apstone-project-2-loan-defaulters

March 30, 2023

[64]:
```
import pandas as pd
import numpy as np
import os
import re
import datetime as dt
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
%matplotlib inline
```

****Importing and Inspecting Data set****

[2]:
```
data= pd.read_excel("loan data.xlsx")
```

[3]:
```
data.head()
```

[3]:
```
   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]
```

[4]:
```python
data.columns
```

[4]:
```
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')
```

[5]:
```python
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
```

Checking Null Values

[6]:
```
data.isnull().sum()
```

[6]:
```
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
```

Missing values found in Employement type column only. As it is catagorial data, fill the missing values with Mode value using pandas.

[8]:
```
data['Employment.Type'].fillna(data['Employment.Type'].mode()[0], inplace=True)
```

verify after fill NA.

[9]:
```
data.isnull().sum()
```

[9]:
```
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
```

[10]:
```
data.shape
```

[10]: (233154, 41)

[11]:
```
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                      233154 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
```

[12]:
```
data.dtypes
```

[12]:
```
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                          datetime64[ns]
Employment.Type                                object
DisbursalDate                          datetime64[ns]
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
```

0.0.1 Performing EDA

[13]:
```python
data.describe()
```

[13]:
```
            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
```

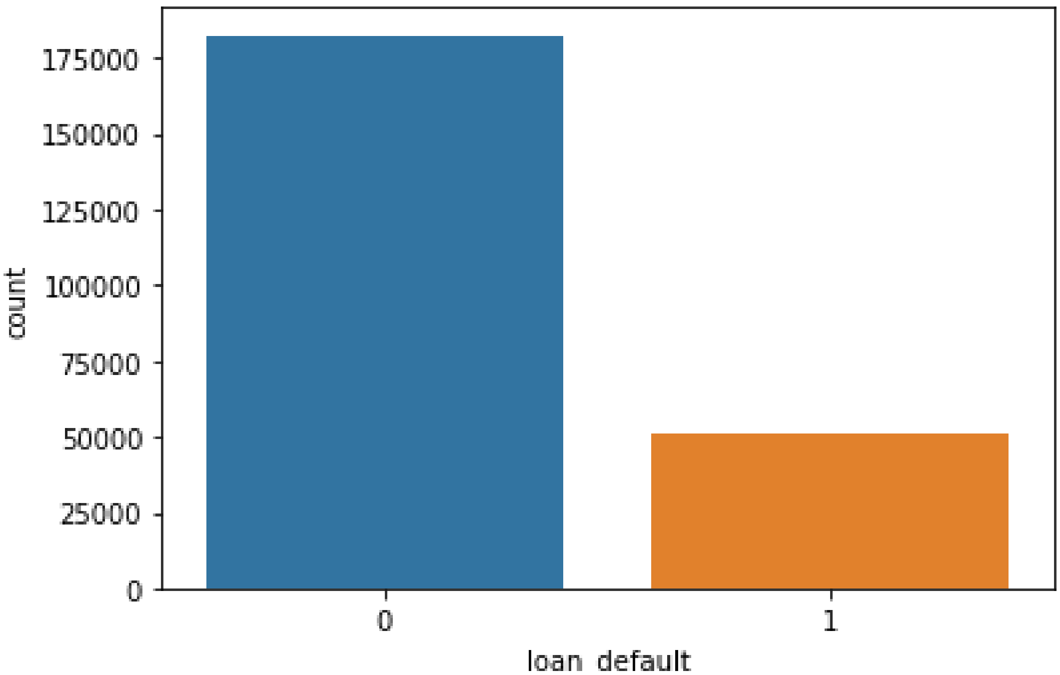
```
75%         0.000000e+00         0.000000e+00         0.000000e+00
max         3.603285e+07         3.000000e+07         3.000000e+07

       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]
```

Checking the overall distribution of variables

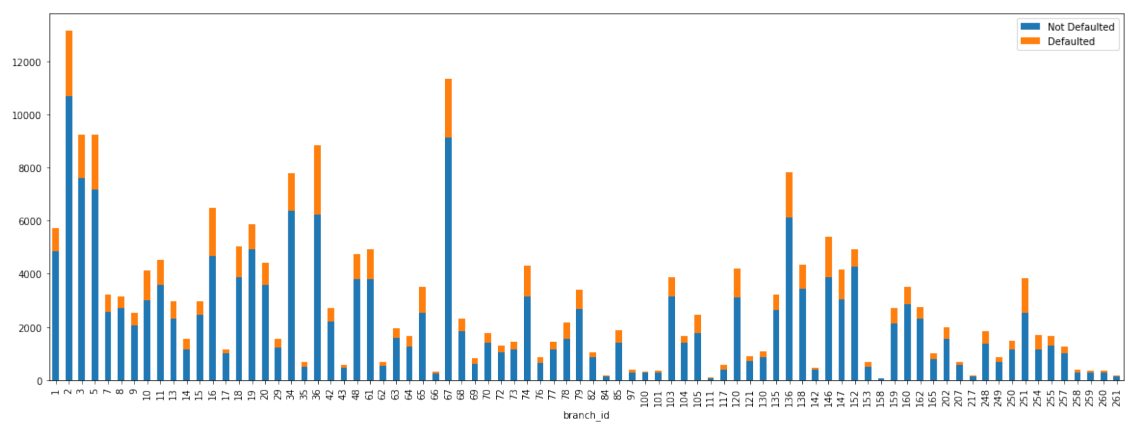
[20]:
```
sns.countplot(data["loan_default"])
```

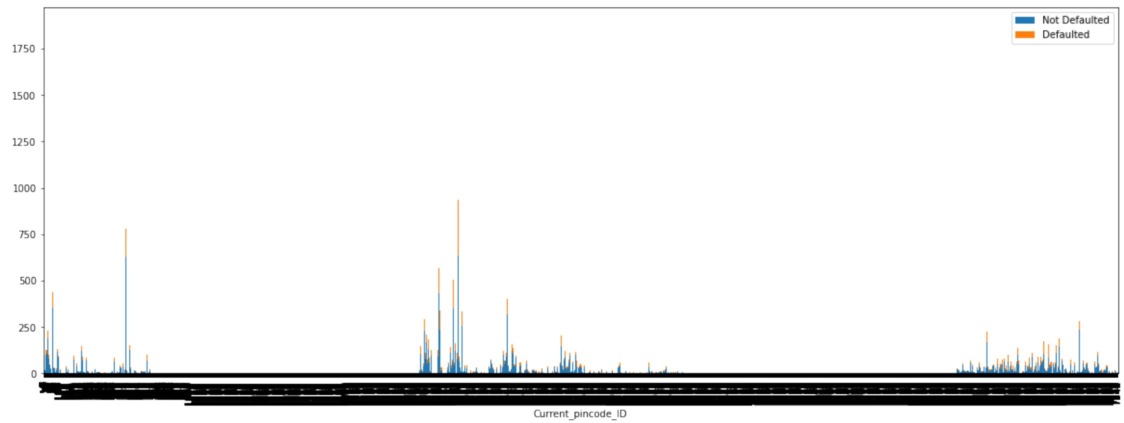
```
/usr/local/lib/python3.7/site-packages/seaborn/_decorators.py:43: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only
valid positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  FutureWarning
```

