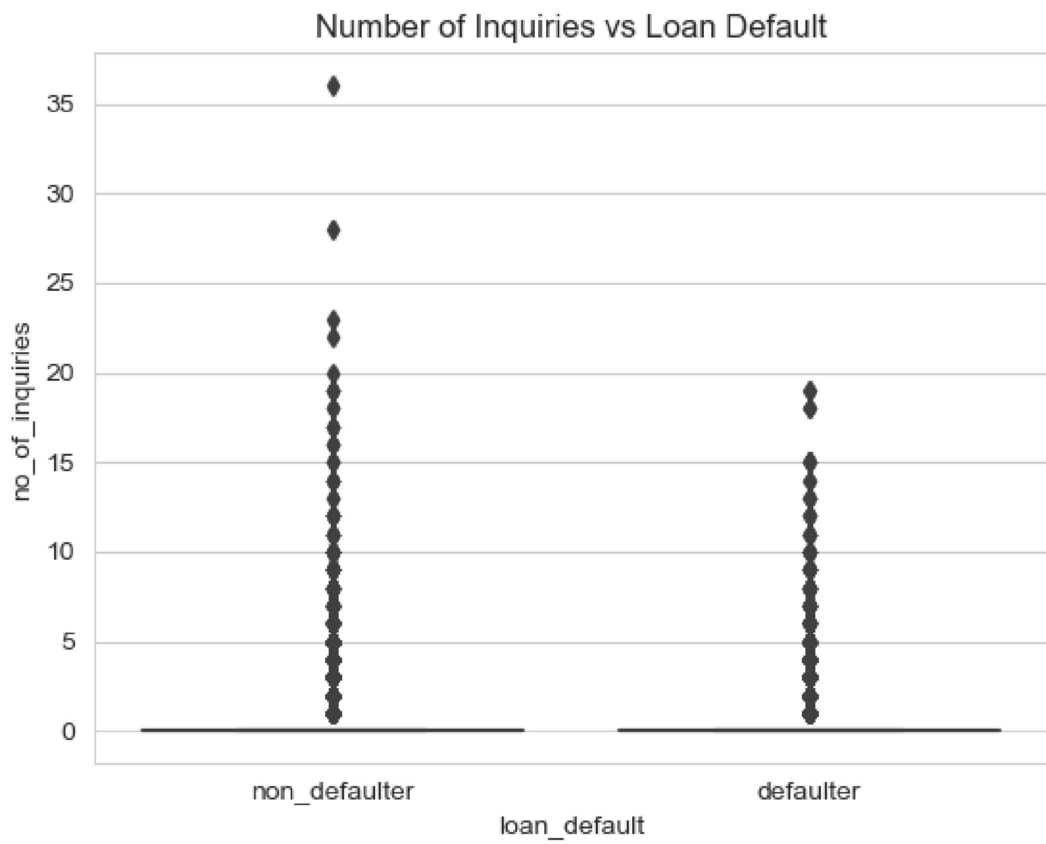
```python
plt.title('Primary Sanctioned Amount - Defaulters vs. Non-Defaulters')

plt.subplot(1, 2, 2)
sns.boxplot(data=df, y='pri_disbursed_amount', x='loan_default')
plt.title('Primary Disbursed Amount - Defaulters vs. Non-Defaulters')

# Box plots for secondary loan amounts
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
sns.boxplot(data=df, y='sec_sanctioned_amount', x='loan_default')
plt.title('Secondary Sanctioned Amount - Defaulters vs. Non-Defaulters')

plt.subplot(1, 2, 2)
sns.boxplot(data=df, y='sec_disbursed_amount', x='loan_default')
plt.title('Secondary Disbursed Amount - Defaulters vs. Non-Defaulters')

plt.show()
```





0.3.6 3.4 Inquiry counts and risk

[39]:
```
sns.boxplot(x='loan_default', y='no_of_inquiries', data=df)
plt.xticks(df['loan_default'].unique(), ['non_defaulter','defaulter'])
plt.title('Number of Inquiries vs Loan Default')
plt.show()
```



[40]:
```
corr = df[['loan_default','no_of_inquiries']].corr(method = 'pearson')
corr
```

[40]:

	loan_default	no_of_inquiries
loan_default	1.000000	0.043678
no_of_inquiries	0.043678	1.000000

