MATH2319 Machine Learning Project Phase 1
Predicting "Whether it will be Payment default in the first EMI on Vehicle Loan on due date or not" using the Loan Default Prediction Dataset

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Chapter 1

Introduction

1.1 Objective

The objective of this project is to predict whether it will be Payment default in the first EMI on Vehicle Loan on due date or not using the Loan Default Prediction Dataset from Kaggle[1]. The original dataset came from L&T Financial Services & Analytics Vidhya presented 'DataScience FinHack' competition.
This project has two phases. Phase I focuses on data pre-processing and exploration of the data, as covered in this report. We shall present model building in Phase II. The rest of this report is organised as follows. Section 2 describes the data sets and their attributes. Section 3 covers data pre-processing. In Section 4, we explore each attribute and their inter-relationships. The last section presents a brief summary of the report. Compiled from Jupyter Notebook, this report contains both narratives and the Python codes used for data pre-processing and exploration as a part of phase I of the project.

1.2 Data Sets

The Kaggle Machine Learning datasets provides one data set named 'train.csv' under the heading 'Loan Default Prediction'. Names of attributes are adapted from the data description provided in Kaggle. Data set consist of 40 descriptive features and one target feature. In Phase II, we will build the classifiers from the the data set and evaluate their performance using cross-validation.

1.2.1 Target Feature

The response feature is loan_default which is given as:

The target feature has two classes and hence it is a binary classification problem. To reiterate, the goal is to predict **whether or not it will be Payment default in the first EMI on due date by Customer**.

1.2.2 Descriptive Features

The variable description is produced here from the data description itself :

- `UniqueID`: Identifier for customers
- `disbursed_amount`: Amount of Loan disbursed
- `asset_cost`: Cost of the Asset
- `ltv`: Loan to Value of the asset
- `branch_id`: Branch where the loan was disbursed
- `supplier_id`: Vehicle Dealer where the loan was disbursed
- `manufacturer_id`: Vehicle manufacturer(Hero, Honda, TVS etc.)
- `Current_pincode_ID`: Current pincode of the customer
- `Date.of.Birth`: Date of birth of the customer

- `Employment.Type`: Employment Type of the customer (Salaried/Self Employed)
- `DisbursalDate`: Date of disbursement
- `State_ID`: State of disbursement
- `Employee_code_ID`: Employee of the organization who logged the disbursement
- `MobileNo_Avl_Flag`: if Mobile no. was shared by the customer then flagged as 1
- `Aadhar_flag`: if aadhar was shared by the customer then flagged as 1
- `PAN_flag`: if pan was shared by the customer then flagged as 1
- `VoterID_flag`: if voter was shared by the customer then flagged as 1
- `Driving_flag`: if DL was shared by the customer then flagged as 1
- `Passport_flag`: if passport was shared by the customer then flagged as 1
- `PERFORM_CNS.SCORE`: Bureau Score
- `PERFORM_CNS.SCORE.DESCRIPTION`: Bureau score description
- `PRI.NO.OF.ACCTS`: count of total loans taken by the customer at the time of disbursement
- `PRI.ACTIVE.ACCTS`: count of active loans taken by the customer at the time of disbursement
- `PRI.OVERDUE.ACCTS`: count of default accounts at the time of disbursement
- `PRI.CURRENT.BALANCE`: total Principal outstanding amount of the active loans at the time of disbursement
- `PRI.SANCTIONED.AMOUNT`: total amount that was sanctioned for all the loans at the time of disbursement
- `PRI.DISBURSED.AMOUNT`: total amount that was disbursed for all the loans at the time of disbursement
- `SEC.NO.OF.ACCTS`: count of total loans taken by the customer at the time of disbursement
- `SEC.ACTIVE.ACCTS`: count of active loans taken by the customer at the time of disbursement
- `SEC.OVERDUE.ACCTS`: count of default accounts at the time of disbursement
- `SEC.CURRENT.BALANCE`: total Principal outstanding amount of the active loans at the time of disbursement
- `SEC.SANCTIONED.AMOUNT`: total amount that was sanctioned for all the loans at the time of disbursement
- `SEC.DISBURSED.AMOUNT`: total amount that was disbursed for all the loans at the time of disbursement
- `PRIMARY.INSTAL.AMT`: EMI Amount of the primary loan
- `SEC.INSTAL.AMT`: EMI Amount of the secondary loan
- `NEW.ACCTS.IN.LAST.SIX.MONTHS`: New loans taken by the customer in last 6 months before the disbursment
- `DELINQUENT.ACCTS.IN.LAST.SIX.MONTHS`: Loans defaulted in the last 6 months
- `AVERAGE.ACCT.AGE`: Average loan tenure
- `CREDIT.HISTORY.LENGTH`: Time since first loan
- `NO.OF_INQUIRIES`: Enquries done by the customer for loans
- `loan_default`: Payment default in the first EMI on due date

Chapter 2

Data Pro-processsing

2.1 Preliminaries

We read dataset from the local storage. Also, since the data set contains the attribute names, we do not need to explicitly specify those during loading the data sets.

```
In [1]: #pd.show_versions(as_json=False)
        import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        import seaborn as sns
        from pandas.plotting import scatter_matrix

In [2]: Loan_Data = pd.read_csv('Loan_Default_Data.csv', sep = ",")

In [3]: Loan_Data.head()

Out[3]:    UniqueID  disbursed_amount  asset_cost    ltv  branch_id  supplier_id  \
        0    420825             50578       58400  89.55         67        22807
        1    537409             47145       65550  73.23         67        22807
        2    417566             53278       61360  89.63         67        22807
        3    624493             57513       66113  88.48         67        22807
        4    539055             52378       60300  88.39         67        22807

           manufacturer_id  Current_pincode_ID Date.of.Birth Employment.Type  ...  \
        0               45                1441      01-01-84        Salaried  ...
        1               45                1502      31-07-85   Self employed  ...
        2               45                1497      24-08-85   Self employed  ...
        3               45                1501      30-12-93   Self employed  ...
        4               45                1495      09-12-77   Self employed  ...

          SEC.SANCTIONED.AMOUNT  SEC.DISBURSED.AMOUNT  PRIMARY.INSTAL.AMT  \
        0                     0                     0                   0
        1                     0                     0                1991
        2                     0                     0                   0
        3                     0                     0                  31
        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                                    1        1yrs 11mon
2                                    0         0yrs 0mon
3                                    0         0yrs 8mon
4                                    0         0yrs 0mon

   CREDIT.HISTORY.LENGTH  NO.OF_INQUIRIES  loan_default
0              0yrs 0mon                0             0
1             1yrs 11mon                0             1
2              0yrs 0mon                0             0
3              1yrs 3mon                1             1
4              0yrs 0mon                1             1

[5 rows x 41 columns]
```

2.2 Data Cleaning and Transformation

First, we confirmed that the feature types matches the description as outlined in the documentation.

In [4]:
```
print(f"Dimension of the data set is{Loan_Data.shape}\n")
print(f"Data Types are:")
print(Loan_Data.dtypes)
```

```
Dimension of the data set is(233154, 41)

Data Types are:
UniqueID                                 int64
disbursed_amount                         int64
asset_cost                               int64
ltv                                    float64
branch_id                                int64
supplier_id                              int64
manufacturer_id                          int64
Current_pincode_ID                       int64
Date.of.Birth                           object
Employment.Type                         object
DisbursalDate                           object
State_ID                                 int64
Employee_code_ID                         int64
MobileNo_Avl_Flag                        int64
Aadhar_flag                              int64
PAN_flag                                 int64
VoterID_flag                             int64
Driving_flag                             int64
Passport_flag                            int64
PERFORM_CNS.SCORE                        int64
PERFORM_CNS.SCORE.DESCRIPTION           object
PRI.NO.OF.ACCTS                          int64
PRI.ACTIVE.ACCTS                         int64
```

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

As can be seen, Only `Employment.Type` contains NA values in the dataset. We need to replace those values. We will check the value counts for this attribute and then come up with solution to replace these values in next section and remove unnecessary columns from the dataset.

```
In [5]: print('Initial Null Counts: ')
        print('')
        Loan_Data.isnull().sum()
```

```
Initial Null Counts:
```

```
Out[5]: 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
```

Employement Type has two categories of Employment, self employed and salaried. There can be people who are not employed. So we will replce NA values with third category of Employment.Type i.e. 'Unemployed'.

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

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

```
In [7]: Loan_Data['Employment.Type'].fillna('Unemployed', inplace = True)
```

We will check the value counts for all unique IDs.

```
In [8]: categoricalColumn = ['UniqueID', 'branch_id', 'supplier_id', 'manufacturer_id',
                             'Current_pincode_ID', 'State_ID', 'Employee_code_ID']

        for col in categoricalColumn:
            print('Unique Valuess for ' + col)
            print(Loan_Data[col].nunique())
            print('')
```

```
Unique Valuess for UniqueID
233154

Unique Valuess for branch_id
82

Unique Valuess for supplier_id
2953

Unique Valuess for manufacturer_id
11

Unique Valuess for Current_pincode_ID
```

```
6698

Unique Valuess for State_ID
22

Unique Valuess for Employee_code_ID
3270
```

As discussed the in previous section, `UniqueID`, `supplier_id`, `Current_pincode_ID`, `DisbursalDate`, `Employee_code_ID` are removed as they are unnecessary & do not have any directly related predicting power. We will remove `Date.of.Birth` after extracting year part from the date for the age of customer. So, we will use dataset with 34 featues instead of 40 after ignoring these 6 features.

```
In [9]: columns_to_drop = ['UniqueID', 'supplier_id', 'Current_pincode_ID', 'DisbursalDate',
                           'Employee_code_ID']
        Loan_Data.drop(columns_to_drop, axis=1, inplace=True)
        Loan_Data.shape
```

```
Out[9]: (233154, 36)
```

Some attributes are categorical but they are in integer so we will convert them into categorical.

```
In [10]: Loan_Data['branch_id'] = Loan_Data['branch_id'].astype('category')
         Loan_Data['manufacturer_id'] = Loan_Data['manufacturer_id'].astype('category')
         Loan_Data['State_ID'] = Loan_Data['State_ID'].astype('category')
         Loan_Data['NEW.ACCTS.IN.LAST.SIX.MONTHS'] = Loan_Data['NEW.ACCTS.IN.LAST.SIX.MONTHS'].astype('
         Loan_Data['DELINQUENT.ACCTS.IN.LAST.SIX.MONTHS'] = Loan_Data['DELINQUENT.ACCTS.IN.LAST.SIX.MON
         Loan_Data['NO.OF_INQUIRIES'] = Loan_Data['NO.OF_INQUIRIES'].astype('category')
         Loan_Data['loan_default'] = Loan_Data['loan_default'].astype('category')
         Loan_Data['Employment.Type'] = Loan_Data['Employment.Type'].astype('category')
```

We have checked for the NaN values in a dataset.

```
In [11]: for i in ['disbursed_amount', 'asset_cost', 'ltv', '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']:
             print(i+' = '+str(np.isnan(Loan_Data[i]).sum()))
```

```
disbursed_amount = 0
asset_cost = 0
ltv = 0
MobileNo_Avl_Flag = 0
Aadhar_flag = 0
PAN_flag = 0
VoterID_flag = 0
Driving_flag = 0
Passport_flag = 0
PERFORM_CNS.SCORE = 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
```

Table 1 shows that `AVERAGE.ACCT.AGE` & `CREDIT.HISTORY.LENGTH` are having string values for length in years and months with 192 & 294 unique values respectively. We will extract year & month part of the String to know Average Loan Tenure & Time since first loan in months as it is more informative than String values.

```
In [12]: from IPython.display import display, HTML

         display(HTML('<b>Summary Table of continuous features</b>'))
         display(Loan_Data.describe())

         display(HTML('<b>Summary Table of object features</b>'))
         display(Loan_Data.describe(include = 'object'))

         display(HTML('<b>Summary Table of categorical features</b>'))
         display(Loan_Data.describe(include = 'category'))
```

```
<IPython.core.display.HTML object>


       disbursed_amount    asset_cost            ltv  MobileNo_Avl_Flag  \
count     233154.000000  2.331540e+05  233154.000000           233154.0
mean       54356.993528  7.586507e+04      74.746530                1.0
std        12971.314171  1.894478e+04      11.456636                0.0
min        13320.000000  3.700000e+04      10.030000                1.0
25%        47145.000000  6.571700e+04      68.880000                1.0
50%        53803.000000  7.094600e+04      76.800000                1.0
75%        60413.000000  7.920175e+04      83.670000                1.0
max       990572.000000  1.628992e+06      95.000000                1.0

        Aadhar_flag       PAN_flag   VoterID_flag   Driving_flag  \
count  233154.00000  233154.000000  233154.000000  233154.000000
mean        0.84032       0.075577       0.144943       0.023242
std         0.36631       0.264320       0.352044       0.150672
min         0.00000       0.000000       0.000000       0.000000
25%         1.00000       0.000000       0.000000       0.000000
50%         1.00000       0.000000       0.000000       0.000000
75%         1.00000       0.000000       0.000000       0.000000
max         1.00000       1.000000       1.000000       1.000000

       Passport_flag  PERFORM_CNS.SCORE  ...  PRI.SANCTIONED.AMOUNT  \
```

```
count  233154.000000      233154.000000  ...           2.331540e+05
mean        0.002127         289.462994  ...           2.185039e+05
std         0.046074         338.374779  ...           2.374794e+06
min         0.000000           0.000000  ...           0.000000e+00
25%         0.000000           0.000000  ...           0.000000e+00
50%         0.000000           0.000000  ...           0.000000e+00
75%         0.000000         678.000000  ...           6.250000e+04
max         1.000000         890.000000  ...           1.000000e+09

       PRI.DISBURSED.AMOUNT  SEC.NO.OF.ACCTS  SEC.ACTIVE.ACCTS  \
count          2.331540e+05    233154.000000     233154.000000
mean           2.180659e+05         0.059081          0.027703
std            2.377744e+06         0.626795          0.316057
min            0.000000e+00         0.000000          0.000000
25%            0.000000e+00         0.000000          0.000000
50%            0.000000e+00         0.000000          0.000000
75%            6.080000e+04         0.000000          0.000000
max            1.000000e+09        52.000000         36.000000

       SEC.OVERDUE.ACCTS  SEC.CURRENT.BALANCE  SEC.SANCTIONED.AMOUNT  \
count      233154.000000         2.331540e+05           2.331540e+05
mean            0.007244         5.427793e+03           7.295923e+03
std             0.111079         1.702370e+05           1.831560e+05
min             0.000000        -5.746470e+05           0.000000e+00
25%             0.000000         0.000000e+00           0.000000e+00
50%             0.000000         0.000000e+00           0.000000e+00
75%             0.000000         0.000000e+00           0.000000e+00
max             8.000000         3.603285e+07           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

[8 rows x 24 columns]


<IPython.core.display.HTML object>


       Date.of.Birth PERFORM_CNS.SCORE.DESCRIPTION AVERAGE.ACCT.AGE  \
count         233154                        233154           233154
unique         15433                            20              192
top         01-01-88   No Bureau History Available        0yrs 0mon
freq            2173                        116950           119373

       CREDIT.HISTORY.LENGTH
count                 233154
unique                   294
top                0yrs 0mon
```

```
freq                  119127
```

```
<IPython.core.display.HTML object>
```

```
        branch_id  manufacturer_id Employment.Type  State_ID  \
count      233154           233154          233154    233154
unique         82               11               3        22
top             2               86   Self employed         4
freq        13138           109534          127635     44870

        NEW.ACCTS.IN.LAST.SIX.MONTHS  DELINQUENT.ACCTS.IN.LAST.SIX.MONTHS  \
count                         233154                               233154
unique                            26                                   14
top                                0                                    0
freq                          181494                               214959

        NO.OF_INQUIRIES  loan_default
count            233154        233154
unique               25             2
top                   0             0
freq             201961        182543
```

