CHAPTER 1: DEFINITION OF THE PROBLEM STATEMENT AND EXPLORATORY DATA ANALYSIS

INTRODUCTION TO `LOAN TAP`

`LoanTap` is a Fintech company (RBI registered NBFC) committtted to deliver flexible loan products to salaried professionals. It offers innovative loans to help millennials achieve a life that they desire. In the midst of a crowded `Personal Loan Segment`, The fastest Personal loans are delivered by `LoanTap` at customer friendly terms.

LoanTap deploys formal credit to salaried individuals and businesses in four different financial ways:

```
1. Personal Loan
2. EMI Free Loan
3. Personal Overdraft
4. Advance Salary Loan
```

DEFINITION OF PROBLEM

The data science team at LoanTap is building an underwriting layer to determine the creditworthiness of MSMEs as well as individuals

Given a set of attributes for an individual, The case study determines if a credit line should be extended to them. if so, what should the repayment terms be in business recommendations

TRADE OFF QUESTIONS:

How can we make sure that our model can detect real defaulters and there are less false positives? (This is important as we can lose out on an oppurtunity to finance more individuals and earn interest on it)

Since NPA (non performing asset) is real problem in this industry, It's important we play safe and shouldn't disburse loans to anyone

IMPORTING THE LIBRARIES AND DATASET

Importing all the required libraries

```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from itertools import combinations,permutations
from pandas.api.types import is_datetime64_any_dtype
```

```
import math
import warnings
from sklearn.impute import SimpleImputer,KNNImputer
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from imblearn.over_sampling import SMOTE
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import
accuracy_score,log_loss,f1_score,recall_score,precision_score,roc_auc_
score,matthews_corrcoef
from statsmodels.stats.outliers_influence import
variance_inflation_factor
import statsmodels.api as sm
from scipy import stats
from sklearn.pipeline import make_pipeline
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
from sklearn.metrics import fbeta_score
from sklearn.metrics import roc_curve, roc_auc_score
from sklearn.metrics import precision_recall_curve
from sklearn.metrics import auc
from sklearn.metrics import classification_report
```

Importing the Dataset

```
LoanTap = pd.read_csv("LoanTapData.csv")

# Changing the pandas option to display all columns of table
pd.set_option('display.max_columns',None)

# top 10 rows of the dataset
LoanTap.head(10)
```

```
   loan_amnt        term  int_rate  installment grade sub_grade  \
0    10000.0   36 months     11.44       329.48     B        B4
1     8000.0   36 months     11.99       265.68     B        B5
2    15600.0   36 months     10.49       506.97     B        B3
3     7200.0   36 months      6.49       220.65     A        A2
4    24375.0   60 months     17.27       609.33     C        C5
5    20000.0   36 months     13.33       677.07     C        C3
6    18000.0   36 months      5.32       542.07     A        A1
7    13000.0   36 months     11.14       426.47     B        B2
8    18900.0   60 months     10.99       410.84     B        B3
9    26300.0   36 months     16.29       928.40     C        C5

                       emp_title emp_length home_ownership  annual_inc
\
0                      Marketing  10+ years           RENT    117000.0

1                 Credit analyst     4 years       MORTGAGE     65000.0
```

```
2                    Statistician   < 1 year           RENT     43057.0

3                 Client Advocate    6 years           RENT     54000.0

4        Destiny Management Inc.    9 years       MORTGAGE     55000.0

5                   HR Specialist  10+ years       MORTGAGE     86788.0

6  Software Development Engineer    2 years       MORTGAGE    125000.0

7                    Office Depot  10+ years           RENT     46000.0

8           Application Architect  10+ years           RENT    103000.0

9              Regado Biosciences    3 years       MORTGAGE    115000.0


  verification_status   issue_d  loan_status             purpose  \
0        Not Verified  Jan-2015   Fully Paid            vacation
1        Not Verified  Jan-2015   Fully Paid  debt_consolidation
2     Source Verified  Jan-2015   Fully Paid         credit_card
3        Not Verified  Nov-2014   Fully Paid         credit_card
4            Verified  Apr-2013  Charged Off         credit_card
5            Verified  Sep-2015   Fully Paid  debt_consolidation
6     Source Verified  Sep-2015   Fully Paid    home_improvement
7        Not Verified  Sep-2012   Fully Paid         credit_card
8            Verified  Oct-2014   Fully Paid  debt_consolidation
9            Verified  Apr-2012   Fully Paid  debt_consolidation

                     title    dti earliest_cr_line  open_acc  pub_rec
\
0                 Vacation  26.24         Jun-1990      16.0      0.0

1       Debt consolidation  22.05         Jul-2004      17.0      0.0

2  Credit card refinancing  12.79         Aug-2007      13.0      0.0

3  Credit card refinancing   2.60         Sep-2006       6.0      0.0

4    Credit Card Refinance  33.95         Mar-1999      13.0      0.0

5       Debt consolidation  16.31         Jan-2005       8.0      0.0

6         Home improvement   1.36         Aug-2005       8.0      0.0

7     No More Credit Cards  26.87         Sep-1994      11.0      0.0

8       Debt consolidation  12.52         Jun-1994      13.0      0.0

9       Debt Consolidation  23.69         Dec-1997      13.0      0.0
```

```
   revol_bal  revol_util  total_acc initial_list_status
application_type  \
0    36369.0        41.8       25.0                   w
INDIVIDUAL
1    20131.0        53.3       27.0                   f
INDIVIDUAL
2    11987.0        92.2       26.0                   f
INDIVIDUAL
3     5472.0        21.5       13.0                   f
INDIVIDUAL
4    24584.0        69.8       43.0                   f
INDIVIDUAL
5    25757.0       100.6       23.0                   f
INDIVIDUAL
6     4178.0         4.9       25.0                   f
INDIVIDUAL
7    13425.0        64.5       15.0                   f
INDIVIDUAL
8    18637.0        32.9       40.0                   w
INDIVIDUAL
9    22171.0        82.4       37.0                   f
INDIVIDUAL

   mort_acc  pub_rec_bankruptcies  \
0       0.0                   0.0
1       3.0                   0.0
2       0.0                   0.0
3       0.0                   0.0
4       1.0                   0.0
5       4.0                   0.0
6       3.0                   0.0
7       0.0                   0.0
8       3.0                   0.0
9       1.0                   0.0

                                             address
0     0174 Michelle Gateway\r\nMendozaberg, OK 22690
1  1076 Carney Fort Apt. 347\r\nLoganmouth, SD 05113
2  87025 Mark Dale Apt. 269\r\nNew Sabrina, WV 05113
3            823 Reid Ford\r\nDelacruzside, MA 00813
4             679 Luna Roads\r\nGreggshire, VA 11650
5  1726 Cooper Passage Suite 129\r\nNorth Deniseb...
6  1008 Erika Vista Suite 748\r\nEast Stephanie, ...
7                        USCGC Nunez\r\nFPO AE 30723
8                         USCGC Tran\r\nFPO AP 22690
9             3390 Luis Rue\r\nMauricestad, VA 00813
```

Description regarding each column of the dataset

Column Name	Description
loan_amnt	The listed amount of the loan applied by the borrower. If at some point in time, the credit department reduces the loan amount, then it will be reflected in this value.
term	The number of payments on the loan. Values are in months and can be either 36 or 60.
int_rate	Interest Rate on the loan
installment	The monthly payment owed by the borrower if the loan originates. **Formulae: EMI = installment = (loan_amnt * (int_rate/100) * (1+(int_rate/100))^term)/((1+(int_rate/100))^(term-1))**
grade	LoanTap assigned loan grade.(**Loan grading is the process of assigning a quality score to a loan application to identify a risk of default. This score is based on the borrower's credit history, quality of the collateral, and likelihood of repayment.Generally A grade means Lower interest, Lower loan losses, Lower expected returns. G grade means Higher interest, Higher loan losses, Higher expected returns**)
sub_grade	LoanTap assigned loan subgrade(**each loan grade is again subdivided into subgrades. Generally 1 means lowest interest rate in that loan grade. 5 means highest interest rate in that loan grade**)
emp_title	The job title supplied by the Borrower when applying for the loan.*
emp_length	Employment length in years. Possible values are between 0 and 10 where 0 means less than one year and 10 means ten or more years.
home_ownership	The home ownership status provided by the borrower during registration or obtained from the credit report.
annual_inc	The self-reported annual income provided by the borrower during registration.
verification_status	Indicates if income was verified by LoanTap, not verified, or if the income source was verified
issue_d	The month which the loan was funded
loan_status	Current status of the loan **Target Variable**
purpose	A category provided by the borrower for the

Column Name	Description
	loan request.
title	The loan title provided by the borrower
dti	A ratio calculated using the borrower’s total monthly debt payments on the total debt obligations, excluding mortgage and the requested LoanTap loan, divided by the borrower’s self-reported monthly income. **total debt(excluding mortgage and loan tap loan)/monthly income**
earliest_cr_line	The month the borrower's earliest reported credit line was opened (**credit line means a debt account**)
open_acc	The number of open credit lines in the borrower's credit file. **implies number of debt accounts at present**
pub_rec	Number of derogatory public records **implies number of negative records publicly**
revol_bal	Total credit revolving balance **implies present total credit amount yet to be paid by the borrower**
revol_util	Revolving line utilization rate, or the amount of credit the borrower is using relative to all available revolving credit. **implies total debt/total available credit**
total_acc	The total number of credit lines currently in the borrower's credit file **implies total number of debt accounts opened in borrower life. Some of them may be closed/cleared by now.**
initial_list_status	The initial listing status of the loan. Possible values are – W, F. **W = Whole loan amount funded by single investor, F = Fractional Loan invest implies Number of investors funded the loan amount**
application_type	Indicates whether the loan is an individual application or a joint application with two co-borrowers
mort_acc	Number of mortgage accounts **implies Number of accounts related to home loan or real estate related loan**
pub_rec_bankruptcies	Number of public record bankruptcies **implies number of times borrower has filed bankruptcies in court**
Address	Address of the individual

ANALYSING BASIC METRICS OF DATASET

Shape of the data

```
print(f"Number of rows in the dataset = {LoanTap.shape[0]}")
print(f"Number of columns in the dataset = {LoanTap.shape[1]}")

Number of rows in the dataset = 396030
Number of columns in the dataset = 27
```

Datatypes of all the attributes

```
LoanTap.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 396030 entries, 0 to 396029
Data columns (total 27 columns):
 #   Column                Non-Null Count   Dtype  
---  ------                --------------   -----  
 0   loan_amnt             396030 non-null  float64
 1   term                  396030 non-null  object 
 2   int_rate              396030 non-null  float64
 3   installment           396030 non-null  float64
 4   grade                 396030 non-null  object 
 5   sub_grade             396030 non-null  object 
 6   emp_title             373103 non-null  object 
 7   emp_length            377729 non-null  object 
 8   home_ownership        396030 non-null  object 
 9   annual_inc            396030 non-null  float64
 10  verification_status   396030 non-null  object 
 11  issue_d               396030 non-null  object 
 12  loan_status           396030 non-null  object 
 13  purpose               396030 non-null  object 
 14  title                 394275 non-null  object 
 15  dti                   396030 non-null  float64
 16  earliest_cr_line      396030 non-null  object 
 17  open_acc              396030 non-null  float64
 18  pub_rec               396030 non-null  float64
 19  revol_bal             396030 non-null  float64
 20  revol_util            395754 non-null  float64
 21  total_acc             396030 non-null  float64
 22  initial_list_status   396030 non-null  object 
 23  application_type      396030 non-null  object 
 24  mort_acc              358235 non-null  float64
 25  pub_rec_bankruptcies  395495 non-null  float64
 26  address               396030 non-null  object 
dtypes: float64(12), object(15)
memory usage: 81.6+ MB
```

Observations:

12 float datatype columns

15 object datatype columns

Total 27 columns and 396030 rows

Null values are present in the data

Doubt: Should we have to convert Datatypes? Which Columns?

term --> int

emp_length --> int

issue_d and earliest cr line--> feature engineer to age

issue_d and earliest cr line --> date format

extract State from address(feature engineering), City and Pincode looking like wrong ones

Conversion of dates to datetime datatype

```
# Conversion of issue_d and earliest_cr_line columns to datetime
datatype
LoanTap["issue_d"] = LoanTap["issue_d"].astype('datetime64[ns]')
LoanTap["earliest_cr_line"] =
LoanTap["earliest_cr_line"].astype('datetime64[ns]')
```

Missing value or Null Value Detection

```
# Null value count
LoanTap.isna().sum()
```

```
loan_amnt                 0
term                      0
int_rate                  0
installment               0
grade                     0
sub_grade                 0
emp_title             22927
emp_length            18301
home_ownership            0
annual_inc                0
verification_status       0
issue_d                   0
loan_status               0
purpose                   0
title                  1755
dti                       0
earliest_cr_line          0
open_acc                  0
pub_rec                   0
revol_bal                 0
revol_util              276
```

```
total_acc                         0
initial_list_status               0
application_type                  0
mort_acc                      37795
pub_rec_bankruptcies            535
address                           0
dtype: int64
```

```
# Percenatage of Null Values
(LoanTap.isna().sum() / LoanTap.shape[0]) * 100
```

```
loan_amnt               0.000000
term                    0.000000
int_rate                0.000000
installment             0.000000
grade                   0.000000
sub_grade               0.000000
emp_title               5.789208
emp_length              4.621115
home_ownership          0.000000
annual_inc              0.000000
verification_status     0.000000
issue_d                 0.000000
loan_status             0.000000
purpose                 0.000000
title                   0.443148
dti                     0.000000
earliest_cr_line        0.000000
open_acc                0.000000
pub_rec                 0.000000
revol_bal               0.000000
revol_util              0.069692
total_acc               0.000000
initial_list_status     0.000000
application_type        0.000000
mort_acc                9.543469
pub_rec_bankruptcies    0.135091
address                 0.000000
dtype: float64
```

```
# Filtering the columns which have zero null values and sorting in
descending order
def missing_LoanTap(LoanTap):
    total_missing_LoanTap = LoanTap.isna().sum().sort_values(ascending
= False)
    percentage_missing_LoanTap =
((LoanTap.isna().sum()/len(LoanTap)*100)).sort_values(ascending =
False)
    missingLoanTap = pd.concat([total_missing_LoanTap,
percentage_missing_LoanTap],axis = 1, keys=['Total', 'Percent'])
```

```
    return missingLoanTap


missing_LoanTap = missing_LoanTap(LoanTap)
missing_LoanTap[missing_LoanTap["Total"]>0]
```

	Total	Percent
mort_acc	37795	9.543469
emp_title	22927	5.789208
emp_length	18301	4.621115
title	1755	0.443148
pub_rec_bankruptcies	535	0.135091
revol_util	276	0.069692

```
# Sum of all individual null value counts in each column
37795+22927+18301+1755+535+276
```

```
81589
```

```
# Number of rows with null values with atleast one null value
LoanTap.isnull().any(axis=1).sum()
```

```
60162
```

```
LoanTap.isnull().any(axis=1).sum()*100/len(LoanTap)
```

```
15.191273388379669
```

Observations:

- 15% rows are having null values. 15% is higher value. Should not delete them. Should handle the null value properly
- May be it is possible to impute some of the null values of title using purpose column as both columns are similar in nature
- emp title null can be modified to UNKNOWN title
- As Loan Tap main motto is to provide as many loans as possible (even it is less secure), pub_rec_bankruptcies can be treated as 0.
- Let's try to use formulae to calculate revol_utilisation rate if possible (to clear null values)
- Lets use some formulae to impute null values in emp_length
- Let's find relation between mortgage acc and other colums. If no relation, impute them to default value 0.

Descriptive Statistics regarding each column of dataset

```
# Numerical columns descriptive statistics
LoanTap.describe()
```

```
            loan_amnt       int_rate    installment     annual_inc  \
count  396030.000000  396030.000000  396030.000000   3.960300e+05
mean    14113.888089      13.639400     431.849698   7.420318e+04
std      8357.441341       4.472157     250.727790   6.163762e+04
min       500.000000       5.320000      16.080000   0.000000e+00
25%      8000.000000      10.490000     250.330000   4.500000e+04
50%     12000.000000      13.330000     375.430000   6.400000e+04
75%     20000.000000      16.490000     567.300000   9.000000e+04
max     40000.000000      30.990000    1533.810000   8.706582e+06

                  dti       open_acc        pub_rec      revol_bal  \
count  396030.000000  396030.000000  396030.000000   3.960300e+05
mean       17.379514      11.311153       0.178191   1.584454e+04
std        18.019092       5.137649       0.530671   2.059184e+04
min         0.000000       0.000000       0.000000   0.000000e+00
25%        11.280000       8.000000       0.000000   6.025000e+03
50%        16.910000      10.000000       0.000000   1.118100e+04
75%        22.980000      14.000000       0.000000   1.962000e+04
max      9999.000000      90.000000      86.000000   1.743266e+06

           revol_util      total_acc       mort_acc
pub_rec_bankruptcies
count  395754.000000  396030.000000  358235.000000
395495.000000
mean       53.791749      25.414744       1.813991
0.121648
std        24.452193      11.886991       2.147930
0.356174
min         0.000000       2.000000       0.000000
0.000000
25%        35.800000      17.000000       0.000000
0.000000
50%        54.800000      24.000000       1.000000
0.000000
75%        72.900000      32.000000       3.000000
0.000000
max       892.300000     151.000000      34.000000
8.000000
```

Observations:

- mean loan amount = $14113 and median loan amount = $12000. As there is difference between them, Outliers may be present.
- mean installment = $431 and median installment = $375 As there is difference between them, Outliers may be present.
- 75th percentile of dti = 22.98 but max of dti = 9999 . so definitely outliers present in dti column
- 75th percentile of open_acc = 14 but max of open_acc = 90 . so definitely outliers present in open_acc column

75th percentile of pub_rec = 0 but max of pub_rec = 86 . so definitely outliers present in pub_rec column

75th percentile of revol_bal = 19620 but max of revol_bal = 1743266 . so definitely outliers present in revol_bal column

75th percentile of revol_util = 72.9 but max of revol_util = 892.3 . so definitely outliers present in revol_util column

75th percentile of total_acc = 32 but max of total_acc = 151 . so definitely outliers present in total_acc column

75th percentile of mort_acc = 3 but max of mort_acc = 34 . so definitely outliers present in mort_acc column

75th percentile of pub_rec_bankruptcies = 0 but max of pub_rec_bankruptcies = 8 . so definitely outliers present in pub_rec_bankruptcies column

```
# Object datatype columns descriptive statistics
LoanTap.describe(include="object")
```

```
              term   grade sub_grade emp_title emp_length
home_ownership  \
count       396030  396030    396030    373103     377729
396030
unique           2       7        35    173105         11
6
top      36 months       B        B3   Teacher  10+ years
MORTGAGE
freq        302005  116018     26655      4389     126041
198348

       verification_status loan_status             purpose  \
count               396030      396030              396030
unique                   3           2                  14
top               Verified  Fully Paid  debt_consolidation
freq                139563      318357              234507

                      title initial_list_status application_type  \
count                394275              396030           396030
unique                48817                   2                3
top      Debt consolidation                   f       INDIVIDUAL
freq                 152472              238066           395319

                              address
count                          396030
unique                         393700
top      USCGC Smith\r\nFPO AE 70466
freq                                8
```

Number of unique values in each column of given dataset

```
for i in LoanTap.columns:
    print(i,":",LoanTap[i].nunique())
```

```
loan_amnt : 1397
term : 2
int_rate : 566
installment : 55706
grade : 7
sub_grade : 35

emp_title : 173105
emp_length : 11
home_ownership : 6
annual_inc : 27197
verification_status : 3
issue_d : 115
loan_status : 2
purpose : 14
title : 48817
dti : 4262
earliest_cr_line : 684
open_acc : 61
pub_rec : 20
revol_bal : 55622
revol_util : 1226
total_acc : 118
initial_list_status : 2
application_type : 3
mort_acc : 33
pub_rec_bankruptcies : 9
address : 393700
```

Unique values of columns whose nunique < 500

```
for i in LoanTap.columns:
    if LoanTap[i].nunique() < 500:
        print(i,LoanTap[i].unique(),"",sep = "\n")
```

```
term
[' 36 months' ' 60 months']

grade
['B' 'A' 'C' 'E' 'D' 'F' 'G']

sub_grade
['B4' 'B5' 'B3' 'A2' 'C5' 'C3' 'A1' 'B2' 'C1' 'A5' 'E4' 'A4' 'A3' 'D1'
 'C2' 'B1' 'D3' 'D5' 'D2' 'E1' 'E2' 'E5' 'F4' 'E3' 'D4' 'G1' 'F5' 'G2'
 'C4' 'F1' 'F3' 'G5' 'G4' 'F2' 'G3']
```

```
emp_length
['10+ years' '4 years' '< 1 year' '6 years' '9 years' '2 years' '3
years'
 '8 years' '7 years' '5 years' '1 year' nan]

home_ownership
['RENT' 'MORTGAGE' 'OWN' 'OTHER' 'NONE' 'ANY']

verification_status
['Not Verified' 'Source Verified' 'Verified']

issue_d
['2015-01-01T00:00:00.000000000' '2014-11-01T00:00:00.000000000'
 '2013-04-01T00:00:00.000000000' '2015-09-01T00:00:00.000000000'
 '2012-09-01T00:00:00.000000000' '2014-10-01T00:00:00.000000000'
 '2012-04-01T00:00:00.000000000' '2013-06-01T00:00:00.000000000'
 '2014-05-01T00:00:00.000000000' '2015-12-01T00:00:00.000000000'
 '2015-04-01T00:00:00.000000000' '2012-10-01T00:00:00.000000000'
 '2014-07-01T00:00:00.000000000' '2013-02-01T00:00:00.000000000'
 '2015-10-01T00:00:00.000000000' '2014-01-01T00:00:00.000000000'
 '2016-03-01T00:00:00.000000000' '2014-04-01T00:00:00.000000000'
 '2011-06-01T00:00:00.000000000' '2010-04-01T00:00:00.000000000'
 '2014-06-01T00:00:00.000000000' '2013-10-01T00:00:00.000000000'
 '2013-05-01T00:00:00.000000000' '2015-02-01T00:00:00.000000000'
 '2011-10-01T00:00:00.000000000' '2015-06-01T00:00:00.000000000'
 '2013-08-01T00:00:00.000000000' '2014-02-01T00:00:00.000000000'
 '2011-12-01T00:00:00.000000000' '2013-03-01T00:00:00.000000000'
 '2016-06-01T00:00:00.000000000' '2014-03-01T00:00:00.000000000'
 '2013-11-01T00:00:00.000000000' '2014-12-01T00:00:00.000000000'
 '2016-04-01T00:00:00.000000000' '2013-09-01T00:00:00.000000000'
 '2016-05-01T00:00:00.000000000' '2015-07-01T00:00:00.000000000'
 '2013-07-01T00:00:00.000000000' '2014-08-01T00:00:00.000000000'
 '2008-05-01T00:00:00.000000000' '2010-03-01T00:00:00.000000000'
 '2013-12-01T00:00:00.000000000' '2012-03-01T00:00:00.000000000'
 '2015-03-01T00:00:00.000000000' '2011-09-01T00:00:00.000000000'
 '2012-07-01T00:00:00.000000000' '2012-12-01T00:00:00.000000000'
 '2014-09-01T00:00:00.000000000' '2012-11-01T00:00:00.000000000'
 '2015-11-01T00:00:00.000000000' '2011-01-01T00:00:00.000000000'
 '2012-05-01T00:00:00.000000000' '2016-02-01T00:00:00.000000000'
 '2012-06-01T00:00:00.000000000' '2012-08-01T00:00:00.000000000'
 '2016-01-01T00:00:00.000000000' '2015-05-01T00:00:00.000000000'
 '2016-10-01T00:00:00.000000000' '2015-08-01T00:00:00.000000000'
 '2016-07-01T00:00:00.000000000' '2009-05-01T00:00:00.000000000'
 '2016-08-01T00:00:00.000000000' '2012-01-01T00:00:00.000000000'
 '2013-01-01T00:00:00.000000000' '2010-11-01T00:00:00.000000000'
 '2011-07-01T00:00:00.000000000' '2011-03-01T00:00:00.000000000'
 '2012-02-01T00:00:00.000000000' '2011-05-01T00:00:00.000000000'
 '2010-08-01T00:00:00.000000000' '2016-11-01T00:00:00.000000000'
 '2010-07-01T00:00:00.000000000' '2010-09-01T00:00:00.000000000'
 '2010-12-01T00:00:00.000000000' '2011-02-01T00:00:00.000000000'
```

```
 '2009-06-01T00:00:00.000000000' '2011-08-01T00:00:00.000000000'
 '2016-12-01T00:00:00.000000000' '2009-03-01T00:00:00.000000000'
 '2010-06-01T00:00:00.000000000' '2010-05-01T00:00:00.000000000'
 '2011-11-01T00:00:00.000000000' '2016-09-01T00:00:00.000000000'
 '2009-10-01T00:00:00.000000000' '2008-03-01T00:00:00.000000000'
 '2008-11-01T00:00:00.000000000' '2009-12-01T00:00:00.000000000'
 '2010-10-01T00:00:00.000000000' '2009-09-01T00:00:00.000000000'
 '2007-10-01T00:00:00.000000000' '2009-08-01T00:00:00.000000000'
 '2009-07-01T00:00:00.000000000' '2009-11-01T00:00:00.000000000'
 '2010-01-01T00:00:00.000000000' '2008-12-01T00:00:00.000000000'
 '2009-02-01T00:00:00.000000000' '2008-10-01T00:00:00.000000000'
 '2009-04-01T00:00:00.000000000' '2010-02-01T00:00:00.000000000'
 '2011-04-01T00:00:00.000000000' '2008-04-01T00:00:00.000000000'
 '2008-08-01T00:00:00.000000000' '2009-01-01T00:00:00.000000000'
 '2008-02-01T00:00:00.000000000' '2007-08-01T00:00:00.000000000'
 '2008-09-01T00:00:00.000000000' '2007-12-01T00:00:00.000000000'
 '2008-01-01T00:00:00.000000000' '2007-09-01T00:00:00.000000000'
 '2008-06-01T00:00:00.000000000' '2008-07-01T00:00:00.000000000'
 '2007-06-01T00:00:00.000000000' '2007-11-01T00:00:00.000000000'
 '2007-07-01T00:00:00.000000000']

loan_status
['Fully Paid' 'Charged Off']

purpose
['vacation' 'debt_consolidation' 'credit_card' 'home_improvement'
 'small_business' 'major_purchase' 'other' 'medical' 'wedding' 'car'
 'moving' 'house' 'educational' 'renewable_energy']

open_acc
[16. 17. 13.  6.  8. 11.  5. 30.  9. 15. 12. 10. 18.  7.  4. 14. 20.
19.
 21. 23.  3. 26. 42. 22. 25. 28.  2. 34. 24. 27. 31. 32. 33.  1. 29.
36.
 40. 35. 37. 41. 44. 39. 49. 48. 38. 51. 50. 43. 46.  0. 47. 57. 53.
58.
 52. 54. 45. 90. 56. 55. 76.]

pub_rec
[ 0.  1.  2.  3.  4.  6.  5.  8.  9. 10. 11.  7. 19. 13. 40. 17. 86.
12.
 24. 15.]

total_acc
[ 25.  27.  26.  13.  43.  23.  15.  40.  37.  61.  35.  22.  20.  36.
  38.   7.  18.  10.  17.  29.  16.  21.  34.   9.  14.  59.  41.  19.
  12.  30.  56.  24.  28.   8.  52.  31.  44.  39.  50.  11.  62.  32.
   5.  33.  46.  42.   6.  49.  45.  57.  48.  67.  47.  51.  58.   3.
  55.  63.  53.   4.  71.  69.  54.  64.  81.  72.  60.  68.  65.  73.
  78.  84.   2.  76.  75.  79.  87.  77. 104.  89.  70. 105.  97.  66.
```

```
 108.   74.   80.   82.   91.   93. 106.   90.   85.   88.   83. 111.   86. 101.
 135.   92.   94.   95.   99. 102. 129. 110. 124. 151. 107. 118. 150. 115.
 117.   96.   98. 100. 116. 103.]

initial_list_status
['w' 'f']

application_type
['INDIVIDUAL' 'JOINT' 'DIRECT_PAY']

mort_acc
[ 0.  3.  1.  4.  2.  6.  5. nan 10.  7. 12. 11.  8.  9. 13. 14. 22.
34.
 15. 25. 19. 16. 17. 32. 18. 24. 21. 20. 31. 28. 30. 23. 26. 27.]

pub_rec_bankruptcies
[ 0.  1.  2.  3. nan  4.  5.  6.  7.  8.]
```