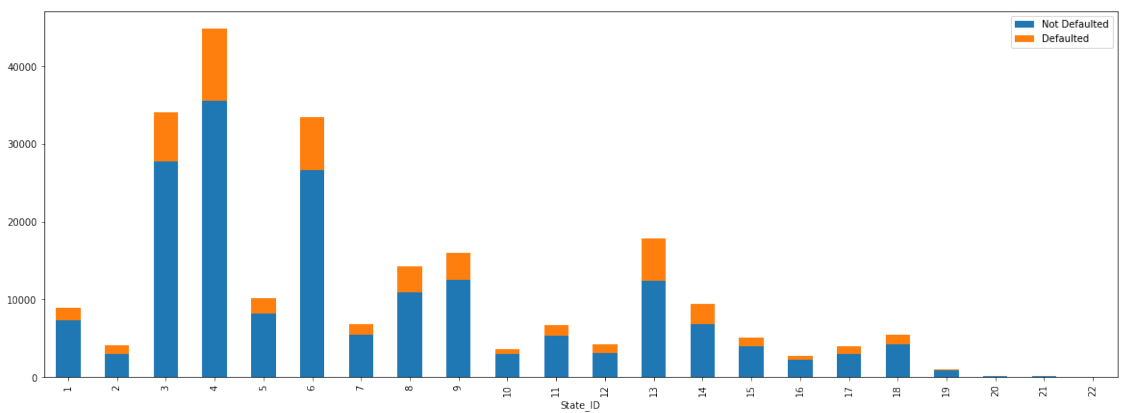
[20]: <AxesSubplot:xlabel='loan_default', ylabel='count'>

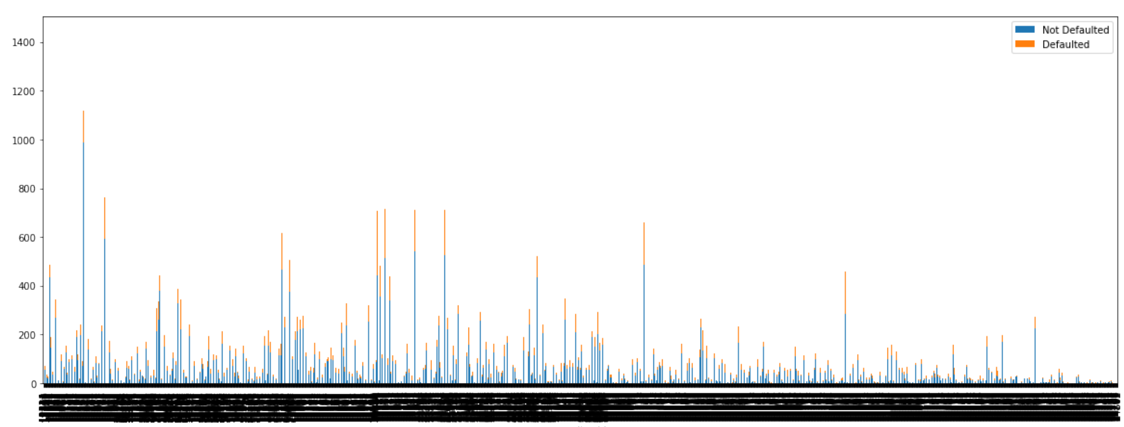


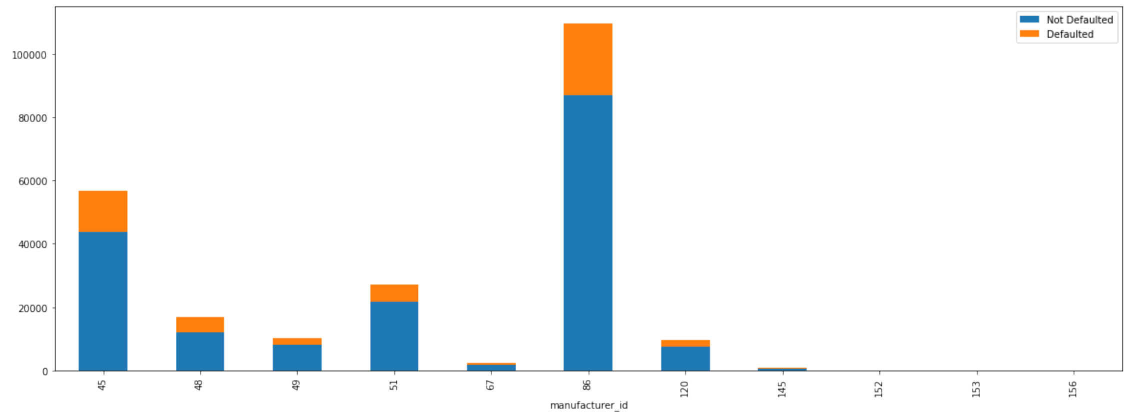
[15]:
```
for i in ['branch_id','Current_pincode_ID','State_ID','supplier_id','manufacturer_id']:
    ct = pd.crosstab(data[i],data['loan_default'])
    ct.plot.bar(stacked = True,figsize=(20,7))
    plt.legend(labels=['Not Defaulted','Defaulted'])
    plt.show()
```




Not Defaulted
Defaulted
1750
1500
1250
1000
750
500
250
0
Current_pincode_ID


Not Defaulted
Defaulted
40000
30000
20000
10000
0
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
State_ID


Not Defaulted
Defaulted
1400
1200
1000
800
600
400
200
0
supplier_id



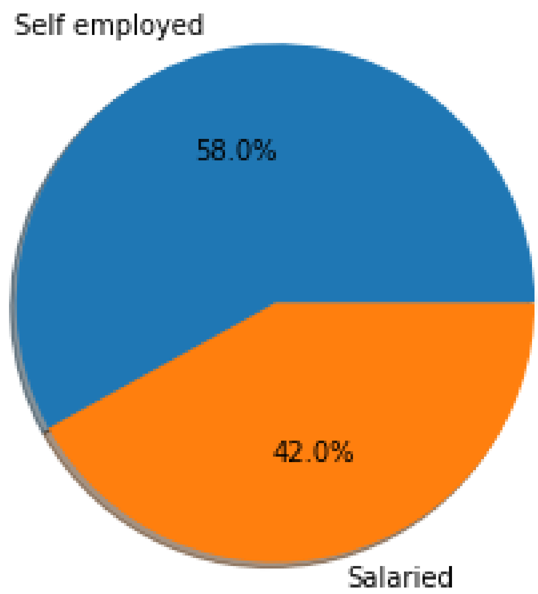
Finding the different types of employment given in the data

[19]:
```
data['Employment.Type'].value_counts()
```

[19]:
```
Self employed    135296
Salaried          97858
Name: Employment.Type, dtype: int64
```

Pie Chart

[21]:
```
labels = ['Self employed', 'Salaried']
sizes = data['Employment.Type'].value_counts()

fig1, ax1 = plt.subplots()
ax1.pie(sizes, labels=labels, autopct='%1.1f%%', shadow=True)
ax1.axis('equal')
plt.show()
```



[23]:
```
pct_loan_default = data['loan_default'].value_counts(normalize=True)*100
pct_loan_default
```

[23]:
```
0    78.292888
1    21.707112
Name: loan_default, dtype: float64
```

[28]:
```
print('% of salaried customer only who have defaulted:',
      np.round(data[(data['Employment.Type']=='Salaried')
                    & (data['loan_default']==1)].shape[0]/
 ↪(data[data['Employment.Type']=='Salaried'].shape[0])*100,2))
```

```
% of salaried customer only who have defaulted: 20.35
```