2.2.1 Categorical & Continuous Features

All the categorical variables have valid unque values, so we do not need to apply `lower()` or `strip()` functions to any of the features.

```
In [13]: categoricalColumn = ['Employment.Type', 'branch_id', 'manufacturer_id', 'State_ID',
                              'NEW.ACCTS.IN.LAST.SIX.MONTHS','DELINQUENT.ACCTS.IN.LAST.SIX.MONTHS',
                             'NO.OF_INQUIRIES','loan_default']

         for col in categoricalColumn:
             print('Value Counts for ' + col)
             print(Loan_Data[col].value_counts())
             print('')
```

```
Value Counts for Employment.Type
Self employed    127635
Salaried          97858
Unemployed         7661
Name: Employment.Type, dtype: int64

Value Counts for branch_id
2      13138
67     11328
3       9230
5       9218
36      8832
136     7833
34      7794
16      6466
19      5860
```

```
1       5709
146     5376
18      5032
152     4933
61      4906
48      4725
11      4506
20      4431
138     4352
74      4297
120     4210
147     4160
10      4125
103     3878
251     3844
65      3509
160     3505
79      3413
7       3222
135     3203
8       3146
       ...
77      1445
72      1294
257     1256
17      1160
130     1069
82      1035
165     1021
121      884
249      858
76       855
69       810
35       693
153      692
62       691
207      689
43       584
117      558
142      473
97       389
258      374
260      372
101      368
259      346
100      331
66       314
217      183
261      176
84       156
111       89
158       69
Name: branch_id, Length: 82, dtype: int64
```

```
Value Counts for manufacturer_id
86     109534
45      56626
51      27204
48      16710
49      10220
120      9658
67       2405
145       778
153        12
152         6
156         1
Name: manufacturer_id, dtype: int64

Value Counts for State_ID
4     44870
3     34078
6     33505
13    17884
9     16022
8     14197
5     10177
14     9414
1      8936
7      6786
11     6721
18     5412
15     5049
12     4210
2      4160
17     3991
10     3605
16     2685
19     1035
20      185
21      156
22       76
Name: State_ID, dtype: int64

Value Counts for NEW.ACCTS.IN.LAST.SIX.MONTHS
0     181494
1      32099
2      11015
3       4458
4       1957
5        964
6        480
7        302
8        147
9         79
10        55
11        31
12        20
13        15
```

```
14        11
16         6
17         6
20         3
15         2
18         2
19         2
23         2
28         1
21         1
22         1
35         1
Name: NEW.ACCTS.IN.LAST.SIX.MONTHS, dtype: int64

Value Counts for DELINQUENT.ACCTS.IN.LAST.SIX.MONTHS
0     214959
1      14941
2       2470
3        537
4        138
5         58
6         20
7         13
8          7
12         3
11         3
10         2
9          2
20         1
Name: DELINQUENT.ACCTS.IN.LAST.SIX.MONTHS, dtype: int64

Value Counts for NO.OF_INQUIRIES
0     201961
1      22285
2       5409
3       1767
4        760
5        343
6        239
7        135
8        105
9         44
10        34
11        15
12        14
14         8
15         7
13         6
19         6
17         4
18         4
16         3
28         1
20         1
```

```
22         1
23         1
36         1
Name: NO.OF_INQUIRIES, dtype: int64

Value Counts for loan_default
0    182543
1     50611
Name: loan_default, dtype: int64
```

We have encoded bureau score of PERFORM_CNS.SCORE.DESCRIPTION feature from category to integer.

```
In [14]: temp_col = ['PERFORM_CNS.SCORE.DESCRIPTION']

         Loan_Data[temp_col] = Loan_Data[temp_col].replace('No Bureau History Available', 0)
         Loan_Data[temp_col] = Loan_Data[temp_col].replace('Not Scored: Sufficient History Not Availabl
         Loan_Data[temp_col] = Loan_Data[temp_col].replace('Not Scored: Not Enough Info available on th
         Loan_Data[temp_col] = Loan_Data[temp_col].replace('Not Scored: No Activity seen on the custome
         Loan_Data[temp_col] = Loan_Data[temp_col].replace('Not Scored: No Updates available in last 36
         Loan_Data[temp_col] = Loan_Data[temp_col].replace('Not Scored: Only a Guarantor', 0)
         Loan_Data[temp_col] = Loan_Data[temp_col].replace('Not Scored: More than 50 active Accounts fo
         Loan_Data[temp_col] = Loan_Data[temp_col].replace('M-Very High Risk', 1)
         Loan_Data[temp_col] = Loan_Data[temp_col].replace('L-Very High Risk', 1)
         Loan_Data[temp_col] = Loan_Data[temp_col].replace('K-High Risk', 2)
         Loan_Data[temp_col] = Loan_Data[temp_col].replace('J-High Risk', 2)
         Loan_Data[temp_col] = Loan_Data[temp_col].replace('I-Medium Risk', 3)
         Loan_Data[temp_col] = Loan_Data[temp_col].replace('H-Medium Risk', 3)
         Loan_Data[temp_col] = Loan_Data[temp_col].replace('G-Low Risk', 4)
         Loan_Data[temp_col] = Loan_Data[temp_col].replace('F-Low Risk', 4)
         Loan_Data[temp_col] = Loan_Data[temp_col].replace('E-Low Risk', 4)
         Loan_Data[temp_col] = Loan_Data[temp_col].replace('D-Very Low Risk', 5)
         Loan_Data[temp_col] = Loan_Data[temp_col].replace('C-Very Low Risk', 5)
         Loan_Data[temp_col] = Loan_Data[temp_col].replace('B-Very Low Risk', 5)
         Loan_Data[temp_col] = Loan_Data[temp_col].replace('A-Very Low Risk', 5)
```

Checking Unique values in each categorical attributes.

```
In [15]: categoricalColumn = ['Employment.Type', 'branch_id', 'manufacturer_id', 'State_ID',
                               'NEW.ACCTS.IN.LAST.SIX.MONTHS','DELINQUENT.ACCTS.IN.LAST.SIX.MONTHS',
                              'NO.OF_INQUIRIES', 'PERFORM_CNS.SCORE.DESCRIPTION', 'loan_default']

         for col in categoricalColumn:
             print('Unique values for ' + col)
             print(Loan_Data[col].unique())
             print('')
```

```
Unique values for Employment.Type
[Salaried, Self employed, Unemployed]
Categories (3, object): [Salaried, Self employed, Unemployed]

Unique values for branch_id
[67, 78, 34, 130, 74, ..., 14, 121, 217, 84, 100]
Length: 82
```

```
Categories (82, int64): [67, 78, 34, 130, ..., 121, 217, 84, 100]

Unique values for manufacturer_id
[45, 86, 48, 51, 120, ..., 145, 67, 153, 156, 152]
Length: 11
Categories (11, int64): [45, 86, 48, 51, ..., 67, 153, 156, 152]

Unique values for State_ID
[6, 4, 3, 9, 5, ..., 8, 20, 19, 22, 21]
Length: 22
Categories (22, int64): [6, 4, 3, 9, ..., 20, 19, 22, 21]

Unique values for NEW.ACCTS.IN.LAST.SIX.MONTHS
[0, 1, 4, 2, 6, ..., 23, 16, 20, 18, 21]
Length: 26
Categories (26, int64): [0, 1, 4, 2, ..., 16, 20, 18, 21]

Unique values for DELINQUENT.ACCTS.IN.LAST.SIX.MONTHS
[0, 1, 2, 3, 5, ..., 9, 12, 10, 20, 11]
Length: 14
Categories (14, int64): [0, 1, 2, 3, ..., 12, 10, 20, 11]

Unique values for NO.OF_INQUIRIES
[0, 1, 4, 2, 3, ..., 23, 28, 16, 22, 36]
Length: 25
Categories (25, int64): [0, 1, 4, 2, ..., 28, 16, 22, 36]

Unique values for PERFORM_CNS.SCORE.DESCRIPTION
[0 3 1 5 4 2]

Unique values for loan_default
[0, 1]
Categories (2, int64): [0, 1]
```

We have defined 2 functions **AvgAcctAge(x)** & **calcAge(x)** for calculate age of account in months & age of customer in years respectively.

```
In [16]: def AvgAcctAge(x):
             year = int(x.split(" ")[0].split("y")[0])
             month = int(x.split(" ")[1].split("m")[0])
             time_int = (12*year) + month
             return time_int


         def calcAge(x):
             year = int(x.split('-')[2])
             if(year<=19):
                 age = 20-year
             else:
                 age = 100 + (20-year)
             return age
```

We will apply this function to our columns to gain values.

```
In [17]: Loan_Data['Age']=Loan_Data['Date.of.Birth'].apply(calcAge)

         Loan_Data["AvgAcctAge"] = Loan_Data['AVERAGE.ACCT.AGE'].apply(AvgAcctAge)
         Loan_Data['CredAcctAge'] = Loan_Data['CREDIT.HISTORY.LENGTH'].apply(AvgAcctAge)
```

Now we will drop `Date.of.Birth`, `AVERAGE.ACCT.AGE` and `CREDIT.HISTORY.LENGTH` columns.

```
In [18]: columns_to_drop = ['Date.of.Birth', 'AVERAGE.ACCT.AGE', 'CREDIT.HISTORY.LENGTH']
         Loan_Data.drop(columns_to_drop, axis=1, inplace=True)
```

Final Check for Null Counts & Shape of Dataset

```
In [19]: print('Final Null Counts : ')
         print(Loan_Data.isnull().sum())
         print('')
         print('Final shape of Dataset : '+str(Loan_Data.shape))
```

```
Final Null Counts :
disbursed_amount                       0
asset_cost                             0
ltv                                    0
branch_id                              0
manufacturer_id                        0
Employment.Type                        0
State_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
NO.OF_INQUIRIES                        0
loan_default                           0
Age                                    0
AvgAcctAge                             0
CredAcctAge                            0
dtype: int64
```

```
Final shape of Dataset : (233154, 36)
```

Chapter 3

Data Exploration

3.1 Univariate Visualisation

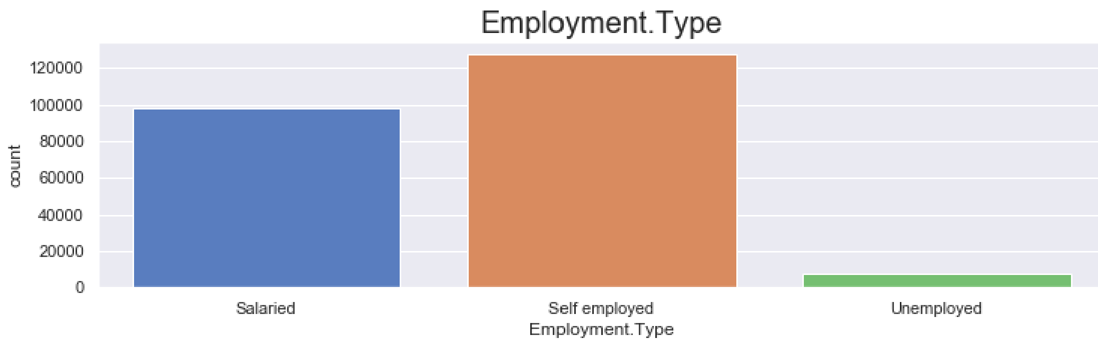
To avoid code repeatation, we defined two functions named `BarPlot(x)`[2] and `BoxAndHistogramPlot(x)`[3] for categorical and numerical features respectively. For given an input categorical column `x`, `BarPlot(x)` returns a bar chart. A bar chart is useful to present the proportions by categories. For given an input numerical column `x`, `BoxHistogramPlot(x)` plots a histogram and a box plot. A histogram is useful to visualize the shape of the underlying distribution whereas a box plot tells the range of the attribute and helps detect any outliers. The following chunk codes show how these function were defined using the `numpy` library and the matplotlib library.

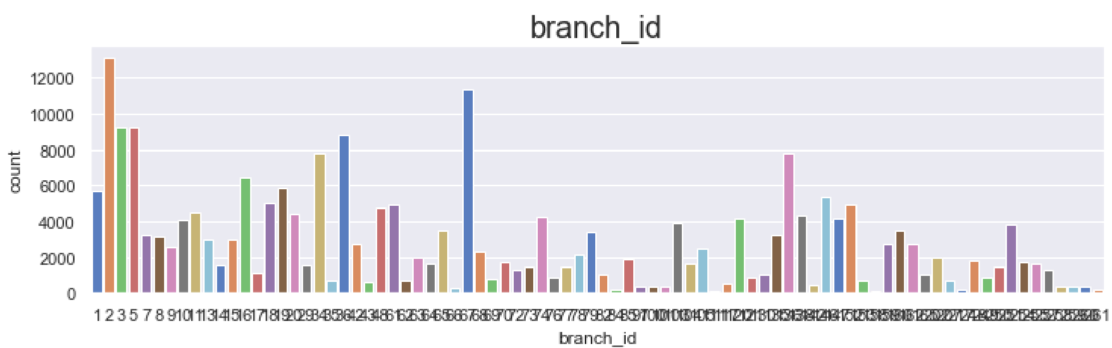
```
In [20]: import matplotlib.pyplot as plt
         import matplotlib as mpl
         sns.set(color_codes=True)

         def BarPlot(x):
             sns.countplot(Loan_Data[x], palette = 'muted')
             plt.title(x,  fontsize = 20)

         def BoxAndHistogramPlot(x):
             f, (ax_box, ax_hist) = plt.subplots(2, sharex=True,
                                         gridspec_kw={"height_ratios": (.15, .85)})
             sns.boxplot(x, ax=ax_box, color='red')
             sns.distplot(x, ax=ax_hist, color='magenta')

             ax_box.set(yticks=[])
             sns.despine(ax=ax_hist)
             sns.despine(ax=ax_box, left=True)
             plt.show()
```

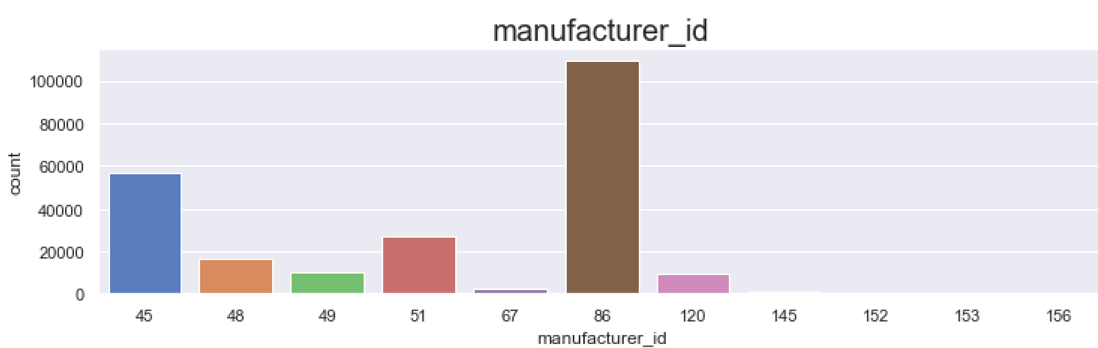
As can be seen from the graphs of categorical variables, Different branches of Bank, different Employment type, different manufacturer or ,state has different proportions of loan sanctioned. The bar plot of `NEW.ACCTS.IN.LAST.SIX.MONTHS` and `DELINQUENT.ACCTS.IN.LAST.SIX.MONTHS` suggests than more than 80 percent customers have 0 Default Account in last six months or 0 new loans taken in last six months before the disbursement. The proportions of customer defaulting on fir EMI loan is, 21% outcomes with result **Yes** and 79% outcomes with result **No** in the dataset.