Conversion of some Object columns to Categorical dtype for object columns with nunique<50 only

```
cat_cols = []
num_cols = []
date_cols = []
for i in LoanTap.columns:
    if not(isinstance(LoanTap[i][0],float) or
(is_datetime64_any_dtype(LoanTap[i]))):
        cat_cols.append(i)
        if LoanTap[i].nunique()< 50:
            # term, grade, sub grade , emp length are logically in
order
            if (i in ["term","grade","sub_grade","emp_length"]):
                LoanTap[i] = pd.Categorical(LoanTap[i],ordered = True)
            else:
                LoanTap[i] = pd.Categorical(LoanTap[i],ordered =
False)
    elif (is_datetime64_any_dtype(LoanTap[i])):
        date_cols.append(i)
    else:
        num_cols.append(i)

# Separating the column names to three lists - cat_cols, num_cols,
date_cols
print(f"categorical columns are {cat_cols}",f"Numerical columns are
{num_cols}",\
    f"datetime columns are {date_cols}",sep= "\n")

categorical columns are ['term', 'grade', 'sub_grade', 'emp_title',
'emp_length', 'home_ownership', 'verification_status', 'loan_status',
```

```
'purpose', 'title', 'initial_list_status', 'application_type',
'address']
Numerical columns are ['loan_amnt', 'int_rate', 'installment',
'annual_inc', 'dti', 'open_acc', 'pub_rec', 'revol_bal', 'revol_util',
'total_acc', 'mort_acc', 'pub_rec_bankruptcies']
datetime columns are ['issue_d', 'earliest_cr_line']
```

```
# Setting the emp_length column in logical order
LoanTap["emp_length"] = pd.Categorical(LoanTap["emp_length"],
categories=["NaN",'< 1 year','1 year','2 years', '3 years','4
years','5 years', '6 years', '7 years','8 years','9 years','10+
years'],ordered = True)

LoanTap.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 396030 entries, 0 to 396029
Data columns (total 27 columns):
 #   Column                Non-Null Count   Dtype
---  ------                --------------   -----
 0   loan_amnt             396030 non-null  float64
 1   term                  396030 non-null  category
 2   int_rate              396030 non-null  float64
 3   installment           396030 non-null  float64
 4   grade                 396030 non-null  category
 5   sub_grade             396030 non-null  category
 6   emp_title             373103 non-null  object
 7   emp_length            377729 non-null  category
 8   home_ownership        396030 non-null  category
 9   annual_inc            396030 non-null  float64
 10  verification_status   396030 non-null  category
 11  issue_d               396030 non-null  datetime64[ns]
 12  loan_status           396030 non-null  category
 13  purpose               396030 non-null  category
 14  title                 394275 non-null  object
 15  dti                   396030 non-null  float64
 16  earliest_cr_line      396030 non-null  datetime64[ns]
 17  open_acc              396030 non-null  float64
 18  pub_rec               396030 non-null  float64
 19  revol_bal             396030 non-null  float64
 20  revol_util            395754 non-null  float64
 21  total_acc             396030 non-null  float64
 22  initial_list_status   396030 non-null  category
 23  application_type      396030 non-null  category
 24  mort_acc              358235 non-null  float64
 25  pub_rec_bankruptcies  395495 non-null  float64
 26  address               396030 non-null  object
dtypes: category(10), datetime64[ns](2), float64(12), object(3)
memory usage: 55.1+ MB
```

Observation:

memory usage was decreased from 81.6 MB to 55.1 MB because of Categorical Conversions

Range of values of all numerical and date columns

```
for i in LoanTap.columns:
    if isinstance(LoanTap[i][0],float) or
(is_datetime64_any_dtype(LoanTap[i])):
        print(f"Maximum of {i}",LoanTap[i].max())
        print(f"Minimum of {i}",LoanTap[i].min())
        print()
```

```
Maximum of loan_amnt 40000.0
Minimum of loan_amnt 500.0

Maximum of int_rate 30.99
Minimum of int_rate 5.32

Maximum of installment 1533.81
Minimum of installment 16.08

Maximum of annual_inc 8706582.0
Minimum of annual_inc 0.0

Maximum of issue_d 2016-12-01 00:00:00
Minimum of issue_d 2007-06-01 00:00:00

Maximum of dti 9999.0
Minimum of dti 0.0

Maximum of earliest_cr_line 2013-10-01 00:00:00
Minimum of earliest_cr_line 1944-01-01 00:00:00

Maximum of open_acc 90.0
Minimum of open_acc 0.0

Maximum of pub_rec 86.0
Minimum of pub_rec 0.0

Maximum of revol_bal 1743266.0
Minimum of revol_bal 0.0

Maximum of revol_util 892.3
Minimum of revol_util 0.0

Maximum of total_acc 151.0
Minimum of total_acc 2.0

Maximum of mort_acc 34.0
Minimum of mort_acc 0.0
```

```
Maximum of pub_rec_bankruptcies 8.0
Minimum of pub_rec_bankruptcies 0.0
```

Value counts of all categorical columns

```
for i in LoanTap.columns:
    if not isinstance(LoanTap[i][0],float):
        print("Value Counts of {}".format(i),end="\n\n")
        print(LoanTap[i].value_counts(),end="\n\n")
```

```
Value Counts of term

 36 months    302005
 60 months     94025
Name: term, dtype: int64

Value Counts of grade

B    116018
C    105987
A     64187
D     63524
E     31488
F     11772
G      3054
Name: grade, dtype: int64

Value Counts of sub_grade

B3    26655
B4    25601
C1    23662
C2    22580
B2    22495
B5    22085
C3    21221
C4    20280
B1    19182
A5    18526
C5    18244
D1    15993
A4    15789
D2    13951
D3    12223
D4    11657
A3    10576
A1     9729
D5     9700
```

```
A2     9567
E1     7917
E2     7431
E3     6207
E4     5361
E5     4572
F1     3536
F2     2766
F3     2286
F4     1787
F5     1397
G1     1058
G2      754
G3      552
G4      374
G5      316
Name: sub_grade, dtype: int64

Value Counts of emp_title


Teacher                      4389
Manager                      4250
Registered Nurse             1856
RN                           1846
Supervisor                   1830
                             ...
Postman                         1
McCarthy & Holthus, LLC         1
jp flooring                     1
Histology Technologist          1
Gracon Services, Inc            1
Name: emp_title, Length: 173105, dtype: int64

Value Counts of emp_length

10+ years    126041
2 years       35827
< 1 year      31725
3 years       31665
5 years       26495
1 year        25882
4 years       23952
6 years       20841
7 years       20819
8 years       19168
9 years       15314
NaN               0
Name: emp_length, dtype: int64
```

```
Value Counts of home_ownership

MORTGAGE    198348
RENT        159790
OWN          37746
OTHER          112
NONE            31
ANY              3
Name: home_ownership, dtype: int64

Value Counts of verification_status

Verified           139563
Source Verified    131385
Not Verified       125082
Name: verification_status, dtype: int64

Value Counts of issue_d

2014-10-01    14846
2014-07-01    12609
2015-01-01    11705
2013-12-01    10618
2013-11-01    10496
              ...
2007-07-01       26
2008-09-01       25
2007-11-01       22
2007-09-01       15
2007-06-01        1
Name: issue_d, Length: 115, dtype: int64

Value Counts of loan_status

Fully Paid     318357
Charged Off     77673
Name: loan_status, dtype: int64

Value Counts of purpose

debt_consolidation    234507
credit_card            83019
home_improvement       24030
other                  21185
major_purchase          8790
small_business          5701
car                     4697
medical                 4196
moving                  2854
vacation                2452
```

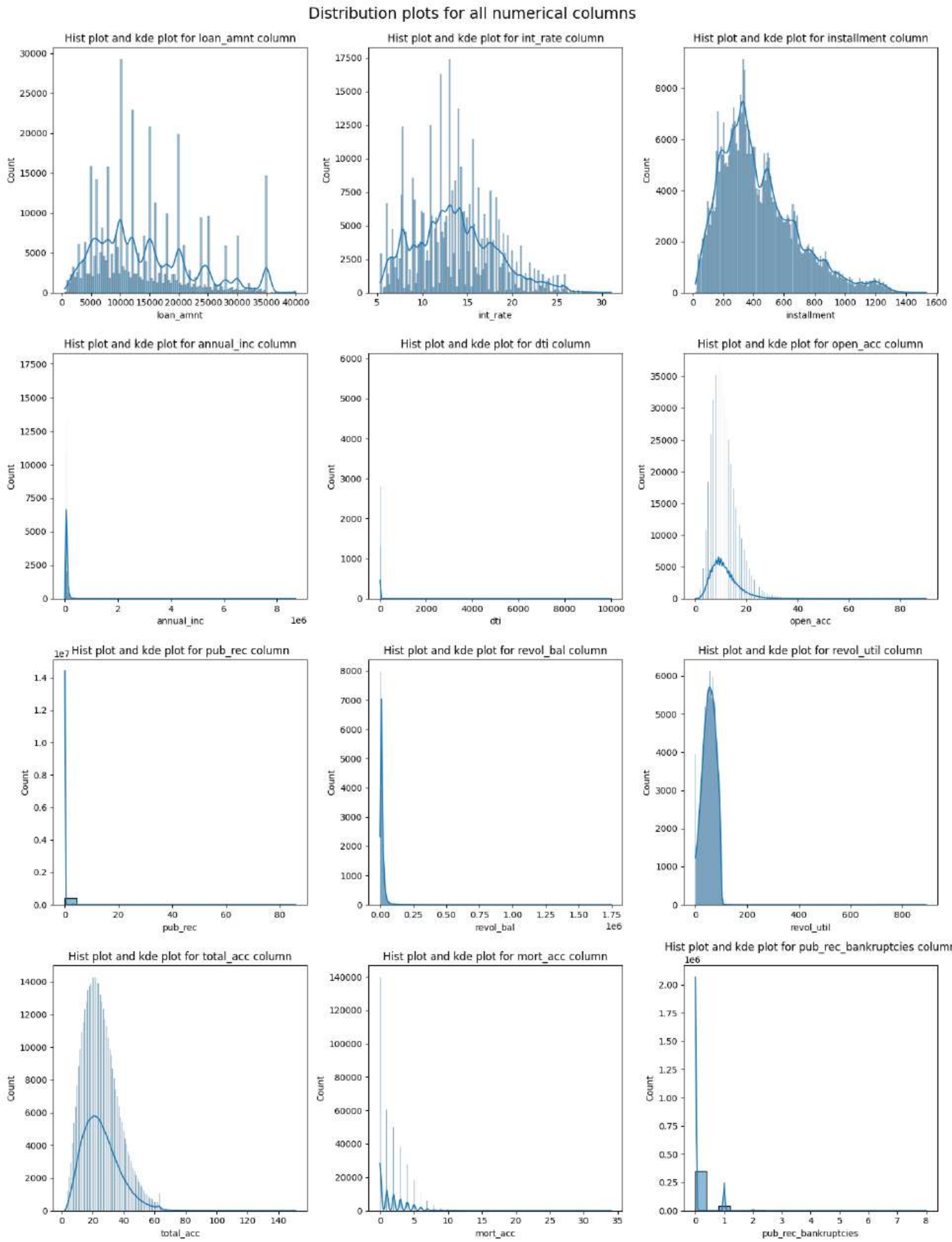
```
house                     2201
wedding                   1812
renewable_energy           329
educational                257
Name: purpose, dtype: int64

Value Counts of title

Debt consolidation            152472
Credit card refinancing        51487
Home improvement               15264
Other                          12930
Debt Consolidation             11608
                               ...
Graduation/Travel Expenses         1
Daughter's Wedding Bill            1
gotta move                         1
creditcardrefi                     1
Toxic Debt Payoff                  1
Name: title, Length: 48817, dtype: int64

Value Counts of earliest_cr_line

2000-10-01    3017
2000-08-01    2935
2001-10-01    2896
2001-08-01    2884
2000-11-01    2736
              ...
1958-07-01       1
1957-11-01       1
1953-01-01       1
1955-07-01       1
1959-08-01       1
Name: earliest_cr_line, Length: 684, dtype: int64

Value Counts of initial_list_status

f    238066
w    157964
Name: initial_list_status, dtype: int64

Value Counts of application_type

INDIVIDUAL    395319
JOINT            425
DIRECT_PAY       286
Name: application_type, dtype: int64

Value Counts of address
```

```
USCGC Smith\r\nFPO AE 70466                                8
USS Johnson\r\nFPO AE 48052                                8
USNS Johnson\r\nFPO AE 05113                               8
USS Smith\r\nFPO AP 70466                                  8
USNS Johnson\r\nFPO AP 48052                               7
                                                          ..
455 Tricia Cove\r\nAustinbury, FL 00813                    1
7776 Flores Fall\r\nFernandezshire, UT 05113               1
6577 Mia Harbors Apt. 171\r\nRobertshire, OK 22690         1
8141 Cox Greens Suite 186\r\nMadisonstad, VT 05113         1
787 Michelle Causeway\r\nBriannaton, AR 48052              1
Name: address, Length: 393700, dtype: int64
```

UNIVARIATE ANALYSIS

Distribution plots of all numerical cols

```
fig = plt.figure(figsize = (15,20))
fig.suptitle("Distribution plots for all numerical columns\n",fontsize
= "xx-large" )
k = 1
for i in num_cols:
    plt.subplot(4,3,k)
    plt.title("Hist plot and kde plot for {} column".format(i))
    sns.histplot(data=LoanTap, x=i, kde=True)
    k = k+1
plt.tight_layout()
plt.show()
```



Observation

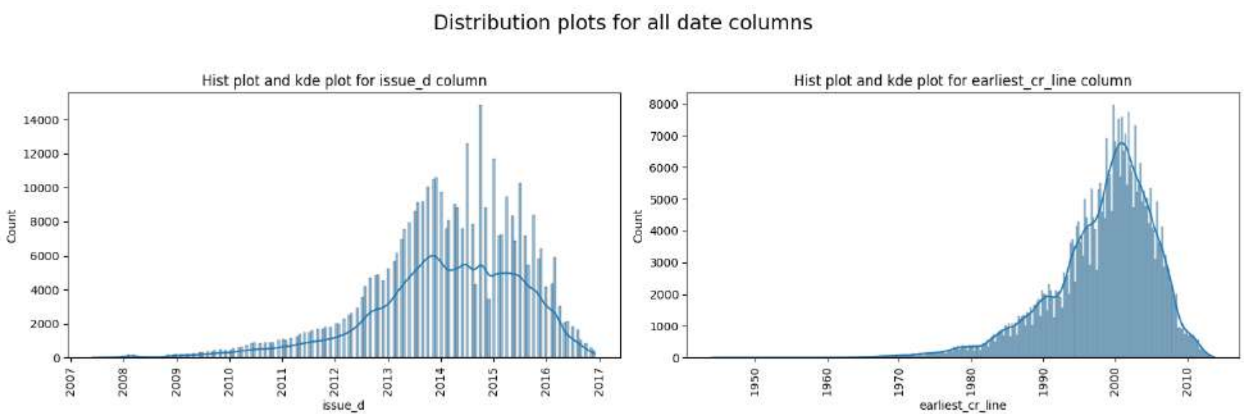
Spikes can be observed in loan amount histplot particularly at round figures like 5000, 10000, 15000, 20000, 25000, 30000, 35000

Most of the Numerical are concentrated at lower values like annual inc, dti, pub_rec, revol_bal, pub_rec_bankrupticies. But Maximum value is very large compared to that concentrated value. This implies It is log normal distribution. (Should check with np.log)

Loan_amnt, int_rate, installment, total_acc, revol_util, open_acc, total_acc has approximated right skewed distribution.

Exponential Decreasing trend can be observed in mort_acc

```
fig = plt.figure(figsize = (15,5))
fig.suptitle("Distribution plots for all date columns\n",fontsize =
"xx-large" )
k = 1
for i in date_cols:
    plt.subplot(1,2,k)
    plt.title("Hist plot and kde plot for {} column".format(i))
    sns.histplot(data=LoanTap, x=i, kde=True)
    plt.xticks(rotation = 90)
    k = k+1
plt.tight_layout()
plt.show()
```



Observations:

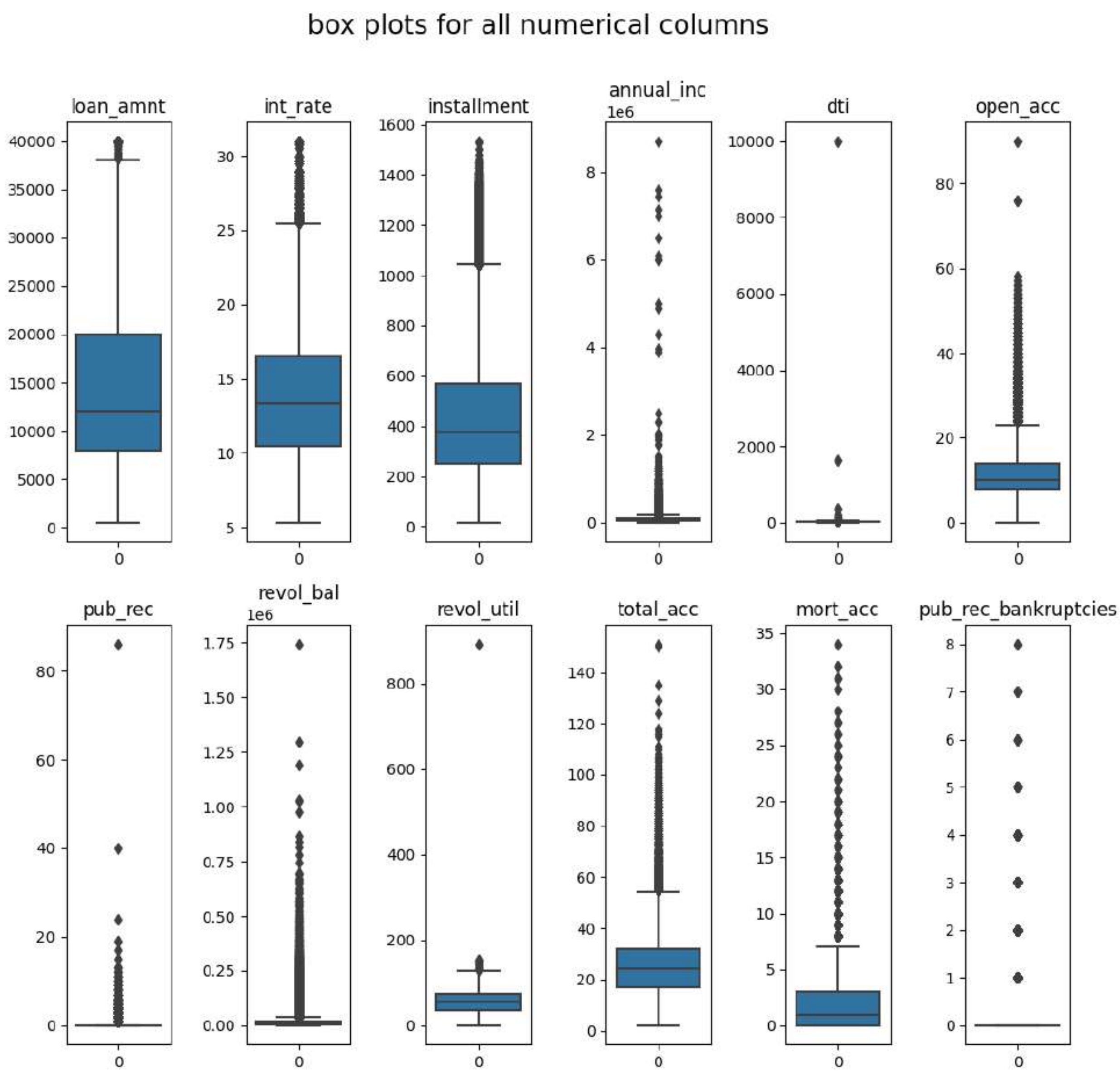
Above graphs suggests that Loantap started issuing loans from 2007. Gradually improvement upto 2015. Later there is dip in count value.

In a way earliest cr line indicates the customer age, Loan Tap has customers with earliest cr year around 1950 to 2010. Most of the customers are started taking loans from 1990 to 2010.

Box plots of all numerical columns

```
fig = plt.figure(figsize = (10,10))
fig.suptitle("box plots for all numerical columns\n",fontsize = "xx-
large" )
```

```python
k = 1
for i in num_cols:
    plt.subplot(2,6,k)
    plt.title("{}".format(i))
    sns.boxplot(data=LoanTap[i])
    k = k+1
plt.tight_layout()
plt.show()
```



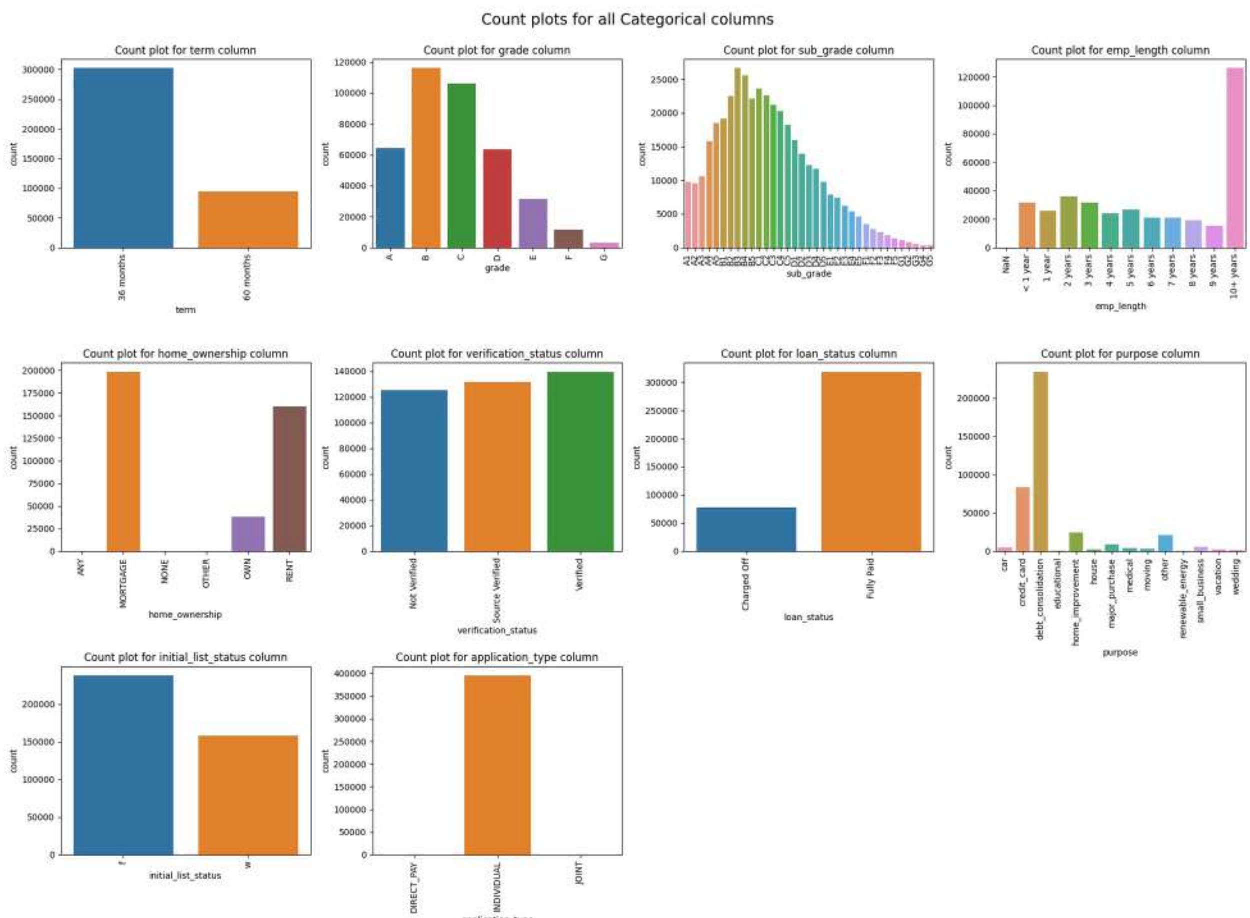
Observation

Clearly all numerical columns have outliers

Distribution plots of all the continuous variables, Barplots/Countplots of all the categorical variables

Count plots for all categorical columns

```
fig = plt.figure(figsize = (20,15))
fig.suptitle("Count plots for all Categorical columns\n",fontsize =
"xx-large" )
k = 1
for i in cat_cols:
    if LoanTap[i].nunique()<50:
        plt.subplot(3,4,k)
        plt.title("Count plot for {} column".format(i))
        sns.countplot(data=LoanTap, x=i)
        plt.xticks(rotation = 90)
        k = k+1
plt.tight_layout()
plt.show()
```




```
LoanTap["loan_status"].value_counts()
```

```
Fully Paid     318357
Charged Off     77673
Name: loan_status, dtype: int64
```

```
318357*100/(318357+77673)
```

```
80.38709188697825
```

Observations

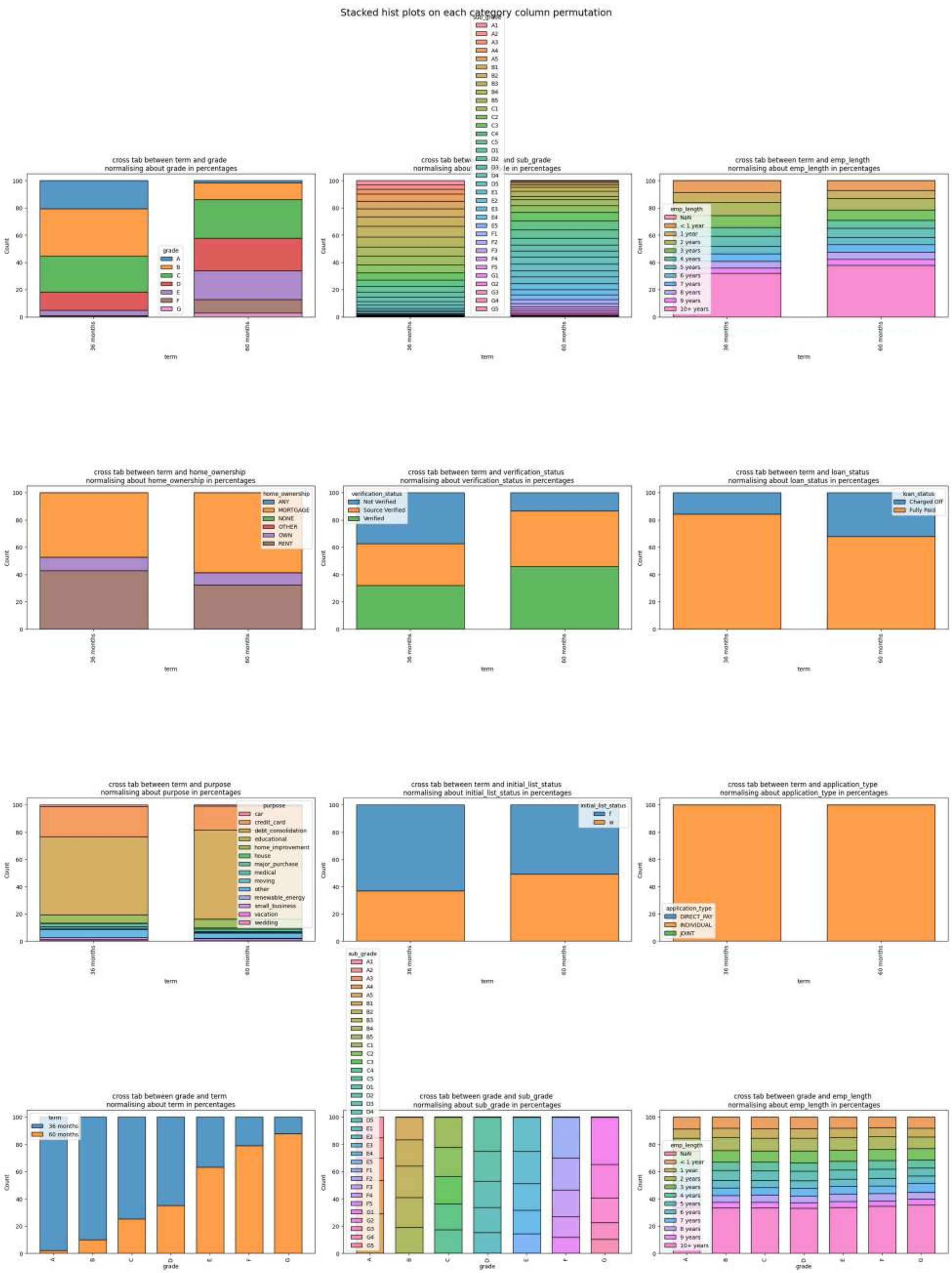
- 36 months loans are significantly more than 60 months loans
- B Grade has higher amount loans, G Grade has least number. Grades indicates interest rates or risk in a way.
- Sub grade also mimics the grade behaviour. B3 grade has higher amount of loans, G5 has lower amount of loans.
- 10+ years emp length are prefering to take loans
- Most of home ownership occupied either mortage(trying to get home), Own or Rent. (Can negelect remaining categories)
- **Loan Status (target variable) is clearly imbalanced and 80.38% are fully paid**
- debt_cosolidation and credit card is dominating purpose.
- initial _list _status fractional(F) > Whole(W)
- Almost all customers are Individual application type only