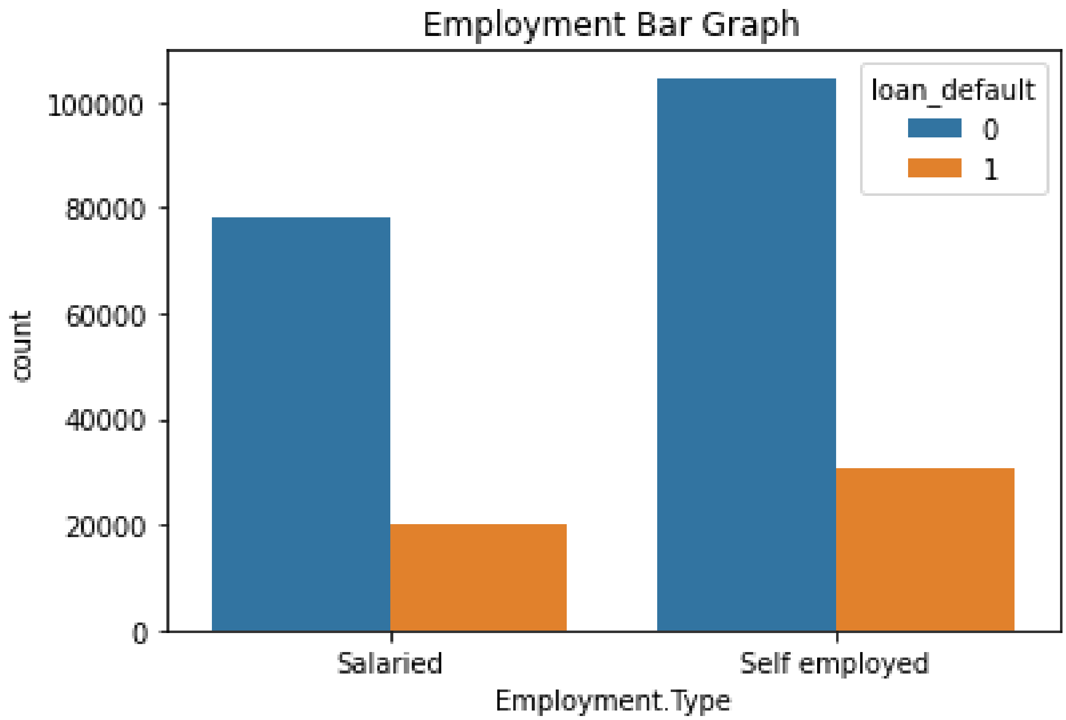
[30]:
```
print('% of self employed customer only who have defaulted:',
      np.round(data[(data['Employment.Type']=='Self employed')
                    & (data['loan_default']==1)].shape[0]/
 ↪(data[data['Employment.Type']=='Self employed'].shape[0])*100,2))
```

```
% of self employed customer only who have defaulted: 22.69
```

Bar Chart to draw the employment vs loan default

[32]:
```
sns.countplot(x='Employment.Type',hue='loan_default',data=data)
plt.title('Employment Bar Graph')
```

[32]:
```
Text(0.5, 1.0, 'Employment Bar Graph')
```

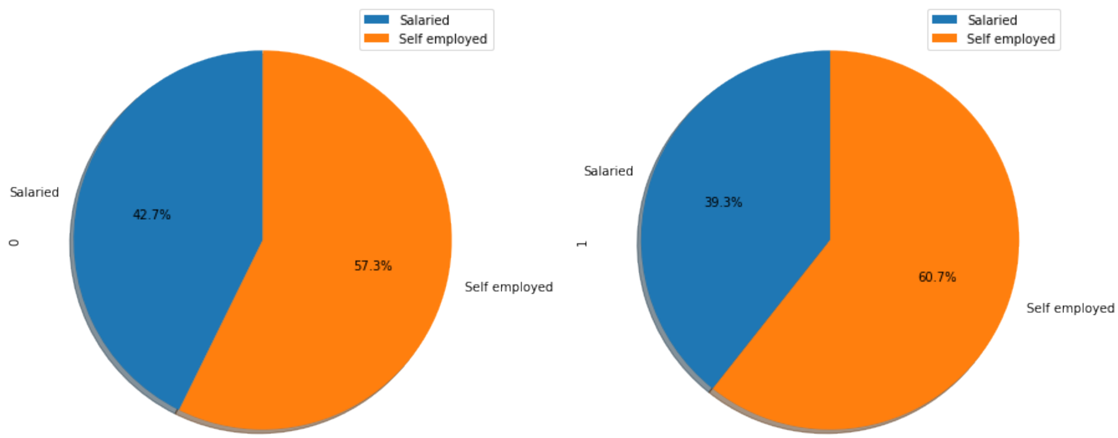


[34]:
```
loan=pd.crosstab(data['Employment.Type'],data['loan_default'])
loan
```

[34]:
```
loan_default          0      1
Employment.Type
Salaried          77948  19910
Self employed    104595  30701
```

[35]:
```
loan.groupby(['Employment.Type']).sum().plot(kind='pie', subplots=True, shadow␣
 ↪= True,startangle=90,
figsize=(15,10), autopct='%1.1f%%')
```

[35]:
```
array([<AxesSubplot:ylabel='0'>, <AxesSubplot:ylabel='1'>], dtype=object)
```

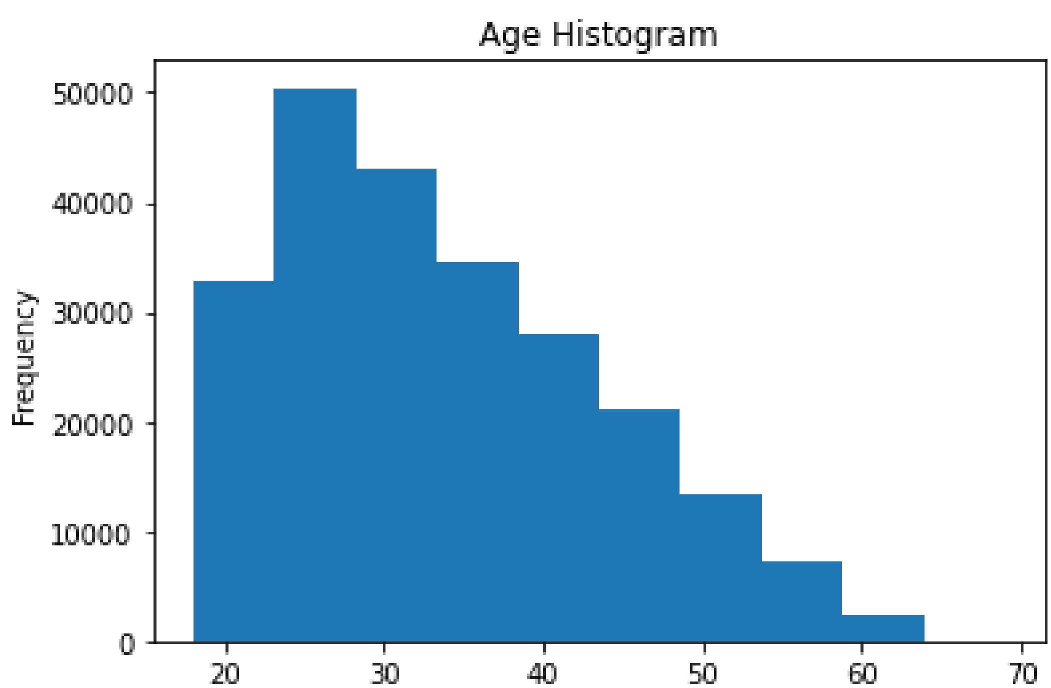


Distribution of age w.r.t. to defaulters and non-defaulters

[37]:
```
data['age'] = pd.DatetimeIndex(data['DisbursalDate']).year - pd.
↪DatetimeIndex(data['Date.of.Birth']).year
```

[41]:
```
data['age'].plot.hist()
plt.title('Age Histogram')
```

[41]: Text(0.5, 1.0, 'Age Histogram')