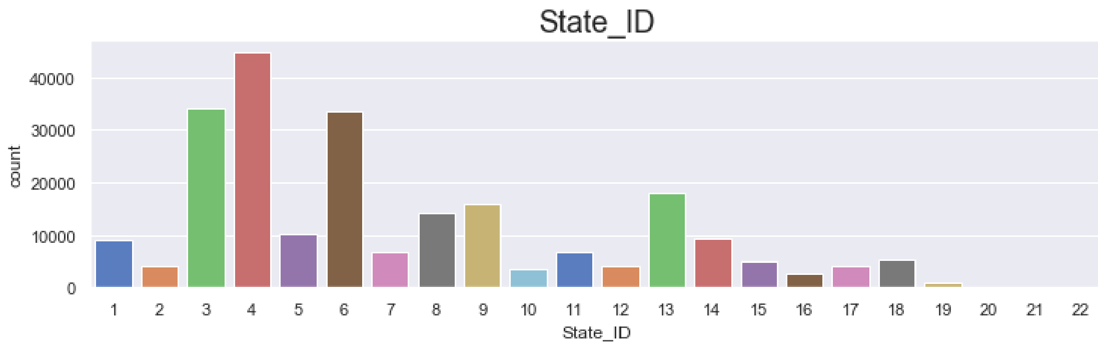
```
In [21]: i = 1
         for col in ['Employment.Type', 'branch_id', 'manufacturer_id', 'State_ID',
                             'NEW.ACCTS.IN.LAST.SIX.MONTHS','DELINQUENT.ACCTS.IN.LAST.SIX.MONTHS',
                            'NO.OF_INQUIRIES', 'PERFORM_CNS.SCORE.DESCRIPTION', 'loan_default']:
```

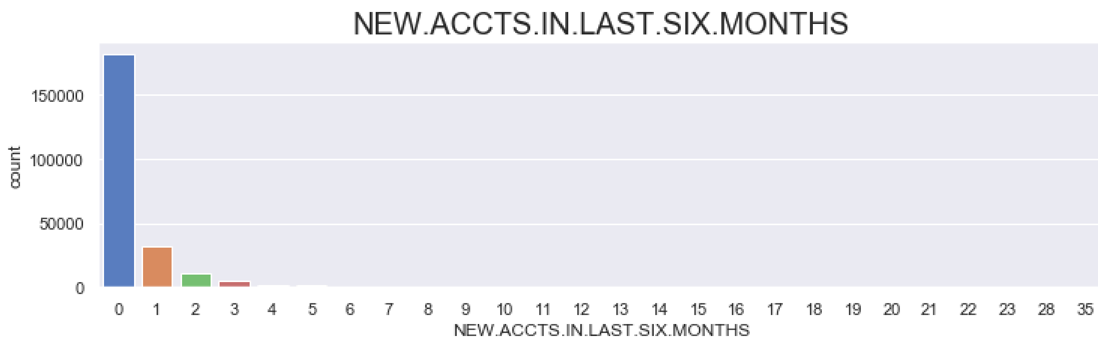
```
plt.figure(figsize=(12,3))
plt.title("Figure " + str(i) + ": Bar Chart of " + col, fontsize = 12)
BarPlot(col)
plt.show()
i = i + 1
```

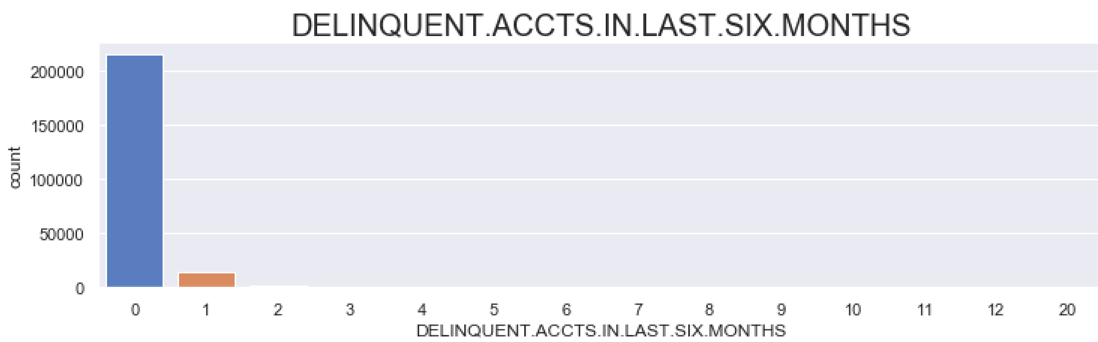


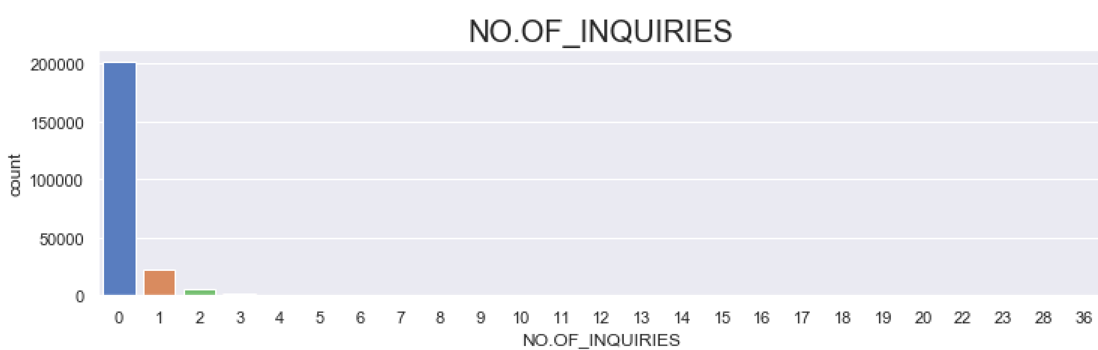


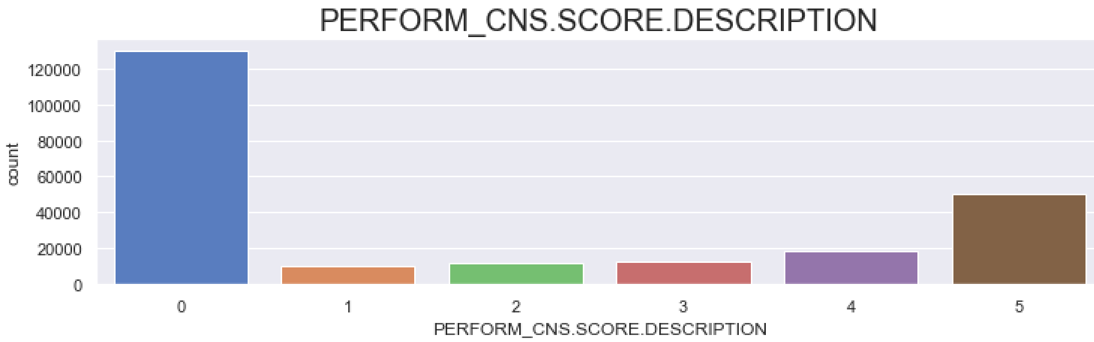


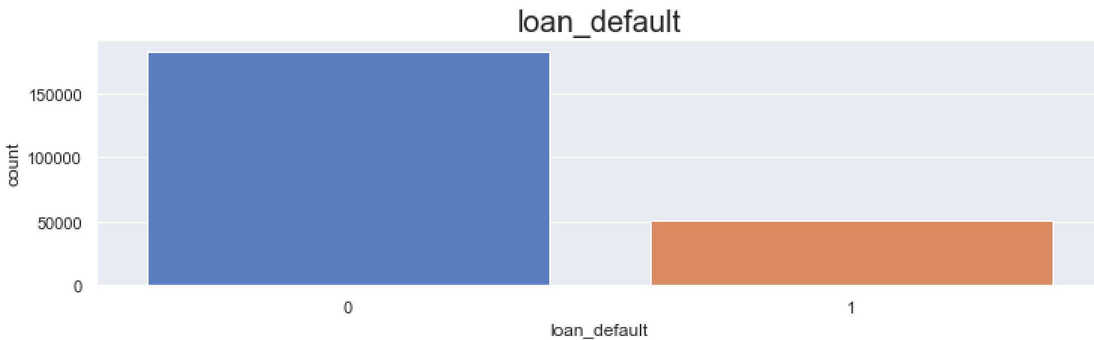

State_ID
count
0
10000
20000
30000
40000
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22
State_ID


NEW.ACCTS.IN.LAST.SIX.MONTHS
count
0
50000
100000
150000
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 28 35
NEW.ACCTS.IN.LAST.SIX.MONTHS


DELINQUENT.ACCTS.IN.LAST.SIX.MONTHS
count
0
50000
100000
150000
200000
0 1 2 3 4 5 6 7 8 9 10 11 12 20
DELINQUENT.ACCTS.IN.LAST.SIX.MONTHS

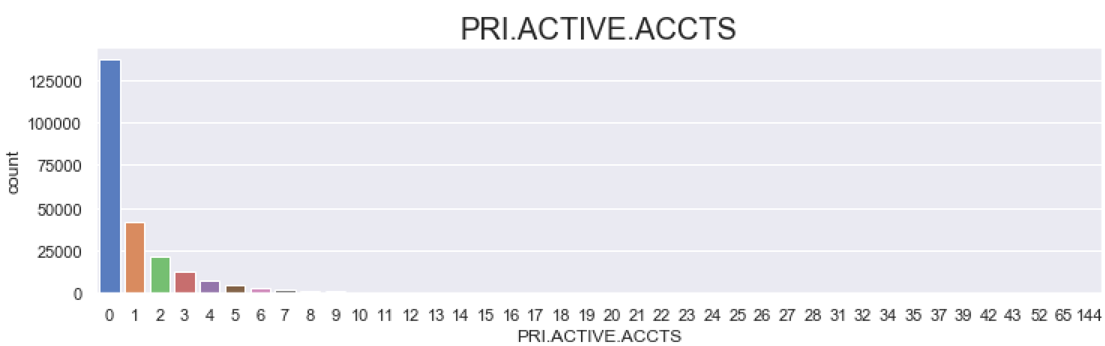

NO.OF_INQUIRIES
count
0
50000
100000
150000
200000
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 22 23 28 36
NO.OF_INQUIRIES

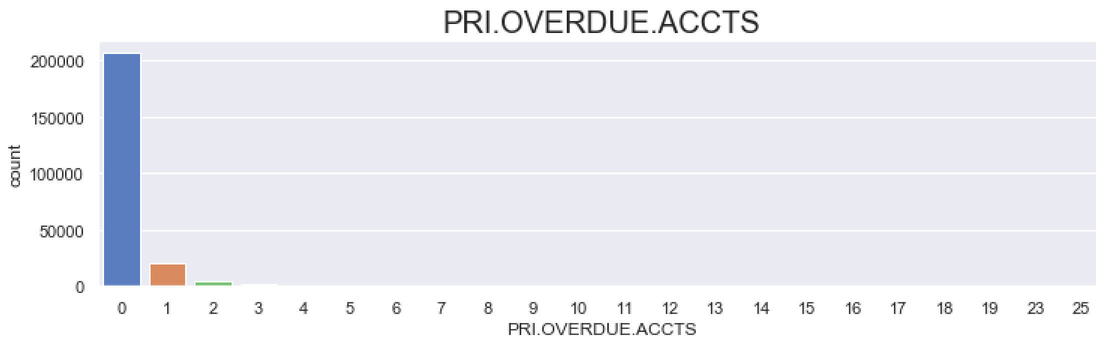


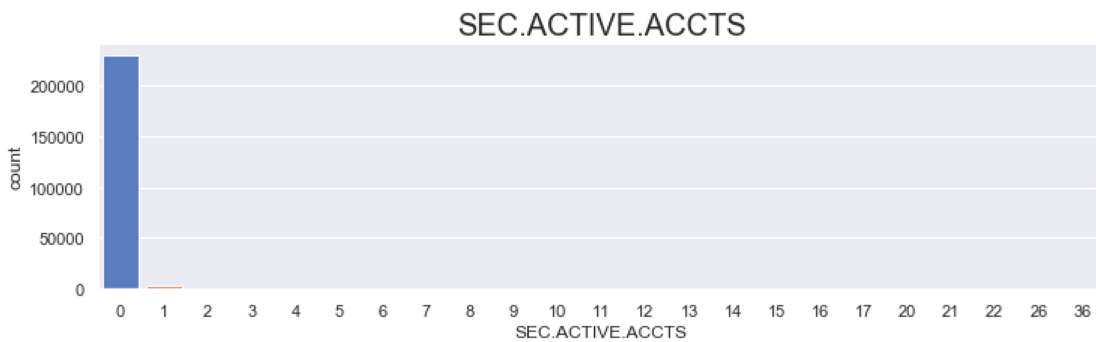


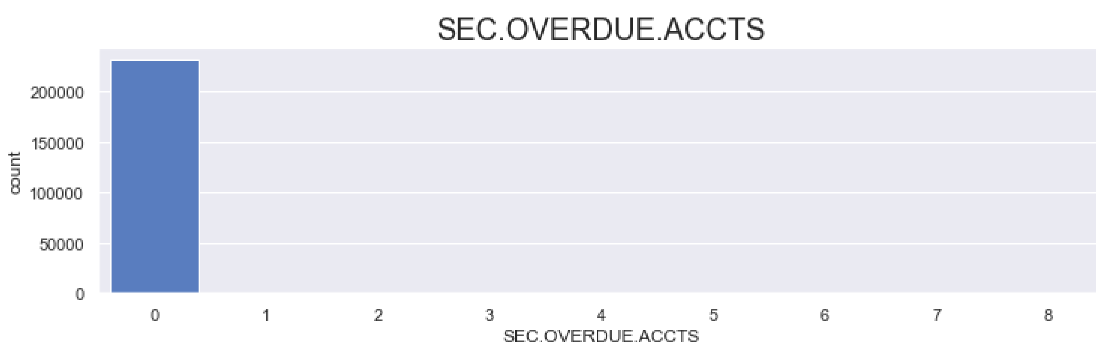
We have also plotted graphs for `PRI.ACTIVE.ACCTS`, `PRI.OVERDUE.ACCTS`, `SEC.ACTIVE.ACCTS` and `SEC.OVERDUE.ACCTS` attributes to visualize the proportions of number of active and overdue loan accounts for customers.

```
In [22]: for col in ['PRI.ACTIVE.ACCTS',
                     'PRI.OVERDUE.ACCTS', 'SEC.ACTIVE.ACCTS',
                     'SEC.OVERDUE.ACCTS']:
             plt.figure(figsize=(12,3))
             plt.title("Figure " + str(i) + ": Bar Chart of " + col, fontsize = 12)
             BarPlot(col)
             plt.show()
             i = i + 1
```



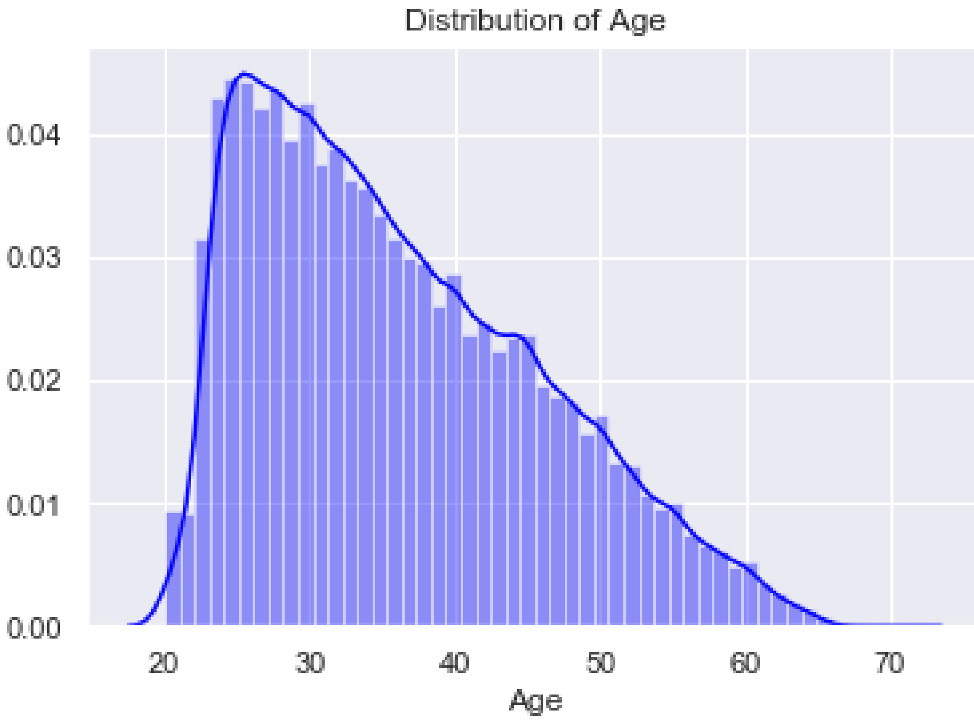






The Feature derived from the attribute `Dtae.of.Birth`; `Age` is plotted here using `distplot()` funftion of 'seaborn' library. Majority of the loan takers are in the age group of 25 to 40 years.