There is not much significant relation with no_of_inquiries and loan default

0.3.7 3.5 Credit history factors

[41]:
```
df2 = df.copy()

df2[['average_acct_age', 'new_accts_in_last_six_months',␣
↪'delinquent_accts_in_last_six_months', 'credit_history_length']]
```

[41]:

	average_acct_age	new_accts_in_last_six_months \
0	0yrs 0mon	0
1	0yrs 0mon	0
2	0yrs 0mon	0

```
3             0yrs 0mon                              0
4             0yrs 0mon                              0
…                …                              …
233149        2yrs 4mon                              0
233150        1yrs 5mon                              0
233151        0yrs 9mon                             35
233152        1yrs 2mon                              9
233153       2yrs 11mon                              5

        delinquent_accts_in_last_six_months credit_history_length
0                                         0            0yrs 0mon
1                                         0            0yrs 0mon
2                                         0            0yrs 0mon
3                                         0            0yrs 0mon
4                                         0            0yrs 0mon
…                                       …                 …
233149                                    0            2yrs 4mon
233150                                    0            1yrs 5mon
233151                                    5           3yrs 10mon
233152                                    1            3yrs 2mon
233153                                    0            5yrs 4mon

[233154 rows x 4 columns]
```

Converting average_acct_age and credit_history_length to months format

[42]:
```python
df2[['average_acct_age','credit_history_length']].isnull().sum()
```

[42]:
```
average_acct_age         0
credit_history_length    0
dtype: int64
```

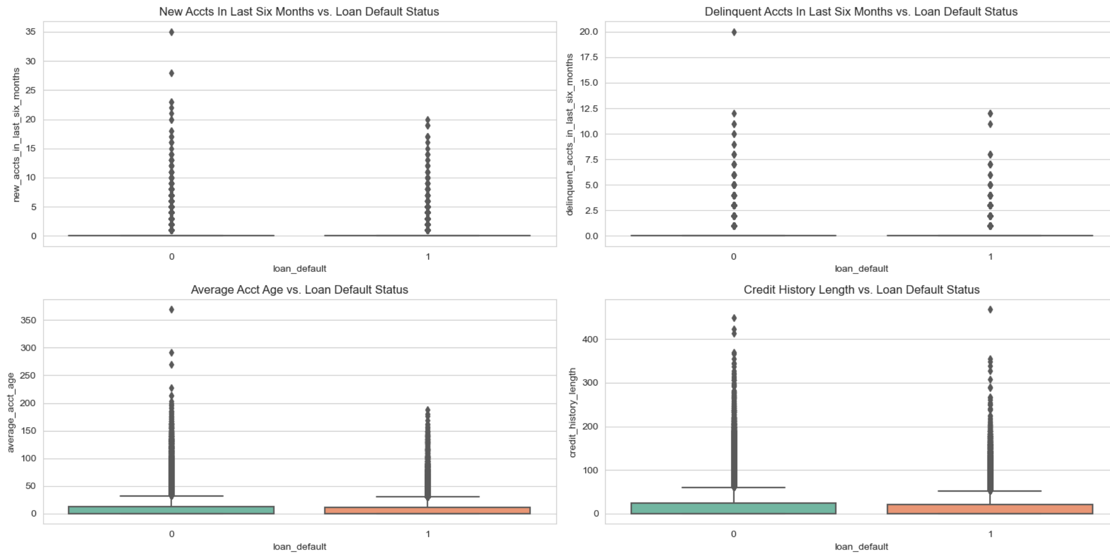
[43]:
```python
combined_cols = ['average_acct_age','credit_history_length']

for col in combined_cols:
    df2[col] = df2[col].str.replace('[yrsmon]','',regex = True)
    df2[col]= df2[col].str.replace(' ',',',regex = True)
    df2[col] = df2[col].apply(lambda x : int(x.split(',')[0])*12 + int(x.
 ↪split(',')[1]))
    print(col, 'is: \n',df2[col].unique())
```

```
average_acct_age is:
 [  0  60  21  23   8  12  13  18  69   3  56   4   2  11  35  27  96  42
  97  15  37  39  40   9  10  25  33  22  49   6 140  24   7 105 121  74
  26  95 131   5  43  32  20  62  92  17  31 175 128  19  41  78 114 132
  38  45  61  44  86  16  52  63  75 103  14  55   1  99  29  65  48 122
 150  46  72 142 161  89 101  71  30  67  70  34  28  57 119  54  36 102
 117  88  68  84 113 185  64  90 162 167  98 126  50 115 214 123 147  85
  80  59  77 129 134  81 168 145 135 139  53 107 120 130 148 133 118  82
```