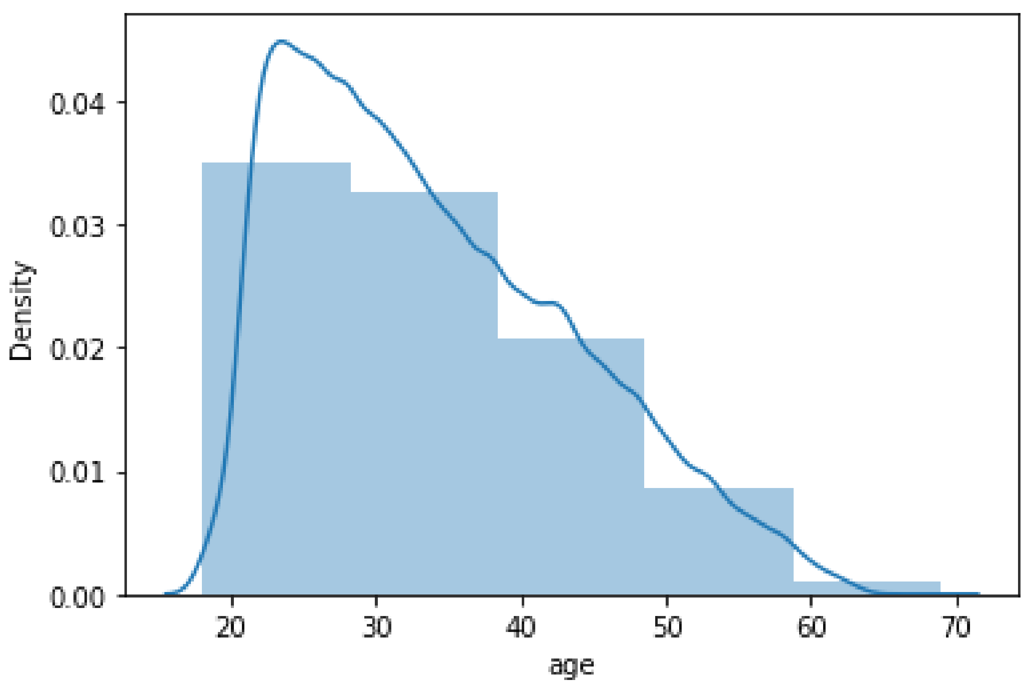
[42]:
```
data.age.describe()
```

[42]:
```
count    233154.000000
mean         34.100946
std           9.805992
min          18.000000
25%          26.000000
50%          32.000000
75%          41.000000
max          69.000000
Name: age, dtype: float64
```

[43]:
```
sns.distplot(data["age"],bins=5)
```

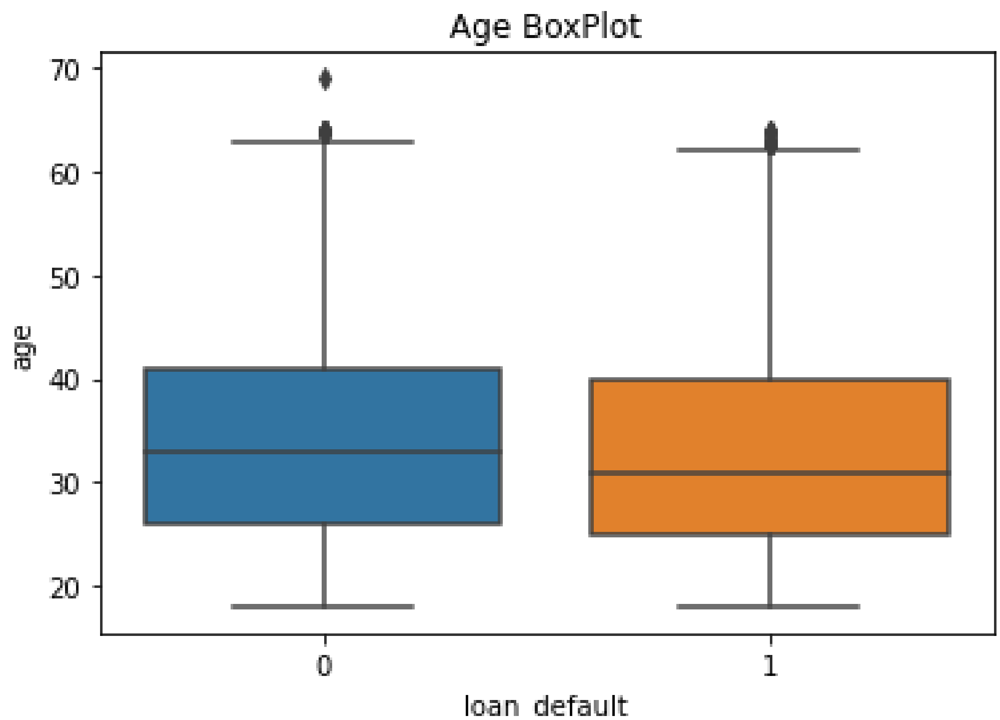
```
/usr/local/lib/python3.7/site-packages/seaborn/distributions.py:2619:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
```

[43]:
```
<AxesSubplot:xlabel='age', ylabel='Density'>
```



```
[44]: sns.boxplot(x='loan_default', y='age',data=data)
plt.title('Age BoxPlot')
```

```
[44]: Text(0.5, 1.0, 'Age BoxPlot')
```



Finding the type of ID was presented by most of the customers for proof

```
[45]: data["MobileNo_Avl_Flag"].value_counts()
```

```
[45]: 1    233154
Name: MobileNo_Avl_Flag, dtype: int64
```

```
[46]: data["Aadhar_flag"].value_counts()
```

```
[46]: 1    195924
0     37230
Name: Aadhar_flag, dtype: int64
```

```
[47]: data["PAN_flag"].value_counts()
```

```
[47]: 0    215533
1     17621
Name: PAN_flag, dtype: int64
```

[48]:
```
data["VoterID_flag"].value_counts()
```

[48]:
```
0    199360
1     33794
Name: VoterID_flag, dtype: int64
```

[49]:
```
data["Passport_flag"].value_counts()
```

[49]:
```
0    232658
1       496
Name: Passport_flag, dtype: int64
```

—–>**most of the users given Aadhar as their ID**

Credit bureau score distribution

[53]:
```
data["PERFORM_CNS.SCORE"].describe()
```

[53]:
```
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
```

Distribution for defaulters vs non-defaulters

[55]:
```
non_default = data[data['loan_default']==0]['PERFORM_CNS.SCORE']
default = data[data['loan_default']==1]['PERFORM_CNS.SCORE']
```

[56]:
```
pd.DataFrame([non_default.describe(), default.describe()],␣
↪index=['non_defaulters','defaulters'])
```

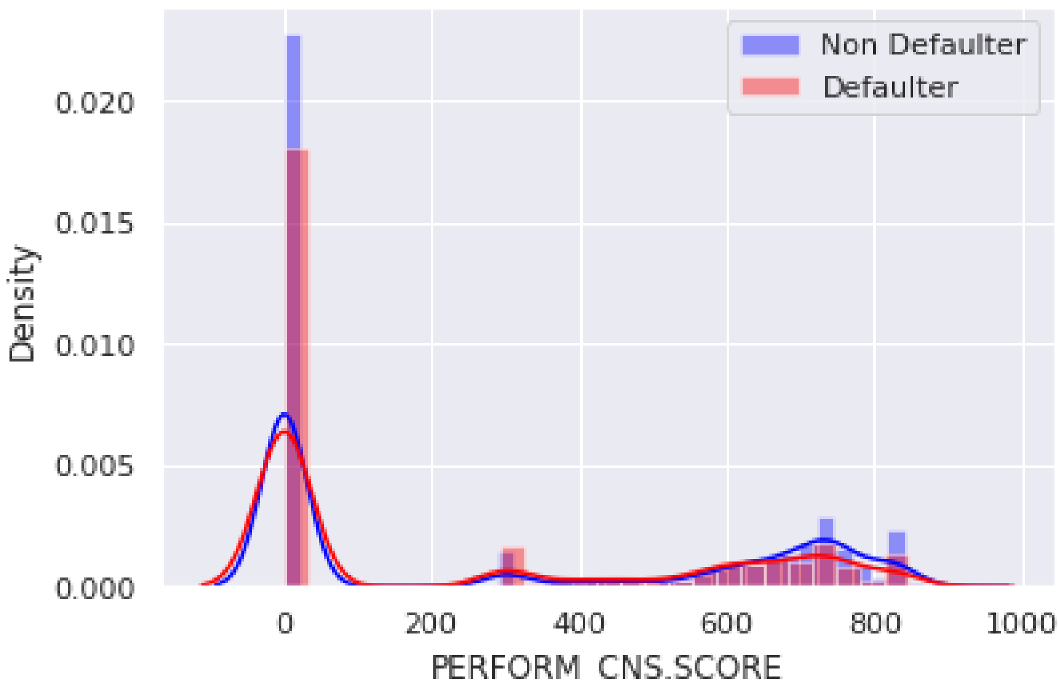
[56]:

	count	mean	std	min	25%	50%	75%	max
non_defaulters	182543.0	299.784270	342.883794	0.0	0.0	15.0	690.0	890.0
defaulters	50611.0	252.236372	318.826242	0.0	0.0	0.0	610.0	879.0