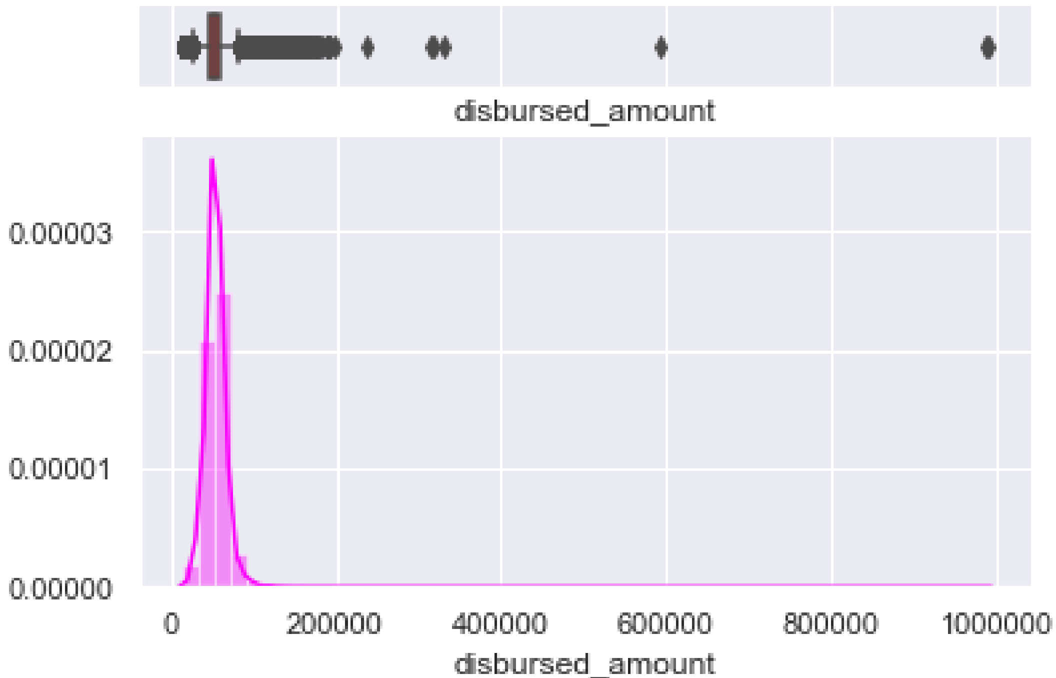
```
In [23]: import seaborn as sns

         sns.distplot(Loan_Data['Age'], color = 'blue')
         plt.title('Distribution of Age')

Out[23]: Text(0.5, 1.0, 'Distribution of Age')
```



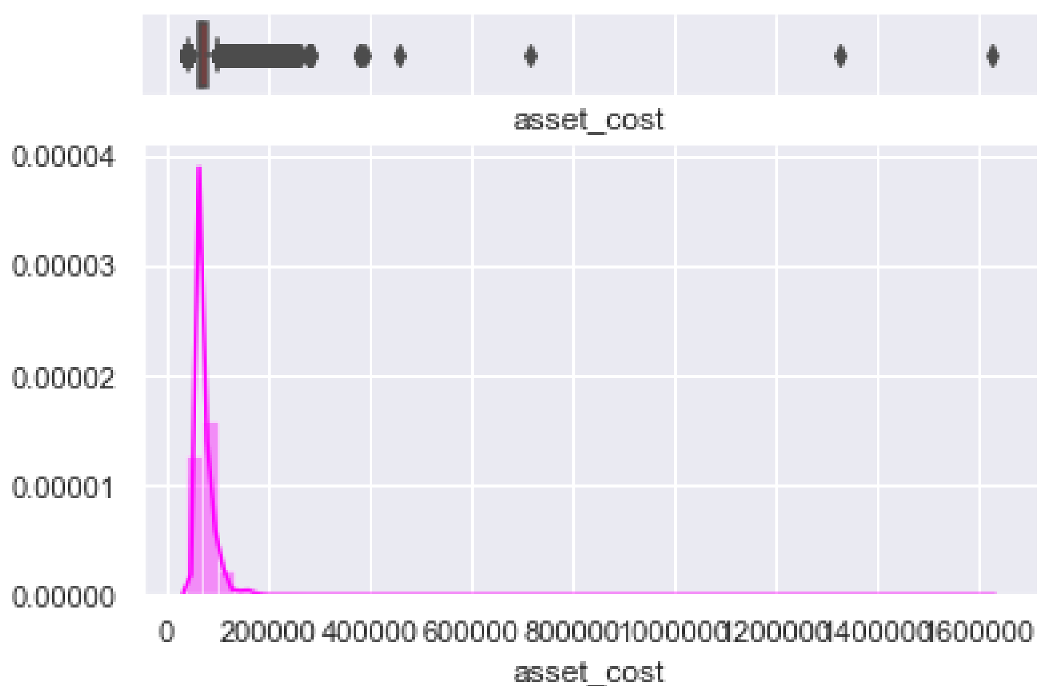
The histograms & box plots of all continuous variables are plotted below. Histograms of `disbursed_amount` and `asset_cost` shows approximately **normally distributed values** with outliers. While large proportion of `PERFORM_CNS.SCORE` falls on zero, it has some values with a mean score of around 700 (Bureau or CIBIL Score). Graph of `ltv` has outliers and a **multiple spike** around the centre with the mean value of around 80. Rest of the attributes have majority of the values near to zero compare to other values. i.e. the data for `PRI.NO.OF.ACCTS`, `PRI.CURRENT.BALANCE`, `PRI.SANCTIONED.AMOUNT`, `PRI.DISBURSED.AMOUNT`, `SEC.NO.OF.ACCTS`, `SEC.CURRENT.BALANCE`, `SEC.SANCTIONED.AMOUNT`, `SEC.DISBURSED.AMOUNT`, `PRIMARY.INSTAL.AMT` and `SEC.INSTAL.AMT` are having higher upper bound outliers with rest of the values in the range.

```
In [24]: for col in ['disbursed_amount', 'asset_cost', 'ltv', 'PERFORM_CNS.SCORE','PRI.NO.OF.ACCTS',
                     'PRI.CURRENT.BALANCE', 'PRI.SANCTIONED.AMOUNT','PRI.DISBURSED.AMOUNT',
                     'SEC.NO.OF.ACCTS', 'SEC.CURRENT.BALANCE', 'SEC.SANCTIONED.AMOUNT',
                     'SEC.DISBURSED.AMOUNT', 'PRIMARY.INSTAL.AMT', 'SEC.INSTAL.AMT']:
             plt.suptitle("Figure " + str(i) + ": Histogram and Box Plot of " + col)
             BoxAndHistogramPlot(Loan_Data[col])
             plt.show()
             i = 1 + i
```

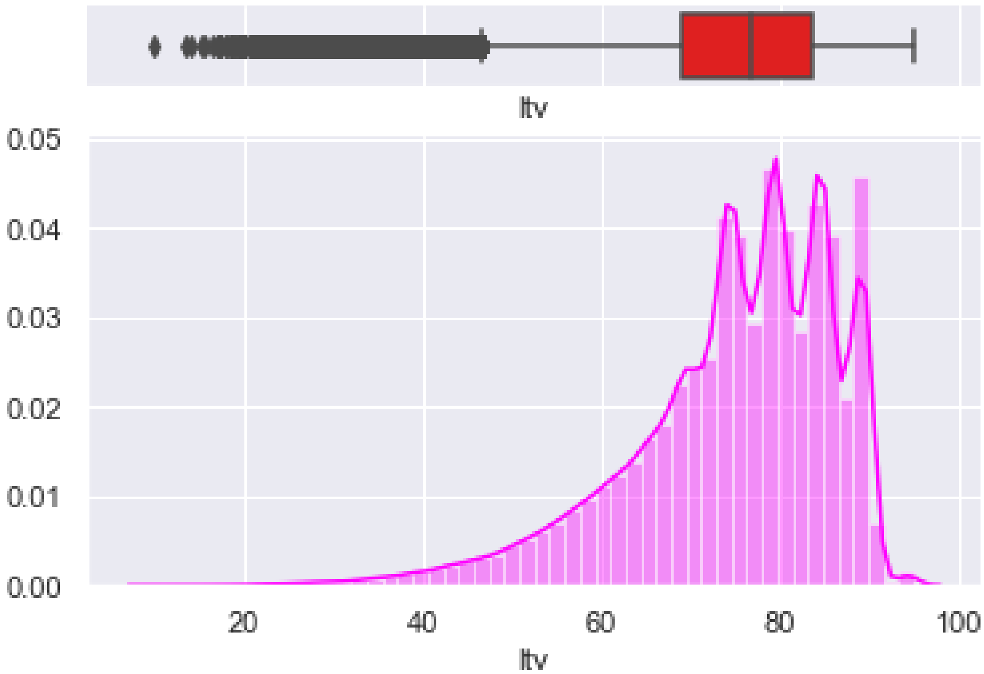
```
<Figure size 432x288 with 0 Axes>
```



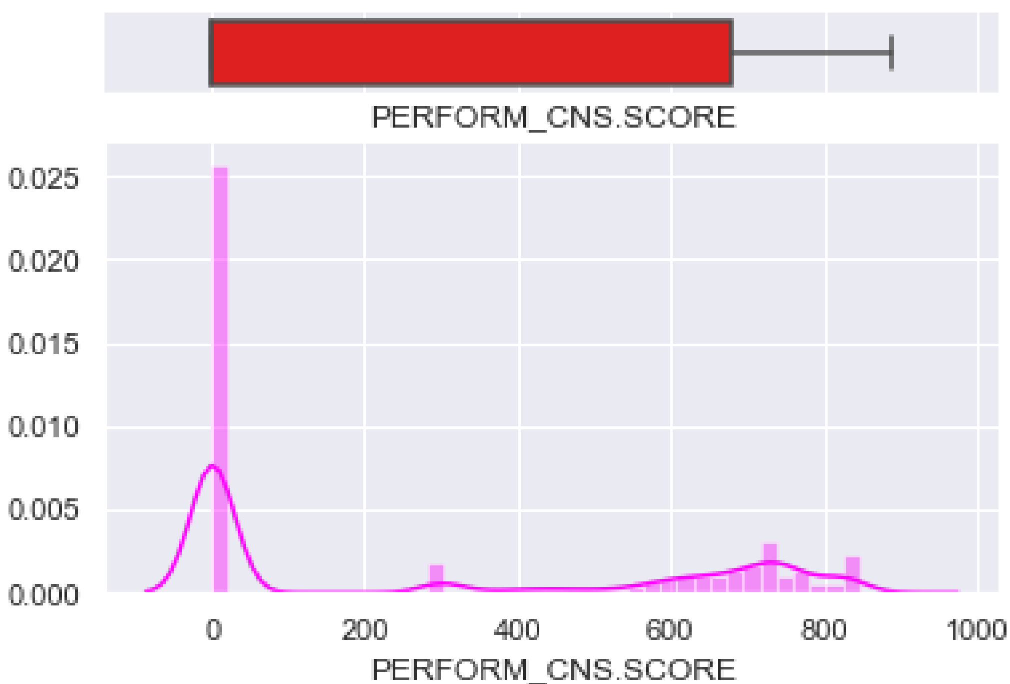

```
<Figure size 432x288 with 0 Axes>
```