BIVARIATE ANALYSIS

Categorical Vs Categorical

```
cat_perm = list(permutations(cat_cols,2))
cat_comb = list(combinations(cat_cols,2))

fig = plt.figure(figsize = (3*8,len(cat_perm)*8/3))
plt.suptitle("Stacked hist plots on each category column permutation\
n",fontsize="xx-large")
k = 1
for p,q in cat_perm:
    if (LoanTap[p].nunique()<50) and (LoanTap[q].nunique()<50):
        plt.subplot(math.ceil(len(cat_perm)/3),3,k)
        plt.title(f"cross tab between {p} and {q} \nnormalising about
{q} in percentages")
        k += 1
        plot = LoanTap.groupby([p])
[q].value_counts(normalize=True).mul(100).reset_index(name='percentage
')
        sns.histplot(x = p , hue = q, weights= 'percentage', multiple
= 'stack',data=plot,shrink = 0.7)
        plt.xticks(rotation = 90)
```

```
        warnings.filterwarnings('ignore')
plt.tight_layout()
plt.subplots_adjust(top=0.97)
plt.show()
warnings.filterwarnings('ignore')
```



Stacked hist plots on each category column permutation
cross tab between term and grade
normalising about grade in percentages
cross tab between term and sub_grade
normalising about sub_grade in percentages
cross tab between term and emp_length
normalising about emp_length in percentages
cross tab between term and home_ownership
normalising about home_ownership in percentages
cross tab between term and verification_status
normalising about verification_status in percentages
cross tab between term and loan_status
normalising about loan_status in percentages
cross tab between term and purpose
normalising about purpose in percentages
cross tab between term and initial_list_status
normalising about initial_list_status in percentages
cross tab between term and application_type
normalising about application_type in percentages
cross tab between grade and term
normalising about term in percentages
cross tab between grade and sub_grade
normalising about sub_grade in percentages
cross tab between grade and emp_length
normalising about emp_length in percentages

Observations: `term` vs

> `grade` or 'subgrade' indicates in 36 months --> B grade, 60 months --> C Grade dominates (avg interes rates will be higher for 60 months)
>
> `verification_status` indicates 36 months has less verified than 60 months (60 months required high security in verification of annual income)
>
> `loan_status` (target variable) indicates 36 months dominates in fully paid loan_status (60 months is riskier than 36 months)
>
> `initial_list_status` indicates 60 months has more whole funding investors (60 months category attracts whole funding investors as they have high interest but high risk too)

`grade` vs

> `term` indicates Gradual increase in count of 60 months form A to G (Relationship exists between grade and term)
>
> `subgrade` indicates Count of 1st categories like (A1,B1,C1,....)(less int_rate) decreases from A to G and count of 5th categories like (A5,B5,C5,....)(high_int_rate) increases from A to G. (risk takers are increasing from A to G)
>
> `home_ownership` indicates clearly that A grade has dominating Mortage home_ownership compared to other grades.
>
> `verification_status` indicates "not verified" members gradually decreases from A to G
>
> `loan_status` indicates Charged off candidates increases from A to G
>
> `initial_list_status` indicates no relationship (fluctuates)

`subgrade` mimics the behaviour of grade (with more categories). (strong relationship can be observed between grade and subgrade

`emp_length` vs

> `home_ownership` indicates mortgage person increase from 1year to 10 years gradually (more number of people takes home with increase in working experience)

`home_ownership` vs

> `verification_status` indicates with ANY and None category should be verified at any cost. (as there is no home loan, loan tap can't acquire any assets of individual if they are charged off)
>
> `loan_status` indicates interestingly "any" catgory has dominating full paid cadidates.
>
> `purpose` indicates except in "any" category remaining category has debt consolidation as dominating category. But "any" has other or renewable energy as dominating purpose
>
> 'initial_list_status' indicates "any" has whole funding investors only

`loan_status` vs (target variable)

`term` indicates 60 months has more charged off persons

`grade` indicates C grade dominates in charged off, B grade dominates in Fully paid.

`home_ownership` indicates rent category persons has charged off more as rent persons can change their home address easily

`verification_status` indicates even verified persons has charged off more. Verification maynot sufficient to decrease the charged off.

**`initial_list_status` indicates that it is identical in for charged off and fully paid.

`purpose` vs

`term` indicates education category has mostly 36 months term

`emp_length` there is some correlation between purpose and emp_length.

`home_ownership` indicates Mortgage and home_improvement has strong relation. Moving and rent has strong relation. House and rent has strong relation.

`verification_status` indicates education has more not verified status.

`loan_status` indicates there is no relation between them(fluctuates)

`initial_list_status` indicates education has fully fractional listing status. wedding also has fractional list status as highly dominating.

`application_type` vs

`term` indicates Joint applications have 60 months term dominating

`grade` indicates Direct pay have DEFG grades dominating. Individual and Joint have ABCD grades dominating

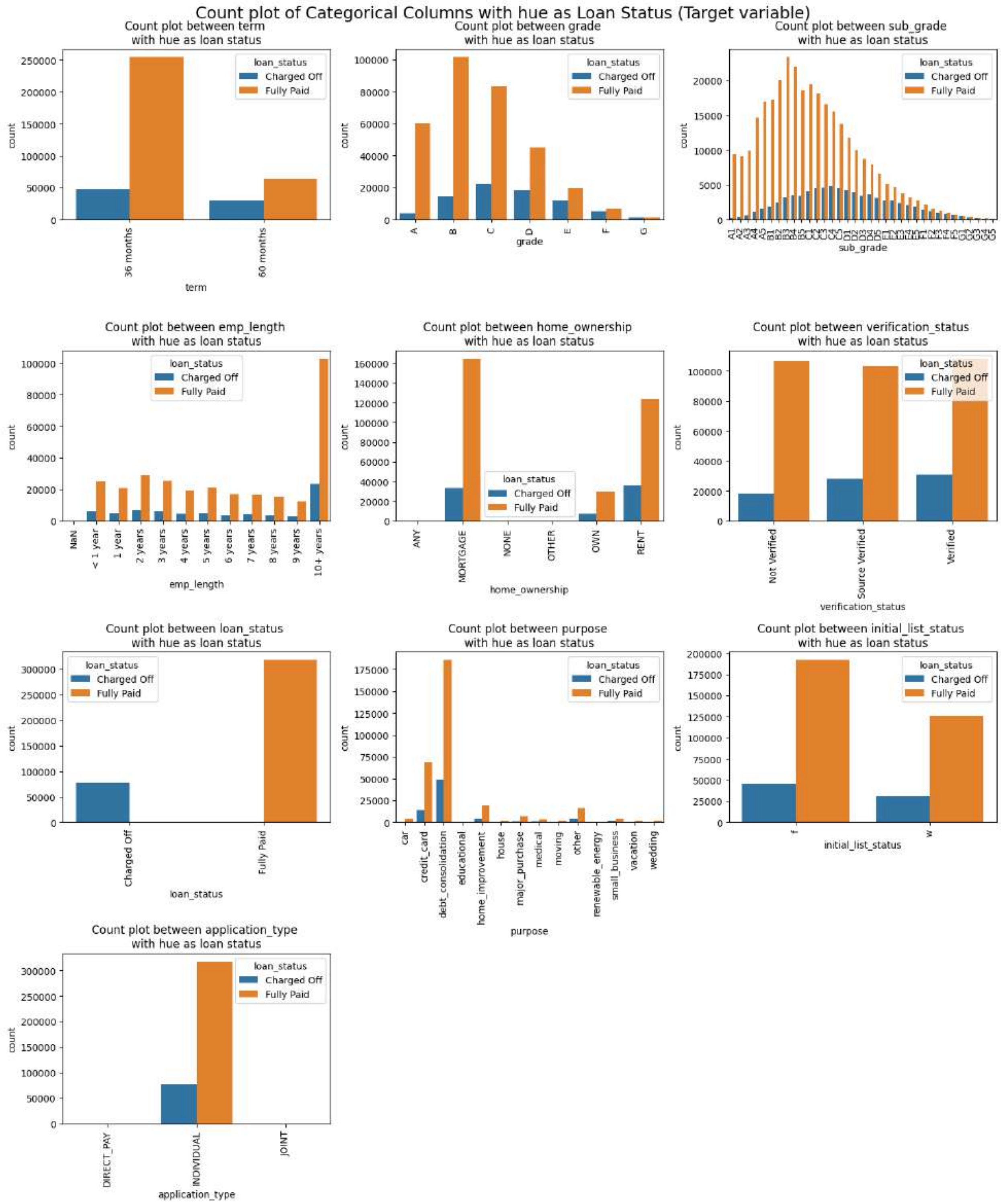
`home_ownership` indicates Mortgage dominates in JOINT applicatin than Direct pay

`verification_status` indicates Direct Pay and Joint has more verified applications than Individual

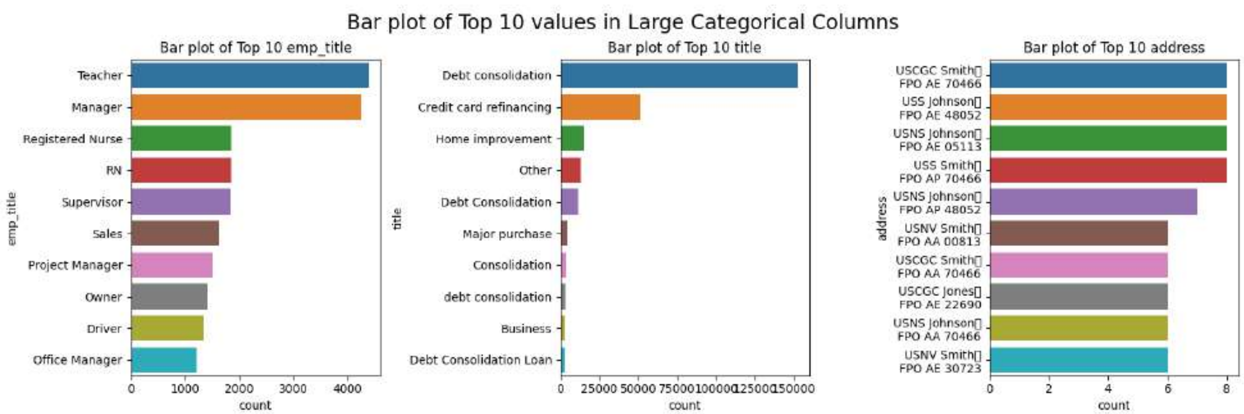
`loan_status` indicates Direct Pay has more charged off persons than Joint applications

```
fig = plt.figure(figsize = (3*5,len(cat_cols)*5/3))
plt.suptitle("Count plot of Categorical Columns with hue as Loan
Status (Target variable)\n",fontsize = "xx-large")
k = 1
for p in cat_cols:
    if LoanTap[p].nunique()<=50:
        plt.subplot(math.ceil(len(cat_cols)/3),3,k)
        plt.title(f"Count plot between {p} \nwith hue as loan status")
        k += 1
        sns.countplot(data = LoanTap,x = p,hue ="loan_status")
        plt.xticks(rotation = 90)
plt.tight_layout()
plt.subplots_adjust(top=0.95)
```

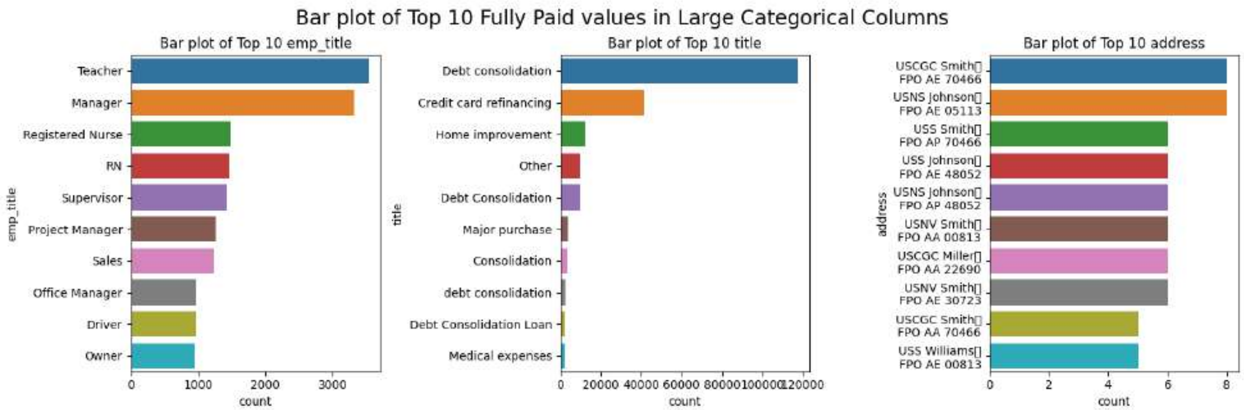
```
plt.show()
warnings.filterwarnings('ignore')
```



```python
fig = plt.figure(figsize = (15, 5))
plt.suptitle("Bar plot of Top 10 values in Large Categorical Columns\
n",fontsize = "xx-large")
k = 1
for p in cat_cols:
    if LoanTap[p].nunique()>=50:
        plt.subplot(1,3,k)
        plt.title(f"Bar plot of Top 10 {p}")
        k += 1
        top_10 = LoanTap[p].value_counts()[:10].reset_index()
        top_10.columns = [p, 'count']
        sns.barplot(x='count', y=p, data=top_10, orient='h')
plt.tight_layout()
plt.subplots_adjust(top=0.87)
plt.show()
warnings.filterwarnings('ignore')
```




```python
fig = plt.figure(figsize = (15, 5))
plt.suptitle("Bar plot of Top 10 Fully Paid values in Large
Categorical Columns\n",fontsize = "xx-large")
k = 1
for p in cat_cols:
    if LoanTap[p].nunique()>=50:
        plt.subplot(1,3,k)
        plt.title(f"Bar plot of Top 10 {p}")
        k += 1
        top_10 = LoanTap[LoanTap["loan_status"]=="Fully Paid"]
[p].value_counts()[:10].reset_index()
        top_10.columns = [p, 'count']
        sns.barplot(x='count', y=p, data=top_10, orient='h')
plt.tight_layout()
plt.subplots_adjust(top=0.87)
plt.show()
warnings.filterwarnings('ignore')
```




```
LoanTap[LoanTap["loan_status"]=="Fully Paid"]["emp_title"]
```

```
array(['Fully Paid', 'Charged Off'], dtype=object)
```

Observations

- B grade and B3 Sub grade have highest fully paid status
- C grade and C4 Sub grade have highest charged off status
- Even verified status has same proportion of charged off candidates
- debt consolidation has highest chance to pay fully paid loan
- 10+ years have highest chance to pay the loan fully
- 36 months have highest chance to pay the loan fully
- Mortgage and Rent are having highest chance to pay the loan fully
- Teacher and manager have more loan applications
- similar to purpose, Debt cosolidation and credit card refinancing has highest applications in title.

Relationships between important variables

```
Cat_Vs_Num = []
for i in range(len(cat_cols)):
    for j in range(len(num_cols)):
        if (LoanTap[cat_cols[i]].nunique()<50):
            Cat_Vs_Num.append((cat_cols[i], num_cols[j]))
print(Cat_Vs_Num)
print(len(Cat_Vs_Num))
```

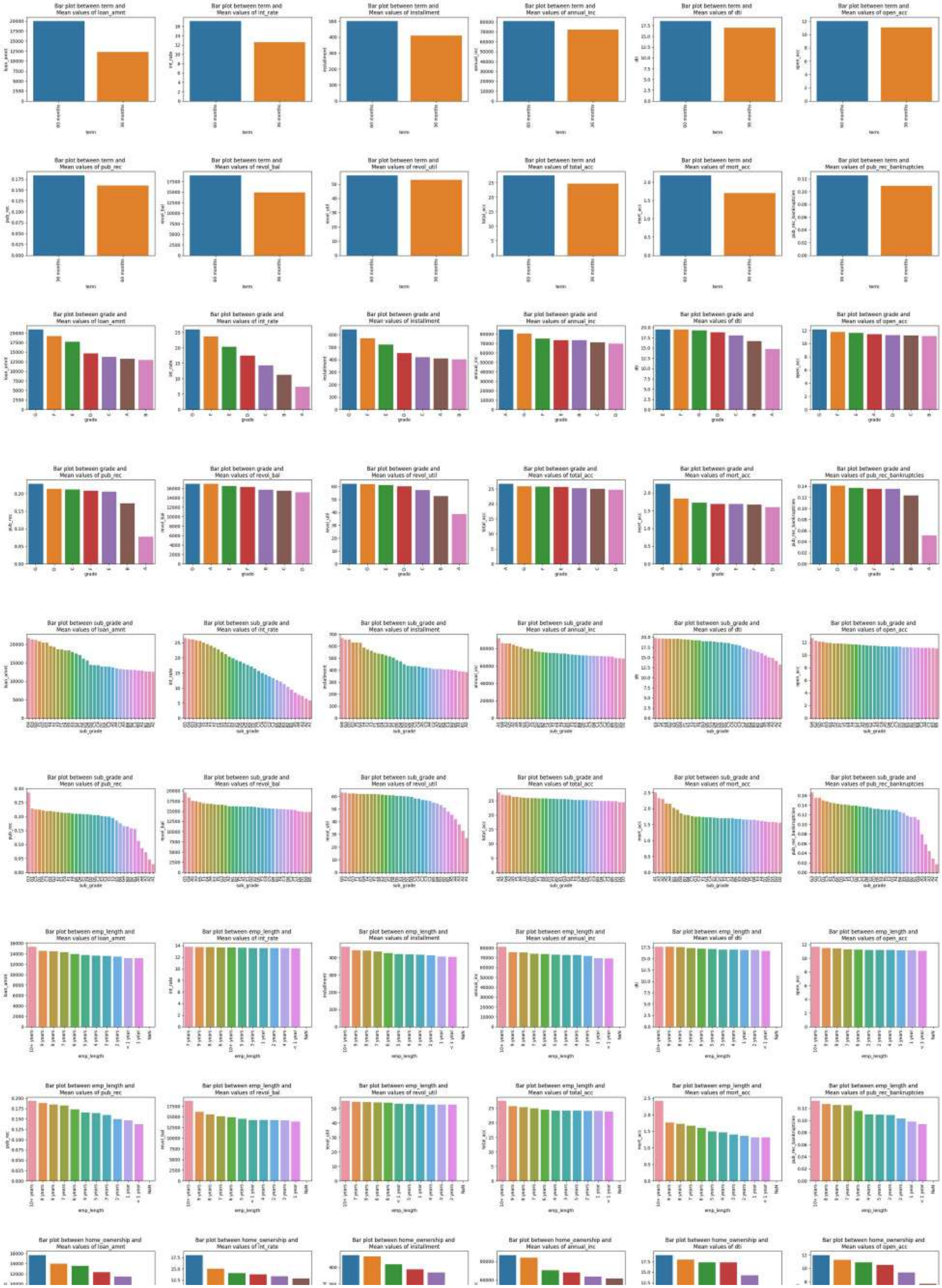
```
[('term', 'loan_amnt'), ('term', 'int_rate'), ('term', 'installment'),
('term', 'annual_inc'), ('term', 'dti'), ('term', 'open_acc'),
('term', 'pub_rec'), ('term', 'revol_bal'), ('term', 'revol_util'),
('term', 'total_acc'), ('term', 'mort_acc'), ('term',
'pub_rec_bankruptcies'), ('grade', 'loan_amnt'), ('grade',
'int_rate'), ('grade', 'installment'), ('grade', 'annual_inc'),
('grade', 'dti'), ('grade', 'open_acc'), ('grade', 'pub_rec'),
```

```
('grade', 'revol_bal'), ('grade', 'revol_util'), ('grade',
'total_acc'), ('grade', 'mort_acc'), ('grade',
'pub_rec_bankruptcies'), ('sub_grade', 'loan_amnt'), ('sub_grade',
'int_rate'), ('sub_grade', 'installment'), ('sub_grade',
'annual_inc'), ('sub_grade', 'dti'), ('sub_grade', 'open_acc'),
('sub_grade', 'pub_rec'), ('sub_grade', 'revol_bal'), ('sub_grade',
'revol_util'), ('sub_grade', 'total_acc'), ('sub_grade', 'mort_acc'),
('sub_grade', 'pub_rec_bankruptcies'), ('emp_length', 'loan_amnt'),
('emp_length', 'int_rate'), ('emp_length', 'installment'),
('emp_length', 'annual_inc'), ('emp_length', 'dti'), ('emp_length',
'open_acc'), ('emp_length', 'pub_rec'), ('emp_length', 'revol_bal'),
('emp_length', 'revol_util'), ('emp_length', 'total_acc'),
('emp_length', 'mort_acc'), ('emp_length', 'pub_rec_bankruptcies'),
('home_ownership', 'loan_amnt'), ('home_ownership', 'int_rate'),
('home_ownership', 'installment'), ('home_ownership', 'annual_inc'),
('home_ownership', 'dti'), ('home_ownership', 'open_acc'),
('home_ownership', 'pub_rec'), ('home_ownership', 'revol_bal'),
('home_ownership', 'revol_util'), ('home_ownership', 'total_acc'),
('home_ownership', 'mort_acc'), ('home_ownership',
'pub_rec_bankruptcies'), ('verification_status', 'loan_amnt'),
('verification_status', 'int_rate'), ('verification_status',
'installment'), ('verification_status', 'annual_inc'),
('verification_status', 'dti'), ('verification_status', 'open_acc'),
('verification_status', 'pub_rec'), ('verification_status',
'revol_bal'), ('verification_status', 'revol_util'),
('verification_status', 'total_acc'), ('verification_status',
'mort_acc'), ('verification_status', 'pub_rec_bankruptcies'),
('loan_status', 'loan_amnt'), ('loan_status', 'int_rate'),
('loan_status', 'installment'), ('loan_status', 'annual_inc'),
('loan_status', 'dti'), ('loan_status', 'open_acc'), ('loan_status',
'pub_rec'), ('loan_status', 'revol_bal'), ('loan_status',
'revol_util'), ('loan_status', 'total_acc'), ('loan_status',
'mort_acc'), ('loan_status', 'pub_rec_bankruptcies'), ('purpose',
'loan_amnt'), ('purpose', 'int_rate'), ('purpose', 'installment'),
('purpose', 'annual_inc'), ('purpose', 'dti'), ('purpose',
'open_acc'), ('purpose', 'pub_rec'), ('purpose', 'revol_bal'),
('purpose', 'revol_util'), ('purpose', 'total_acc'), ('purpose',
'mort_acc'), ('purpose', 'pub_rec_bankruptcies'),
('initial_list_status', 'loan_amnt'), ('initial_list_status',
'int_rate'), ('initial_list_status', 'installment'),
('initial_list_status', 'annual_inc'), ('initial_list_status', 'dti'),
('initial_list_status', 'open_acc'), ('initial_list_status',
'pub_rec'), ('initial_list_status', 'revol_bal'),
('initial_list_status', 'revol_util'), ('initial_list_status',
'total_acc'), ('initial_list_status', 'mort_acc'),
('initial_list_status', 'pub_rec_bankruptcies'), ('application_type',
'loan_amnt'), ('application_type', 'int_rate'), ('application_type',
'installment'), ('application_type', 'annual_inc'),
('application_type', 'dti'), ('application_type', 'open_acc'),
```

```
('application_type', 'pub_rec'), ('application_type', 'revol_bal'),
('application_type', 'revol_util'), ('application_type', 'total_acc'),
('application_type', 'mort_acc'), ('application_type',
'pub_rec_bankruptcies')]
120
```

```
fig = plt.figure(figsize = (6*5,len(Cat_Vs_Num)*5/6))
plt.suptitle("Barplot of Mean Values of Numerical column with respect
to Categorical Columns\n",fontsize = "xx-large")
k = 1
for p,q in Cat_Vs_Num:
    plt.subplot(math.ceil(len(Cat_Vs_Num)/6),6,k)
    plt.title(f"Bar plot between {p} and \nMean values of {q}")
    k += 1
    df = pd.DataFrame(LoanTap.groupby([p])[[q]].mean().reset_index())
    sns.barplot(data = df,x = p,y= q,order =
df.sort_values(q,ascending = False)[p])
    plt.xticks(rotation = 90)
plt.tight_layout()
plt.subplots_adjust(top=0.97)
plt.show()
warnings.filterwarnings('ignore')
```

Barplot of Mean Values of Numerical column with respect to Categorical Columns



Observations: `term` vs

> mean value of all the numerical columns except `pub_rec, pub_rec_bankruptcies` 60 months > 30 months

`grade` vs

> G grade has highest mean `loan amnt, int rate, installment, open acc, pub_rec, revol bal`
>
> A grade has highest mean `annual inc, total acc, mort_acc`
>
> E grade has highest mean `dti`
>
> F grade has highest mean `revol util`
>
> C grade has highest mean `pub_rec_bankruptcies`
>
> B grade has lowest mean `loan_amnt, installment, open_acc`
>
> A grade has lowest mean `int_rate, dti, pub_rec, revol_util, pub_rec_bankruptcies`
>
> D grade has lowest mean `annual inc, revol_bal, mort_acc`

`emp_length` is following similar trend with all numerical columns

`home ownership` vs

> Mortgage has highest mean in `loan_amnt, installment, open acc, revol bal, total acc, mort acc`
>
> Any has highest mean in `int rate, annual inc`
>
> Rent has highest mean in `pub rec bankruptcies`
>
> Any or none or other is prevailing in lowest mean of all numerical columns

`verification status` vs

> Not verified las lowest mean in all numerical columns

`loan status` (target variable) vs

> **Charged off has highest mean for all numerical columns except `annual inc, revol bal, total acc, mort acc`**

`purpose` vs

> house, home improvement are having highest mean in `loan amnt, annual inc, pub rec, total acc, mort acc, pub rec bankruptcies`
>
> small business is having highest mean in `int rate, installment`
>
> debt cosolidation is having highest mean in `dti`
>
> credit card is having highest mean in `open acc, revol balance, revol, util`