[66]:
```
sns.distplot( a = non_default, color='blue', label = 'Non Defaulter')
sns.distplot(a = default, color='red', label = 'Defaulter')
plt.legend()
plt.show()
```

```
/usr/local/lib/python3.7/site-packages/seaborn/distributions.py:2619:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `histplot` (an axes-level function for
```

```
histograms).
  warnings.warn(msg, FutureWarning)
/usr/local/lib/python3.7/site-packages/seaborn/distributions.py:2619:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
```



****Finding whether there is difference between the sanctioned and disbursed amount of primary and secondary loans(T-test)****

For Primary accounts

[70]:
```
_,p_value=stats.ttest_rel(a=data["PRI.SANCTIONED.AMOUNT"],b=data["PRI.DISBURSED.
↪AMOUNT"])
```

[71]:
```
print(p_value)
```

```
0.07550682707997997
```

[72]:
```
if p_value<0.05:
    print("Rejected,There is significant difference between primary loan␣
↪sanctioned and disbursed")
else:
```

```
    print("Accepted,There is no significant difference between primary loan␣
↪sanctioned and disbursed")
```

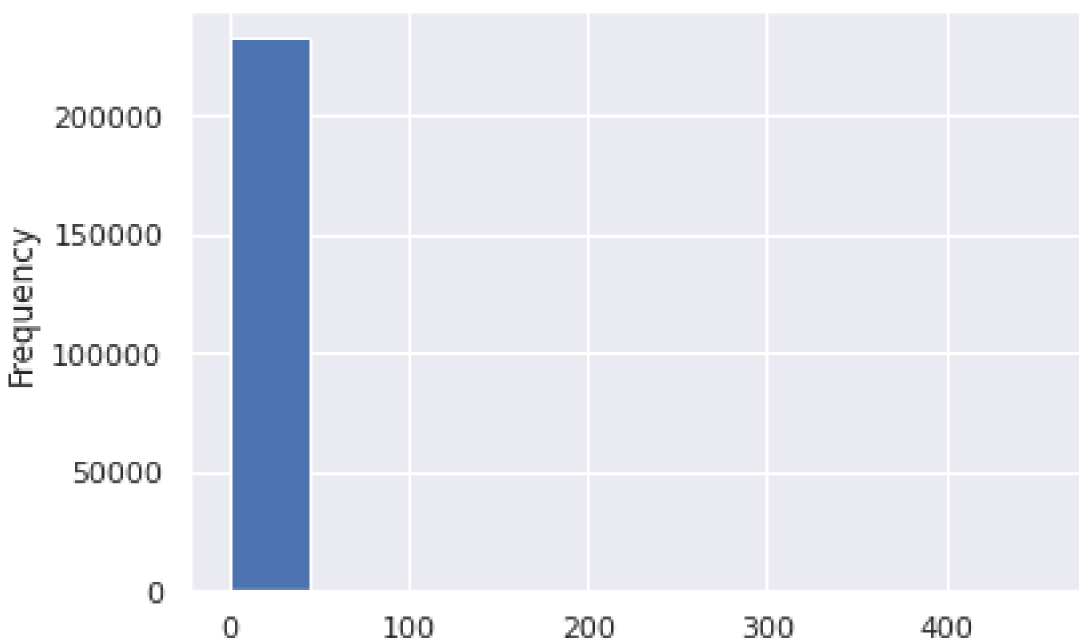
```
Accepted,There is no significant difference between primary loan sanctioned and
disbursed
```

[73]:
```
data["pri_diff_sanc_dis"]=data["PRI.SANCTIONED.AMOUNT"]-data["PRI.DISBURSED.
↪AMOUNT"]
```

[74]:
```
data["pri_diff_sanc_dis"].sum()
```

[74]: 102111349

[88]:
```
data['PRI.NO.OF.ACCTS'].plot(kind='hist')
plt.figure(figsize=(5,2))
plt.show()
```




```
<Figure size 360x144 with 0 Axes>
```

[81]:
```
pri_non_default = data[data['loan_default']==0]['PRI.NO.OF.ACCTS']
pri_default = data[data['loan_default']==1]['PRI.NO.OF.ACCTS']
```

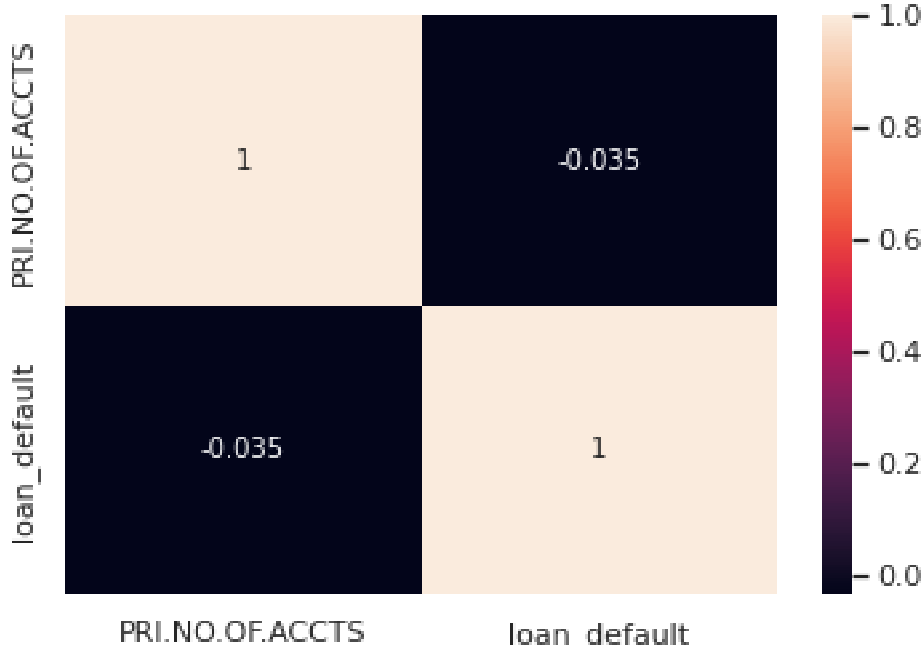
[82]:
```
pd.DataFrame([pri_non_default.describe(), pri_default.describe()],␣
↪index=['non_defaulters','defaulters'])
```

[82]:

	count	mean	std	min	25%	50%	75%	max
non_defaulters	182543.0	2.538038	5.261142	0.0	0.0	1.0	3.0	354.0
defaulters	50611.0	2.089328	5.040134	0.0	0.0	0.0	2.0	453.0

Checking the correlation between primary and loan deafult vairable

[87]:
```
sns.heatmap(data[['PRI.NO.OF.ACCTS','loan_default']].corr(),annot=True)
plt.show()
```



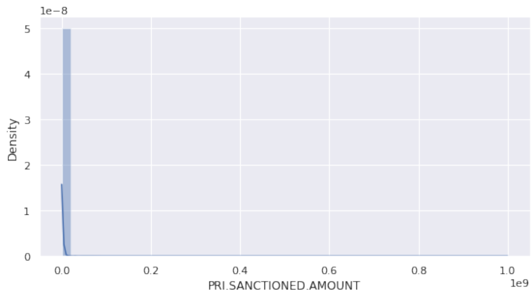
difference between the sanctioned and disbursed amount of primary loans

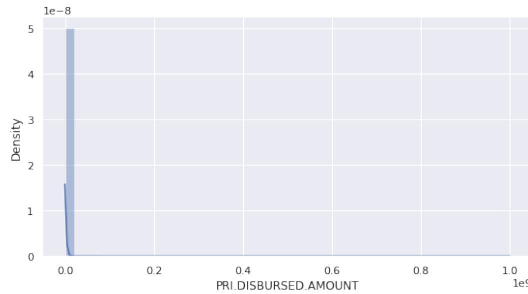
[89]:
```
pri_acct_loan_amt =['PRI.SANCTIONED.AMOUNT', 'PRI.DISBURSED.AMOUNT']
```