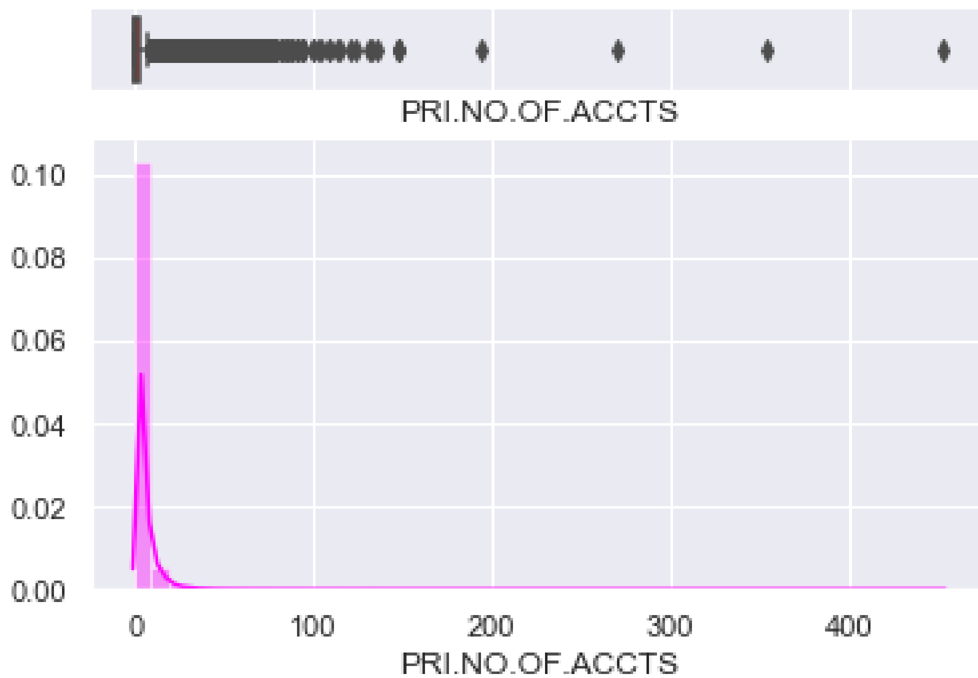
<Figure size 432x288 with 0 Axes>



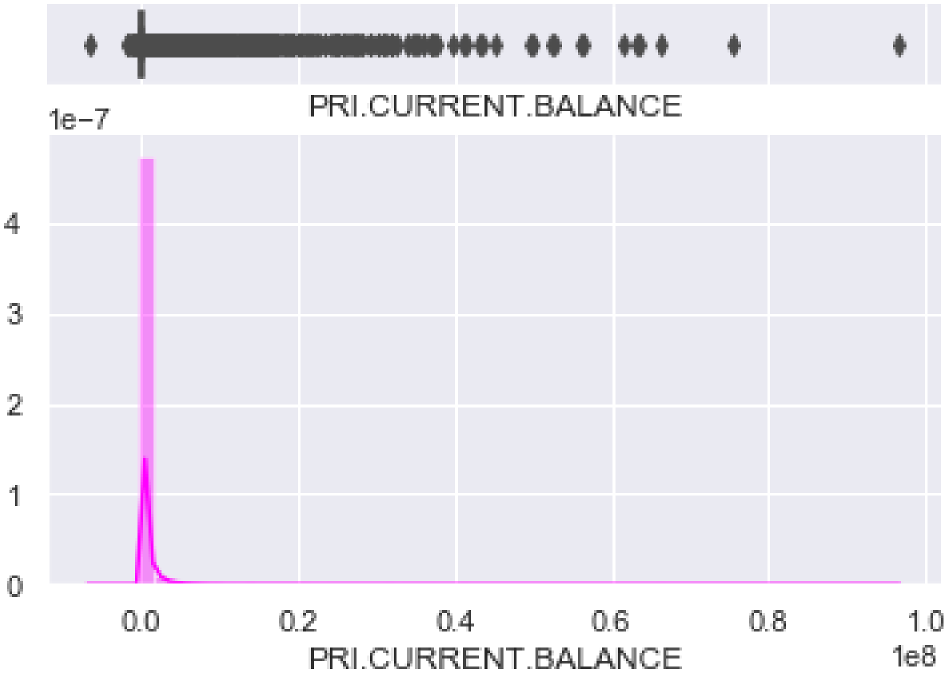
<Figure size 432x288 with 0 Axes>



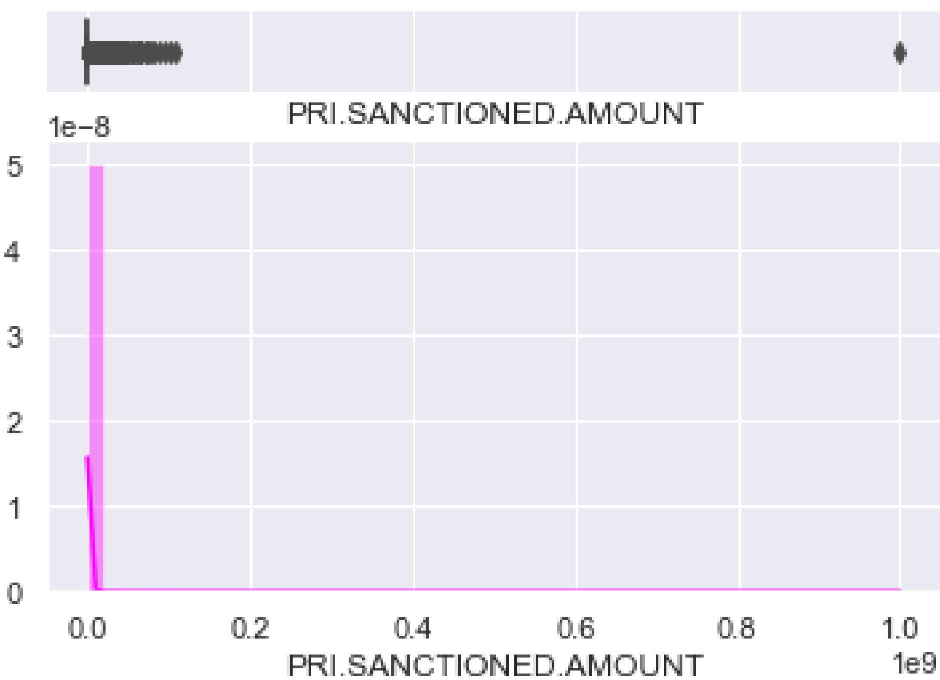
<Figure size 432x288 with 0 Axes>



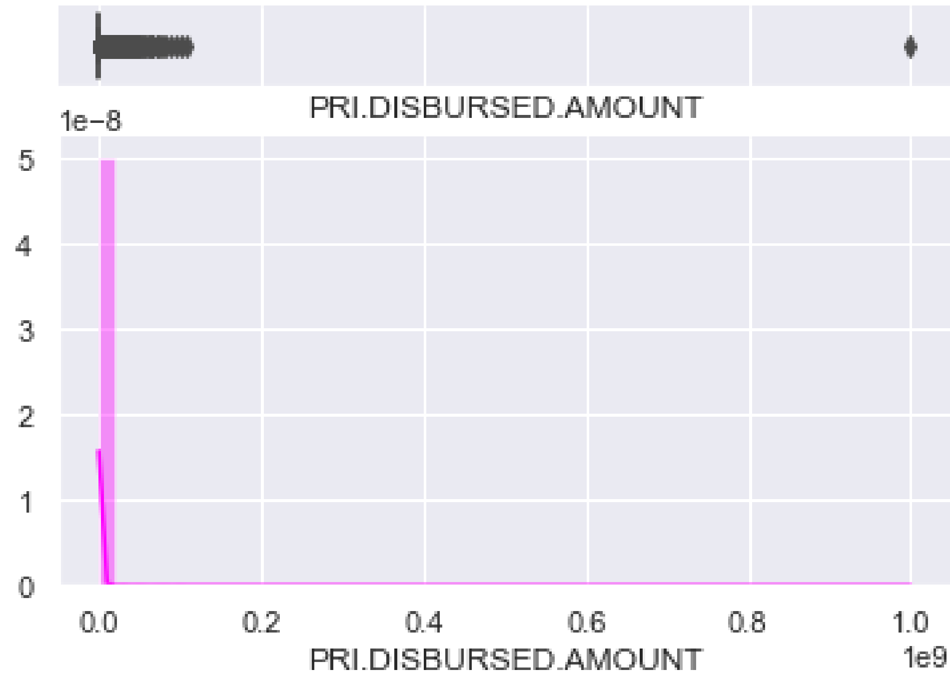
<Figure size 432x288 with 0 Axes>



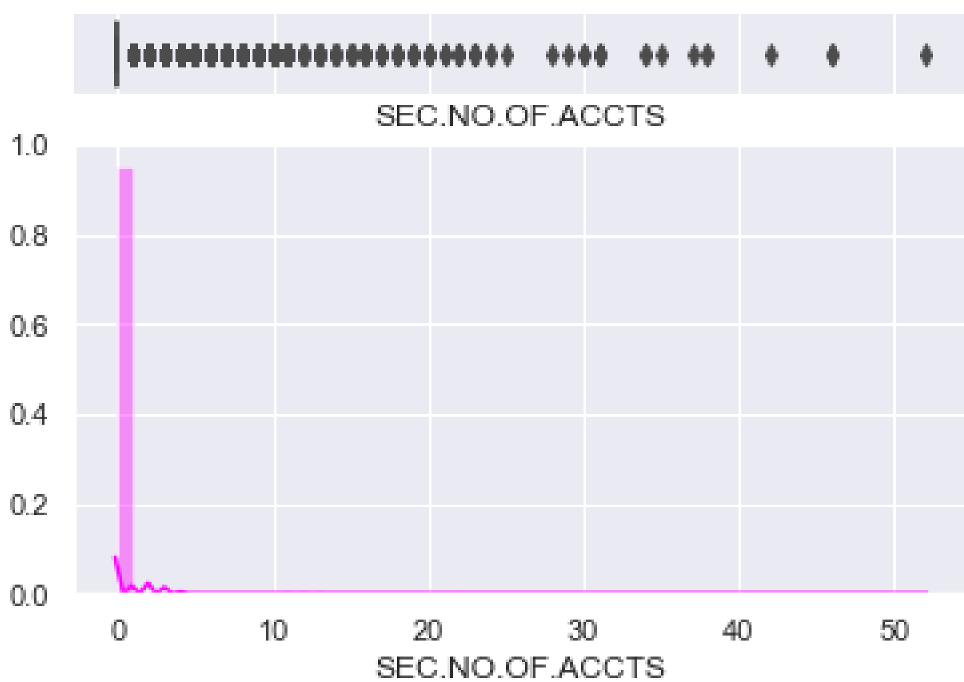

```
<Figure size 432x288 with 0 Axes>
```



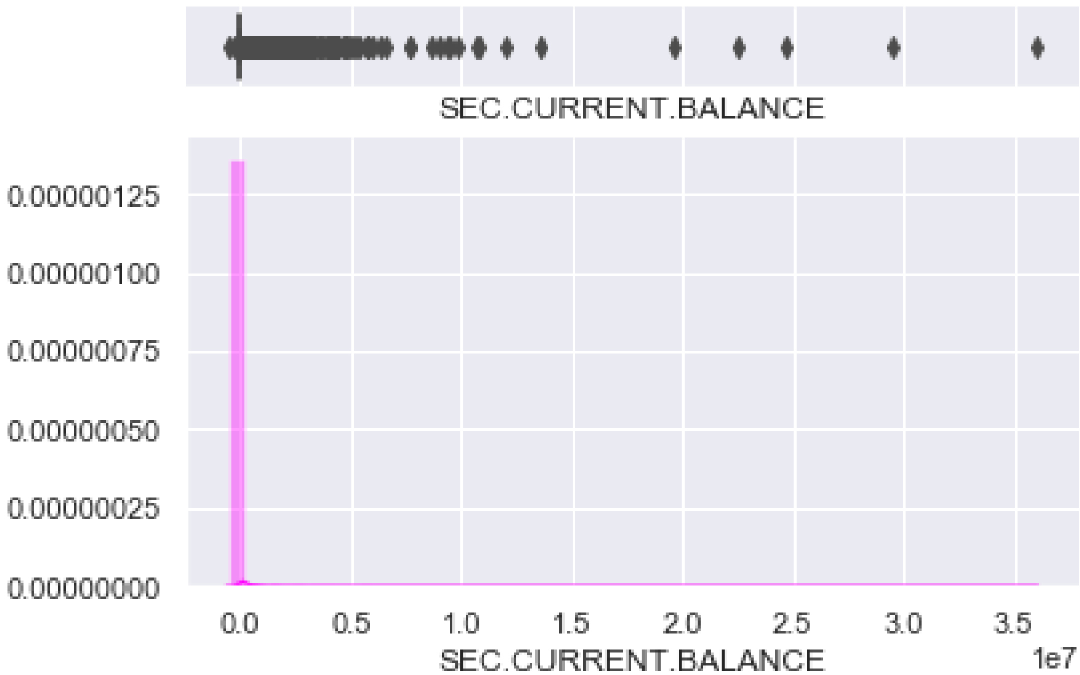
<Figure size 432x288 with 0 Axes>



<Figure size 432x288 with 0 Axes>



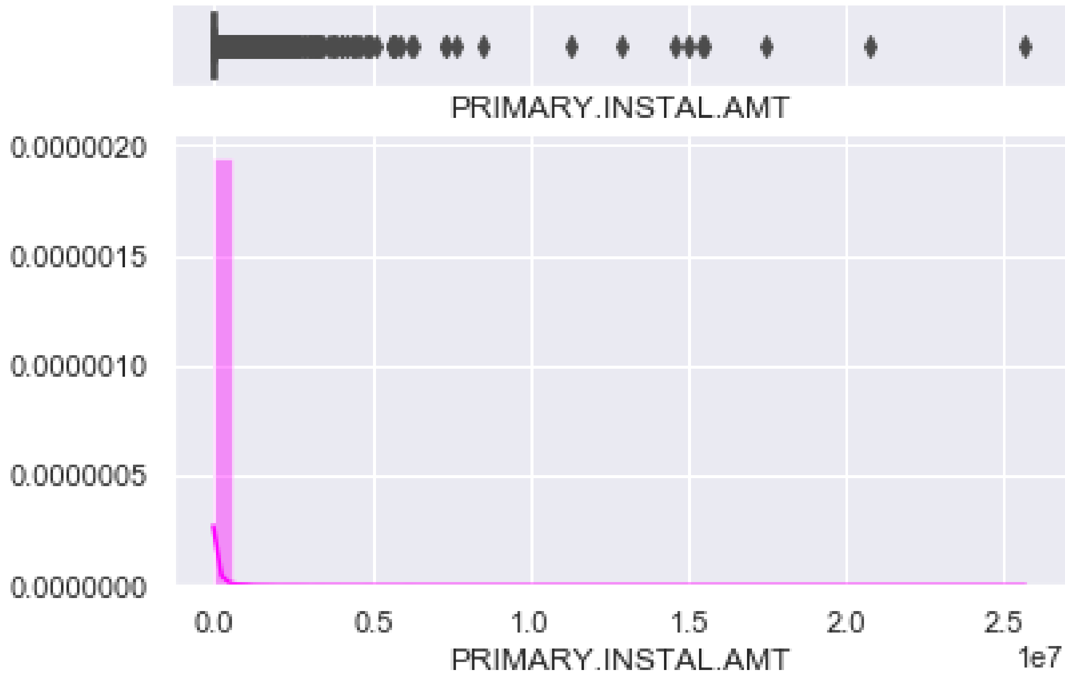
<Figure size 432x288 with 0 Axes>



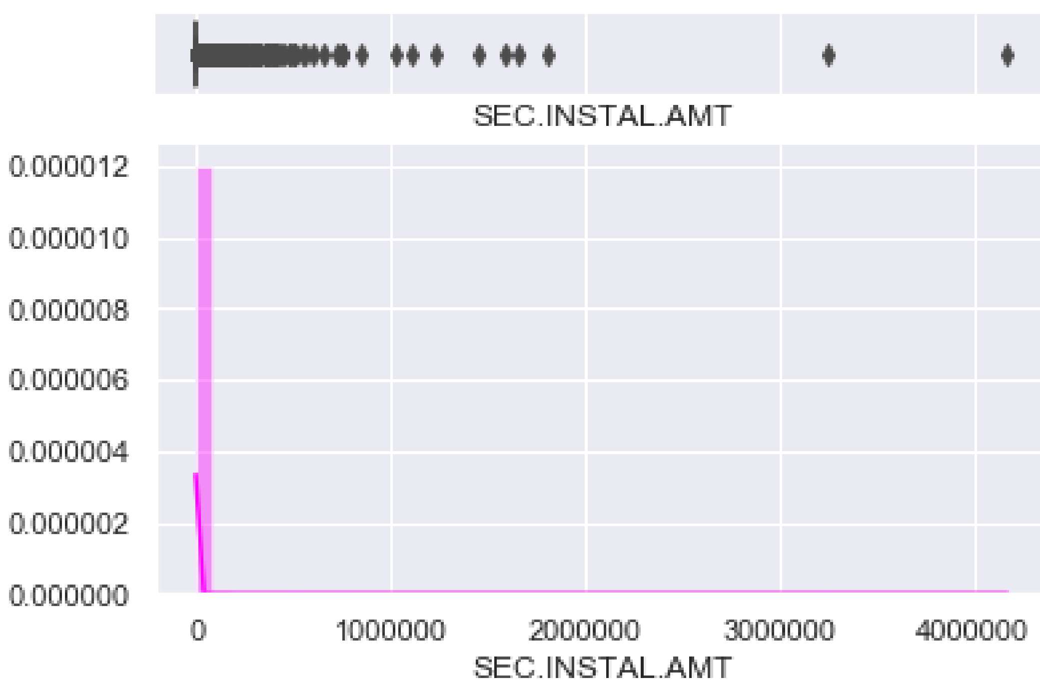
<Figure size 432x288 with 0 Axes>

<Figure size 432x288 with 0 Axes>

<Figure size 432x288 with 0 Axes>



<Figure size 432x288 with 0 Axes>



3.2 Multivariate Visualisation

3.2.1 Histogram of Numeric Features Segregated by RainTomorrow

The following are histograms[4] for each continuous attributes segregated by loan_default. Here it is observed that approximately 79% of the data is for the **No** value of target `loan_default` and 21% for **Yes** prediction for whether it will be Payment default or not in the first EMI on due date. Figure 31, 32, 35, 36, 37, 38 and 39 are left skewed in favour of it will not be Payment default in the first EMI on due date. This denotes that **Lower Disbursement Amount**, **Lower Asset cost** and **Lower active Loans Outstanding** tends to have **lower chances of Payment default in the first EMI on due date**. Also from the figure 29 & 30, it is obvious that **higher Loan to Value of the asset** and **higher Principal Outstanding Amount of the active loans** have **more chances of Payment default**. As for the `PERFORM_CNS.SCORE`, customers with **lower score** have **more chances of Payment defaults** & customer with **higher score** have **less chances of Payment defaults**.

```
In [25]: for col in ['disbursed_amount', 'asset_cost', 'ltv', 'PERFORM_CNS.SCORE',
                                   'PRI.CURRENT.BALANCE', 'PRI.SANCTIONED.AMOUNT',
                            'PRI.DISBURSED.AMOUNT','SEC.CURRENT.BALANCE', 'SEC.SANCTIONED.AMOUNT',
                            'SEC.DISBURSED.AMOUNT', 'PRIMARY.INSTAL.AMT', 'SEC.INSTAL.AMT']:
             data1 = Loan_Data.loc[Loan_Data['loan_default']==0, col]
             data2 = Loan_Data.loc[Loan_Data['loan_default']==1, col]

             #sns.distplot( data1 , color="skyblue", label="No", hist_kws=dict(alpha=0.9))
             #sns.distplot( data1 , color="red", label="Yes", hist_kws=dict(alpha=0.6))
             plt.hist(data1, alpha = 0.3, bins = 30, color='tan')
             plt.hist(data2, alpha = 0.3, bins = 30, color='lime')
             plt.title("Figure " + str(i) + ": Histogram of " + col + " segregated by loan_default")
             i = i + 1
             plt.legend(Loan_Data['loan_default'].unique(), bbox_to_anchor=(1.05, 1),
                        loc=2, borderaxespad=0.)
             plt.show()
```