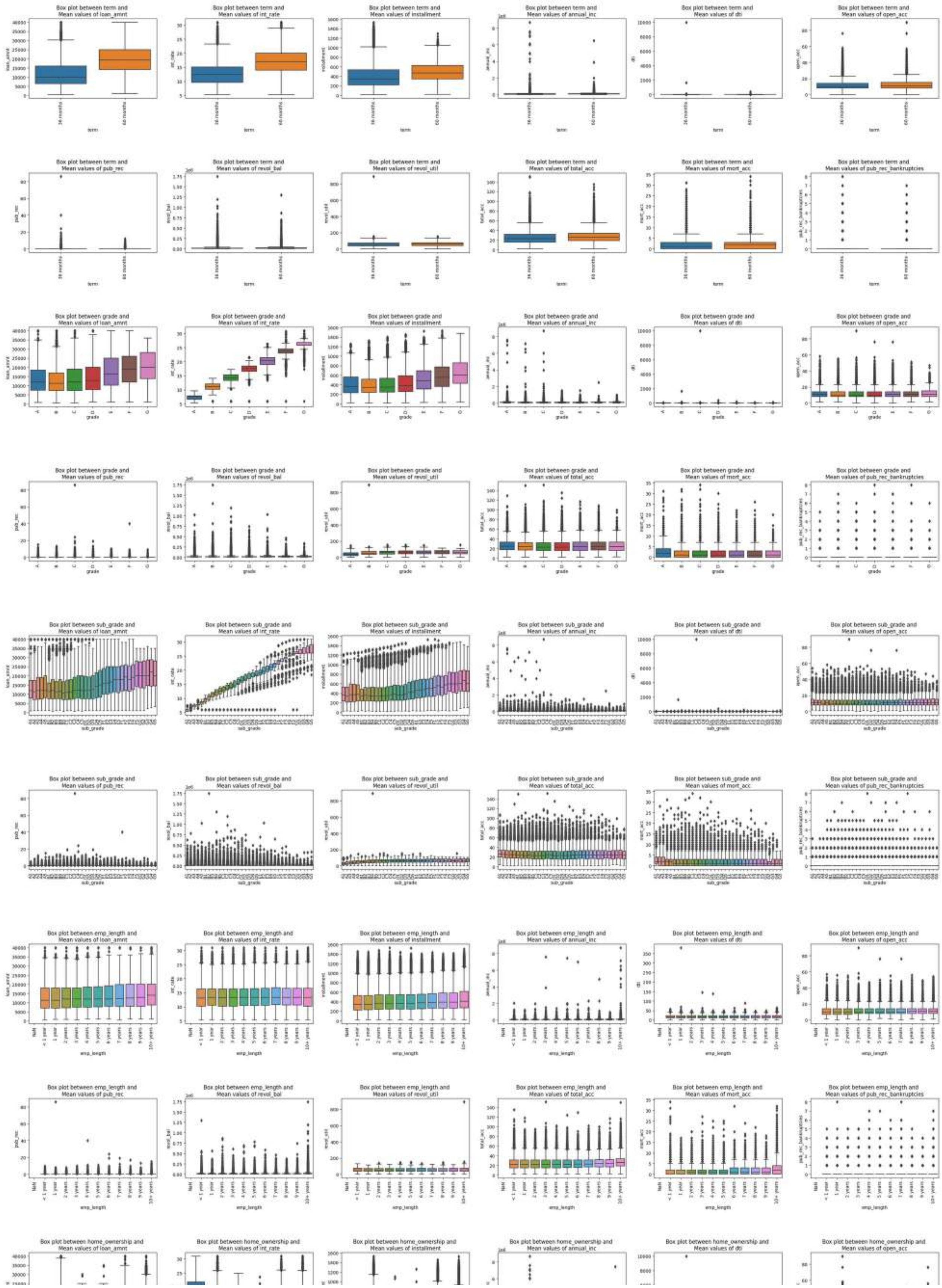
`initial list status` - whole has highest mean in all numerical columns except `int rate, revol_util`

`application` vs

> Joint type has highest mean in `loan amnt, installment, dti, pub rec, revol bal, mort acc, pub rec bankruptcies`
>
> Direct pay has highest mean in `int rate, open acc, revol bal, total acc`
>
> Individual has highest mean in `annual inc`

```
fig = plt.figure(figsize = (6*5,len(Cat_Vs_Num)*5/6))
plt.suptitle("Boxplot of Numerical column with respect to Categorical
Columns",fontsize = "xx-large")
k = 1
for p,q in Cat_Vs_Num:
    plt.subplot(math.ceil(len(Cat_Vs_Num)/6),6,k)
    plt.title(f"Box plot between {p} and \nMean values of {q}")
    k += 1
    sns.boxplot(data = LoanTap,x = p,y= q)
    plt.xticks(rotation = 90)
plt.tight_layout()
plt.subplots_adjust(top=0.97)
plt.show()
warnings.filterwarnings('ignore')
```

Boxplot of Numerical column with respect to Categorical Columns

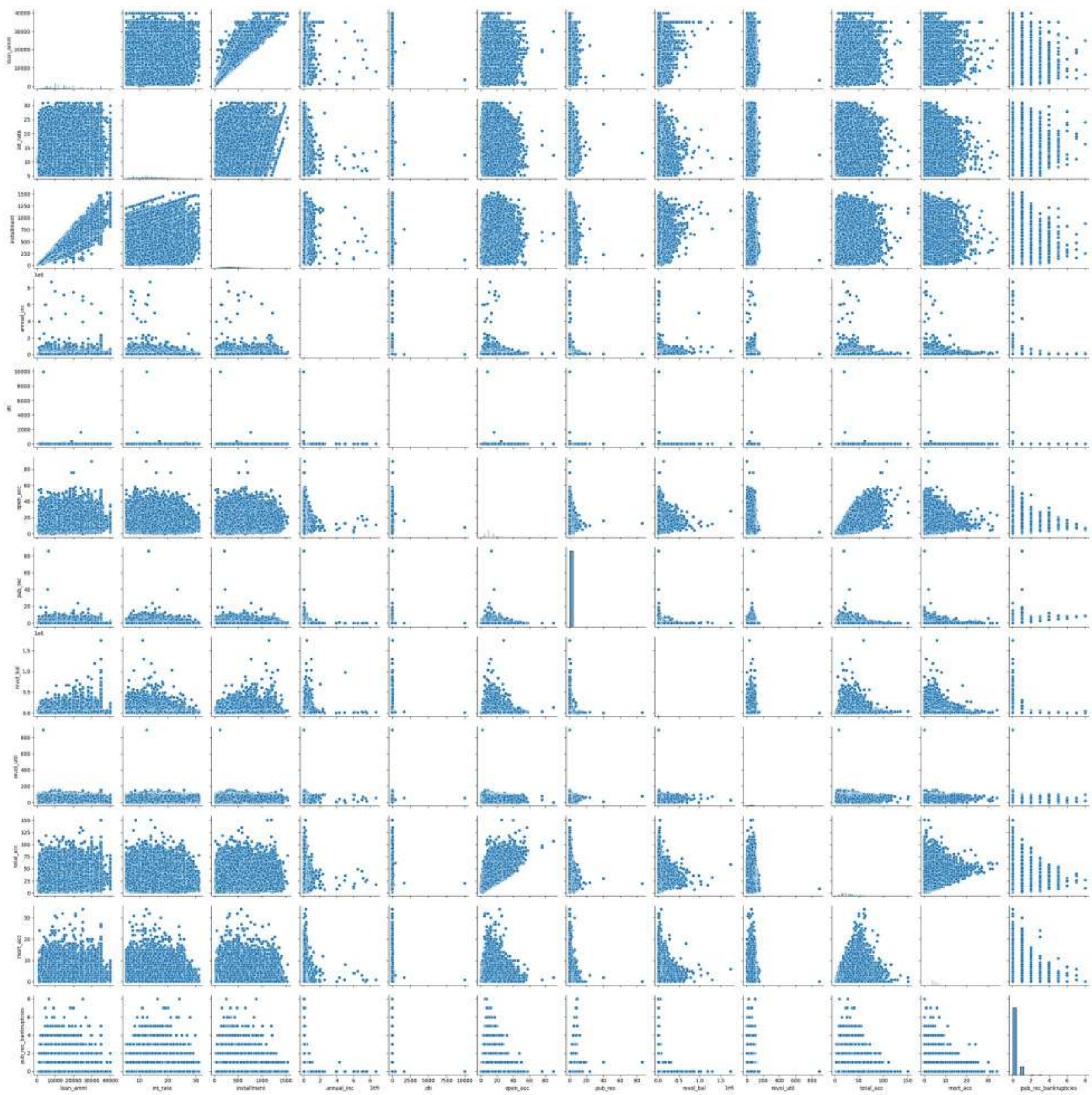


Observations:

Outliers are present in all combinations

```
sns.pairplot(data = LoanTap)
```

```
<seaborn.axisgrid.PairGrid at 0x175a0510150>
```



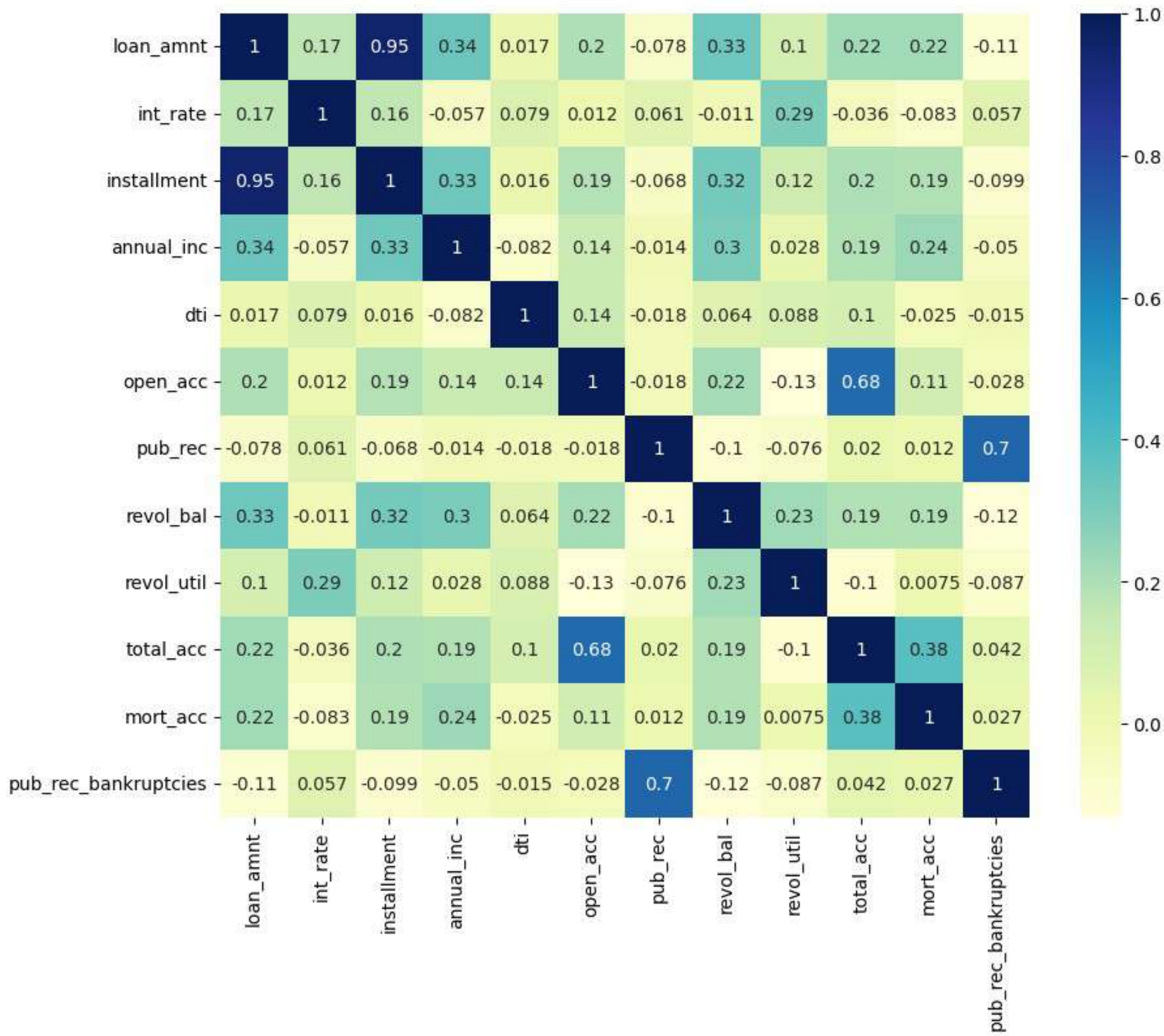
Observations

Linear trend is not observed in any pair plot

```
fig = plt.figure(figsize= (10,8))
sns.heatmap(LoanTap.corr(), cmap="YlGnBu", annot=True)
```

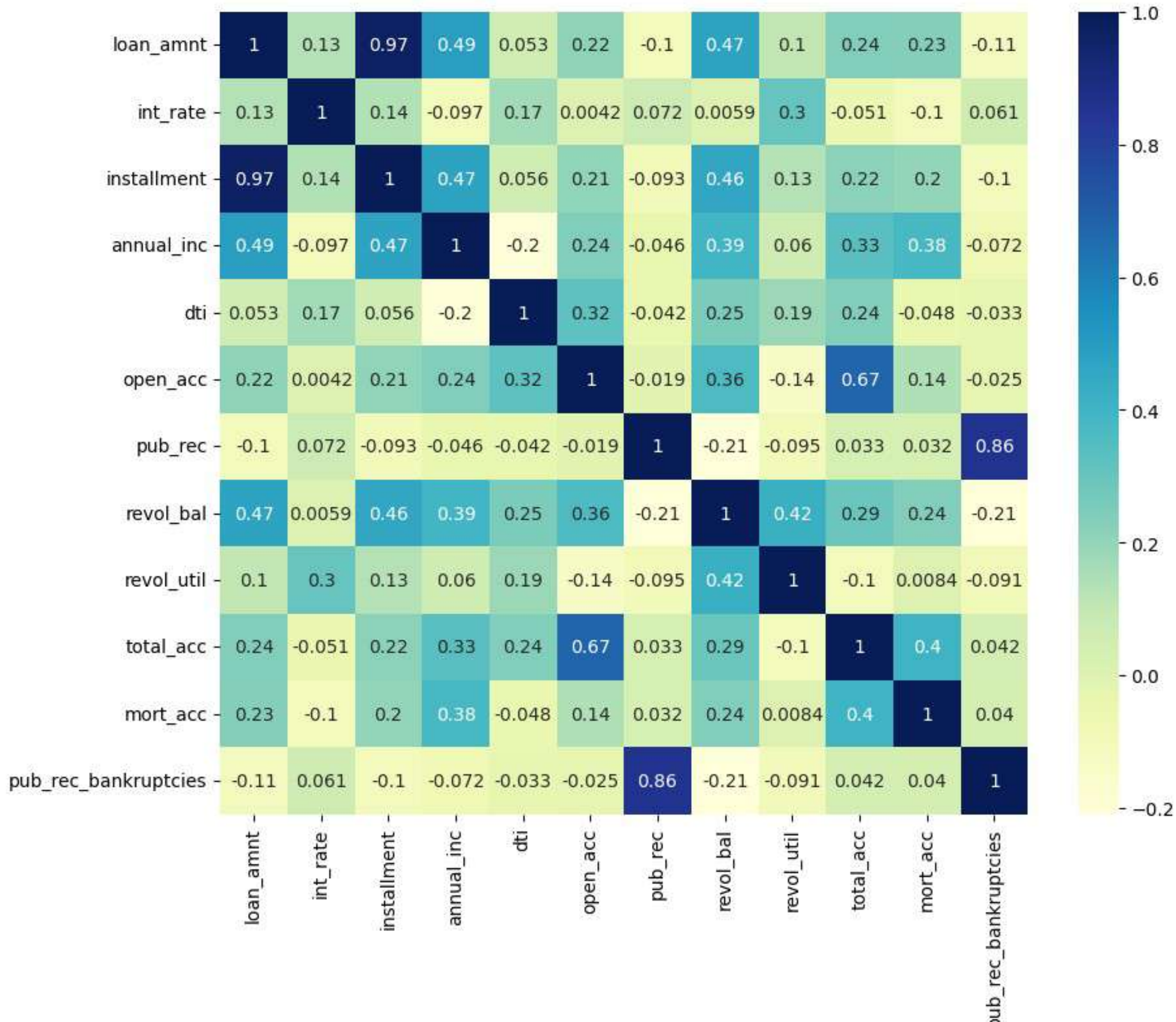
```
C:\Users\saina\AppData\Local\Temp\ipykernel_12096\3063054567.py:2:
FutureWarning: The default value of numeric_only in DataFrame.corr is
deprecated. In a future version, it will default to False. Select only
valid columns or specify the value of numeric_only to silence this
warning.
  sns.heatmap(LoanTap.corr(), cmap="YlGnBu", annot=True)
```

```
<Axes: >
```




```
fig = plt.figure(figsize= (10,8))
sns.heatmap(LoanTap.corr(method = "spearman"), cmap="YlGnBu",
annot=True)
```

```
C:\Users\saina\AppData\Local\Temp\ipykernel_12096\4068929963.py:2:
FutureWarning: The default value of numeric_only in DataFrame.corr is
deprecated. In a future version, it will default to False. Select only
valid columns or specify the value of numeric_only to silence this
warning.
  sns.heatmap(LoanTap.corr(method = "spearman"), cmap="YlGnBu",
annot=True)

<Axes: >
```



Observations

High correlations between (> 0.6)

```
1. loan amnt vs installment
2. total acc vs open acc
3. pub rec bank ruptcies vs pub rec
```

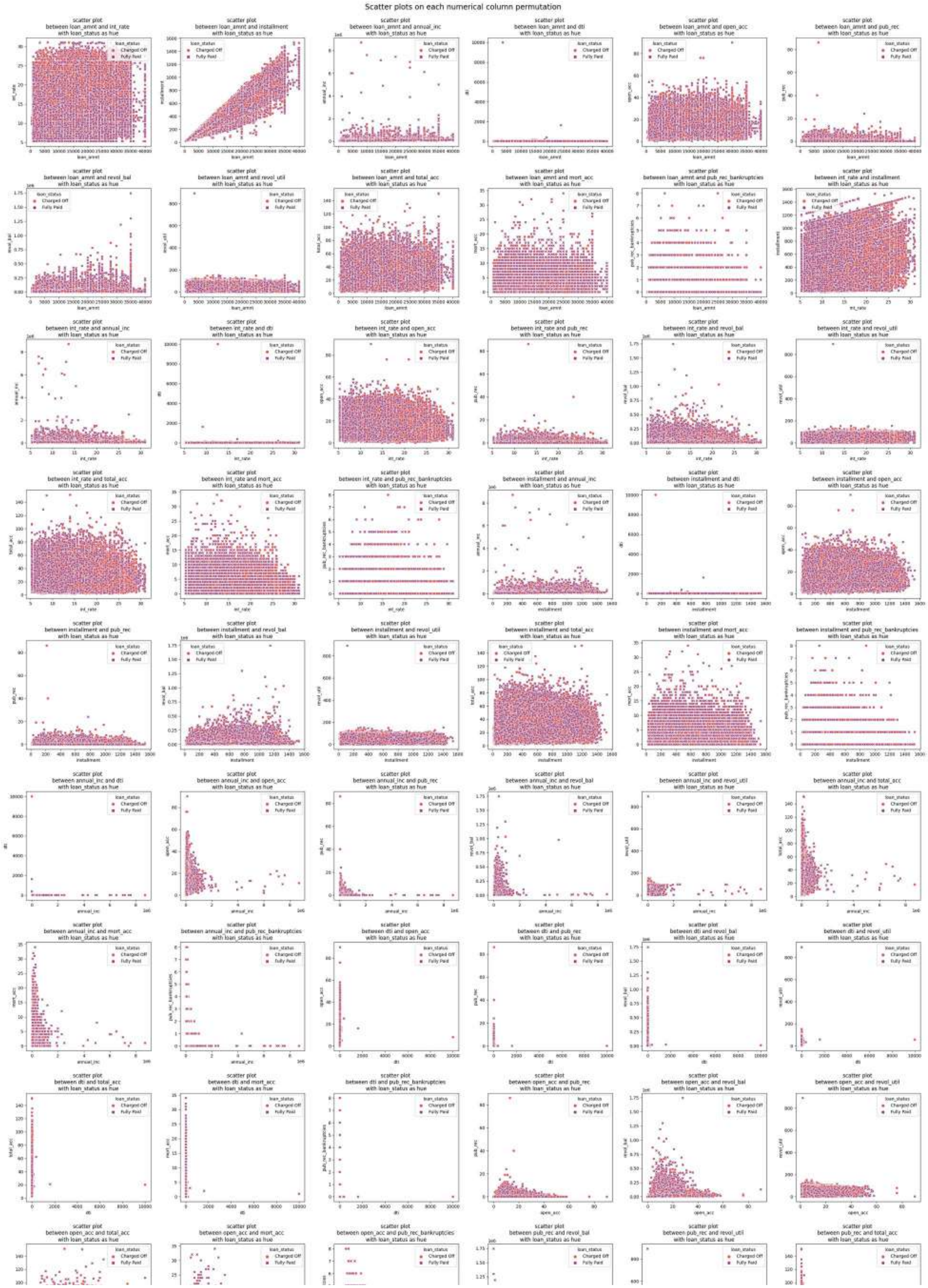
```python
#combinations of three in such a way that first two are numerical columns and third is categorical col (considering only target column)
Num_Num_Cat = []
num_comb = list(combinations(num_cols,2))
for i in range(len(num_comb)):
    Num_Num_Cat.append(list(num_comb[i])+["loan_status"])
print(Num_Num_Cat)
print(len(Num_Num_Cat))
```

```
[['loan_amnt', 'int_rate', 'loan_status'], ['loan_amnt',
'installment', 'loan_status'], ['loan_amnt', 'annual_inc',
'loan_status'], ['loan_amnt', 'dti', 'loan_status'], ['loan_amnt',
'open_acc', 'loan_status'], ['loan_amnt', 'pub_rec', 'loan_status'],
['loan_amnt', 'revol_bal', 'loan_status'], ['loan_amnt', 'revol_util',
'loan_status'], ['loan_amnt', 'total_acc', 'loan_status'],
['loan_amnt', 'mort_acc', 'loan_status'], ['loan_amnt',
'pub_rec_bankruptcies', 'loan_status'], ['int_rate', 'installment',
'loan_status'], ['int_rate', 'annual_inc', 'loan_status'],
['int_rate', 'dti', 'loan_status'], ['int_rate', 'open_acc',
'loan_status'], ['int_rate', 'pub_rec', 'loan_status'], ['int_rate',
'revol_bal', 'loan_status'], ['int_rate', 'revol_util',
'loan_status'], ['int_rate', 'total_acc', 'loan_status'], ['int_rate',
'mort_acc', 'loan_status'], ['int_rate', 'pub_rec_bankruptcies',
'loan_status'], ['installment', 'annual_inc', 'loan_status'],
['installment', 'dti', 'loan_status'], ['installment', 'open_acc',
'loan_status'], ['installment', 'pub_rec', 'loan_status'],
['installment', 'revol_bal', 'loan_status'], ['installment',
'revol_util', 'loan_status'], ['installment', 'total_acc',
'loan_status'], ['installment', 'mort_acc', 'loan_status'],
['installment', 'pub_rec_bankruptcies', 'loan_status'], ['annual_inc',
'dti', 'loan_status'], ['annual_inc', 'open_acc', 'loan_status'],
['annual_inc', 'pub_rec', 'loan_status'], ['annual_inc', 'revol_bal',
'loan_status'], ['annual_inc', 'revol_util', 'loan_status'],
['annual_inc', 'total_acc', 'loan_status'], ['annual_inc', 'mort_acc',
'loan_status'], ['annual_inc', 'pub_rec_bankruptcies', 'loan_status'],
['dti', 'open_acc', 'loan_status'], ['dti', 'pub_rec', 'loan_status'],
['dti', 'revol_bal', 'loan_status'], ['dti', 'revol_util',
'loan_status'], ['dti', 'total_acc', 'loan_status'], ['dti',
'mort_acc', 'loan_status'], ['dti', 'pub_rec_bankruptcies',
'loan_status'], ['open_acc', 'pub_rec', 'loan_status'], ['open_acc',
'revol_bal', 'loan_status'], ['open_acc', 'revol_util',
'loan_status'], ['open_acc', 'total_acc', 'loan_status'], ['open_acc',
'mort_acc', 'loan_status'], ['open_acc', 'pub_rec_bankruptcies',
'loan_status'], ['pub_rec', 'revol_bal', 'loan_status'], ['pub_rec',
'revol_util', 'loan_status'], ['pub_rec', 'total_acc', 'loan_status'],
['pub_rec', 'mort_acc', 'loan_status'], ['pub_rec',
'pub_rec_bankruptcies', 'loan_status'], ['revol_bal', 'revol_util',
'loan_status'], ['revol_bal', 'total_acc', 'loan_status'],
['revol_bal', 'mort_acc', 'loan_status'], ['revol_bal',
'pub_rec_bankruptcies', 'loan_status'], ['revol_util', 'total_acc',
```

```
'loan_status'], ['revol_util', 'mort_acc', 'loan_status'],
['revol_util', 'pub_rec_bankruptcies', 'loan_status'], ['total_acc',
'mort_acc', 'loan_status'], ['total_acc', 'pub_rec_bankruptcies',
'loan_status'], ['mort_acc', 'pub_rec_bankruptcies', 'loan_status']]
66
```

```
fig = plt.figure(figsize = (6*5,len(Num_Num_Cat)*5/6))
plt.suptitle("Scatter plots on each numerical column permutation\
n",fontsize="xx-large")
k = 1
for p,q,r in Num_Num_Cat:
    plt.subplot(math.ceil(len(Num_Num_Cat)/6),6,k)
    plt.title(f"scatter plot \nbetween {p} and {q} \nwith {r} as hue")
    k += 1
    sns.scatterplot(data=LoanTap,x=p,y=q,hue = r,style = r, palette =
"flare")
    warnings.filterwarnings('ignore')
plt.tight_layout()
plt.subplots_adjust(top=0.96)
plt.show()
warnings.filterwarnings('ignore')
```

Scatter plots on each numerical column permutation



Observations

> Scatter plot with respect to loan status has mixed up. (Not separated clusters, not homogenous)

CHAPTER 2: DATA PREPROCESSING

DUPLICATE VALUE CHECK

```
LoanTap.duplicated().sum()
```

```
0
```

MISSING VALUE TREATMENT

Missing value treatment of emp_title

> Replacing the NaN emp_titles as new category -> UNKNOWN

```
LoanTap["emp_title"].fillna("UNKNOWN",inplace = True)
```

Missing value treatment of title

```
Null_replace_dict_purpose_title = {}
for i in LoanTap["purpose"].unique():
    Null_replace_dict_purpose_title[i] = LoanTap[LoanTap["purpose"] ==
i]["title"].mode()[0]
print(Null_replace_dict_purpose_title)
```

```
{'vacation': 'Vacation', 'debt_consolidation': 'Debt consolidation',
'credit_card': 'Credit card refinancing', 'home_improvement': 'Home
improvement', 'small_business': 'Business', 'major_purchase': 'Major
purchase', 'other': 'Other', 'medical': 'Medical expenses', 'wedding':
'Wedding Loan', 'car': 'Car financing', 'moving': 'Moving and
relocation', 'house': 'Home buying', 'educational': 'Student Loan',
'renewable_energy': 'Green loan'}
```

```
LoanTap["title"] =
LoanTap["title"].fillna(LoanTap["purpose"].map(Null_replace_dict_purpo
se_title))
```

Missing value treatment of emp_length

```
Imputer = SimpleImputer(strategy="most_frequent")
LoanTap["emp_length"] =
Imputer.fit_transform(LoanTap["emp_length"].values.reshape(-1,1))
```

Missing value treatement of remaining numerical columns - pub_rec_bankruptcies, revol_util, mort_acc

```
pub_rec_median = LoanTap.groupby("pub_rec").median().mort_acc
def fill_pub_rec_bankruptcies(pub_rec,pub_rec_bankruptcies):
    if np.isnan(pub_rec_bankruptcies):
        return pub_rec_median[pub_rec].round()
    else:
        return pub_rec_bankruptcies
LoanTap['pub_rec_bankruptcies']=LoanTap.apply(lambda x:
fill_pub_rec_bankruptcies(x['pub_rec'],x['pub_rec_bankruptcies']),axis
=1)
```

```
C:\Users\saina\AppData\Local\Temp\ipykernel_12096\154728262.py:1:
FutureWarning: The default value of numeric_only in
DataFrameGroupBy.median is deprecated. In a future version,
numeric_only will default to False. Either specify numeric_only or
select only columns which should be valid for the function.
  pub_rec_median = LoanTap.groupby("pub_rec").median().mort_acc
```

```
total_acc_median = LoanTap.groupby("total_acc").median().mort_acc
def fill_mort_acc(total_acc,mort_acc):
    if np.isnan(mort_acc):
        return total_acc_median[total_acc].round()
    else:
        return mort_acc
LoanTap['mort_acc']=LoanTap.apply(lambda x:
fill_mort_acc(x['total_acc'],x['mort_acc']),axis=1)
```

```
C:\Users\saina\AppData\Local\Temp\ipykernel_12096\15731850.py:1:
FutureWarning: The default value of numeric_only in
DataFrameGroupBy.median is deprecated. In a future version,
numeric_only will default to False. Either specify numeric_only or
select only columns which should be valid for the function.
  total_acc_median = LoanTap.groupby("total_acc").median().mort_acc
```

```
Imputer = KNNImputer(n_neighbors= 10)
LoanTap["revol_util"]=Imputer.fit_transform(LoanTap["revol_util"].valu
es.reshape(-1,1))
```