[90]:
```
count = 1
plt.figure(figsize=(20,10))
for i in pri_acct_loan_amt:
    plt.subplot(2,2,count)
    sns.distplot(data[i])
    count += 1
plt.show()
```

```
/usr/local/lib/python3.7/site-packages/seaborn/distributions.py:2619:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `histplot` (an axes-level function for
histograms).
```

```
  warnings.warn(msg, FutureWarning)
/usr/local/lib/python3.7/site-packages/seaborn/distributions.py:2619:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
```





For Secondary accounts

[75]:
```
_,p_value=stats.ttest_rel(a=data["SEC.SANCTIONED.AMOUNT"],b=data["SEC.DISBURSED.
↪AMOUNT"])
```

[76]:
```
print(p_value)
```

```
2.8873358771164625e-30
```

[77]:
```
if p_value<0.05:
    print("Rejected,There is significant difference between secondary loan␣
↪sanctioned and disbursed")
else:
    print("Accepted,There is no significant difference between secondary loan␣
↪sanctioned and disbursed")
```

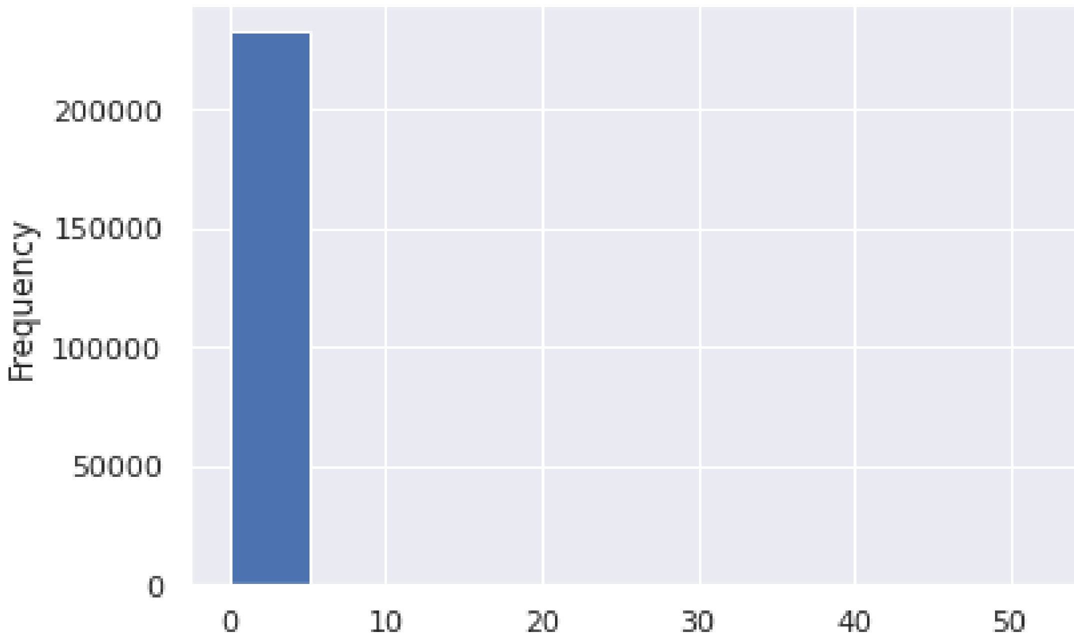
```
Rejected,There is significant difference between secondary loan sanctioned and
disbursed
```

[78]:
```
data["sec_diff_sanc_dis"]=data["SEC.SANCTIONED.AMOUNT"]-data["SEC.DISBURSED.
↪AMOUNT"]
```

[79]:
```
data["sec_diff_sanc_dis"].sum()
```

[79]: 27028488

[85]:
```
data['SEC.NO.OF.ACCTS'].plot(kind='hist')
plt.show()
```



Checking the correlation between seceondary and loan deafult vairable

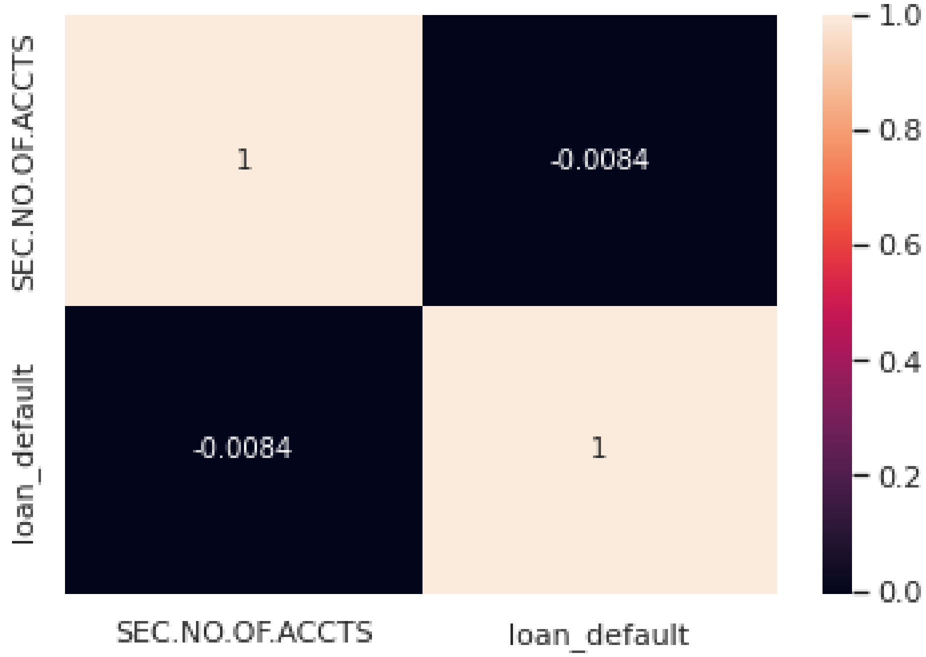
[83]:
```
sec_non_default = data[data['loan_default']==0]['SEC.NO.OF.ACCTS']
sec_default = data[data['loan_default']==1]['SEC.NO.OF.ACCTS']
```

[84]:
```
pd.DataFrame([sec_non_default.describe(), sec_default.describe()],␣
 ↪index=['non_defaulters','defaulters'])
```

[84]:

	count	mean	std	min	25%	50%	75%	max
non_defaulters	182543.0	0.061848	0.651657	0.0	0.0	0.0	0.0	52.0
defaulters	50611.0	0.049100	0.527358	0.0	0.0	0.0	0.0	38.0

[86]:
```
sns.heatmap(data[['SEC.NO.OF.ACCTS','loan_default']].corr(),annot=True)
plt.show()
```

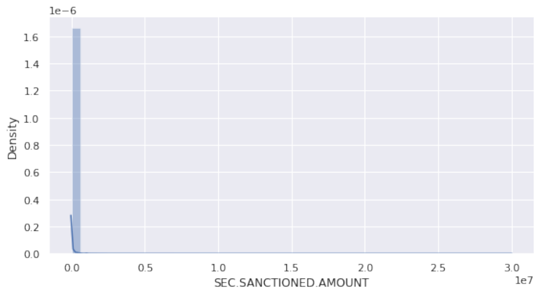


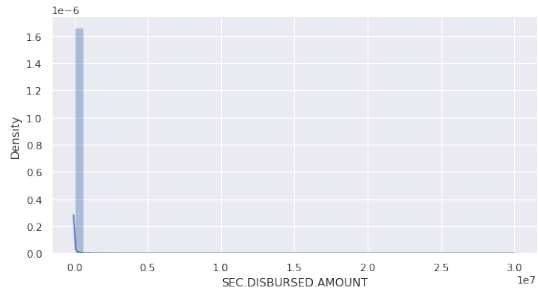
difference between the sanctioned and disbursed amount of secondary loans

[91]:
```
sec_acct_loan_amt =['SEC.SANCTIONED.AMOUNT', 'SEC.DISBURSED.AMOUNT']
```