Figure 28: Histogram of disbursed_amount segregated by loan_default

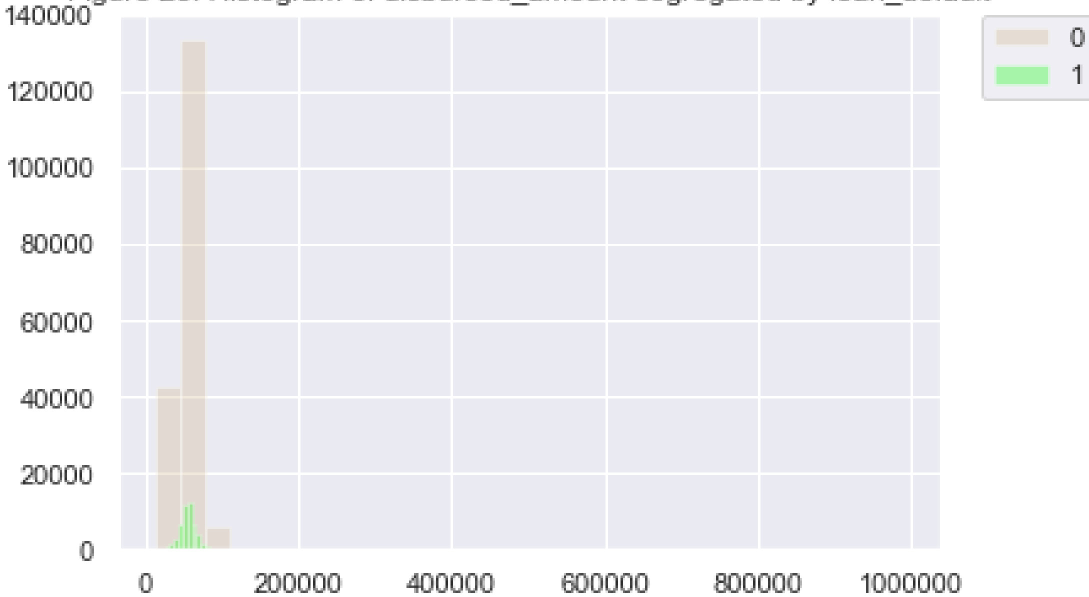


Figure 29: Histogram of asset_cost segregated by loan_default

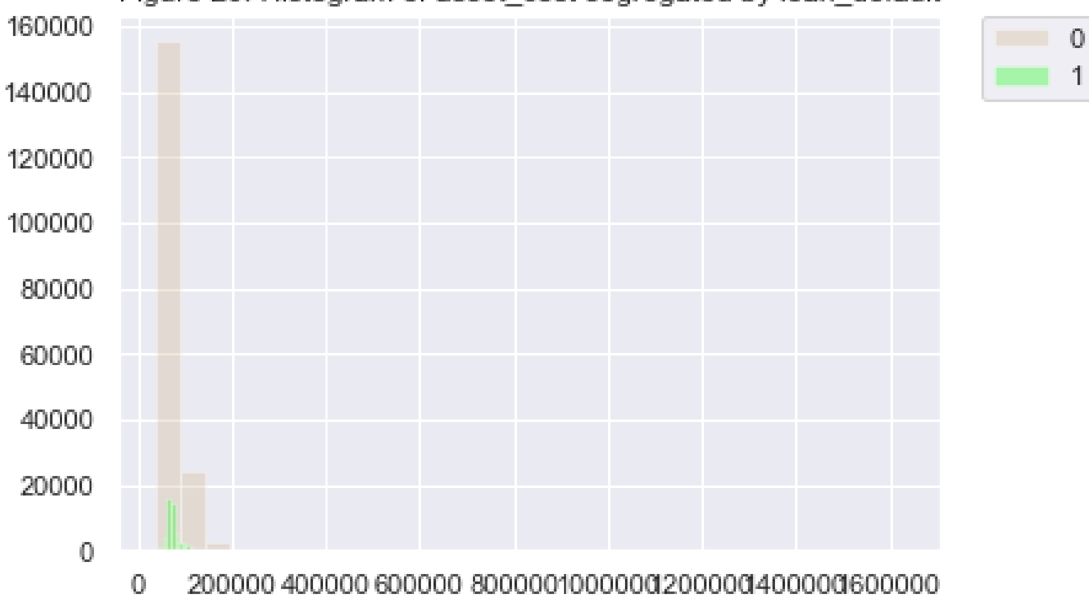


Figure 30: Histogram of ltv segregated by loan_default

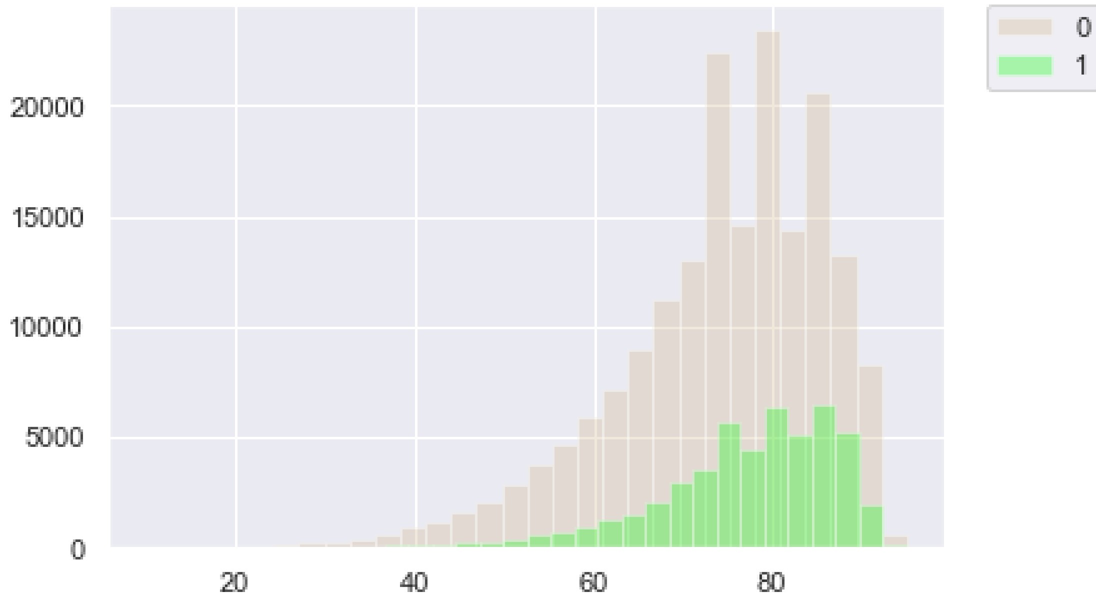


Figure 31: Histogram of PERFORM_CNS.SCORE segregated by loan_default

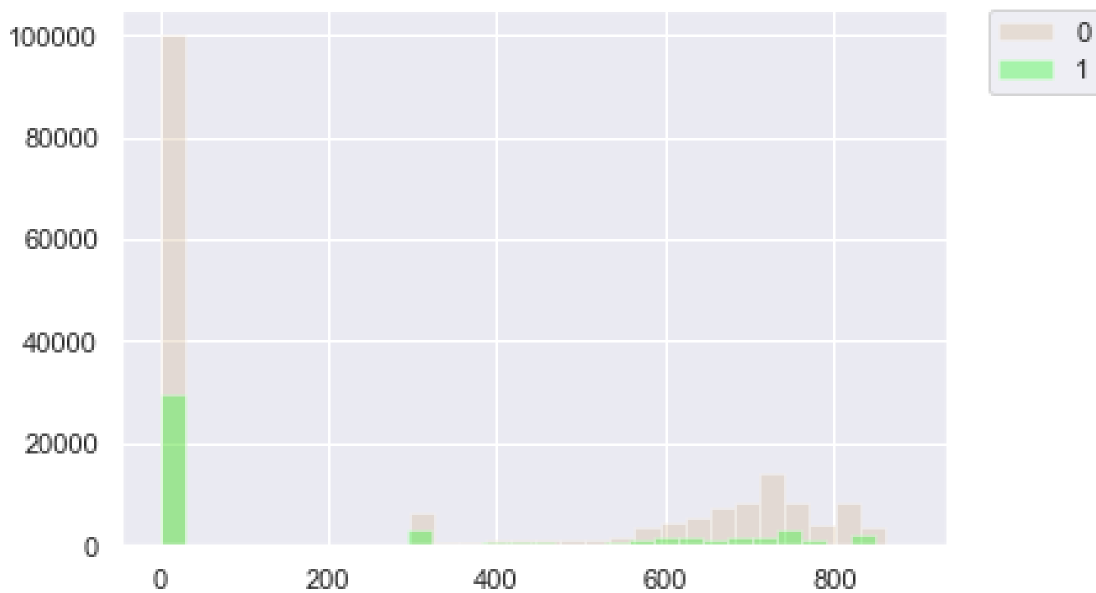


Figure 32: Histogram of PRI.CURRENT.BALANCE segregated by loan_default

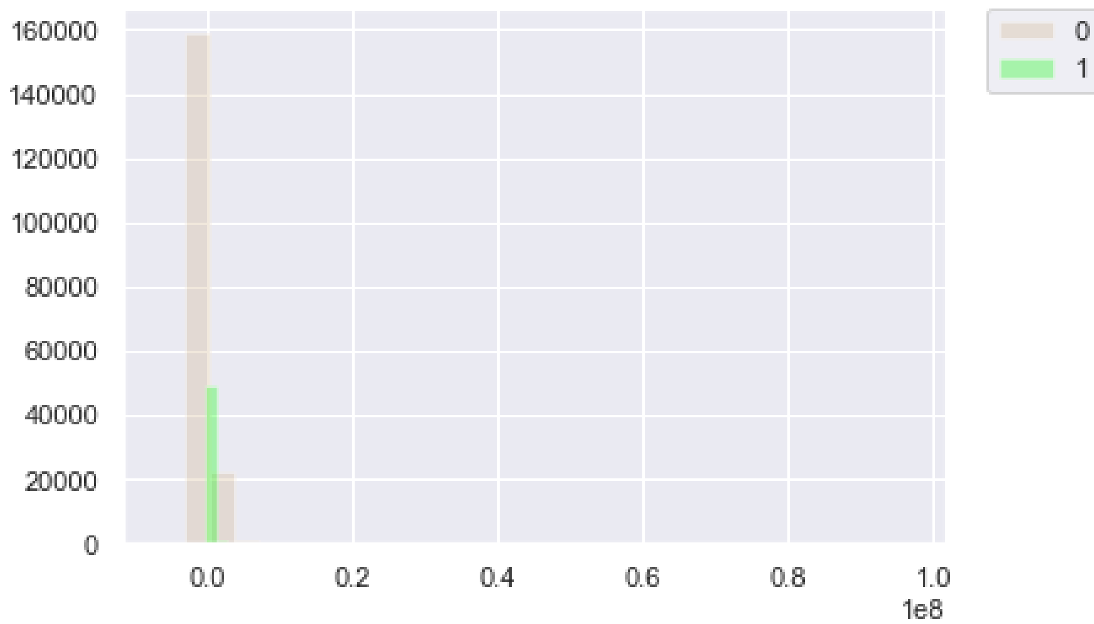


Figure 33: Histogram of PRI.SANCTIONED.AMOUNT segregated by loan_default

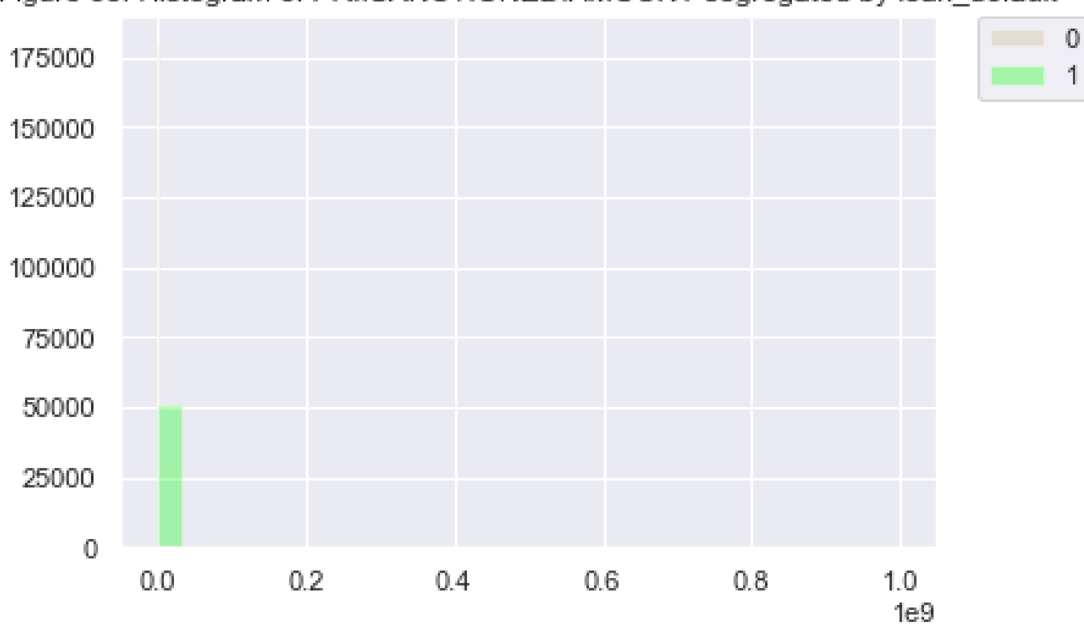


Figure 34: Histogram of PRI.DISBURSED.AMOUNT segregated by loan_default

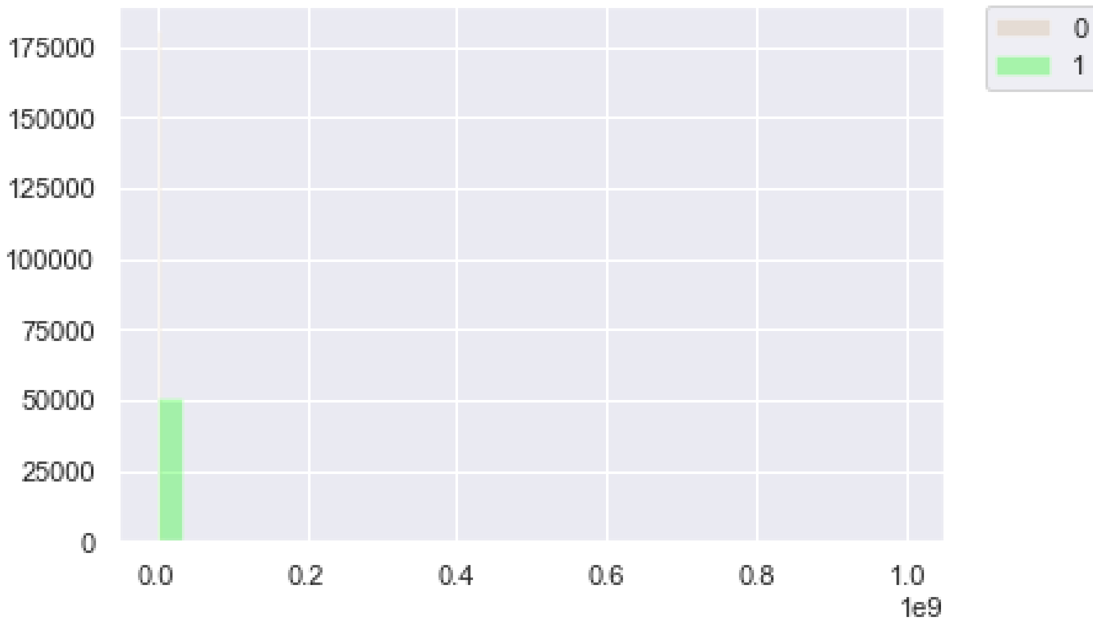


Figure 35: Histogram of SEC.CURRENT.BALANCE segregated by loan_default

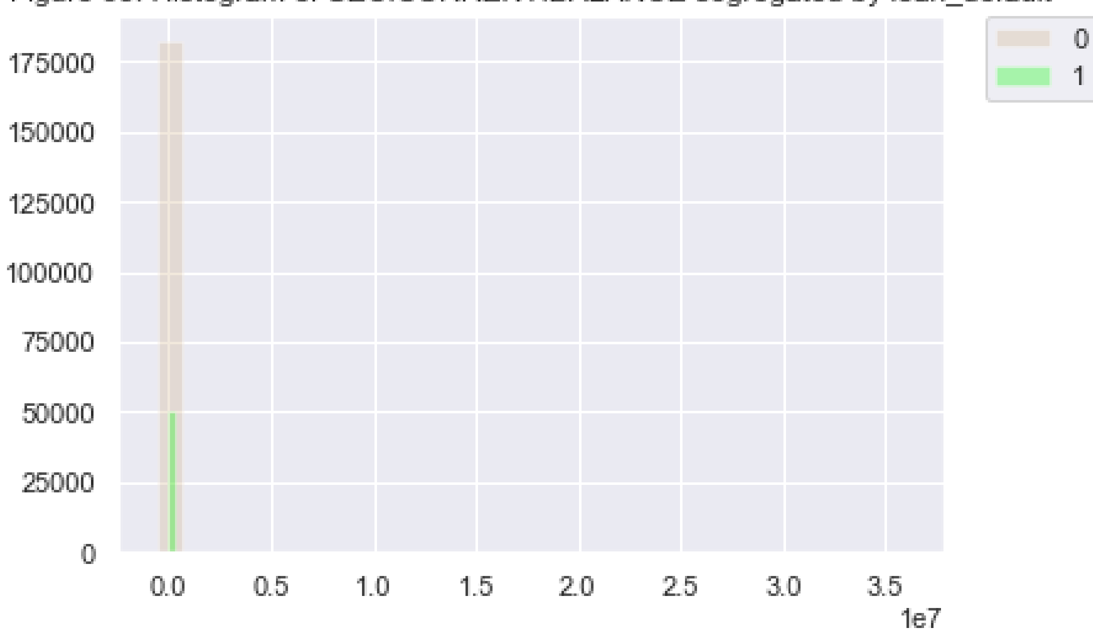


Figure 36: Histogram of SEC.SANCTIONED.AMOUNT segregated by loan_default

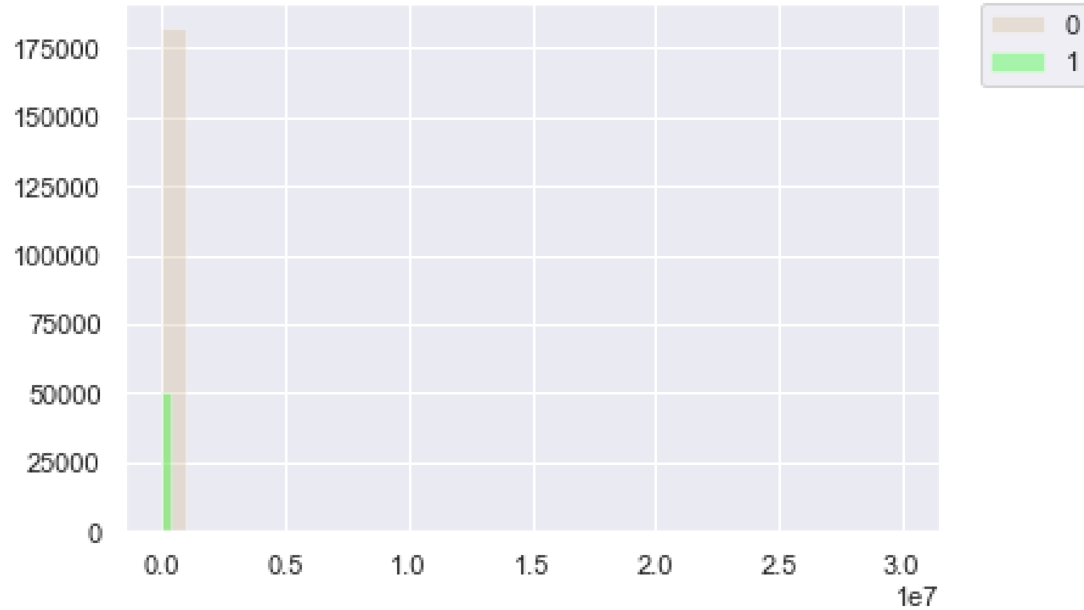


Figure 37: Histogram of SEC.DISBURSED.AMOUNT segregated by loan_default

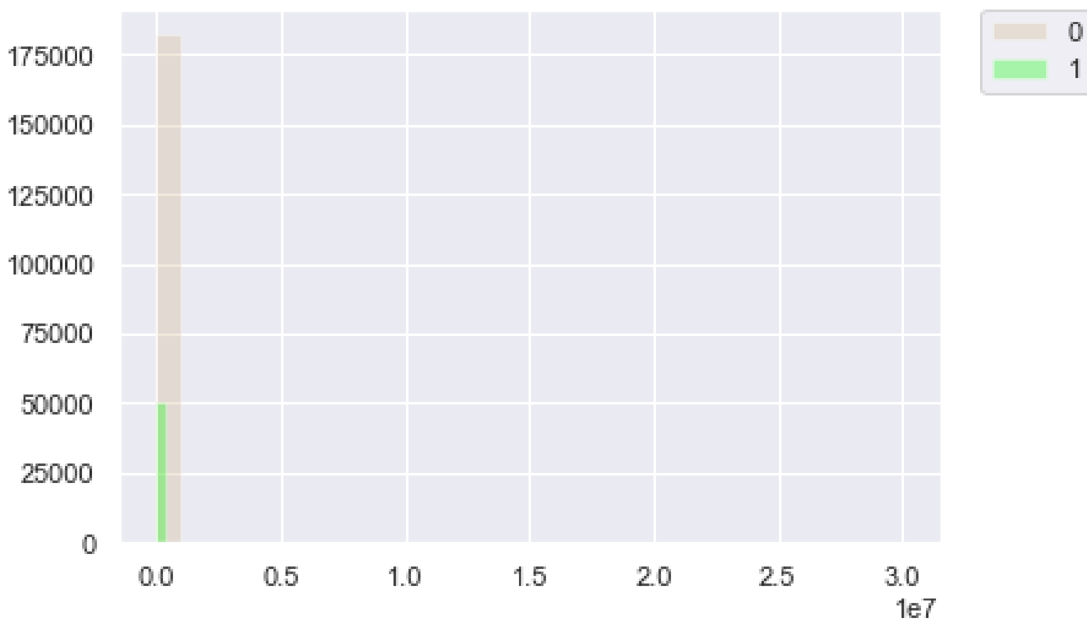


Figure 38: Histogram of PRIMARY.INSTAL.AMT segregated by loan_default

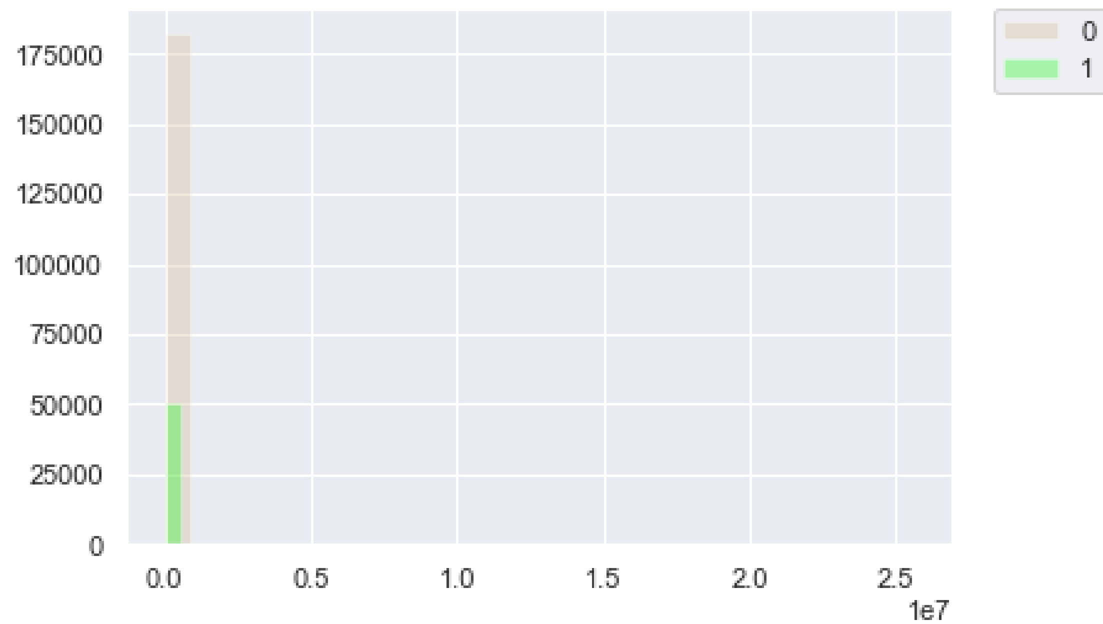
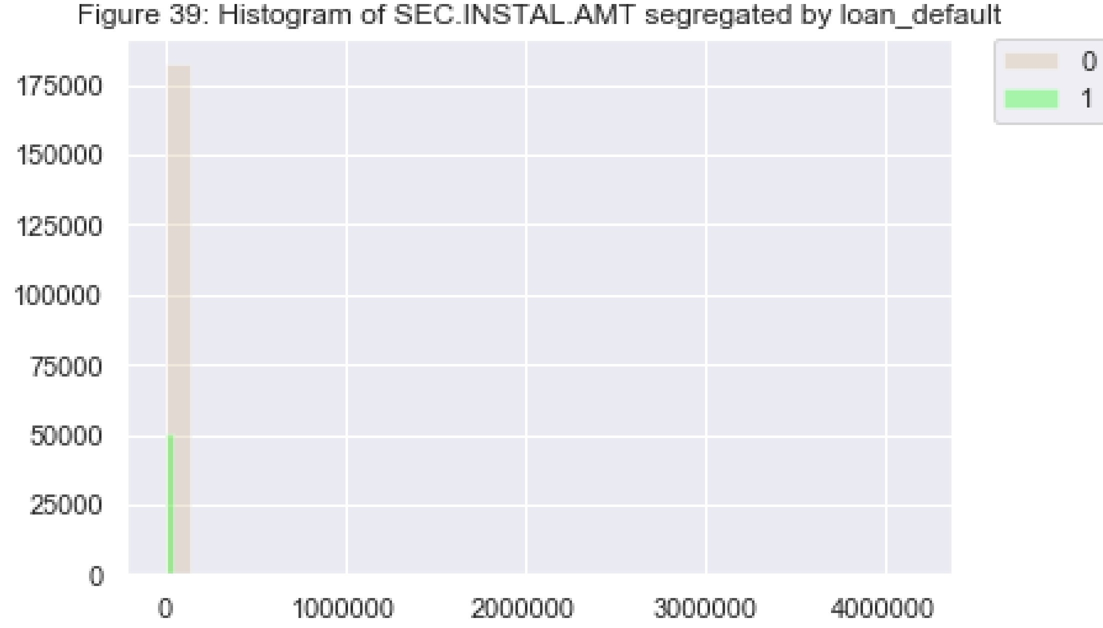


Figure 39: Histogram of SEC.INSTAL.AMT segregated by loan_default

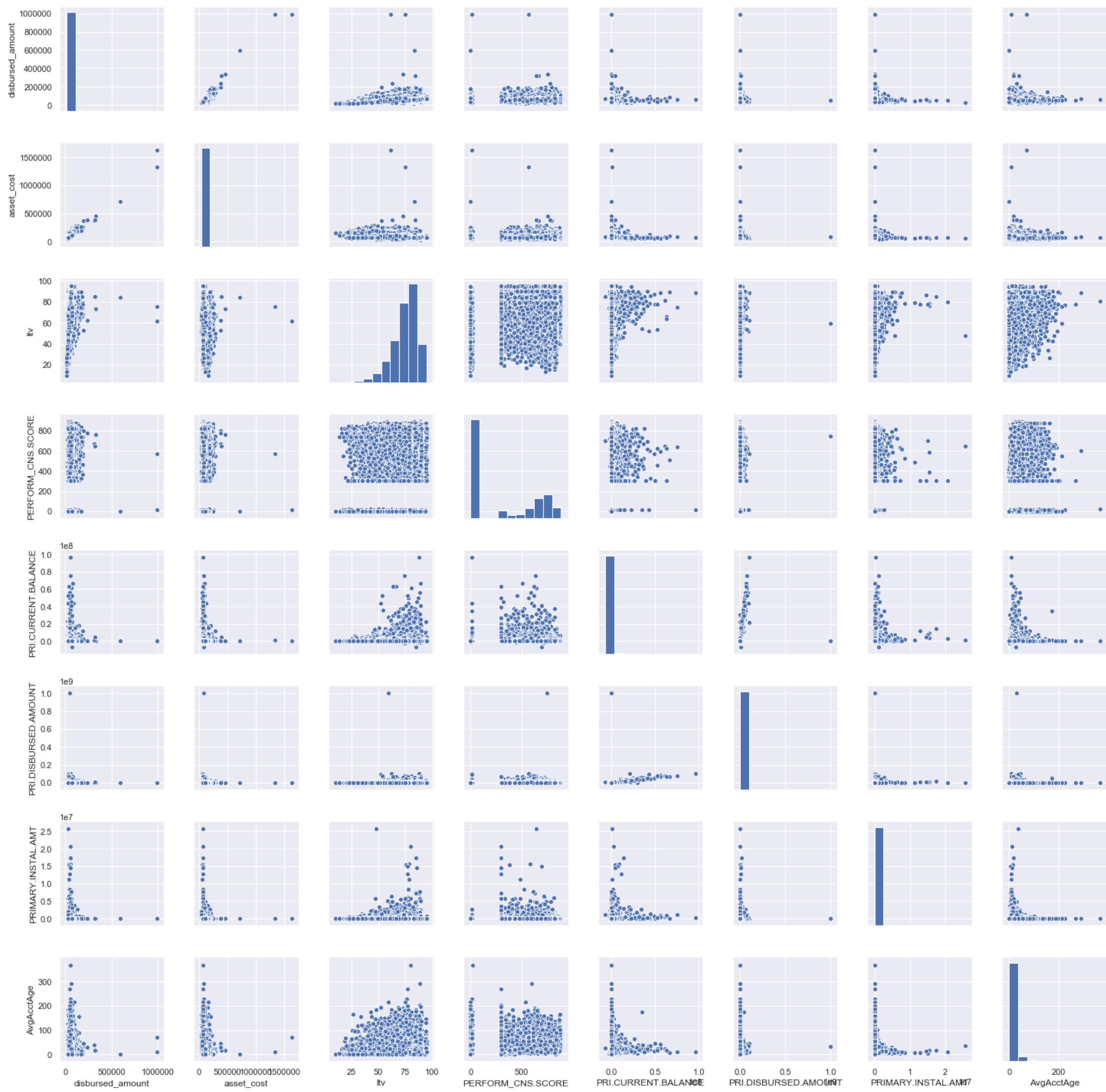


3.2.2 Scatter Matrix (Pair Plot) of All Numeric Features

We have passed a list of some numeric attributes to draw a Scatter Matrix (Pair Plot)[5] to visualize numeric variables to determine co-linearity between the variables. We observed from the scatter matrix that many attributes have **evenly distributed** relationship while others have positive linear other patterns as can be seen from below plot. For it to be displayed properly in report, we could not be able add more than 8 numeric attributes to visualize eplationship between all numeric attributes.

```
In [26]: sns.pairplot(Loan_Data[['disbursed_amount', 'asset_cost', 'ltv', 'PERFORM_CNS.SCORE',
                                  'PRI.CURRENT.BALANCE','PRI.DISBURSED.AMOUNT', 'PRIMARY.INSTAL.AMT',
                                 'AvgAcctAge']])
```

```
Out[26]: <seaborn.axisgrid.PairGrid at 0x12b2cf7b8d0>
```



3.2.3 Categorical Attributes Segregated by RainTomorrow