Missing value check

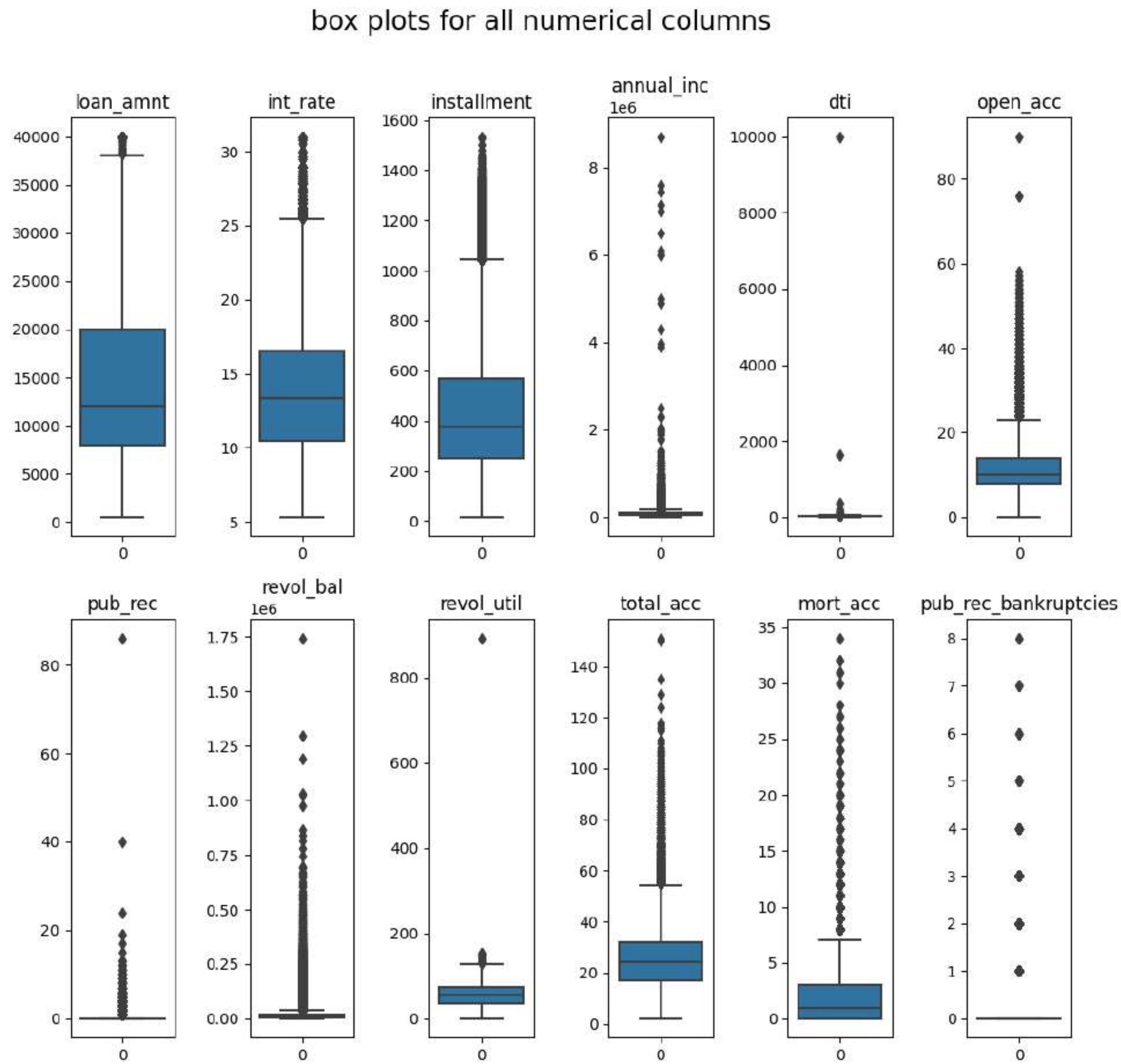
```
sum(LoanTap.isna().sum())
```

```
0
```

OUTLIER TREATMENT

```
fig = plt.figure(figsize = (10,10))
fig.suptitle("box plots for all numerical columns\n",fontsize = "xx-
```

```
large" )
k = 1
for i in num_cols:
    plt.subplot(2,6,k)
    plt.title("{}".format(i))
    sns.boxplot(data=LoanTap[i])
    k = k+1
plt.tight_layout()
plt.show()
```



Removing the outliers of pub_rec, pub_rec_bankruptcies

As all the values other than zero are outliers in `pub_rec, pub_rec_bankruptcies`, To remove the outliers, Treat all Outliers as 1 and zero as 0. Convert them to Binary column

```
def pub_rec(number):
    if number == 0.0:
        return 0
    else:
        return 1
def pub_rec_bankruptcies(number):
    if number == 0.0:
        return 0
    else:
        return 1
LoanTap['pub_rec']=LoanTap.pub_rec.apply(pub_rec)
LoanTap['pub_rec_bankruptcies']=LoanTap.pub_rec_bankruptcies.apply(pub
_rec_bankruptcies)

LoanTap["pub_rec"] = LoanTap["pub_rec"].astype('category')
LoanTap["pub_rec_bankruptcies"] =
LoanTap["pub_rec_bankruptcies"].astype('category')
```

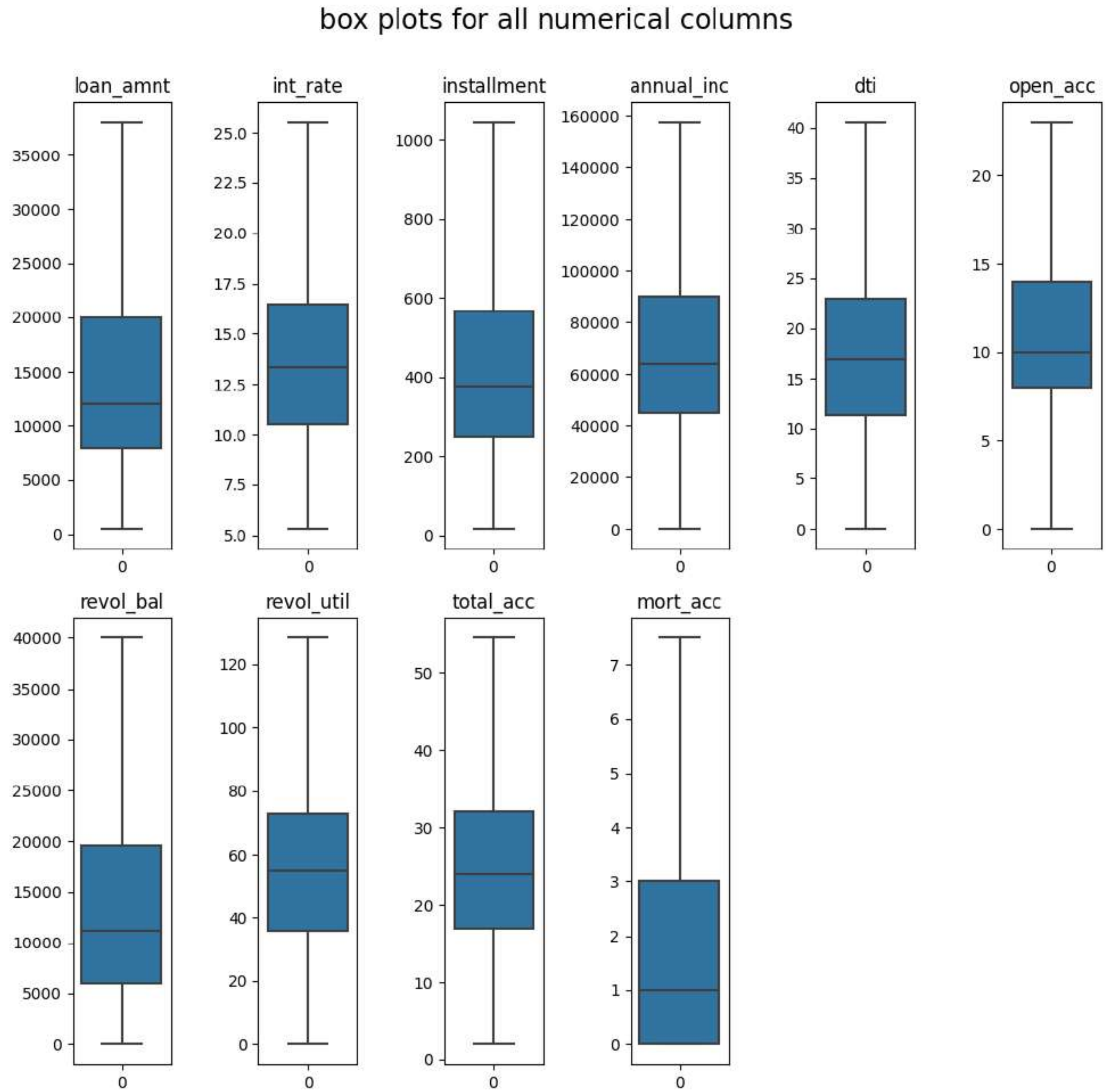
Remove pub_rec, pub_rec_bankruptcies from num_cols as they are binary type column

```
num_cols.remove("pub_rec")
num_cols.remove("pub_rec_bankruptcies")
```

Remove outliers by using IQR capping method for all remaining numerical columns

```
def detect_outliers_iqr(df,i):
    q1 = df[i].quantile(0.25)
    q3 = df[i].quantile(0.75)
    IQR = q3-q1
    lwr_bound = q1-(1.5*IQR)
    upr_bound = q3+(1.5*IQR)
    df[i]= pd.DataFrame(np.where(df[i] > upr_bound, upr_bound,
(np.where(df[i] <lwr_bound,lwr_bound, df[i]))), columns=[i])
for i in num_cols:
    detect_outliers_iqr(LoanTap,i)

fig = plt.figure(figsize = (10,10))
fig.suptitle("box plots for all numerical columns\n",fontsize = "xx-
large" )
k = 1
for i in num_cols:
    plt.subplot(2,6,k)
```

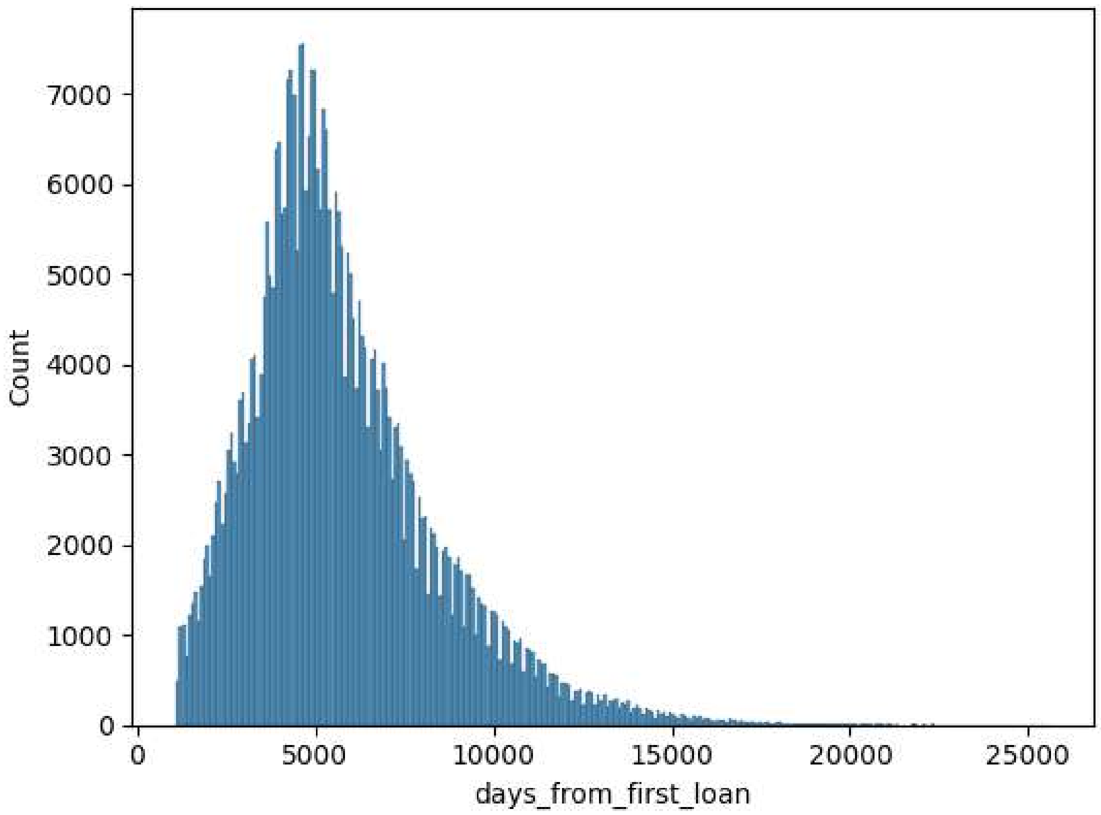
```
    plt.title("{}".format(i))
    sns.boxplot(data=LoanTap[i])
    k = k+1
plt.tight_layout()
plt.show()
```



FEATURE ENGINEERING

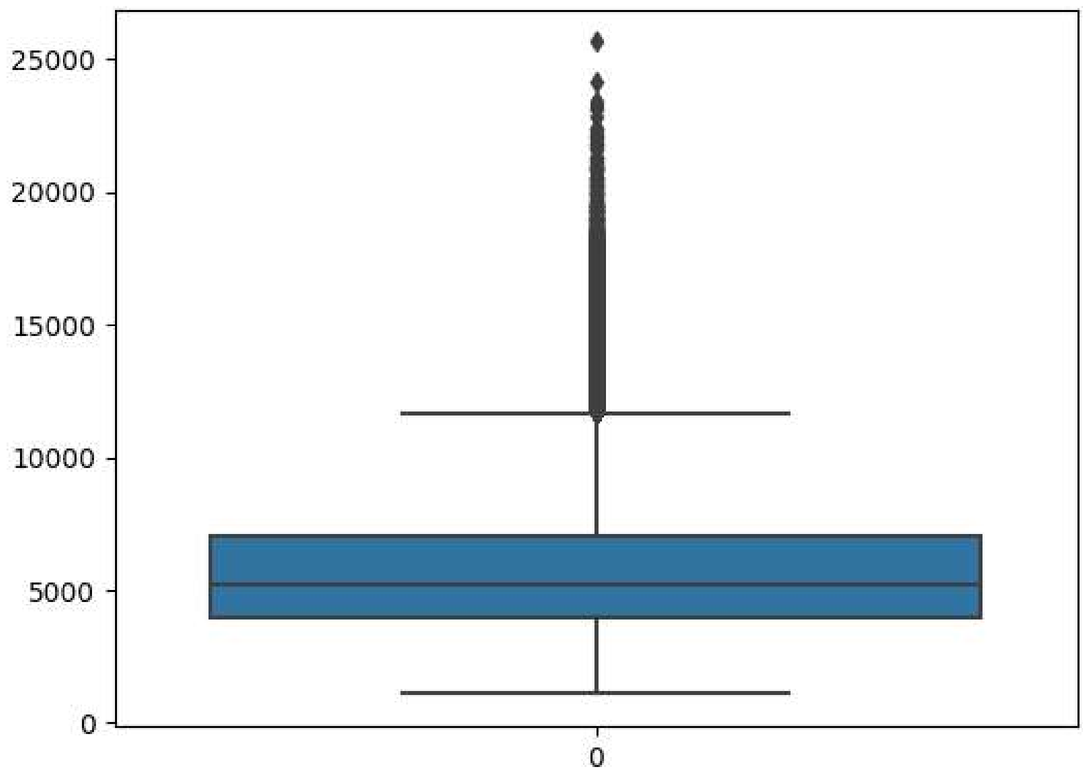
```
LoanTap["days_from_first_loan"] =  (LoanTap["issue_d"]-
LoanTap["earliest_cr_line"]).dt.days

sns.histplot(LoanTap["days_from_first_loan"])
```

```
<Axes: xlabel='days_from_first_loan', ylabel='Count'>
```



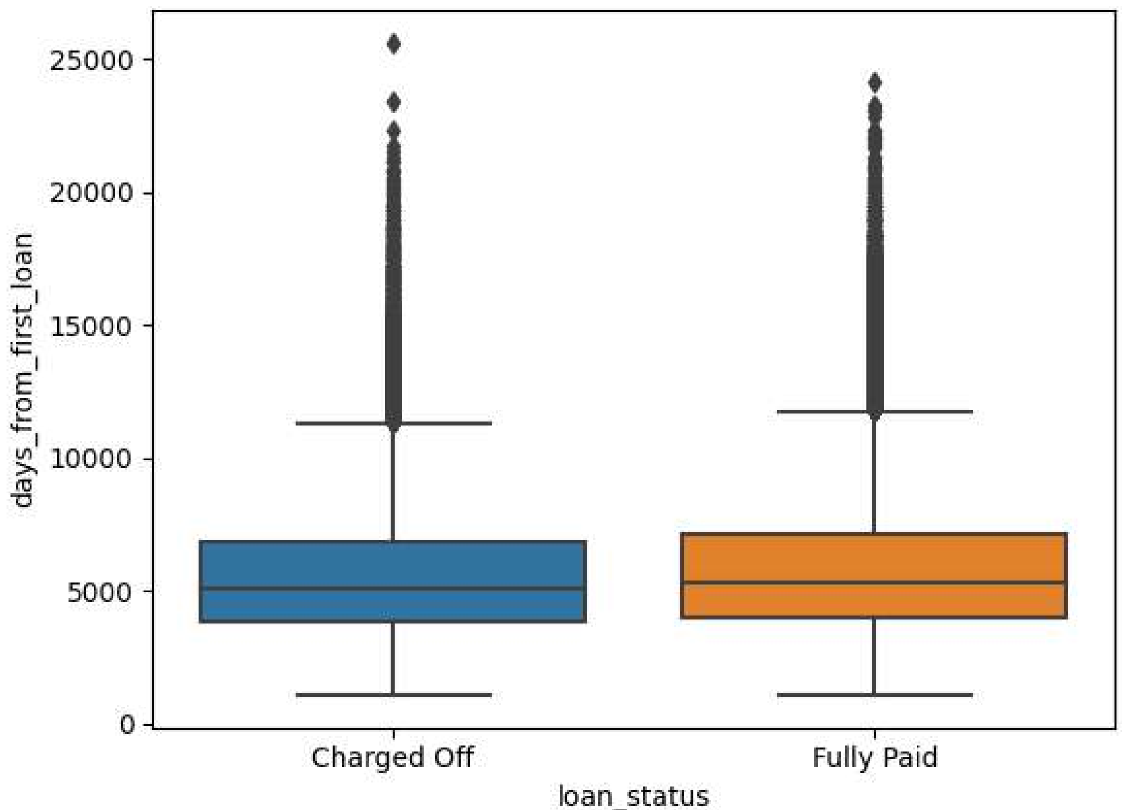

```
sns.boxplot(LoanTap["days_from_first_loan"])
```

```
<Axes: >
```

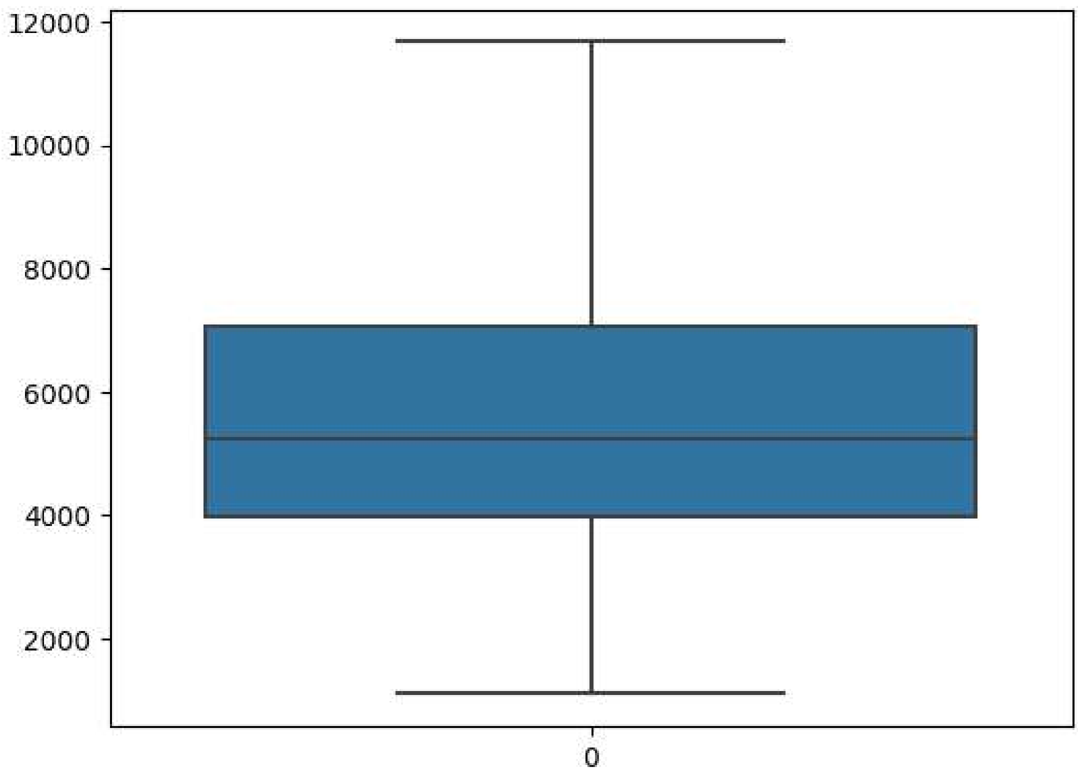



```
sns.boxplot(data = LoanTap,x = "loan_status",
y="days_from_first_loan")
```

```
<Axes: xlabel='loan_status', ylabel='days_from_first_loan'>
```




```
detect_outliers_iqr(LoanTap,"days_from_first_loan")

sns.boxplot(LoanTap["days_from_first_loan"])

<Axes: >
```



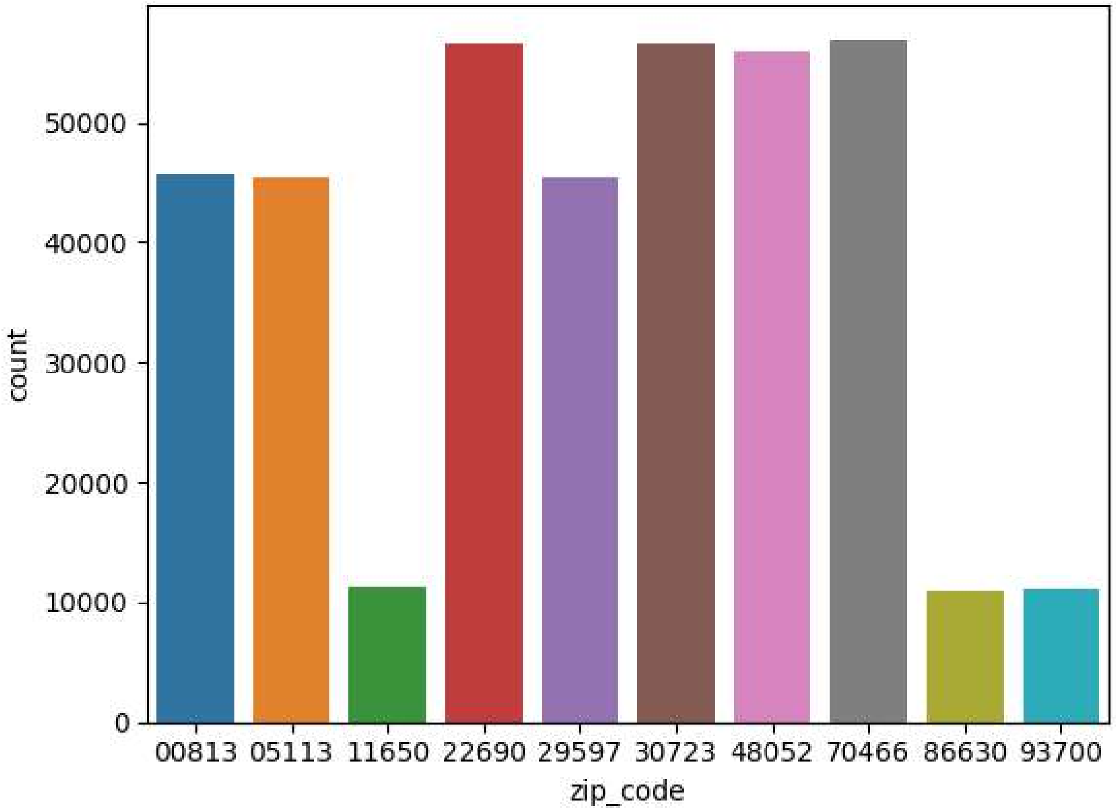
Extract State and ZIP code from Address

```
LoanTap["address"][0].split()
```

```
['0174', 'Michelle', 'Gateway', 'Mendozaberg,', 'OK', '22690']
```

```
LoanTap["zip_code"]= LoanTap["address"].apply(lambda x: x.split()[-1])
LoanTap["state"]= LoanTap["address"].apply(lambda x: x.split()[-2])

LoanTap["zip_code"] = LoanTap["zip_code"].astype("category")

sns.countplot(data = LoanTap, x = "zip_code")
```

```
<Axes: xlabel='zip_code', ylabel='count'>
```




```
LoanTap["state"].nunique()

54

print(sorted(LoanTap["state"].unique()))

['AA', 'AE', 'AK', 'AL', 'AP', 'AR', 'AZ', 'CA', 'CO', 'CT', 'DC',
'DE', 'FL', 'GA', 'HI', 'IA', 'ID', 'IL', 'IN', 'KS', 'KY', 'LA',
'MA', 'MD', 'ME', 'MI', 'MN', 'MO', 'MS', 'MT', 'NC', 'ND', 'NE',
'NH', 'NJ', 'NM', 'NV', 'NY', 'OH', 'OK', 'OR', 'PA', 'RI', 'SC',
'SD', 'TN', 'TX', 'UT', 'VA', 'VT', 'WA', 'WI', 'WV', 'WY']

state_dict = {"AA":"Armed Forces America", "AE":"Armed
Forces","AK":"Alaska","AL":"Alabama",
              "AP":"Armed Forces
Pacific","AR":"Arkansas","AZ":"Arizona","CA":"California",
              "CO":"Colorado","CT":"Connecticut","DC":"Washington
DC","DE":"Delaware",

"FL":"Florida","GA":"Georgia","HI":"Hawaii","IA":"Iowa","ID":"Idaho","
IL":"Illinois",

"IN":"Indiana","KS":"Kansas","KY":"Kentucky","LA":"Louisiana","MA":"Ma
ssachusetts",
```

```
"MD":"Maryland","ME":"Maine","MI":"Michigan","MN":"Minnesota","MO":"Mi
ssouri",
              "MS":"Mississippi","MT":"Montana","NC":"North
Carolina","ND":"North Dakota",
              "NE":"Nebraska","NH":"New Hampshire","NJ":"New
Jersey","NM":"New Mexico","NV":"Nevada",
              "NY":"New
York","OH":"Ohio","OK":"Oklahoma","OR":"Oregon","PA":"Pennsylvania",
              "RI":"Rhode Island","SC":"South Carolina","SD":"South
Dakota","TN":"Tennessee",

"TX":"Texas","UT":"Utah","VA":"Virginia","VT":"Vermont","WA":"Washingt
on",
              "WI":"Wisconsin","WV":"West Virginia","WY":"Wyoming"}
```

```
len(state_dict)
```

```
54
```