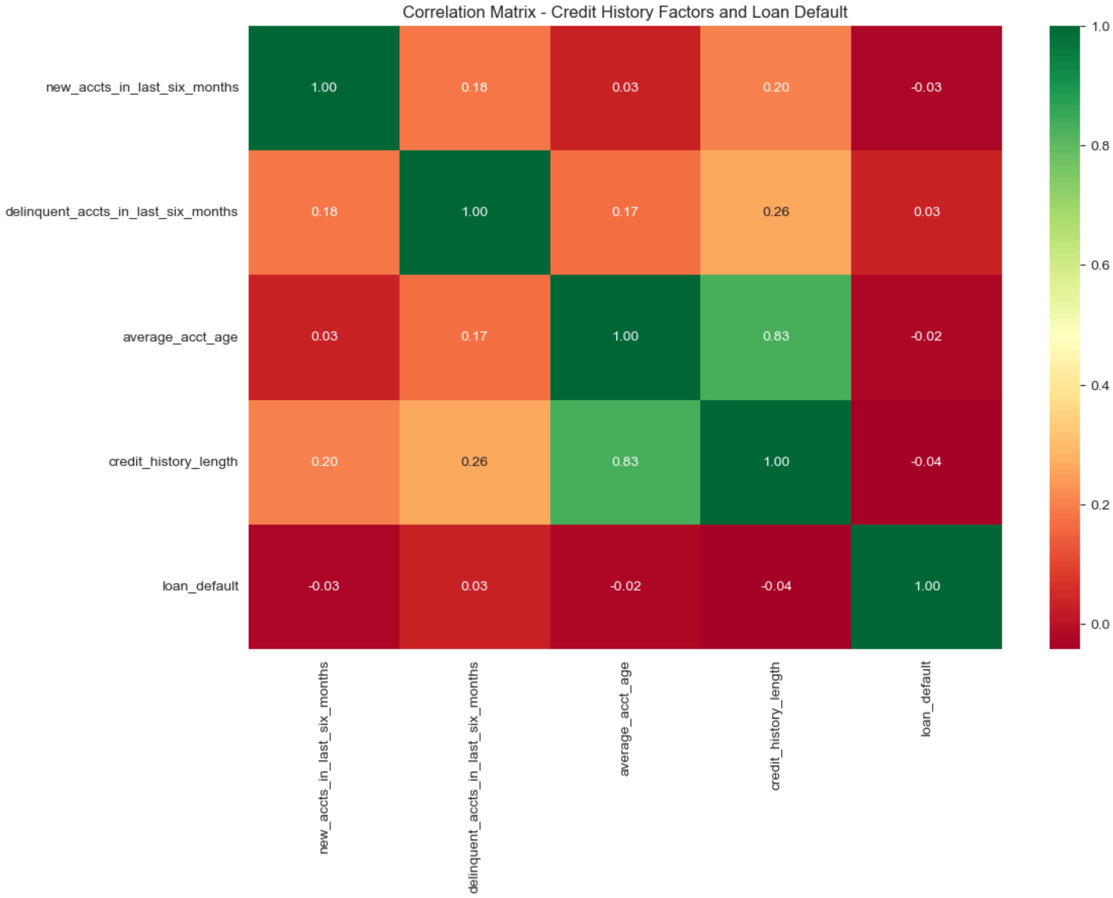
```
 199  58  51 157  87  93 188 110 164 106  79  66 143  47  83 112  76  73
  94 138 111 125 100 124 159 137 109  91 127 116 104 141 108 151 160 155
 136 176 149 154 180 163 191 183 292 166 158 156 184 144 169 171 195 203
 146 153 270 170 192 197 174 369 227 179 173 182]
credit_history_length is:
 [  0  60  21  50  10  12  13  34  69   3  56   4   2  11  35  27  22  96
 145  15  37  39  40   9  25  33  32  49   6  24 140 134  41 121  74  23
  95   8  16 131   5  43  26 128  38  59 175  19  14  18 279  97 114 135
 113   7  47  45 158  44  86  52  71  75 103  28  72  66   1  99  55  29
  20  65  48  46 122  31  76 150  57  36  87 142 161  89 101  58  79  30
  17  70 119  77  78 157 133 102  63 117  88 186 137  84 185  42 126  51
  67 164  90 169 167 115 214  81 123 105 147  85 100 172 129  93  68 168
 132 211 139  53 107 120 130 124  62  92  64 118  82 199 125 136  61  98
  54 188  73 110 159 104 106 146 179  83 162 111 143 144  91 195 141 192
 215 177 160 174 184 109  94 127  80 205 151 173 116 112 196 163 166 200
 108 201 231 206 182 238 187 152 156 138 155 221 171 180 234 153 154 149
 148 181 176 323 208 183 165 198 217 170 204 203 178 270 194 237 249 189
 245 239 210 233 413 235 227 241 218 222 191 190 193 295 255 213 244 253
 282 315 290 224 339 209 246 278 307 242 345 271 207 220 236 248 267 216
 277 197 212 355 337 260 228 292 232 275 306 449 266 257 254 202 468 343
 263 367 264 300 320 226 251 280 308 423 327 274 311 268 296 250 265 349
 288 229 240 261 369 328]
```