We have defined a function called **BarPlotCategory(x,i)** which takes column name of dataset as input **x** and **i** to maintain figure count and plot[6] the bar chart of proportions of all categories of that attributes with repect to target variable.

```
In [27]: def BarPlotCategory(x,i):
             yCounts = (Loan_Data.groupby([x])['loan_default']
```

```
                    .value_counts(normalize=True)
                    .rename('Proportions')
                    .reset_index())

    data1 = yCounts.loc[yCounts['loan_default']==1,'Proportions']
    data2 = yCounts.loc[yCounts['loan_default']==0,'Proportions']

    N = len(Loan_Data[x].unique())
    ind = np.arange(N)  # the x locations for the groups
    width = 0.40        # the width of the bars

    #plt.figure(figsize=(10,4))
    size = 10 if N < 10 else N

    fig, ax = plt.subplots(figsize=(size,5))
    rects1 = ax.bar(ind, data1, width, color='g', alpha = 0.5,edgecolor='blue')
    rects2 = ax.bar(ind + width + 0.01, data2, width - 0.1, color='r',
                    alpha = 0.5,edgecolor='blue')

    ax.set_ylabel('Proportion')
    ax.set_title("Figure " + str(i) +': loan_default by ' + x, fontsize = 12)
    ax.set_xticks(ind + width / 2)
    ax.set_xticklabels(Loan_Data[x].unique())
    ax.set_xlabel(x)

    ax.legend((rects1[0], rects2[0]), ('1', '0'))
    plt.show()
```

Barcharts of 8 attributes are plotted below using the above defined function. From figure 40, we can observe that some **Employment Type** tend to have **more probability of Payment default** than others. Figure 41 shows that customers who took loan from some state tend to have **more probability of Payment default** than other states; same as for `PERFORM_CNS.SCORE.DESCRIPTION`, which can be seen from figure 42. We have also plotted 5 If_flag atributes, from figure 43 to 47 which are numeric along with 3 categorical attributes, because they contain only 0 and 1 value, we can visualize them in terms of our target variable.

```
In [28]: for col in ['Employment.Type', 'State_ID','PERFORM_CNS.SCORE.DESCRIPTION', 'Aadhar_flag',
                'PAN_flag', 'VoterID_flag', 'Driving_flag', 'Passport_flag']:
             print('')
             print('')
             BarPlotCategory(col,i)
             i = 1 + i
```

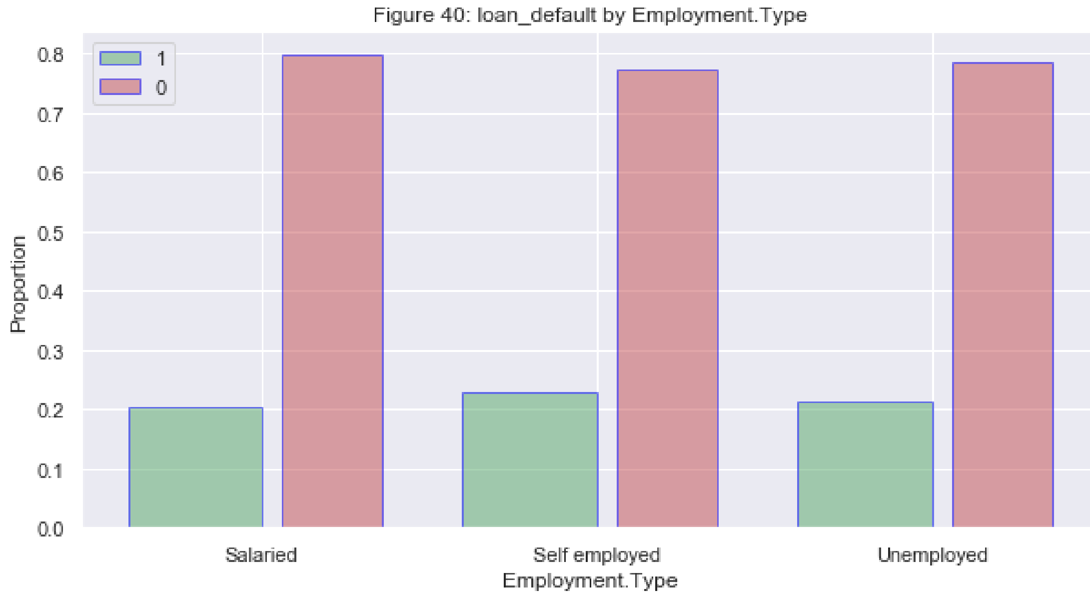


Figure 40: loan_default by Employment.Type
1
0
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
Proportion
Salaried
Self employed
Unemployed
Employment.Type