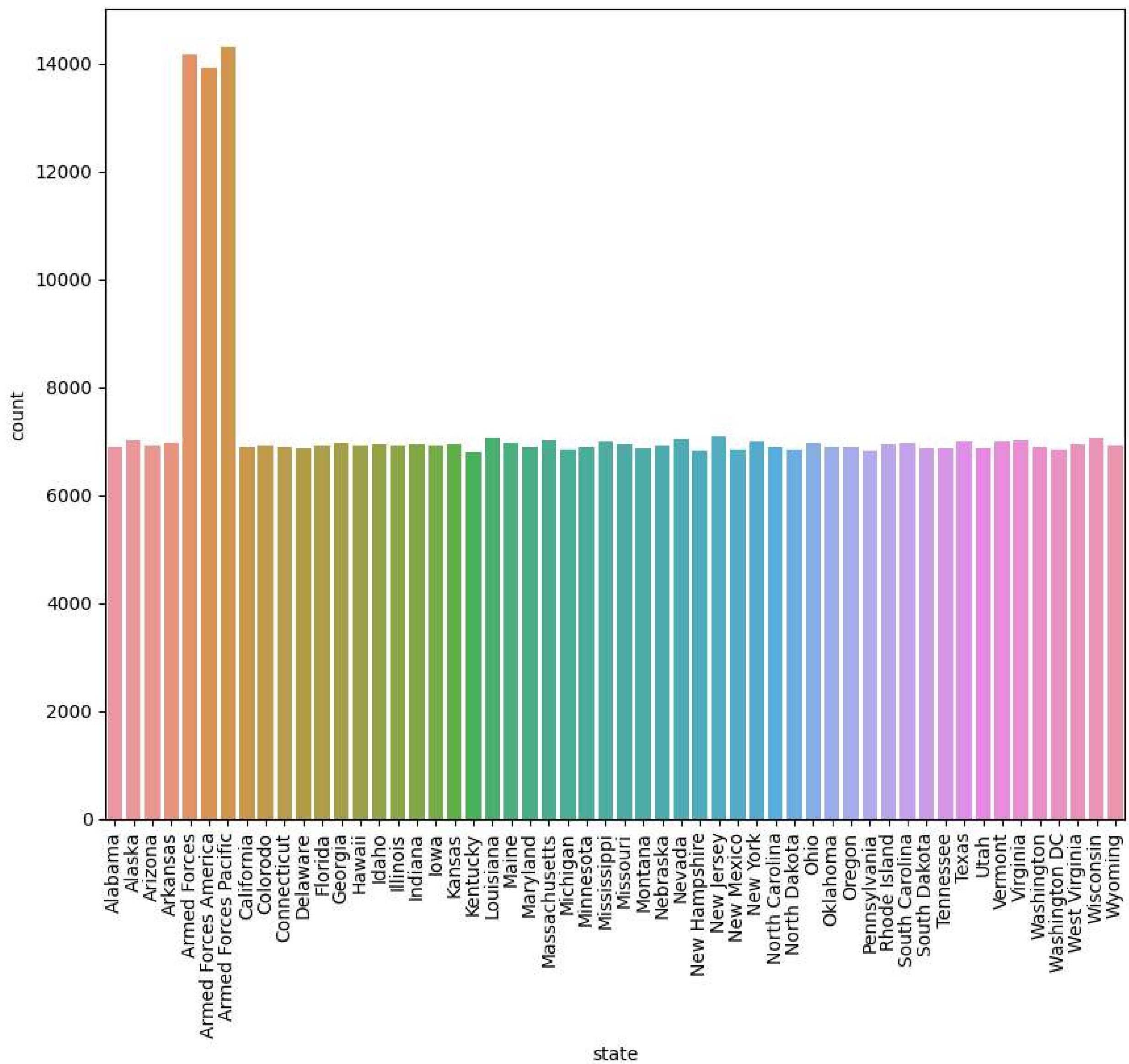
```
LoanTap["state"] = LoanTap.state.map(state_dict)
```

```
LoanTap["state"].unique()
```

```
array(['Oklahoma', 'South Dakota', 'West Virginia', 'Massachusetts',
       'Virginia', 'Delaware', 'Texas', 'Armed Forces',
       'Armed Forces Pacific', 'New Mexico', 'Mississippi', 'Oregon',
       'New Hampshire', 'Hawaii', 'Pennsylvania', 'Colorodo',
'Alabama',
       'Florida', 'Arizona', 'Wisconsin', 'North Carolina', 'Indiana',
       'Missouri', 'Armed Forces America', 'Tennessee', 'Kansas',
       'North Dakota', 'Connecticut', 'Wyoming', 'Nebraska',
       'Rhode Island', 'Arkansas', 'Michigan', 'Illinois',
'Louisiana',
       'New York', 'Iowa', 'Alaska', 'Utah', 'Maryland', 'Washington',
       'Minnesota', 'Ohio', 'Montana', 'New Jersey', 'Washington DC',
       'Nevada', 'Vermont', 'California', 'Maine', 'Idaho', 'Georgia',
       'Kentucky', 'South Carolina'], dtype=object)
```

```
LoanTap["state"] = LoanTap["state"].astype("category")
```

```
plt.figure(figsize=(10,8))
sns.countplot(data = LoanTap, x = "state")
plt.xticks(rotation = 90)
plt.show()
```



Armed forces, Armed forces america and Armed forces pacific dominating these loans

```
LoanTap.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 396030 entries, 0 to 396029
Data columns (total 30 columns):
 #   Column                Non-Null Count   Dtype
---  ------                --------------   -----
 0   loan_amnt             396030 non-null  float64
 1   term                  396030 non-null  category
 2   int_rate              396030 non-null  float64
 3   installment           396030 non-null  float64
 4   grade                 396030 non-null  category
 5   sub_grade             396030 non-null  category
```

```
 6   emp_title             396030 non-null  object
 7   emp_length            396030 non-null  object
 8   home_ownership        396030 non-null  category
 9   annual_inc            396030 non-null  float64
 10  verification_status   396030 non-null  category
 11  issue_d               396030 non-null  datetime64[ns]
 12  loan_status           396030 non-null  category
 13  purpose               396030 non-null  category
 14  title                 396030 non-null  object
 15  dti                   396030 non-null  float64
 16  earliest_cr_line      396030 non-null  datetime64[ns]
 17  open_acc              396030 non-null  float64
 18  pub_rec               396030 non-null  category
 19  revol_bal             396030 non-null  float64
 20  revol_util            396030 non-null  float64
 21  total_acc             396030 non-null  float64
 22  initial_list_status   396030 non-null  category
 23  application_type      396030 non-null  category
 24  mort_acc              396030 non-null  float64
 25  pub_rec_bankruptcies  396030 non-null  category
 26  address               396030 non-null  object
 27  days_from_first_loan  396030 non-null  float64
 28  zip_code              396030 non-null  category
 29  state                 396030 non-null  category
dtypes: category(13), datetime64[ns](2), float64(11), object(4)
memory usage: 56.3+ MB
```

DATA PREPARATION FOR MODELLING

```
LoanTap.sample(3)
```

```
        loan_amnt        term  int_rate  installment grade
sub_grade  \
66708     20000.0   36 months     11.53       659.81     B        B5

209591     8500.0   36 months     16.99       303.01     D        D3

232716    15000.0   36 months      8.19       471.37     A        A5


                         emp_title emp_length home_ownership
annual_inc  \
66708   Product Support Specialist  10+ years            OWN
50000.0
209591              Games Manager    3 years           RENT
60000.0
232716           Registered Nurse   < 1 year       MORTGAGE
35000.0

       verification_status    issue_d loan_status             purpose
```

```
\
66708          Not Verified 2015-10-01  Fully Paid         credit_card

209591      Source Verified 2014-10-01  Fully Paid  debt_consolidation

232716      Source Verified 2014-11-01  Fully Paid  debt_consolidation


                          title    dti earliest_cr_line  open_acc
pub_rec  \
66708   Credit card refinancing  12.75       1996-04-01      20.0
0
209591       Debt consolidation  18.84       1994-09-01      14.0
0
232716       Debt consolidation  28.16       1994-05-01      10.0
1

        revol_bal  revol_util  total_acc initial_list_status
application_type  \
66708     10073.0        32.1       27.0                   f
INDIVIDUAL
209591    15815.0        54.2       26.0                   f
INDIVIDUAL
232716     6478.0        24.4       36.0                   f
INDIVIDUAL

        mort_acc pub_rec_bankruptcies  \
66708        0.0                    0
209591       0.0                    0
232716       1.0                    1

                                                  address  \
66708              603 Mary Square\r\nMoodytown, ME 48052
209591  6045 Anderson Lodge Suite 505\r\nPetersshire, ...
232716          9049 Mark Inlet\r\nRobinchester, TX 22690

        days_from_first_loan zip_code     state
66708                 7122.0    48052     Maine
209591                7335.0    70466  New York
232716                7489.0    22690     Texas
```

term : 36 months -> 36, 60 months -> 60

```
term_values={' 36 months': 36, ' 60 months':60}
LoanTap['term'] =LoanTap.term.map(term_values)
```

emp_length

```
LoanTap["emp_length"].unique()
```

```
array(['10+ years', '4 years', '< 1 year', '6 years', '9 years',
       '2 years', '3 years', '8 years', '7 years', '5 years', '1
year'],
      dtype=object)
```

```
emp_length_values={'10+ years':10, '4 years':4, '< 1 year':1, '6
years':6, '9 years':9,
                   '2 years':2, '3 years':3, '8 years':8, '7 years':7,
'5 years':5, '1 year':1}
LoanTap['emp_length'] =LoanTap.emp_length.map(emp_length_values)
```

initial list status

```
initial_list_status_values={'w': 0, 'f':1}
LoanTap['initial_list_status']
=LoanTap.initial_list_status.map(initial_list_status_values)

LoanTap["initial_list_status"] =
LoanTap["initial_list_status"].astype(int)
```

term, pub_rec, pub_rec_bankruptcies to int

```
LoanTap["term"] = LoanTap["term"].astype(int)
LoanTap["pub_rec"] = LoanTap["pub_rec"].astype(int)
LoanTap["pub_rec_bankruptcies"] =
LoanTap["pub_rec_bankruptcies"].astype(int)
```

Loan Status

```
loan_status_values={'Fully Paid': 0, 'Charged Off':1}
LoanTap['loan_status'] =LoanTap.loan_status.map(loan_status_values)

LoanTap["loan_status"] = LoanTap["loan_status"].astype(int)
```

pub_rec

```
LoanTap["pub_rec"].unique()
```

```
array([0, 1])
```

```
LoanTap.dtypes
```

```
loan_amnt                         float64
term                                int32
int_rate                          float64
installment                       float64
grade                            category
sub_grade                        category
emp_title                          object
emp_length                          int64
home_ownership                   category
```

```
annual_inc                           float64
verification_status                 category
issue_d                       datetime64[ns]
loan_status                            int32
purpose                             category
title                                 object
dti                                  float64
earliest_cr_line              datetime64[ns]
open_acc                             float64
pub_rec                                int32
revol_bal                            float64
revol_util                           float64
total_acc                            float64
initial_list_status                    int32
application_type                    category
mort_acc                             float64
pub_rec_bankruptcies                   int32
address                               object
days_from_first_loan                 float64
zip_code                            category
state                               category
dtype: object
```

Drop columns of issue_id and earliest_cr_line

can drop date columns as "days_from_first_loan" feature was created

```
LoanTap.drop(columns = ["issue_d","earliest_cr_line"],inplace=True)
```

can remove address

```
LoanTap.drop(columns = ["address"],inplace=True)
```

Target Encoding of remaining categorical columns

```
target_enc = ['grade',
'sub_grade','emp_title','home_ownership','verification_status',
              'purpose', 'title', 'application_type','zip_code',
'state']
for col in target_enc:
    from category_encoders import TargetEncoder
    TEncoder = TargetEncoder()
    LoanTap[col] =
TEncoder.fit_transform(LoanTap[col],LoanTap["loan_status"])

LoanTap.head()
```

```
   loan_amnt  term  int_rate  installment     grade  sub_grade
emp_title  \
0    10000.0    36     11.44       329.48  0.125730   0.138393
```

```
0.247140
1     8000.0    36     11.99       265.68  0.125730   0.155037
0.217322
2    15600.0    36     10.49       506.97  0.125730   0.123354
0.191993
3     7200.0    36      6.49       220.65  0.062879   0.048186
0.170611
4    24375.0    60     17.27       609.33  0.211809   0.245067
0.300719

   emp_length  home_ownership  annual_inc  verification_status
loan_status  \
0          10        0.226622    117000.0             0.146360
0
1           4        0.169561     65000.0             0.146360
0
2           1        0.226622     43057.0             0.214743
0
3           6        0.226622     54000.0             0.146360
0
4           9        0.169561     55000.0             0.223211
1

    purpose     title    dti  open_acc  pub_rec  revol_bal  revol_util
\
0  0.189233  0.204861  26.24      16.0        0    36369.0        41.8

1  0.207414  0.229931  22.05      17.0        0    20131.0        53.3

2  0.167118  0.192619  12.79      13.0        0    11987.0        92.2

3  0.167118  0.192619   2.60       6.0        0     5472.0        21.5

4  0.167118  0.089580  33.95      13.0        0    24584.0        69.8


   total_acc  initial_list_status  application_type  mort_acc  \
0       25.0                    0          0.196087       0.0
1       27.0                    1          0.196087       3.0
2       26.0                    1          0.196087       0.0
3       13.0                    1          0.196087       0.0
4       43.0                    1          0.196087       1.0

   pub_rec_bankruptcies  days_from_first_loan  zip_code     state
0                     0                8980.0  0.193784  0.192013
1                     0                3836.0  0.000000  0.197038
2                     0                2710.0  0.000000  0.204061
3                     0                2983.0  0.000000  0.196098
4                     0                5145.0  1.000000  0.195101
```

Splitting the data

```
X=LoanTap.drop('loan_status',axis=1)
y=LoanTap['loan_status']

X_tr_cv, X_test, y_tr_cv, y_test = train_test_split(X, y,
test_size=0.2, random_state=1)
X_train, X_val, y_train, y_val = train_test_split(X_tr_cv, y_tr_cv,
test_size=0.25,random_state=1)
print("train data shape: ",X_train.shape)
print("val data shape: ",X_val.shape)
print("test data shape: ",X_test.shape)
```

```
train data shape:  (237618, 26)
val data shape:  (79206, 26)
test data shape:  (79206, 26)
```

Standardization

```
StdSclr = StandardScaler()
StdSclr.fit(X_train) # fit on training data
X_train = StdSclr.transform(X_train)
X_val = StdSclr.transform(X_val)
X_test = StdSclr.transform(X_test)

X_train
```

```
array([[-4.91930526e-01, -5.57566268e-01, -1.04180996e-01, ...,
        -8.11266851e-01, -7.53297353e-01, -4.33172666e-01],
       [ 2.50214157e+00, -5.57566268e-01,  1.04008507e-02, ...,
        -2.55423476e-02, -7.53297353e-01, -2.20647633e-01],
       [ 2.50214157e+00,  1.79350879e+00,  1.03714407e+00, ...,
         1.17559987e-02, -6.65104609e-03,  1.51359323e+00],
       ...,
       [ 1.18474985e+00,  1.79350879e+00,  1.10679186e+00, ...,
        -4.49349931e-01, -7.53297353e-01,  1.06106967e+00],
       [-1.09074494e+00, -5.57566268e-01,  2.28331030e-01, ...,
        -1.08629092e+00, -7.53297353e-01, -6.82346094e-01],
       [-3.72167642e-01, -5.57566268e-01, -1.17585827e+00, ...,
        -1.12845070e-01, -2.33660841e-03,  1.23738502e-01]])
```

```
model = LogisticRegression()
model.fit(X_train,y_train)
print(f"train accuracy --> {accuracy_score(y_train,
model.predict(X_train))}")
print(f"val accuracy -->{accuracy_score(y_val,
model.predict(X_val))}")
print(f"test accuracy -->{accuracy_score(y_test,
model.predict(X_test))}")
print()
print("For imbalanced data Mathews correlation coefficient is better
```

```
metric")
print(f"train matthews_corrcoef --> {matthews_corrcoef(y_train,
model.predict(X_train))}")
print(f"val matthews_corrcoef -->{matthews_corrcoef(y_val,
model.predict(X_val))}")
print(f"test matthews_corrcoef -->{matthews_corrcoef(y_test,
model.predict(X_test))}")
```

```
train accuracy --> 0.9214832209681085
val accuracy -->0.9204984470873419
test accuracy -->0.9214200944372901

For imbalanced data Mathews correlation coefficient is better metric
train matthews_corrcoef --> 0.7380592269328593
val matthews_corrcoef -->0.7361449473780168
test matthews_corrcoef -->0.7398763138773256
```

Assumption check: P-value of Ordinary Least Squares Check

Null Hypothesis of OLS model is that Independent variable has no impact on Dependent Variable So if p-value > 0.05 , We can delete that Independent Variable

```
X_train_sm = sm.add_constant(X_train)  #Statmodels default is without
intercept, to add intercept we need to add constant

sm_model = sm.OLS(y_train, X_train_sm).fit()

print(sm_model.summary())
```

```
                            OLS Regression Results

======================================================================
========
Dep. Variable:            loan_status   R-squared:
0.551
Model:                            OLS   Adj. R-squared:
0.551
Method:                 Least Squares   F-statistic:
1.120e+04
Date:                Thu, 14 Sep 2023   Prob (F-statistic):
0.00
Time:                        21:50:39   Log-Likelihood:
-22377.
No. Observations:              237618   AIC:
4.481e+04
Df Residuals:                  237591   BIC:
4.509e+04
Df Model:                          26

Covariance Type:            nonrobust
```

```
================================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const          0.1955      0.001    358.431      0.000       0.194       0.197
x1            -0.0179      0.004     -4.342      0.000      -0.026      -0.010
x2             0.0289      0.001     22.014      0.000       0.026       0.032
x3             0.0024      0.002      1.000      0.317      -0.002       0.007
x4             0.0247      0.004      6.473      0.000       0.017       0.032
x5             0.0068      0.003      2.627      0.009       0.002       0.012
x6             0.0153      0.003      4.425      0.000       0.009       0.022
x7             0.1225      0.001    202.969      0.000       0.121       0.124
x8            -0.0096      0.001    -16.560      0.000      -0.011      -0.008
x9             0.0094      0.001     14.661      0.000       0.008       0.011
x10            0.0049      0.001      6.514      0.000       0.003       0.006
x11            0.0008      0.001      1.293      0.196      -0.000       0.002
x12           -0.0113      0.001    -18.450      0.000      -0.013      -0.010
x13            0.0351      0.001     54.051      0.000       0.034       0.036
x14            0.0114      0.001     17.273      0.000       0.010       0.013
x15            0.0103      0.001     12.477      0.000       0.009       0.012
x16           -0.0022      0.001     -2.052      0.040      -0.004      -0.000
x17           -0.0027      0.001     -3.431      0.001      -0.004      -0.001
x18            0.0122      0.001     17.910      0.000       0.011       0.014
x19           -0.0040      0.001     -4.644      0.000      -0.006      -0.002
x20            0.0117      0.001     20.406      0.000       0.011       0.013
```

```
x21                 0.0008        0.001        1.390        0.165        -0.000
0.002
x22                -0.0060        0.001       -8.341        0.000        -0.007
-0.005
x23                -0.0028        0.001       -2.601        0.009        -0.005
-0.001
x24                -0.0020        0.001       -3.247        0.001        -0.003
-0.001
x25                 0.2046        0.001      348.606        0.000         0.203
0.206
x26                 0.0028        0.001        5.096        0.000         0.002
0.004
======================================================================
========
Omnibus:                    56941.535   Durbin-Watson:
2.000
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
121383.567
Skew:                           1.406   Prob(JB):
0.00
Kurtosis:                       5.087   Cond. No.
21.1
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
```

Check which column p_value is greater than 0.05

```
col_names = list(X.columns)

i = 1
for j in col_names:
    if sm_model.pvalues[i] > 0.05:
        print(f"{j:<20} --> Weight = {sm_model.params[i]:<10.5}, p-
value = {sm_model.pvalues[i]:<10.5}")
    i += 1

int_rate             --> Weight = 0.0023981 , p-value = 0.3173
verification_status  --> Weight = 0.00076202, p-value = 0.19611
application_type     --> Weight = 0.0007598 , p-value = 0.16461
```

drop int rate ---> 3rd column in numpy array X_train

```
X_train_new = np.delete(X_train, 2, axis=1)

X_val = np.delete(X_val, 2, axis=1)
X_test = np.delete(X_test,2,axis = 1)
```

```
col_names.remove("int_rate")

X_train_sm = sm.add_constant(X_train_new)  #Statmodels default is 
without intercept, to add intercept we need to add constant

sm_model = sm.OLS(y_train, X_train_sm).fit()

print(sm_model.summary())
```

```
                            OLS Regression Results                            
==============================================================================
========
Dep. Variable:            loan_status   R-squared:                       
0.551
Model:                            OLS   Adj. R-squared:                  
0.551
Method:                 Least Squares   F-statistic:                     
1.164e+04
Date:                Thu, 14 Sep 2023   Prob (F-statistic):              
0.00
Time:                        21:50:58   Log-Likelihood:                  
-22378.
No. Observations:              237618   AIC:                             
4.481e+04
Df Residuals:                  237592   BIC:                             
4.508e+04
Df Model:                          25                                         

Covariance Type:            nonrobust                                         

==============================================================================
========
                 coef    std err          t      P>|t|      [0.025      
0.975]
------------------------------------------------------------------------------
--------
const          0.1955      0.001    358.431      0.000       0.194       
0.197
x1            -0.0185      0.004     -4.566      0.000      -0.026      
-0.011
x2             0.0291      0.001     22.283      0.000       0.027       
0.032
x3             0.0254      0.004      6.745      0.000       0.018       
0.033
x4             0.0069      0.003      2.646      0.008       0.002       
0.012
x5             0.0175      0.003      6.575      0.000       0.012       
0.023
x6             0.1225      0.001    202.977      0.000       0.121
```

```
0.124
x7             -0.0096      0.001    -16.533      0.000      -0.011
-0.008
x8              0.0094      0.001     14.680      0.000       0.008
0.011
x9              0.0048      0.001      6.464      0.000       0.003
0.006
x10             0.0008      0.001      1.318      0.187      -0.000
0.002
x11            -0.0113      0.001    -18.424      0.000      -0.012
-0.010
x12             0.0349      0.001     54.638      0.000       0.034
0.036
x13             0.0114      0.001     17.260      0.000       0.010
0.013
x14             0.0103      0.001     12.532      0.000       0.009
0.012
x15            -0.0022      0.001     -2.060      0.039      -0.004
-0.000
x16            -0.0027      0.001     -3.471      0.001      -0.004
-0.001
x17             0.0123      0.001     18.222      0.000       0.011
0.014
x18            -0.0040      0.001     -4.666      0.000      -0.006
-0.002
x19             0.0118      0.001     20.707      0.000       0.011
0.013
x20             0.0008      0.001      1.399      0.162      -0.000
0.002
x21            -0.0060      0.001     -8.314      0.000      -0.007
-0.005
x22            -0.0028      0.001     -2.593      0.010      -0.005
-0.001
x23            -0.0020      0.001     -3.253      0.001      -0.003
-0.001
x24             0.2046      0.001    348.613      0.000       0.203
0.206
x25             0.0028      0.001      5.094      0.000       0.002
0.004
======================================================================
========
Omnibus:                    56935.138   Durbin-Watson:
2.000
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
121364.501
Skew:                           1.406   Prob(JB):
0.00
Kurtosis:                       5.087   Cond. No.
20.4
```

```
================================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
```

```
i = 1
for j in col_names:
    if sm_model.pvalues[i] > 0.05:
        print(f"{j:<20} --> Weight = {sm_model.params[i]:<10.5}, p-
value = {sm_model.pvalues[i]:<10.5}")
    i += 1
```

```
verification_status  --> Weight = 0.00077679, p-value = 0.18744
application_type     --> Weight = 0.00076489, p-value = 0.16178
```

drop verification_ status 10 column in X_train_new numpy array

```
X_train_new = np.delete(X_train_new, 9, axis=1)

X_val = np.delete(X_val, 9, axis=1)
X_test = np.delete(X_test,9,axis = 1)

col_names.remove("verification_status")

X_train_sm = sm.add_constant(X_train_new)  #Statmodels default is
without intercept, to add intercept we need to add constant

sm_model = sm.OLS(y_train, X_train_sm).fit()

print(sm_model.summary())
```

```
                            OLS Regression Results

================================================================================
========
Dep. Variable:            loan_status   R-squared:
0.551
Model:                            OLS   Adj. R-squared:
0.551
Method:                 Least Squares   F-statistic:
1.213e+04
Date:                Thu, 14 Sep 2023   Prob (F-statistic):
0.00
Time:                        21:51:12   Log-Likelihood:
-22379.
No. Observations:              237618   AIC:
4.481e+04
Df Residuals:                  237593   BIC:
4.507e+04
```

```
Df Model:                          24
Covariance Type:            nonrobust
======================================================================
========
                 coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
--------
const          0.1955      0.001    358.431      0.000       0.194
0.197
x1            -0.0185      0.004     -4.561      0.000      -0.026
-0.011
x2             0.0292      0.001     22.365      0.000       0.027
0.032
x3             0.0256      0.004      6.792      0.000       0.018
0.033
x4             0.0068      0.003      2.619      0.009       0.002
0.012
x5             0.0177      0.003      6.645      0.000       0.012
0.023
x6             0.1225      0.001    203.137      0.000       0.121
0.124
x7            -0.0095      0.001    -16.496      0.000      -0.011
-0.008
x8             0.0094      0.001     14.702      0.000       0.008
0.011
x9             0.0049      0.001      6.497      0.000       0.003
0.006
x10           -0.0113      0.001    -18.393      0.000      -0.012
-0.010
x11            0.0349      0.001     54.628      0.000       0.034
0.036
x12            0.0114      0.001     17.382      0.000       0.010
0.013
x13            0.0103      0.001     12.502      0.000       0.009
0.012
x14           -0.0022      0.001     -1.986      0.047      -0.004   -
2.85e-05
x15           -0.0027      0.001     -3.456      0.001      -0.004
-0.001
x16            0.0123      0.001     18.201      0.000       0.011
0.014
x17           -0.0040      0.001     -4.662      0.000      -0.006
-0.002
x18            0.0118      0.001     20.725      0.000       0.011
0.013
x19            0.0008      0.001      1.403      0.161      -0.000
```

```
0.002
x20            -0.0059      0.001     -8.296      0.000      -0.007
-0.005
x21            -0.0028      0.001     -2.625      0.009      -0.005
-0.001
x22            -0.0020      0.001     -3.222      0.001      -0.003
-0.001
x23             0.2046      0.001    348.614      0.000       0.203
0.206
x24             0.0028      0.001      5.095      0.000       0.002
0.004
======================================================================
========
Omnibus:                    56945.008   Durbin-Watson:
2.000
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
121408.455
Skew:                           1.406   Prob(JB):
0.00
Kurtosis:                       5.088   Cond. No.
20.1
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.

i = 1
for j in col_names:
    if sm_model.pvalues[i] > 0.05:
        print(f"{j:<20} --> Weight = {sm_model.params[i]:<10.5}, p-
value = {sm_model.pvalues[i]:<10.5}")
    i += 1

application_type     --> Weight = 0.00076707, p-value = 0.16058
```

drop application type 19th column in X_train_new numpy array

```
X_train_new = np.delete(X_train_new, 18, axis=1)

X_val = np.delete(X_val, 18, axis=1)
X_test = np.delete(X_test,18,axis = 1)

col_names.remove("application_type")

X_train_sm = sm.add_constant(X_train_new)  #Statmodels default is
without intercept, to add intercept we need to add constant

sm_model = sm.OLS(y_train, X_train_sm).fit()
```

```python
print(sm_model.summary())
```

```
                            OLS Regression Results

==============================================================================
========
Dep. Variable:            loan_status   R-squared:
0.551
Model:                            OLS   Adj. R-squared:
0.551
Method:                 Least Squares   F-statistic:
1.266e+04
Date:                Thu, 14 Sep 2023   Prob (F-statistic):
0.00
Time:                        21:51:24   Log-Likelihood:
-22380.
No. Observations:              237618   AIC:
4.481e+04
Df Residuals:                  237594   BIC:
4.506e+04
Df Model:                          23

Covariance Type:            nonrobust

==============================================================================
========
                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
--------
const          0.1955      0.001    358.430      0.000       0.194
0.197
x1            -0.0186      0.004     -4.574      0.000      -0.027
-0.011
x2             0.0292      0.001     22.363      0.000       0.027
0.032
x3             0.0256      0.004      6.800      0.000       0.018
0.033
x4             0.0068      0.003      2.618      0.009       0.002
0.012
x5             0.0177      0.003      6.656      0.000       0.012
0.023
x6             0.1225      0.001    203.137      0.000       0.121
0.124
x7            -0.0095      0.001    -16.503      0.000      -0.011
-0.008
x8             0.0094      0.001     14.711      0.000       0.008
0.011
x9             0.0049      0.001      6.527      0.000       0.003
```

```
0.006
x10              -0.0113      0.001    -18.401      0.000      -0.012
-0.010
x11               0.0349      0.001     54.626      0.000       0.034
0.036
x12               0.0115      0.001     17.468      0.000       0.010
0.013
x13               0.0103      0.001     12.496      0.000       0.009
0.012
x14              -0.0022      0.001     -1.990      0.047      -0.004    -
3.27e-05
x15              -0.0027      0.001     -3.443      0.001      -0.004
-0.001
x16               0.0122      0.001     18.176      0.000       0.011
0.014
x17              -0.0040      0.001     -4.664      0.000      -0.006
-0.002
x18               0.0118      0.001     20.728      0.000       0.011
0.013
x19              -0.0059      0.001     -8.301      0.000      -0.007
-0.005
x20              -0.0028      0.001     -2.625      0.009      -0.005
-0.001
x21              -0.0020      0.001     -3.216      0.001      -0.003
-0.001
x22               0.2046      0.001    348.614      0.000       0.203
0.206
x23               0.0028      0.001      5.091      0.000       0.002
0.004
======================================================================
========
Omnibus:                    56943.487   Durbin-Watson:
2.000
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
121401.607
Skew:                           1.406   Prob(JB):
0.00
Kurtosis:                       5.088   Cond. No.
20.1
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.

i = 1
for j in col_names:
    if sm_model.pvalues[i] > 0.05:
        print(f"{j:<20} --> Weight = {sm_model.params[i]:<10.5}, p-
```

```
value = {sm_model.pvalues[i]:<10.5}")
    i += 1
```