[92]:
```
count=1
plt.figure(figsize=(20,10))
for i in sec_acct_loan_amt:
    plt.subplot(2,2,count)
    sns.distplot(data[i])
    count+=1
plt.show()
```

```
/usr/local/lib/python3.7/site-packages/seaborn/distributions.py:2619:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
/usr/local/lib/python3.7/site-packages/seaborn/distributions.py:2619:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
```





customer who make higher no. of enquiries end up being higher risk candidates

[94]:
```
enquiries_counts = data['NO.OF_INQUIRIES'].value_counts()
enquiries_counts_percent = data['NO.OF_INQUIRIES'].
 ↪value_counts(normalize=True)*100

pd.DataFrame({'counts':enquiries_counts,'(%) Percent_Of_Data':
 ↪enquiries_counts_percent})
```

[94]:

	counts	(%) Percent_Of_Data
0	201961	86.621289
1	22285	9.558060
2	5409	2.319926
3	1767	0.757868
4	760	0.325965
5	343	0.147113
6	239	0.102507
7	135	0.057902
8	105	0.045035
9	44	0.018872
10	34	0.014583
11	15	0.006434
12	14	0.006005
14	8	0.003431
15	7	0.003002
13	6	0.002573
19	6	0.002573
17	4	0.001716
18	4	0.001716
16	3	0.001287
28	1	0.000429
20	1	0.000429
22	1	0.000429
23	1	0.000429
36	1	0.000429

[95]:
```python
no_of_loan_inquiries = pd.crosstab(index=data['NO.OF_INQUIRIES'],
    columns=data['loan_default'])
no_of_loan_inquiries['pct_default'] = (no_of_loan_inquiries[1]/
    no_of_loan_inquiries.sum(axis=1))*100
no_of_loan_inquiries
```

[95]:
```
loan_default          0      1  pct_default
NO.OF_INQUIRIES
0                159404  42557    21.071890
1                 16844   5441    24.415526
2                  3918   1491    27.565169
3                  1250    517    29.258630
4                   526    234    30.789474
5                   212    131    38.192420
6                   148     91    38.075314
7                    80     55    40.740741
8                    61     44    41.904762
9                    30     14    31.818182
10                   23     11    32.352941
11                    8      7    46.666667
12                   10      4    28.571429
13                    2      4    66.666667
14                    6      2    25.000000
15                    3      4    57.142857
16                    3      0     0.000000
17                    4      0     0.000000
18                    2      2    50.000000
19                    4      2    33.333333
20                    1      0     0.000000
22                    1      0     0.000000
23                    1      0     0.000000
28                    1      0     0.000000
36                    1      0     0.000000
```

credit history, i.e. new loans in last six months, loans defaulted in last six months, time since first loan, etc., a significant factor in estimating probability

[96]:
```python
def duration(dur):
    yrs = int(dur.split(' ')[0].replace('yrs',''))
    mon = int(dur.split(' ')[1].replace('mon',''))
    return yrs*12+mon
```

[97]:
```python
data['CREDIT.HISTORY.LENGTH'] =data['CREDIT.HISTORY.LENGTH'].apply(duration)
```

[98]:
```python
data['CREDIT.HISTORY.LENGTH'].describe()
```

[98]:
```
count    233154.000000
mean         16.252404
std          28.581255
min           0.000000
25%           0.000000
50%           0.000000
75%          24.000000
max         468.000000
Name: CREDIT.HISTORY.LENGTH, dtype: float64
```

[99]:
```
credit_non_default = data[data['loan_default'] == 0]['CREDIT.HISTORY.LENGTH']
credit_default = data[data['loan_default'] == 1]['CREDIT.HISTORY.LENGTH']
```

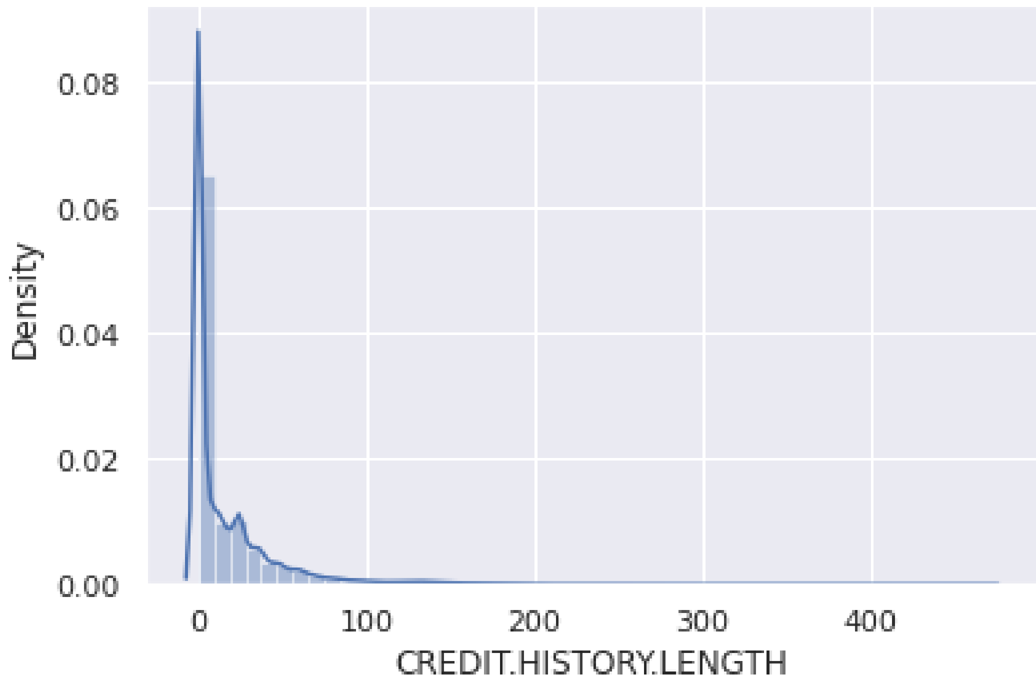
[100]:
```
pd.DataFrame([credit_non_default.describe(), credit_default.describe()],␣
↪index=['non_defaulters','defaulters'])
```

[100]:

	count	mean	std	min	25%	50%	75%	max
non_defaulters	182543.0	16.886377	29.342245	0.0	0.0	0.0	24.0	449.0
defaulters	50611.0	13.965798	25.519395	0.0	0.0	0.0	21.0	468.0

[101]:
```
sns.distplot(data['CREDIT.HISTORY.LENGTH'])
plt.show()
```

```
/usr/local/lib/python3.7/site-packages/seaborn/distributions.py:2619:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
```



[102]:
```
new_acct_counts = data['NEW.ACCTS.IN.LAST.SIX.MONTHS'].value_counts()
new_acct_counts_percent =data['NEW.ACCTS.IN.LAST.SIX.MONTHS'].
 ↪value_counts(normalize=True)*100

pd.DataFrame({'counts':new_acct_counts,'(%) Percent_Of_Data':
 ↪new_acct_counts_percent})
```

[102]:

	counts	(%) Percent_Of_Data
0	181494	77.842971
1	32099	13.767295
2	11015	4.724345
3	4458	1.912041
4	1957	0.839359
5	964	0.413461
6	480	0.205873
7	302	0.129528
8	147	0.063048
9	79	0.033883
10	55	0.023590
11	31	0.013296
12	20	0.008578
13	15	0.006434
14	11	0.004718
16	6	0.002573

```
17        6              0.002573
20        3              0.001287
15        2              0.000858
18        2              0.000858
19        2              0.000858
23        2              0.000858
28        1              0.000429
21        1              0.000429
22        1              0.000429
35        1              0.000429
```