[44]:

```python
plt.figure(figsize=(16, 8))

credit_metrics = ['new_accts_in_last_six_months',␣
 ↪'delinquent_accts_in_last_six_months', 'average_acct_age',␣
 ↪'credit_history_length']

for i, col in enumerate(credit_metrics):
    plt.subplot(2, 2, i + 1)
    sns.boxplot(x='loan_default', y=col, data=df2, palette='Set2')
    plt.title(f'{col.replace("_", " ").title()} vs. Loan Default Status')

# Show all plots
plt.tight_layout()
plt.show()
```



[45]:
```
credit_metrics.append('loan_default')

plt.figure(figsize=(12, 8))
sns.heatmap(df2[credit_metrics].corr(), annot=True, cmap='RdYlGn', fmt='.2f')
plt.title('Correlation Matrix - Credit History Factors and Loan Default')
plt.show()
```



0.3.8 3.6 Logistic Regression Model

[46]:
```
df2.columns
```

[46]:
```
Index(['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', 'age'],
      dtype='object')
```

[47]:
```
# Prepare data for modeling
# Drop non-numeric columns that are not needed for modeling
df_model = df2.drop(['uniqueid', 'loan_default', 'date_of_birth',␣
↪'disbursaldate'], axis=1)
df_model = pd.get_dummies(df_model)  # Convert categorical variables to dummy␣
↪variables
df_model
```