Observations

All the columns with greater than 0.05 p-value are deleted

Assumption check 2: Multi-collinearity

Columns with VIF > 5 can be deleted

```
X_val= pd.DataFrame(data = X_val,columns = col_names)
X_test= pd.DataFrame(data = X_test,columns = col_names)

X_train_new = pd.DataFrame(data = X_train_new,columns = col_names)
vif = pd.DataFrame()
vif['Features'] = X_train_new.columns
vif['VIF'] = [variance_inflation_factor(X_train_new.values, i) for i
in range(X_train_new.shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

	Features	VIF
0	loan_amnt	55.30
2	installment	47.58
4	sub_grade	23.75
3	grade	22.55
1	term	5.72
13	pub_rec	3.98
19	pub_rec_bankruptcies	3.93
16	total_acc	2.45
12	open_acc	2.29
14	revol_bal	2.10
8	annual_inc	1.87
18	mort_acc	1.72
15	revol_util	1.52
11	dti	1.46
7	home_ownership	1.38
10	title	1.37
20	days_from_first_loan	1.31
9	purpose	1.26
5	emp_title	1.22
21	zip_code	1.16
6	emp_length	1.12
17	initial_list_status	1.08
22	state	1.00

```
X_val = X_val.drop(columns = "loan_amnt")
X_test = X_test.drop(columns = "loan_amnt")
```

```
col_names.remove("loan_amnt")

X_train_new = X_train_new.drop(columns = "loan_amnt")

vif = pd.DataFrame()
vif['Features'] = X_train_new.columns
vif['VIF'] = [variance_inflation_factor(X_train_new.values, i) for i
in range(X_train_new.shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

	Features	VIF
3	sub_grade	23.35
2	grade	22.55
12	pub_rec	3.98
18	pub_rec_bankruptcies	3.93
15	total_acc	2.45
11	open_acc	2.28
13	revol_bal	2.09
7	annual_inc	1.86
17	mort_acc	1.72
1	installment	1.54
14	revol_util	1.51
10	dti	1.46
0	term	1.41
6	home_ownership	1.38
9	title	1.37
19	days_from_first_loan	1.31
8	purpose	1.26
4	emp_title	1.22
20	zip_code	1.16
5	emp_length	1.12
16	initial_list_status	1.08
21	state	1.00

```
X_val = X_val.drop(columns = "sub_grade")
X_test = X_test.drop(columns = "sub_grade")

col_names.remove("sub_grade")

X_train_new = X_train_new.drop(columns = "sub_grade")

vif = pd.DataFrame()
vif['Features'] = X_train_new.columns
vif['VIF'] = [variance_inflation_factor(X_train_new.values, i) for i
in range(X_train_new.shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

```
                 Features   VIF
11                pub_rec  3.97
17   pub_rec_bankruptcies  3.93
14              total_acc  2.45
10               open_acc  2.28
12              revol_bal  2.08
6              annual_inc  1.86
16               mort_acc  1.72
2                   grade  1.63
1             installment  1.53
13             revol_util  1.50
9                     dti  1.45
0                    term  1.38
5          home_ownership  1.38
8                   title  1.37
18    days_from_first_loan  1.31
7                 purpose  1.26
3               emp_title  1.22
19               zip_code  1.16
4              emp_length  1.12
15    initial_list_status  1.08
20                  state  1.00
```

Observation

all the columns have VIF < 5

CHAPTER 3: MODEL BUILDING

BUILD THE LOGISTIC REGRESSION MODEL AND COMMENT ON MODEL STATISTICS

Model building using Imbalanced data

```
LogReg = LogisticRegression()
LogReg.fit(X_train_new, y_train)

LogisticRegression()

print("smote Accuracy: 
",accuracy_score(y_train,LogReg.predict(X_train_new)))
print("Test Accuracy: ",accuracy_score(y_test,LogReg.predict(X_test)))
print()
print("smote Negative Log Loss: 
",log_loss(y_train,LogReg.predict(X_train_new)))
print("Test Negative Log Loss: 
",log_loss(y_test,LogReg.predict(X_test)))
```

```
print()
print("smote f1_score:
",f1_score(y_train,LogReg.predict(X_train_new)))
print("Test f1_score: ",f1_score(y_test,LogReg.predict(X_test)))
print()
print("smote recall_score:
",recall_score(y_train,LogReg.predict(X_train_new)))
print("Test recall_score:
",recall_score(y_test,LogReg.predict(X_test)))
print()
print("smote precision_score:
",precision_score(y_train,LogReg.predict(X_train_new)))
print("Test precision_score:
",precision_score(y_test,LogReg.predict(X_test)))
print()
print("smote roc_auc_score:
",roc_auc_score(y_train,LogReg.predict(X_train_new)))
print("Test roc_auc_score:
",roc_auc_score(y_test,LogReg.predict(X_test)))
print()
print("smote matthews_corrcoef:
",matthews_corrcoef(y_train,LogReg.predict(X_train_new)))
print("Test matthews_corrcoef:
",matthews_corrcoef(y_test,LogReg.predict(X_test)))
```

```
smote Accuracy:  0.9215337221927632
Test Accuracy:  0.9216220993359089

smote Negative Log Loss:  2.828211320018219
Test Negative Log Loss:  2.8250258849031553

smote f1_score:  0.780917689912461
Test f1_score:  0.782937062937063

smote recall_score:  0.715315897104725
Test recall_score:  0.7153993610223642

smote precision_score:  0.8597671410090556
Test precision_score:  0.8645559845559846

smote roc_auc_score:  0.8434815650471864
Test roc_auc_score:  0.8439008259577174

smote matthews_corrcoef:  0.7382189907844265
Test matthews_corrcoef:  0.7405445206109296
```

Data Balancing --> SMOTE

```
X_train_new.shape,y_train.shape
```

```
((237618, 21), (237618,))

y_train.value_counts()

0    191163
1     46455
Name: loan_status, dtype: int64

SmoteBL = SMOTE(k_neighbors=10)
X_smote , y_smote = SmoteBL.fit_resample(X_train_new,y_train)

X_smote.shape,  y_smote.shape

((382326, 21), (382326,))

y_smote.value_counts()

0    191163
1    191163
Name: loan_status, dtype: int64

print(X_test.shape)
print(X_smote.shape)
print(X_val.shape)
print(len(col_names))

(79206, 21)
(382326, 21)
(79206, 21)
21
```

Data is Balanced now. Good to Go for Model Building

```
LogReg = LogisticRegression(class_weight="balanced")
LogReg.fit(X_smote, y_smote)
print("smote Accuracy:
",accuracy_score(y_smote,LogReg.predict(X_smote)))
print("Test Accuracy: ",accuracy_score(y_test,LogReg.predict(X_test)))
print()
print("smote Negative Log Loss:
",log_loss(y_smote,LogReg.predict(X_smote)))
print("Test Negative Log Loss:
",log_loss(y_test,LogReg.predict(X_test)))
print()
print("smote f1_score: ",f1_score(y_smote,LogReg.predict(X_smote)))
print("Test f1_score: ",f1_score(y_test,LogReg.predict(X_test)))
print()
print("smote recall_score:
",recall_score(y_smote,LogReg.predict(X_smote)))
print("Test recall_score:
",recall_score(y_test,LogReg.predict(X_test)))
```

```python
print()
print("smote precision_score: ",precision_score(y_smote,LogReg.predict(X_smote)))
print("Test precision_score: ",precision_score(y_test,LogReg.predict(X_test)))
print()
print("smote roc_auc_score: ",roc_auc_score(y_smote,LogReg.predict(X_smote)))
print("Test roc_auc_score: ",roc_auc_score(y_test,LogReg.predict(X_test)))
print()
print("smote matthews_corrcoef: ",matthews_corrcoef(y_smote,LogReg.predict(X_smote)))
print("Test matthews_corrcoef: ",matthews_corrcoef(y_test,LogReg.predict(X_test)))
```

```
smote Accuracy:  0.8951784602668926
Test Accuracy:  0.8930889074060046

smote Negative Log Loss:  3.7781512458536928
Test Negative Log Loss:  3.8534663649097802

smote f1_score:  0.8949597672529028
Test f1_score:  0.7648430991391281

smote recall_score:  0.8930964674126269
Test recall_score:  0.8799361022364217

smote precision_score:  0.8968308582895145
Test precision_score:  0.6763752455795677

smote roc_auc_score:  0.8951784602668927
Test roc_auc_score:  0.8881318751474134

smote matthews_corrcoef:  0.7903637725340795
Test matthews_corrcoef:  0.7072897993702799
```

```python
y_test.value_counts()
```

```
0    63556
1    15650
Name: loan_status, dtype: int64
```

```python
# Dumb model accuracy
63556/(15650+63556)
```

```
0.8024139585384945
```

Observation

Balanced model has slightly lesser metrics compared to Imbalanced model. But we should use balanced data only. As Imbalanced data may provide offset results

LogReg Model has Better accuracy than the Dumb model.

Metric may improve by hyper parameter tuning

Accuracy is bad metric when data is imbalance, So Instead , Mathews corrcoef is used

difference between train and test metrics was not much except in mathews coef and precision score, f1 score. It implies Model is good recall model compared to precision.

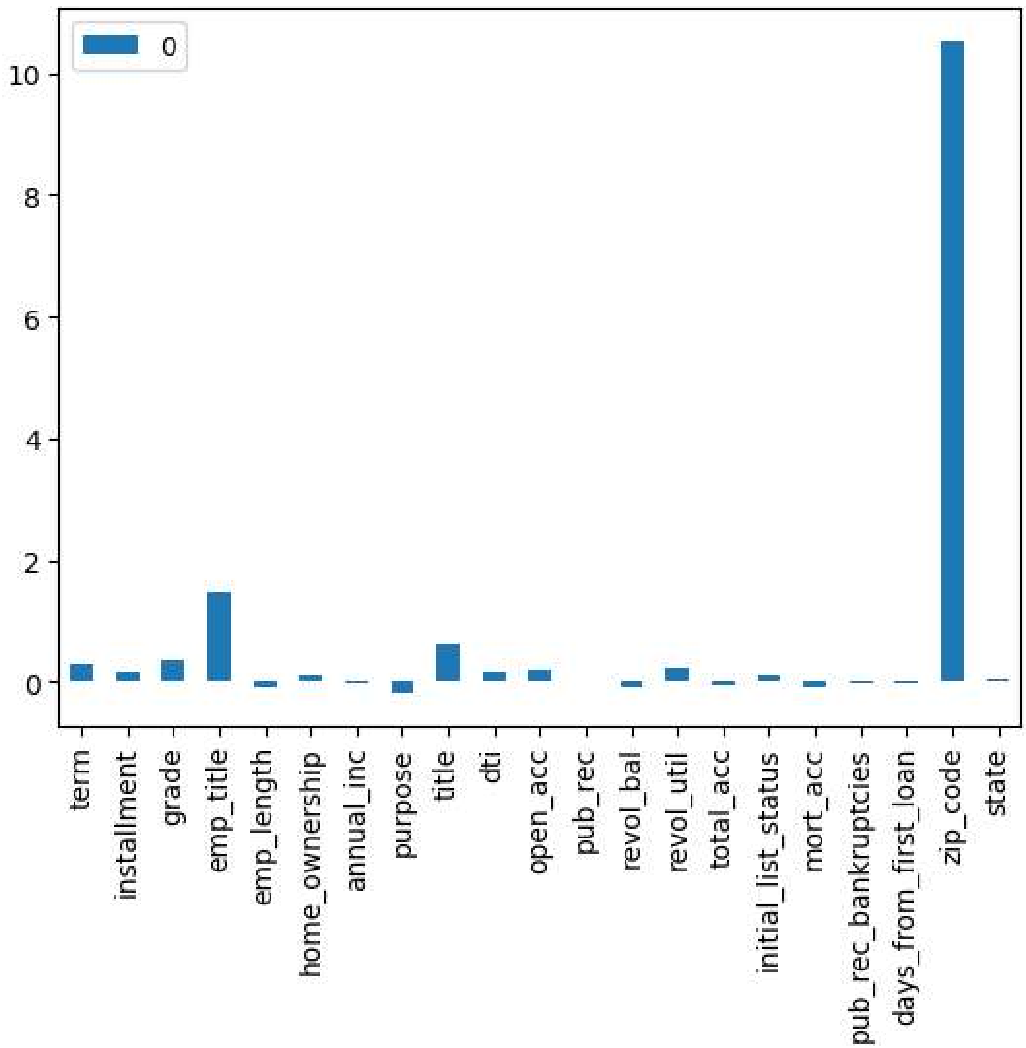
DISPLAY MODEL COEFFCIENTS WITH COLUMN NAMES

```
pd.DataFrame(data=LogReg.coef_,columns=col_names).T
```

	0
term	0.297654
installment	0.171973
grade	0.344763
emp_title	1.466779
emp_length	-0.083563
home_ownership	0.110483
annual_inc	-0.022491
purpose	-0.182589
title	0.599889
dti	0.173457
open_acc	0.207788
pub_rec	-0.001589
revol_bal	-0.077799
revol_util	0.237891
total_acc	-0.069887
initial_list_status	0.101531
mort_acc	-0.096792
pub_rec_bankruptcies	-0.027671
days_from_first_loan	-0.036275
zip_code	10.536872
state	0.048861

```
pd.DataFrame(data=LogReg.coef_,columns=col_names).T.plot(kind = "bar")
```

```
<Axes: >
```




```
LogReg.intercept_
```

```
array([-0.85323162])
```

```
LogReg.predict(X_smote).shape
```

```
(382326,)
```

```
LogReg.predict(X_test).shape
```

```
(79206,)
```

Hyper parameter tuning

```
LogReg = LogisticRegression(class_weight="balanced",solver = "newton-
cholesky")
LogReg.fit(X_smote, y_smote)
print("smote Accuracy:
```

```
",accuracy_score(y_smote,LogReg.predict(X_smote)))
print("Test Accuracy: ",accuracy_score(y_test,LogReg.predict(X_test)))
print()
print("smote Negative Log Loss:
",log_loss(y_smote,LogReg.predict(X_smote)))
print("Test Negative Log Loss:
",log_loss(y_test,LogReg.predict(X_test)))
print()
print("smote f1_score: ",f1_score(y_smote,LogReg.predict(X_smote)))
print("Test f1_score: ",f1_score(y_test,LogReg.predict(X_test)))
print()
print("smote recall_score:
",recall_score(y_smote,LogReg.predict(X_smote)))
print("Test recall_score:
",recall_score(y_test,LogReg.predict(X_test)))
print()
print("smote precision_score:
",precision_score(y_smote,LogReg.predict(X_smote)))
print("Test precision_score:
",precision_score(y_test,LogReg.predict(X_test)))
print()
print("smote roc_auc_score:
",roc_auc_score(y_smote,LogReg.predict(X_smote)))
print("Test roc_auc_score:
",roc_auc_score(y_test,LogReg.predict(X_test)))
print()
print("smote matthews_corrcoef:
",matthews_corrcoef(y_smote,LogReg.predict(X_smote)))
print("Test matthews_corrcoef:
",matthews_corrcoef(y_test,LogReg.predict(X_test)))
```

```
smote Accuracy:  0.8951523045777687
Test Accuracy:  0.8931772845491504

smote Negative Log Loss:  3.7790939924466307
Test Negative Log Loss:  3.850280929794715

smote f1_score:  0.8949368614726557
Test f1_score:  0.7650701096765237

smote recall_score:  0.8931016985504517
Test recall_score:  0.8803194888178913

smote precision_score:  0.8967795817816041
Test precision_score:  0.6765038055487356

smote roc_auc_score:  0.8951523045777688
Test roc_auc_score:  0.8883314355160008
```

```
smote matthews_corrcoef:  0.7903112556775622
Test matthews_corrcoef:  0.707596642128738
```

Not much difference has observed between lbfgs solver and newton cholesky solver.

```
LogReg =
LogisticRegression(class_weight="balanced",penalty="l1",solver =
"saga")
LogReg.fit(X_smote, y_smote)
print("smote Accuracy:
",accuracy_score(y_smote,LogReg.predict(X_smote)))
print("Test Accuracy: ",accuracy_score(y_test,LogReg.predict(X_test)))
print()
print("smote Negative Log Loss:
",log_loss(y_smote,LogReg.predict(X_smote)))
print("Test Negative Log Loss:
",log_loss(y_test,LogReg.predict(X_test)))
print()
print("smote f1_score: ",f1_score(y_smote,LogReg.predict(X_smote)))
print("Test f1_score: ",f1_score(y_test,LogReg.predict(X_test)))
print()
print("smote recall_score:
",recall_score(y_smote,LogReg.predict(X_smote)))
print("Test recall_score:
",recall_score(y_test,LogReg.predict(X_test)))
print()
print("smote precision_score:
",precision_score(y_smote,LogReg.predict(X_smote)))
print("Test precision_score:
",precision_score(y_test,LogReg.predict(X_test)))
print()
print("smote roc_auc_score:
",roc_auc_score(y_smote,LogReg.predict(X_smote)))
print("Test roc_auc_score:
",roc_auc_score(y_test,LogReg.predict(X_test)))
print()
print("smote matthews_corrcoef:
",matthews_corrcoef(y_smote,LogReg.predict(X_smote)))
print("Test matthews_corrcoef:
",matthews_corrcoef(y_test,LogReg.predict(X_test)))

smote Accuracy:  0.8951706135601555
Test Accuracy:  0.8931015327121683

smote Negative Log Loss:  3.7784340698315733
Test Negative Log Loss:  3.853011302750485

smote f1_score:  0.8949499768034953
Test f1_score:  0.7649035124253784
```

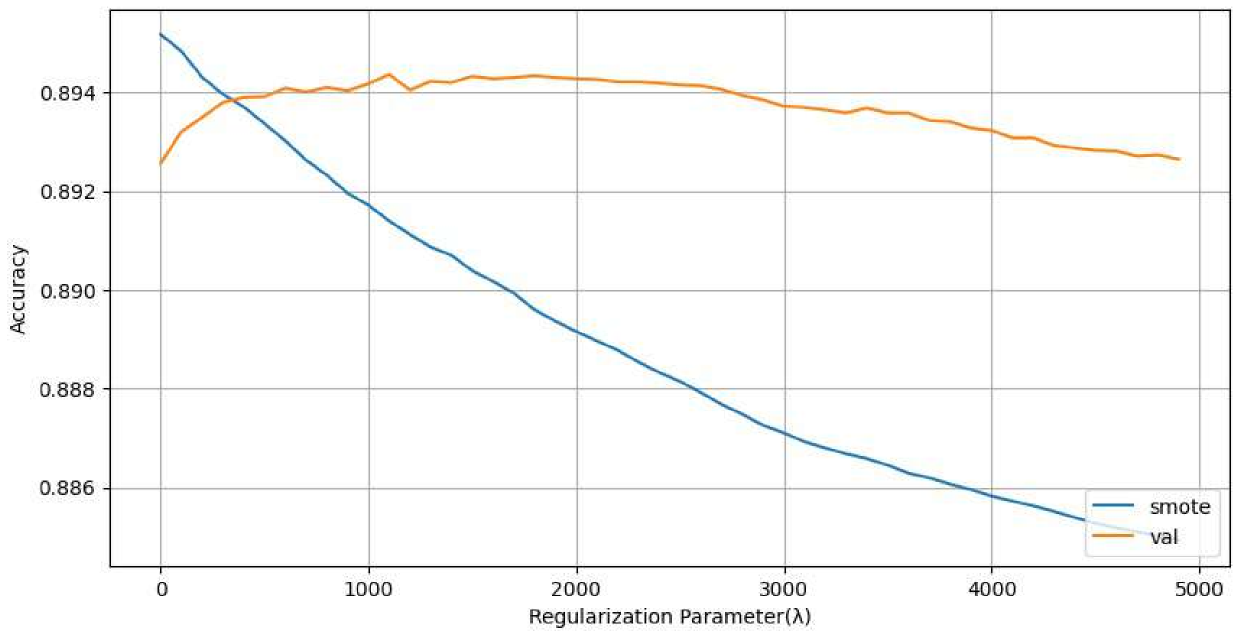
```
smote recall_score:  0.8930703117235029
Test recall_score:  0.8801277955271566

smote precision_score:  0.8968375709182601
Test precision_score:  0.6763564939847778

smote roc_auc_score:  0.8951706135601554
Test roc_auc_score:  0.8882119876370757

smote matthews_corrcoef:  0.7903482000262095
Test matthews_corrcoef:  0.707378990632344
```

Not much difference in saga solver with l1 regularisation also. lets stick to lbfgs

```
smote_scores = []
val_scores = []
for la in np.arange(0.01, 5000.0, 100): # range of values of Lambda
  model = LogisticRegression(C=1/la,class_weight="balanced")
  model.fit(X_smote, y_smote)
  smote_score = accuracy_score(y_smote, model.predict(X_smote))
  val_score = accuracy_score(y_val, model.predict(X_val))
  smote_scores.append(smote_score)
  val_scores.append(val_score)

len(val_scores)
```

```
50
```

```
plt.figure(figsize=(10,5))
plt.plot(list(np.arange(0.01, 5000.0, 100)), smote_scores,
label="smote")
plt.plot(list(np.arange(0.01, 5000.0, 100)), val_scores, label="val")
plt.legend(loc='lower right')
plt.xlabel("Regularization Parameter(λ)")
plt.ylabel("Accuracy")
plt.grid()
plt.show()
```




```
max(val_scores)
```

```
0.8943640633285357
```

```
j = 0
for i in val_scores:
    if i == max(val_scores):
        break
    j += 100
print("lambda for max val_score is",j)
```

```
lambda for max val_score is 1100
```

```
LogReg = LogisticRegression(class_weight="balanced",C = 1/1100)
LogReg.fit(X_smote, y_smote)
print("smote Accuracy:
",accuracy_score(y_smote,LogReg.predict(X_smote)))
print("Test Accuracy: ",accuracy_score(y_test,LogReg.predict(X_test)))
print()
print("smote Negative Log Loss:
",log_loss(y_smote,LogReg.predict(X_smote)))
print("Test Negative Log Loss:
",log_loss(y_test,LogReg.predict(X_test)))
print()
print("smote f1_score: ",f1_score(y_smote,LogReg.predict(X_smote)))
print("Test f1_score: ",f1_score(y_test,LogReg.predict(X_test)))
print()
print("smote recall_score:
",recall_score(y_smote,LogReg.predict(X_smote)))
print("Test recall_score:
",recall_score(y_test,LogReg.predict(X_test)))
```

```
print()
print("smote precision_score:
",precision_score(y_smote,LogReg.predict(X_smote)))
print("Test precision_score:
",precision_score(y_test,LogReg.predict(X_test)))
print()
print("smote roc_auc_score:
",roc_auc_score(y_smote,LogReg.predict(X_smote)))
print("Test roc_auc_score:
",roc_auc_score(y_test,LogReg.predict(X_test)))
print()
print("smote matthews_corrcoef:
",matthews_corrcoef(y_smote,LogReg.predict(X_smote)))
print("Test matthews_corrcoef:
",matthews_corrcoef(y_test,LogReg.predict(X_test)))
```

```
smote Accuracy:  0.8913937320506583
Test Accuracy:  0.8946291947579729

smote Negative Log Loss:  3.9145666778516546
Test Negative Log Loss:  3.7979487814757937

smote f1_score:  0.8900836225312294
Test f1_score:  0.7647821430584522

smote recall_score:  0.8794745845168783
Test recall_score:  0.8669648562300319

smote precision_score:  0.9009517378862416
Test precision_score:  0.6841468334005647

smote roc_auc_score:  0.8913937320506584
Test roc_auc_score:  0.8842030524463145

smote matthews_corrcoef:  0.7830099740289055
Test matthews_corrcoef:  0.7062278579469465
```

CHAPTER 4: RESULTS EVALUATION

```
print('LogReg Accuracy:',LogReg.score(X_test,y_test))
```

```
LogReg Accuracy: 0.8946291947579729
```

```
y_test.value_counts()
```

```
0    63556
1    15650
Name: loan_status, dtype: int64
```

```python
# Dumb model accuracy
63556/(63556+15650)
```

```
0.8024139585384945
```

Accuracy better than dumb model

Precision score

```python
precision_score(y_test, y_pred)
```

```
0.684745240905126
```

Recall score or sensitivity

```python
recall_score(y_test, y_pred)
```

```
0.8527156549520767
```

Precision score is lesser than Recall score

f1 score

```python
print(f'f1Score:{f1_score(y_test,y_pred)}')
```

```
f1Score:0.7595549104983067
```

f1 score is Harmonic mean of Precision and Recall (equal importance to both of them)

f_beta score

```python
print(f'f2Score (Recall important):{fbeta_score(y_test,y_pred,beta = 2)}')
print(f'f0.5Score (Precision important):{fbeta_score(y_test,y_pred,beta = 0.5)}')
```

```
f2Score (Recall important):0.8128372863599265
f0.5Score (Precision important):0.7128282375061429
```

f2 score is slightly giving importance to Recall

f0.5 score is slightly giving importance to Precision

ROC AUC CURVE & COMMENTS

```python
probability = LogReg.predict_proba(X_test)
probability
```

```
array([[9.92347537e-01, 7.65246289e-03],
       [8.83925534e-01, 1.16074466e-01],
       [9.92304709e-01, 7.69529135e-03],
       ...,
```

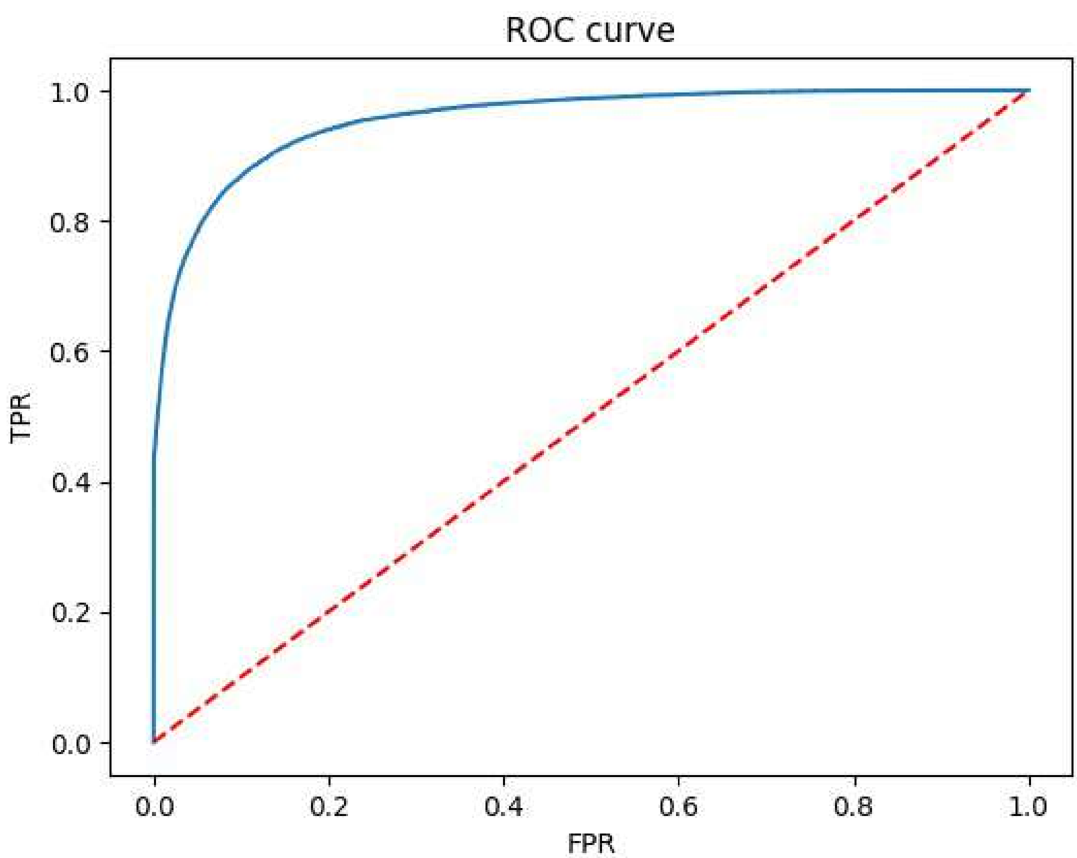
```
       [9.87666032e-01, 1.23339685e-02],
       [6.00987929e-01, 3.99012071e-01],
       [3.14383841e-04, 9.99685616e-01]])
```