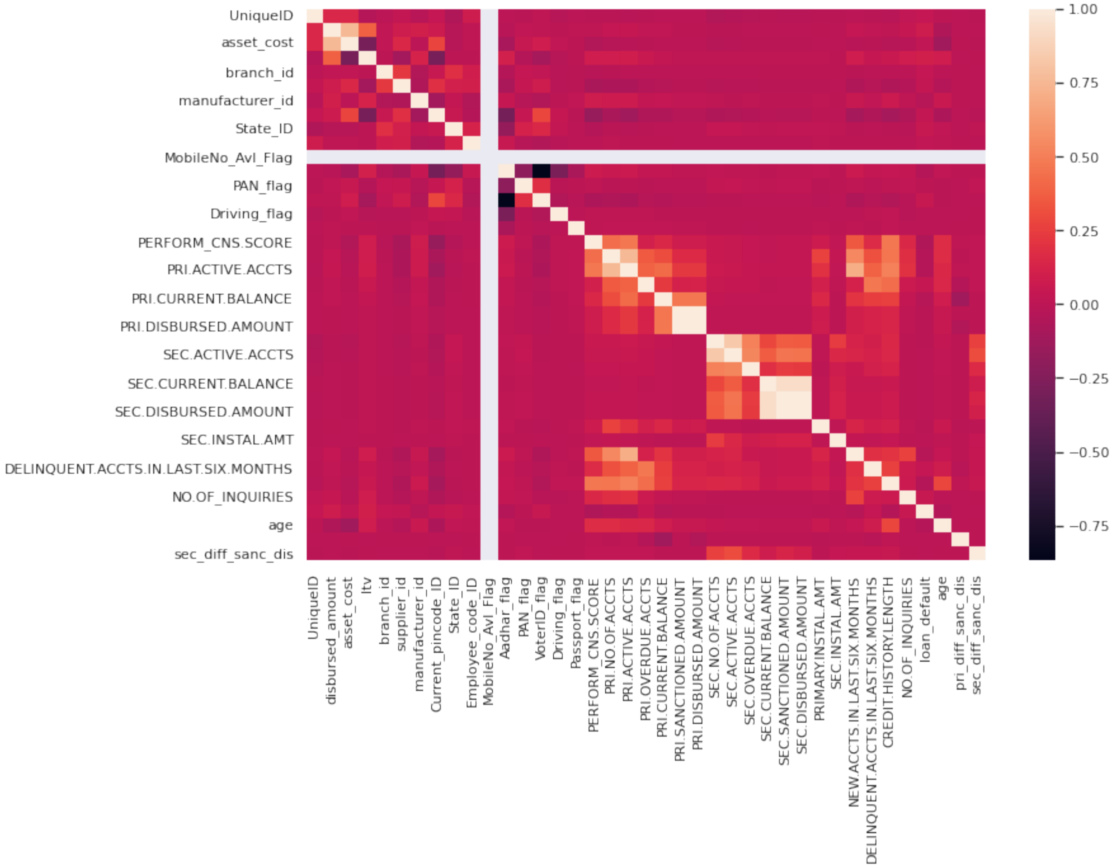
[103]:
```
delinquent_acct_counts = data['DELINQUENT.ACCTS.IN.LAST.SIX.MONTHS'].
 ↪value_counts()
delinquent_acct_counts_percent = data['DELINQUENT.ACCTS.IN.LAST.SIX.MONTHS'].
 ↪value_counts(normalize=True)*100

pd.DataFrame({'counts':delinquent_acct_counts,'delinquent_acct_counts':
 ↪delinquent_acct_counts_percent})
```

[103]:

	counts	delinquent_acct_counts
0	214959	92.196145
1	14941	6.408211
2	2470	1.059386
3	537	0.230320
4	138	0.059188
5	58	0.024876
6	20	0.008578
7	13	0.005576
8	7	0.003002
12	3	0.001287
11	3	0.001287
10	2	0.000858
9	2	0.000858
20	1	0.000429

[106]:
```
plt.figure(figsize=(12,8))
sns.heatmap(data.corr())
```

[106]: <AxesSubplot:>



From the correlation heatmap, Primary and secondary accounts,credit history, that is new loans in last six months, loans defaulted in last six months, time since first loan, are not a significant factor in estimating probability of loan defaulters

0.0.2 Model Building And Performing Prediction

[107]:
```
X=data.iloc[:
↪,[0,1,2,4,5,6,7,12,13,14,15,16,17,18,19,21,22,23,24,25,26,27,28,29,30,31,32,33,34,35,36,39]
y=data.iloc[:,40]
```

[108]:
```
X.head()
```

[108]:
```
   UniqueID  disbursed_amount  asset_cost  branch_id  supplier_id  \
0    420825             50578       58400         67        22807
1    417566             53278       61360         67        22807
2    539055             52378       60300         67        22807
3    529269             46349       61500         67        22807
4    563215             43594       78256         67        22744

   manufacturer_id  Current_pincode_ID  Employee_code_ID  MobileNo_Avl_Flag  \
```

```
0              45             1441           1998                1
1              45             1497           1998                1
2              45             1495           1998                1
3              45             1502           1998                1
4              86             1499           1998                1

   Aadhar_flag  …  SEC.ACTIVE.ACCTS  SEC.OVERDUE.ACCTS  SEC.CURRENT.BALANCE  \
0            1  …                 0                  0                    0
1            1  …                 0                  0                    0
2            1  …                 0                  0                    0
3            1  …                 0                  0                    0
4            1  …                 0                  0                    0

   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  NO.OF_INQUIRIES
0                                    0                0
1                                    0                0
2                                    0                1
3                                    0                0
4                                    0                0

[5 rows x 32 columns]
```

[110]:
```
X.shape
```

[110]: (233154, 32)

[111]:
```
y.shape
```

[111]: (233154,)

train test split

[121]:
```
from sklearn.model_selection import train_test_split
```

[112]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3,␣
↪random_state =42)
```

[113]:
```
print("X_train size: ", X_train.shape)
print("X_test size: ", X_test.shape)
```

```
X_train size:  (163207, 32)
X_test size:  (69947, 32)
```

[114]:
```
def evaluate_model(y_test, y_pred):
    print("Confusion Matrix: \n", metrics.confusion_matrix(y_test, y_pred))
    print("Accuracy: ",metrics.accuracy_score(y_test, y_pred))
    print("Precision: ",metrics.precision_score(y_test, y_pred))
    print("Recall: ",metrics.recall_score(y_test, y_pred))
    print("f1 score: ",metrics.f1_score(y_test, y_pred))
    print("roc_auc_score: ",metrics.roc_auc_score(y_test, y_pred))
```

Scaling data before model training and testing

[116]:
```
from sklearn.preprocessing import StandardScaler
```

[117]:
```
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

Performing Logistic Regression

[118]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
from sklearn import metrics
```

[119]:
```
params = {'C':[0.1, 0.5, 1, 5]}

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

```
/usr/local/lib/python3.7/site-packages/sklearn/linear_model/_logistic.py:818:
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
```

```
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG,
/usr/local/lib/python3.7/site-packages/sklearn/linear_model/_logistic.py:818:
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
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG,
/usr/local/lib/python3.7/site-packages/sklearn/linear_model/_logistic.py:818:
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
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG,
```

```
Confusion Matrix:
 [[54926   126]
 [14831    64]]
Accuracy:  0.7861666690494231
Precision:  0.3368421052631579
Recall:  0.004296743873783149
f1 score:  0.008485250248591316
roc_auc_score:  0.5010039993437069
```

[120]:
```python
from sklearn.metrics import accuracy_score,precision_score,recall_score,f1_score
print('Accuracy score: ',accuracy_score(y_test,y_pred))
print('Precision score: ',precision_score(y_test,y_pred))
print('Precision score: ',precision_score(y_test,y_pred))
print('Recall score: ',recall_score(y_test,y_pred))
print('F1 score: ',f1_score(y_test,y_pred))
```

```
Accuracy score:  0.7861666690494231
Precision score:  0.3368421052631579
Precision score:  0.3368421052631579
Recall score:  0.004296743873783149
F1 score:  0.008485250248591316
```

—>So, the accuracy for the logistic regression model is- 78%

Exporting trained data set for visualisation in Tableau

[122]:
```python
data.to_excel('D:\PGDA\Projects\loan.xlsx', index= False)
```

0.1 Dashboaring

https://public.tableau.com/views/CapstoneProject-2LoanDefaulter/Dashboard1?:language=en-US&:display_count=n&:origin=viz_share_link