[47]:
```
        disbursed_amount  asset_cost    ltv  branch_id  supplier_id  \
0                  50578       58400  89.55         67        22807
1                  53278       61360  89.63         67        22807
2                  52378       60300  88.39         67        22807
3                  46349       61500  76.42         67        22807
4                  43594       78256  57.50         67        22744
…                    …           …     …           …           …
233149             57759       76350  77.28          5        22289
233150             55009       71200  78.72        138        17408
233151             58513       68000  88.24        135        23313
233152             22824       40458  61.79        160        16212
233153             35299       72698  52.27          3        14573

        manufacturer_id  current_pincode_id  state_id  employee_code_id  \
0                    45                1441         6              1998
1                    45                1497         6              1998
2                    45                1495         6              1998
3                    45                1502         6              1998
4                    86                1499         6              1998
…                   …                   …        …                 …
233149               51                3326         9              2229
233150               51                3385         9              2690
233151               45                1797         4                90
233152               48                  96        16              1299
233153               45                  17         1               665

        mobileno_avl_flag  …  perform_cns_score_description_K-High Risk  \
0                       1  …                                          0
1                       1  …                                          0
2                       1  …                                          0
3                       1  …                                          0
4                       1  …                                          0
…                     …  …                                          …
233149                  1  …                                          0
233150                  1  …                                          0
233151                  1  …                                          0
233152                  1  …                                          0
233153                  1  …                                          0
```

```
        perform_cns_score_description_L-Very High Risk  \
0                                                    0
1                                                    0
2                                                    0
3                                                    0
4                                                    0
…                                                 …
233149                                               0
233150                                               0
233151                                               0
233152                                               0
233153                                               0

        perform_cns_score_description_M-Very High Risk  \
0                                                    0
1                                                    0
2                                                    0
3                                                    0
4                                                    0
…                                                 …
233149                                               0
233150                                               0
233151                                               0
233152                                               0
233153                                               0

        perform_cns_score_description_No Bureau History Available  \
0                                                       1
1                                                       1
2                                                       1
3                                                       1
4                                                       1
…                                                    …
233149                                                  0
233150                                                  0
233151                                                  0
233152                                                  0
233153                                                  0

        perform_cns_score_description_Not Scored: More than 50 active Accounts
found  \
0                                                       0
1                                                       0
2                                                       0
3                                                       0
4                                                       0
…                                                    …
```

```
233149                                                      0
233150                                                      0
233151                                                      1
233152                                                      1
233153                                                      1

        perform_cns_score_description_Not Scored: No Activity seen on the
customer (Inactive)  \
0                                                           0
1                                                           0
2                                                           0
3                                                           0
4                                                           0
…                                                       …
233149                                                      0
233150                                                      0
233151                                                      0
233152                                                      0
233153                                                      0

        perform_cns_score_description_Not Scored: No Updates available in last
36 months  \
0                                                           0
1                                                           0
2                                                           0
3                                                           0
4                                                           0
…                                                       …
233149                                                      0
233150                                                      0
233151                                                      0
233152                                                      0
233153                                                      0

        perform_cns_score_description_Not Scored: Not Enough Info available on
the customer  \
0                                                           0
1                                                           0
2                                                           0
3                                                           0
4                                                           0
…                                                       …
233149                                                      0
233150                                                      0
233151                                                      0
233152                                                      0
233153                                                      0
```

```
        perform_cns_score_description_Not Scored: Only a Guarantor  \
0                                                        0
1                                                        0
2                                                        0
3                                                        0
4                                                        0
…                                                    …
233149                                                   1
233150                                                   1
233151                                                   0
233152                                                   0
233153                                                   0

        perform_cns_score_description_Not Scored: Sufficient History Not
Available
0                                                        0
1                                                        0
2                                                        0
3                                                        0
4                                                        0
…                                                    …
233149                                                   0
233150                                                   0
233151                                                   0
233152                                                   0
233153                                                   0

[233154 rows x 59 columns]
```

[48]:
```
X = df_model
y = df2['loan_default']
print('X shape: ',X.shape)
print('y shape: ',y.shape)
```

```
X shape:  (233154, 59)
y shape:  (233154,)
```