```
probabilites = probability[:,1]
```

```
fpr, tpr, thr = roc_curve(y_test,probabilites)
```

```
plt.plot(fpr,tpr)
```

```
#random model
plt.plot(fpr,fpr,'--',color='red' )
plt.title('ROC curve')
plt.xlabel('FPR')
plt.ylabel('TPR')
plt.show()
```




```
roc_auc_score(y_test,probabilites)
```

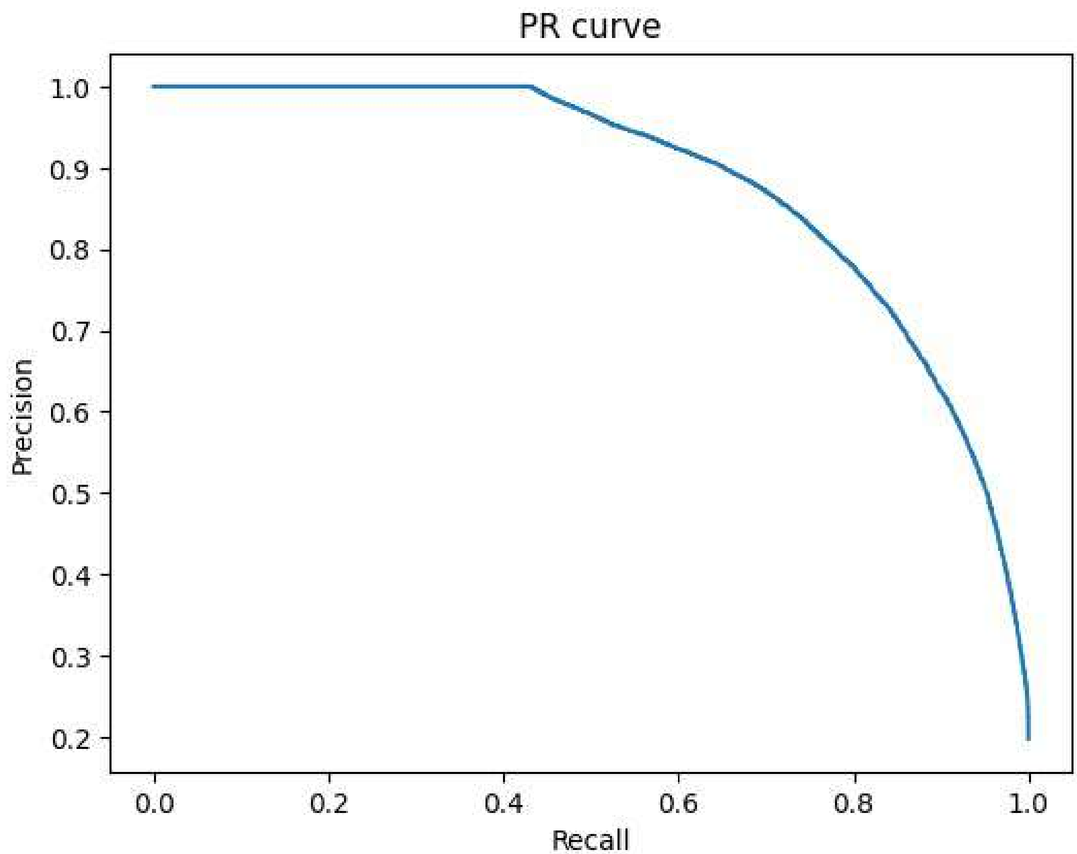
```
0.9559115223685404
```

as Data is imbalanced, AU-ROC is not prefered

Instead F1 score and Precision Recall curve works well with imbalanced data

PRECISION RECALL CURVE & COMMENTS

```
precision, recall, thr = precision_recall_curve(y_test, probabilites)

plt.plot(recall, precision)

plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('PR curve')
plt.show()
```

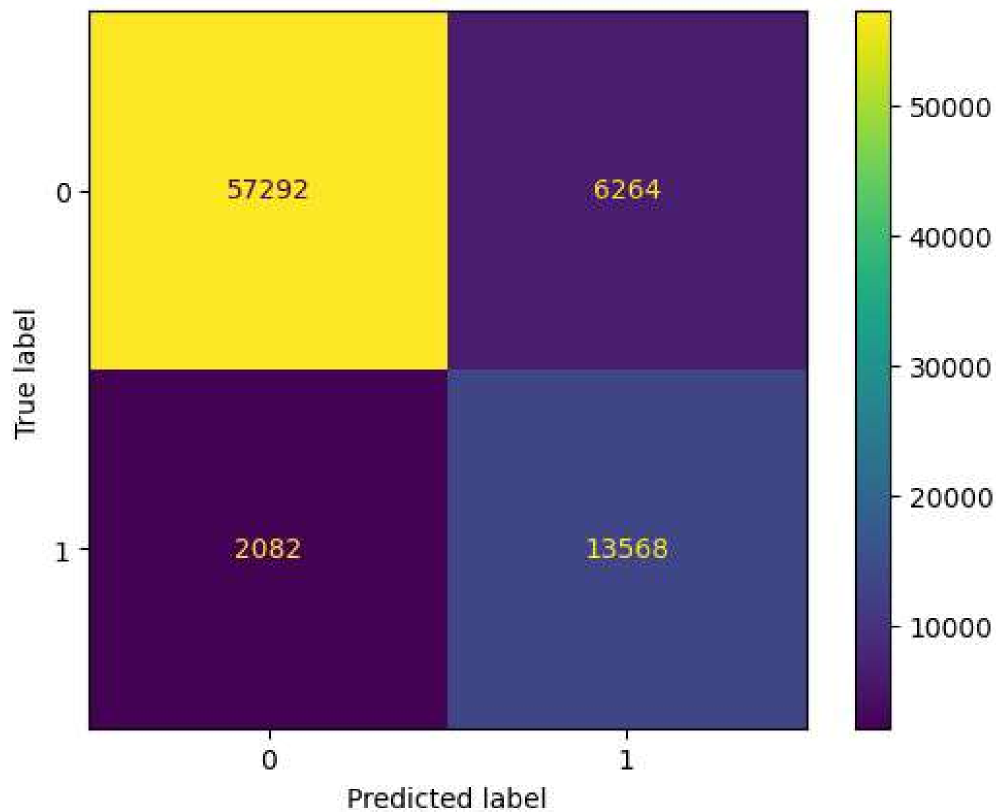



```
auc(recall, precision)

0.8849329232576484

print(f'f1Score:{f1_score(y_test,y_pred)}')

f1Score:0.7595549104983067
```

Now AU-PRC comes little closer to F1 Score. Showing that PRC worked just fine in Imbalanced data

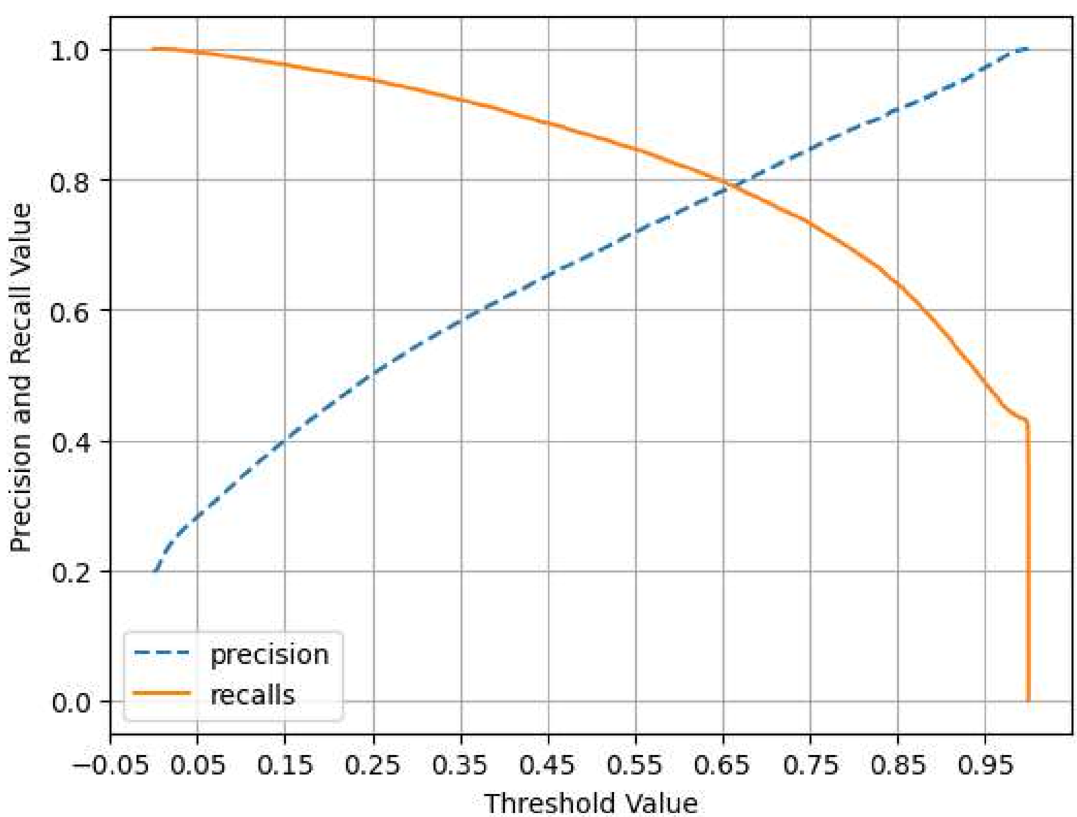
CLASSIFICATION REPORT (CONFUSION MATIRX)

```
y_pred = LogReg.predict(X_test)

conf_matrix = confusion_matrix(y_test, y_pred)
conf_matrix # 2D np array

array([[57292,  6264],
       [ 2082, 13568]], dtype=int64)

ConfusionMatrixDisplay(conf_matrix).plot()

<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1660145e110>
```




```
# accuracy using confusion matrix
np.diag(conf_matrix).sum() / conf_matrix.sum()

0.8946291947579729

print(classification_report(y_test,y_pred))

              precision    recall  f1-score   support

           0       0.96      0.90      0.93     63556
```

```
           1       0.68      0.87      0.76     15650

    accuracy                           0.89     79206
   macro avg       0.82      0.88      0.85     79206
weighted avg       0.91      0.89      0.90     79206


precisions, recalls, thresholds =
precision_recall_curve(y_test,LogReg.predict_proba(X_test)[:,1])

threshold_boundary = thresholds.shape[0]
#plot precision
plt.plot(thresholds,precisions[0:threshold_boundary],linestyle='--',la
bel='precision')
#plot recall
plt.plot(thresholds,recalls[0:threshold_boundary],label='recalls')

start,end=plt.xlim()
plt.xticks(np.round(np.arange(start,end,0.1),2))

plt.xlabel('Threshold Value')
plt.ylabel('Precision and Recall Value')
plt.legend()
plt.grid()
plt.show()
```



```python
for i in range(len(thresholds)):
    if precisions[i] == recalls[i]:
        print(f"Threshold value at which Precision and recall curves intersected is {thresholds[i]}")
```

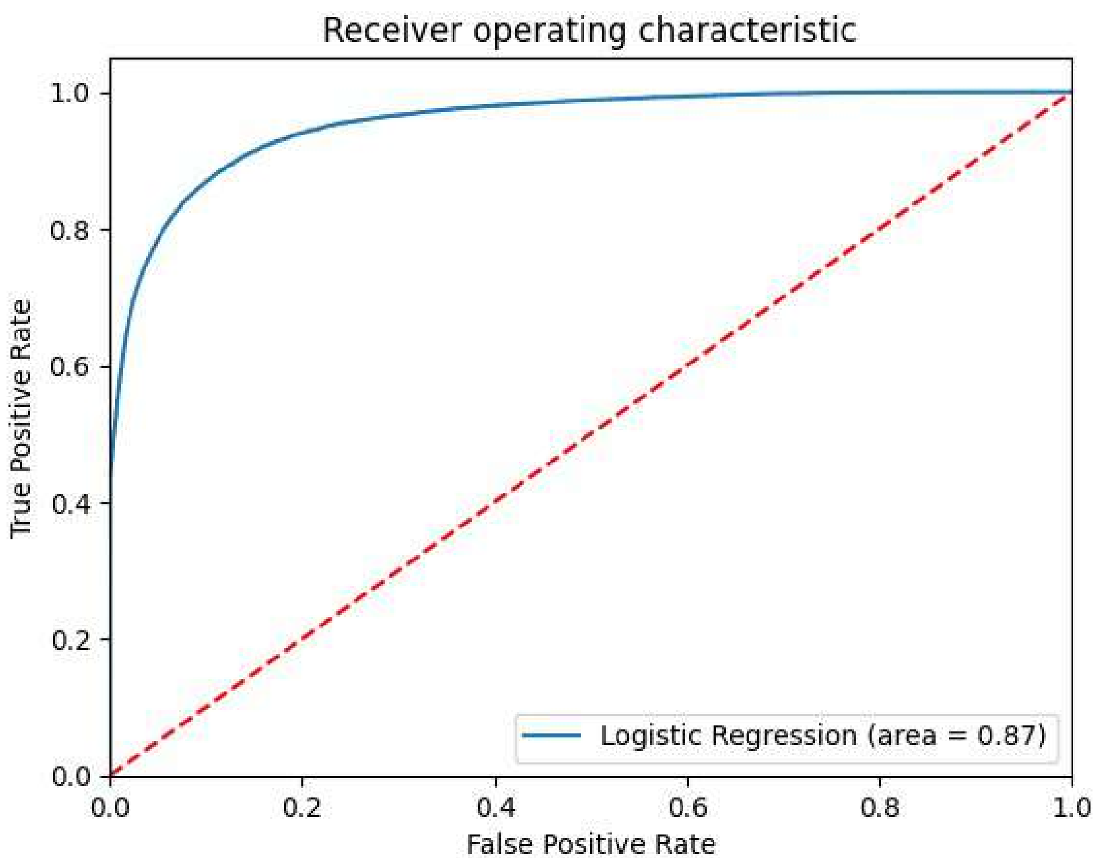
```
Threshold value at which Precision and recall curves intersected is
0.6631027545288799
```

```python
best_threshold = 0.6631027545288799 # Replace with your best threshold value
y_pred = (LogReg.predict_proba(X_test)[:, 1] >=
best_threshold).astype(int)

print("Test Accuracy: ",accuracy_score(y_test,y_pred))
print()
print("Test Negative Log Loss: ",log_loss(y_test,y_pred))
print()
print("Test f1_score: ",f1_score(y_test,y_pred))
print()
print("Test recall_score: ",recall_score(y_test,y_pred))
print()
print("Test precision_score: ",precision_score(y_test,y_pred))
print()
print("Test roc_auc_score: ",roc_auc_score(y_test,y_pred))
print()
print("Test matthews_corrcoef: ",matthews_corrcoef(y_test,y_pred))
```

```
Test Accuracy:  0.9165972274827665

Test Negative Log Loss:  3.0061406243025517

Test f1_score:  0.7889456869009585

Test recall_score:  0.7889456869009585

Test precision_score:  0.7889456869009585

Test roc_auc_score:  0.8684878853033333

Test matthews_corrcoef:  0.7369757706066669
```

```python
logit_roc_auc = roc_auc_score(y_test, y_pred)
fpr, tpr, thresholds = roc_curve(y_test, LogReg.predict_proba(X_test)
[:,1])
plt.figure()
plt.plot(fpr, tpr, label='Logistic Regression (area = %0.2f)' %
logit_roc_auc)
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
```

```
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic')
plt.legend(loc="lower right")
plt.savefig('Log_ROC')
plt.show()
```

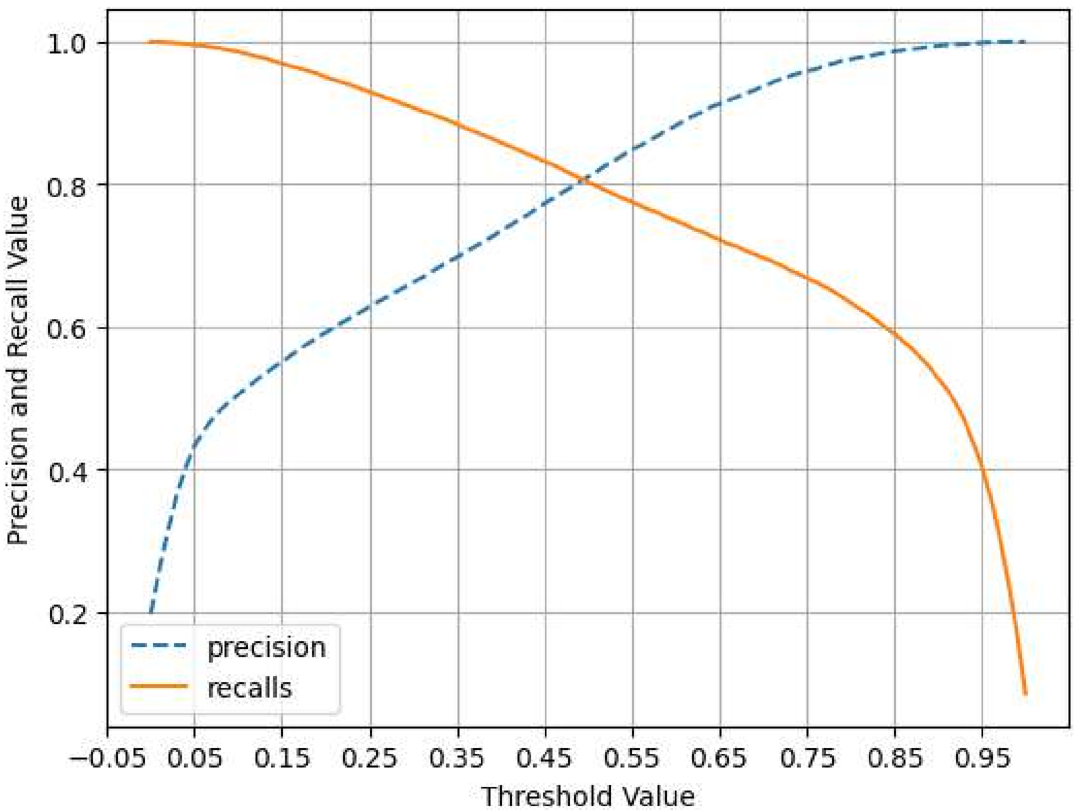



```
from sklearn.ensemble import RandomForestClassifier as RF
clf = RF()
clf.fit(X_smote,y_smote)
```

```
RandomForestClassifier()
```

```
precisions, recalls, thresholds =
precision_recall_curve(y_test,clf.predict_proba(X_test)[:,1])

threshold_boundary = thresholds.shape[0]
#plot precision
plt.plot(thresholds,precisions[0:threshold_boundary],linestyle='--',la
bel='precision')
#plot recall
plt.plot(thresholds,recalls[0:threshold_boundary],label='recalls')

start,end=plt.xlim()
```

```
plt.xticks(np.round(np.arange(start,end,0.1),2))

plt.xlabel('Threshold Value')
plt.ylabel('Precision and Recall Value')
plt.legend()
plt.grid()
plt.show()
```




```
diff = []
for i in range(len(thresholds)):
    diff.append(abs(precisions[i]-recalls[i]))

print(min(diff))
#print(f"Threshold value at which Precision and recall curves
intersected is {thresholds[i]}")
```

```
0.0064155987503986545
```

```
best_threshold = 0.49 # Replace with your best threshold value
y_pred = (clf.predict_proba(X_test)[:, 1] >=
best_threshold).astype(int)
print("Test Accuracy: ",accuracy_score(y_test,y_pred))
print()
print("Test Negative Log Loss: ",log_loss(y_test,y_pred))
```

```
print()
print("Test f1_score: ",f1_score(y_test,y_pred))
print()
print("Test recall_score: ",recall_score(y_test,y_pred))
print()
print("Test precision_score: ",precision_score(y_test,y_pred))
print()
print("Test roc_auc_score: ",roc_auc_score(y_test,y_pred))
print()
print("Test matthews_corrcoef: ",matthews_corrcoef(y_test,y_pred))
```

```
Test Accuracy:  0.9232002626063682

Test Negative Log Loss:  2.768143114991284

Test f1_score:  0.8064280031821799

Test recall_score:  0.8096485623003195

Test precision_score:  0.8032329635499208

Test roc_auc_score:  0.8804048714956818

Test matthews_corrcoef:  0.7585357458618506
```

TRADE OFF QUESTIONS

1. How can we make sure that our model can detect real defaulters and there are less false positives? This is important as we can lose out on an opportunity to finance more individuals and earn interest on it.

Real Defaulters means True positives. So to give more importance to TP and Reduce False Positives. It is indicating that to improve the precision score. That means more weightage should be given for Precision score

f beta score with Beta less than 1 should be selected. Beta can be taken as hyper parameter to find best Beta score. But On decrease of Beta, Recall score will decrease. We can take Specificity as metric, Where TN increases and FP decreases

If False Negatives increases, We lose out an oppurtunity to finance more individuals. SO to minimise the FN, We have use Recall or sensitivity or f Beta score with Beta greater than 1 or False Negative Rate

2. Since NPA (non-performing asset) is a real problem in this industry, it’s important we play safe and shouldn’t disburse loans to anyone.

To play safe, False positive should be minimised. So we have to use F Beta score with Beta less than 1 or Specificity or Recall score as hyper parameter tuning metric

CHAPTER 5: ACTIONABLE INSIGHTS & RECOMMENDATIONS

Actionable Insights

- 396030 data points , 26 features , 1 Target label.
- 80.38% belongs to the class 0 : which is loan fully paid.
- remaining % belongs to the class 1 : which were charged off.
- Loan Amount distribution / median is slightly higher for Charged_off loanStatus.
- Interest Rate mean and median is higher for Charged_off LoanStatus.
- Probability of Charged_off LoanStatus is higher for Loan Grades are E ,F, G.
- G grade has the highest probability of having defaulter.
- Similar pattern is visible in sub_grades probability plot.
- Loan Tap has customers with earliest cr year around 1950 to 2010. Most of the customers are started taking loans from 1990 to 2010.
- 36 months loans are significantly more than 60 months loans
- B Grade has higher amount loans, G Grade has least number. Grades indicates interest rates or risk in a way.
- Sub grade also mimics the grade behaviour. B3 grade has higher amount of loans, G5 has lower amount of loans.
- 10+ years emp length are prefering to take loans
- Most of home ownership occupied either mortage(trying to get home), Own or Rent. (Can negelect remaining categories)
- Teacher and manager have more loan applications
- debt_cosolidation and credit card is dominating purpose.
- Almost all customers are Individual application type only
- For those borrowers who have rental home, has higher probability of defaulters.
- borrowers having their home mortgage and owns have lower probability of defaulter.
- Annual income median is lightly higher for those who's loan status is as fully paid.
- Somehow , verified income borrowers probability of defaulter is higher than those who are not verified by loan tap.
- the probability of defaulters is higher in the small_business owner borrowers.
- debt-to-income ratio is higher for defaulters.
- number of open credit lines in the borrowers credit file is same as for loan status as fully paid and defaulters.
- Total credit revolving balance is almost same for both borrowers who had fully paid loan and declared defaulter but Revolving line utilization rate is higher for defaulter borrowers.

columns like issue_d, earliest_cr_line, address are deleted before assumption check

columns like int rate is deleted as subgrade and grade indicates int rate indirect manner.

columns like verification status and application type are deleted due to OLS p_value

columns like loan amount, sub-grade are having Higher VIF score. So deleted

Most important features/ data for prediction , as per Logistic Regression, Decision tree classifier and Random Forest model are : zipcode, emp_title, title, grade, revol_util, Open acc, term

Balancing with Smote is required an it has improved the metrics slight manner only

If we want probabilities of classes: Log loss

If classes are balanced: Accuracy

IF classes are imbalanced:

1. if we are more concerned about False positive and true positive, then we use precision.
2. If we are more concerned about False Negatives and True positive then we use recall.
3. F1 score is a balance between precision and recall.
4. If our concern is both classes (true negative and true positive) then we use ROC_AUC

If severe imbalance : PR AUC

F beta score can be used to shift the importance towards Precision or Recall with Beta value

```
Final Results given by Logistic Regresion with Best threshold = 0.66,
best lambda = 1/1100, class weight = balanced are
Test Accuracy:  0.9165972274827665

Test Negative Log Loss:  3.0061406243025517

Test f1_score:  0.7889456869009585

Test recall_score:  0.7889456869009585

Test precision_score:  0.7889456869009585

Test roc_auc_score:  0.8684878853033333

Test matthews_corrcoef:  0.7369757706066669
```

Ensemble methods definitely provide more better model than Simple Logistic regression

```
Final Results given by Random Forest classifier is with  best
threshold = 0.49 are

Test Accuracy:  0.9232002626063682

Test Negative Log Loss:  2.768143114991284
```

```
Test f1_score:  0.8064280031821799

Test recall_score:  0.8096485623003195

Test precision_score:  0.8032329635499208

Test roc_auc_score:  0.8804048714956818

Test matthews_corrcoef:  0.7585357458618506
```

Questionnaire

Question and Answers

> What percentage of customers have fully paid their Loan Amount? = 80.38%
>
> correlation between Loan Amount and Installment features --> has 0.97 spearman correlation and 0.95 pearson correlation. So Both are highly correlated as installment can be calculated by using the formulae. EMI = [P x R x (1+R)^N]/[(1+R)^N-1]. So they are multi collinear.
>
> The majority of people have home ownership as Mortagage Home owner ship. Second Majority is Rent.
>
> People with grades 'A' are more likely to fully pay their loan --> False. Actually B has higher probability to fully pay their loan
>
> Name the top 2 afforded job titles --> Teacher and Manager are having more applictions as well as they are paying fully too
>
> If Banks Strictly donot want to disburse loans to real defaulters, So we have to Decrease the False Negatives, So Recall should be higher. (Most of the times it is preferred)
>
> If Banks Strictly donot want to loose the good customers, We have to decrease the False positives , So Precision should be higher
>
> F1 score is Harmonic mean of Precision and recall. (To balance both of them, F1 score can be utilised)
>
> ROC-AUC should be utilised when we need to increase True Negatives and True Positives
>
> PR-AUC should be used for severe Imbalance data
>
> F Beta score with Beta > 1 gives importance to Recall and Beta < 0.5 gives importance to Precision
>
> Gap between the Precision and recall effects in two ways. Either Bank looses good customer or gets Bad customer. We can hyper parameter tune that gap by using Threshold concept
>
> zipcode, emp_title, title, grade, revol_util, Open acc, term features are heavily effecting the outcome

Geographical parameter like state and zip code has weights. so they effect the outcome

Recommendations:

Should improve Verification procedure as Verification status has no effect on model

can provide Easy Loans for Teacher, managers and Mortgage home owners

B grade and C grade interest rates should be preferred to customers

Joint and Direct application should be improved. So Better int rate can be provided for them

F Beta score is better metric to balance the importance between Precision and Recall. Beta can hyper tuned

customer with Higher annual income and lower dti, lower revol util, lower revol bal, more mort acc, no pub_rec, no pub_rec_bankruptcies should be given more preference to disburse the loans