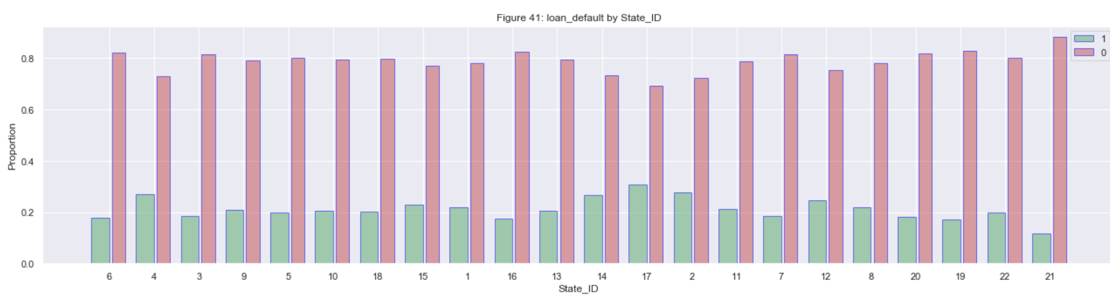


Figure 41: loan_default by State_ID
1
0
0.8
0.6
0.4
0.2
0.0
Proportion
6
4
3
9
5
10
18
15
1
16
13
14
17
2
11
7
12
8
20
19
22
21
State_ID

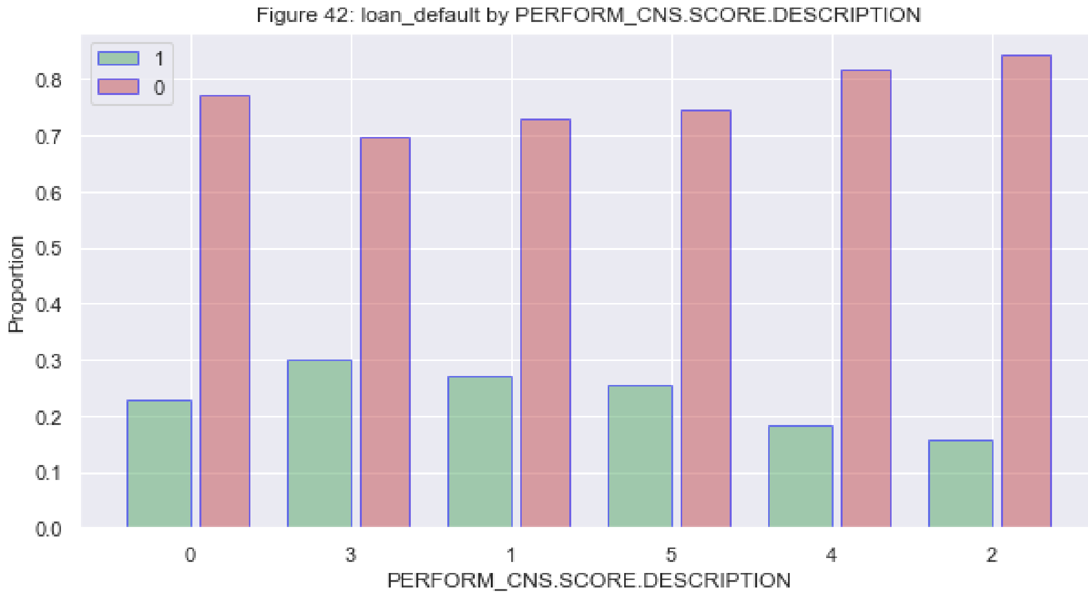


Figure 42: loan_default by PERFORM_CNS.SCORE.DESCRIPTION
1
0
Proportion
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0
3
1
5
4
2
PERFORM_CNS.SCORE.DESCRIPTION

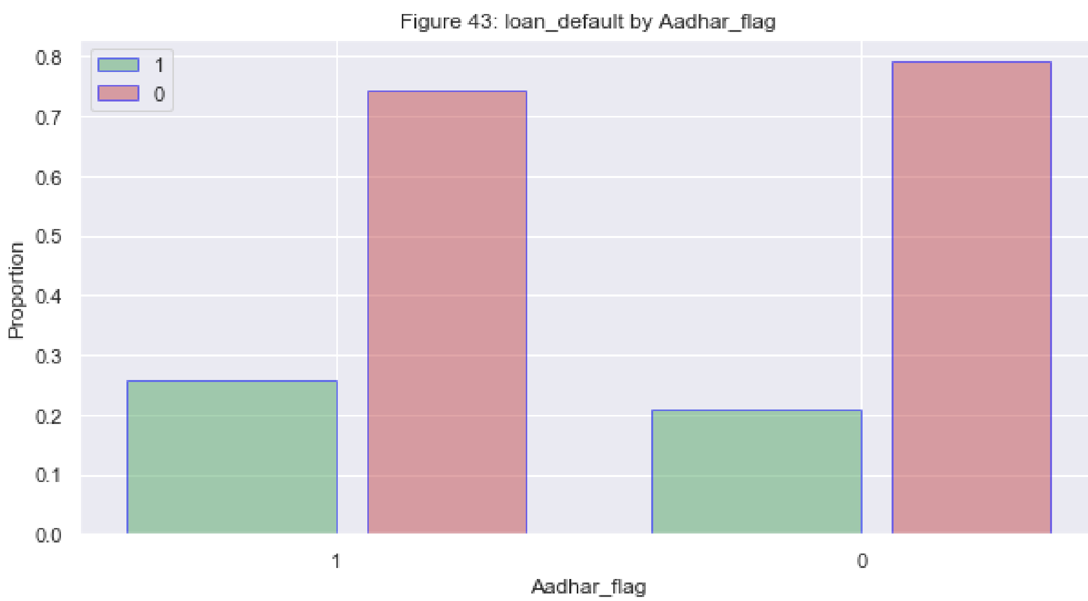


Figure 43: loan_default by Aadhar_flag
1
0
Proportion
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
1
0
Aadhar_flag

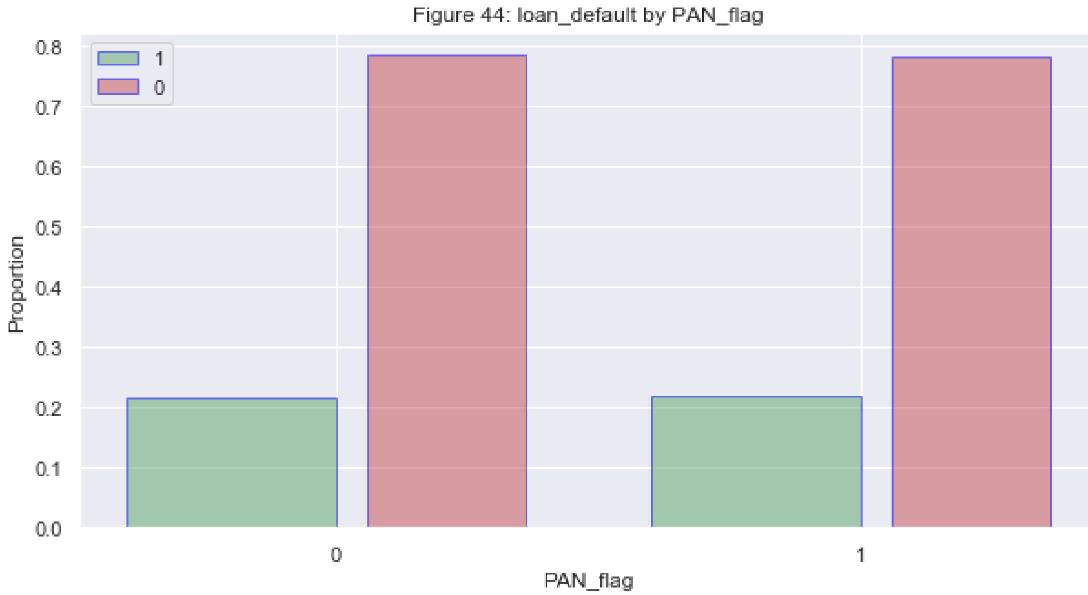


Figure 44: loan_default by PAN_flag
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
Proportion
1
0
0
1
PAN_flag

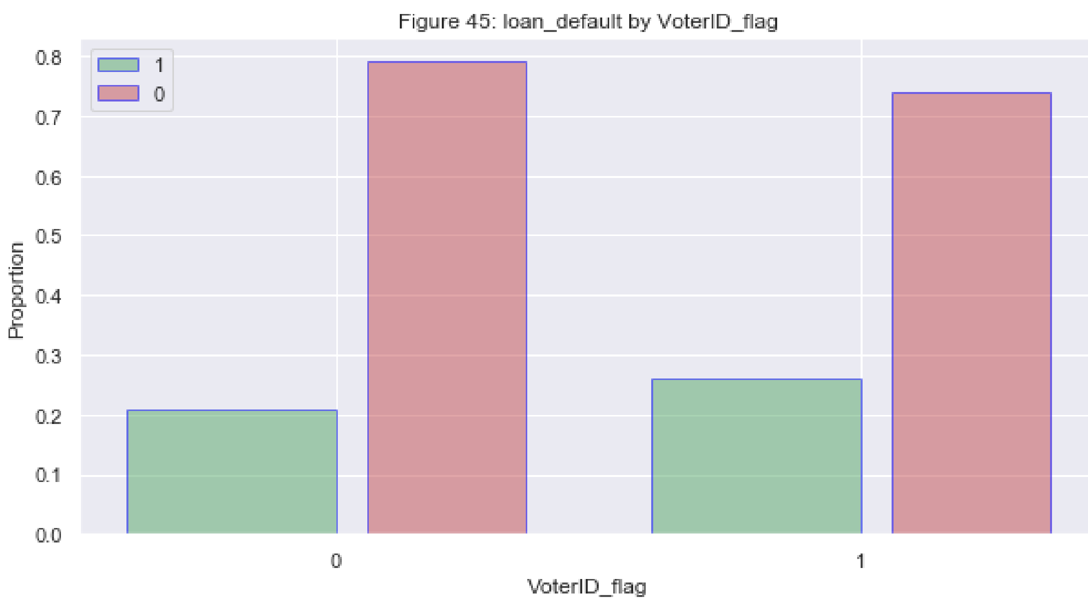


Figure 45: loan_default by VoterID_flag
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
Proportion
1
0
0
1
VoterID_flag

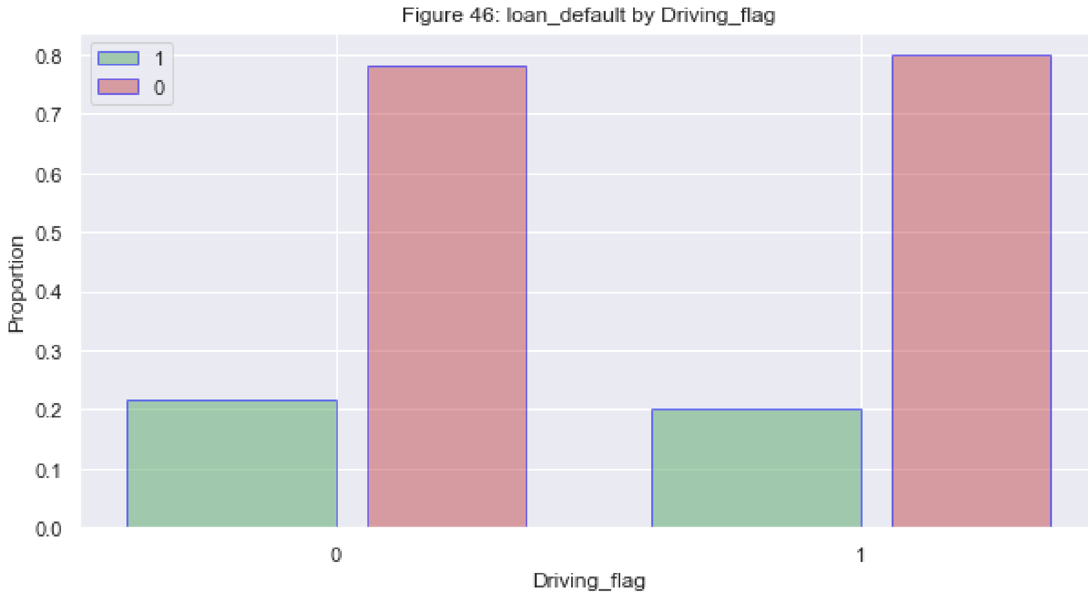


Figure 46: loan_default by Driving_flag
1
0
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
Proportion
0
1
Driving_flag

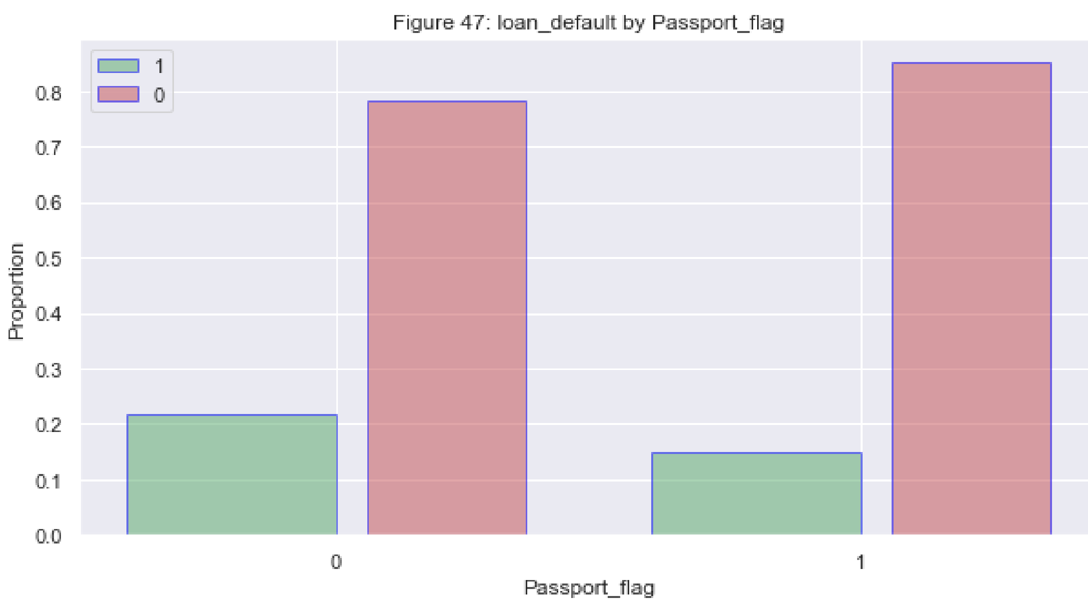


Figure 47: loan_default by Passport_flag
1
0
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
Proportion
0
1
Passport_flag

Chapter 4

Summary

In Phase 1, we removed attribtes UniqueID, supplier_id, Current_pincode_ID, DisbursalDate, Employee_code_ID as they do not play any predicting role in our case. We imputed NA values in Employment.Type by introducing a third category for that attribute; Unemployed & in Continuous features, there were no missing values. We have created 3 new attributes Age, AvgAcctAge & CredAcctAge by using Date.of.Birth, AVERAGE.ACCT.AGE & CREDIT.HISTORY.LENGTH and then dropped these old attributes, and visualized these new attributes as well to find meaningful patterns or information. Also, we have encoded PERFORM_CNS.SCORE.DESCRIPTION to convert it into numeric from category. From the data exploration, we found that **disbursed_amount, asset_cost, ltv, branch_id, manufacturer_id, Employment.Type, State_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, NO.OF_INQUIRIES, ',Age,AvgAcctAge,CredAcctAge** were potentially useful features in predicting the target **loan_default'**.

In Phase 2, We will continue with these processed data and **Normalize & Scale** it if needed, and then continue with our prediction.

Bibliography

[1] roshansharma. Kaggle Machine Learning Data Sets : Loan Default Prediction Dataset : https://www.kaggle.com/roshansharma/loan-default-prediction.

[2] MatplotLib Colors : https://matplotlib.org/users/colors.html.

[3] Python Graph Gallery : https://python-graph-gallery.com/24-histogram-with-a-boxplot-on-top-seaborn/.

[4] MatplotLib Plots.

[5] Seaborn Library : https://seaborn.pydata.org/index.html.

[6] MatplotLib Library : https://matplotlib.org/index.html.