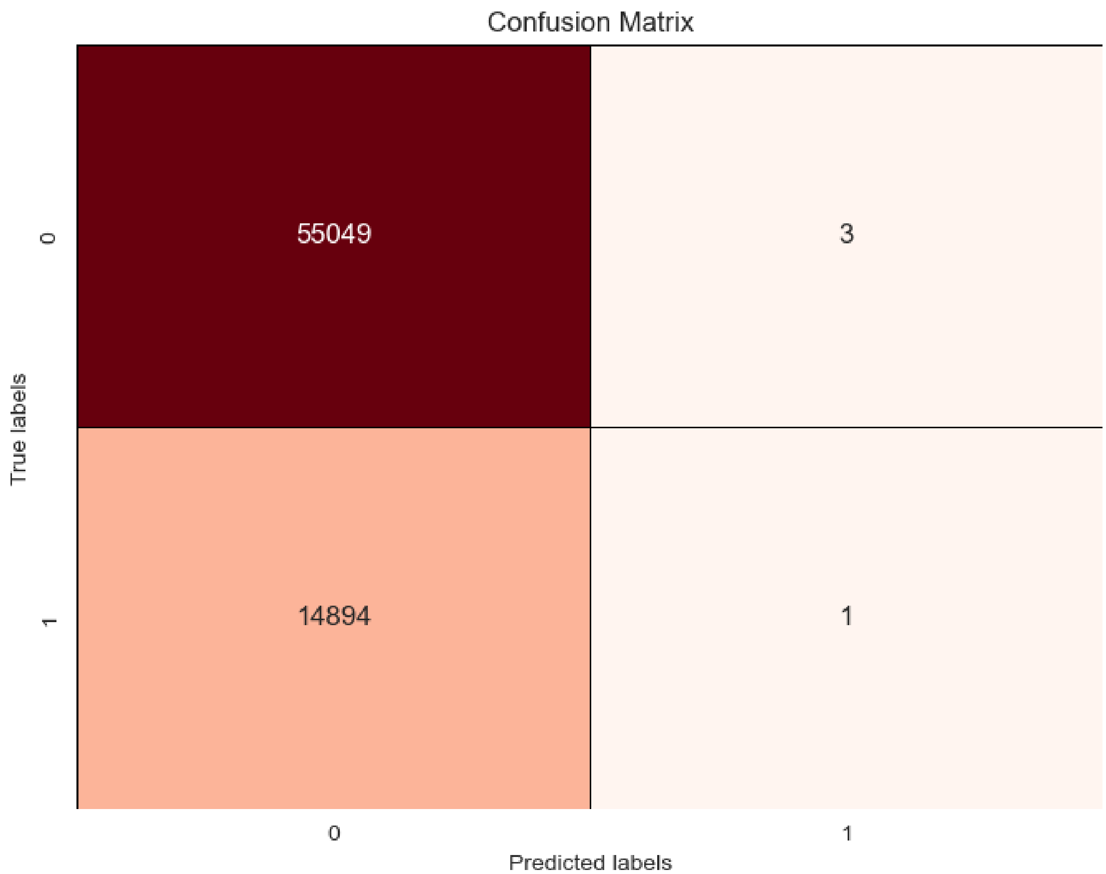
[49]:
```
# Split data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
↪random_state=42)

# Train Logistic Regression model
model = LogisticRegression(max_iter=1000)
model.fit(X_train, y_train)

# Predict and evaluate
```

```
y_pred = model.predict(X_test)
```

```
C:\Users\USER\anaconda3\Lib\site-packages\sklearn\linear_model\_logistic.py:460:
ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

[50]:

```
# Generate confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)

# Plot confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, cmap='Reds', fmt='g', cbar=False,
            annot_kws={"size": 12}, linewidths=0.5, linecolor='black')
plt.xlabel('Predicted labels')
plt.ylabel('True labels')
plt.title('Confusion Matrix')
plt.show()
```



0.3.9 Summary of Confusion Matrix Analysis

The confusion matrix reveals that the model has a high number of true negatives (55,049), indicating effective identification of non-defaulters. However, it has a very low number of true positives (1), reflecting poor performance in detecting actual defaulters. The model shows minimal false positives (3), suggesting high reliability when it predicts a defaulter. Yet, the substantial number of false negatives (14,894) points to a significant issue with missing actual defaulters.

Overall, while the model avoids false positives effectively, its failure to identify most defaulters limits its practical utility. Refining the model to enhance its sensitivity to defaulters is essential for improving its performance in detecting loan defaults.

[51]:
```
print("Classification Report:")
print(classification_report(y_test, y_pred))
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.79      1.00      0.88     55052
           1       0.25      0.00      0.00     14895
```

```
    accuracy                           0.79     69947
   macro avg       0.52      0.50      0.44     69947
weighted avg       0.67      0.79      0.69     69947
```

0.3.10 Summary of Classification Report

The classification report shows the following performance:

- **Class 0 (Non-Defaulters)**: The model excels in identifying non-defaulters with a high recall of 1.00 and a precision of 0.79, resulting in an F1-score of 0.88. It effectively identifies all non-defaulters.
- **Class 1 (Defaulters)**: The model performs poorly in detecting defaulters, with a recall of 0.00 and a precision of 0.25, leading to an F1-score of 0.00. It fails to identify any actual defaulters.
- **Overall Accuracy**: The model achieves an accuracy of 79%, but this is largely due to its strong performance on non-defaulters.
- **Average Metrics**: The macro average metrics reflect moderate overall performance with low scores for defaulters, while the weighted averages show better performance but still highlight issues in defaulter detection.

In summary, the model is effective at predicting non-defaulters but significantly underperforms in identifying defaulters. Improvements are needed to enhance its sensitivity to defaulters.