task

September 20, 2021

```
[ ]:
```

1 Abstract

Business problem - banks faceses heigh loss due to defaulters , we have to predict person will be defaulter or not with probablity of him to be defaulter

ML foormulaion - this is binary classification task - in this task we have predict probablity of person to be defaulter or not - in this problem it is important to have less false posiitve rate becase it can costs heigh loss to the bank - matix for evaluation is auc matrix - interpritability is important to give beacuse of which features preson should be defaulter one

first cut approach - first we will perform basic EDA - Handling of missing data - Handle imbalence dataset - after data perparation we will add some new features - Do required preprocessing over data (numerical ,categorical and text features) - apply ml model - predict submission

```
[ ]: %matplotlib inline
%pip install chart-studio
import warnings
warnings.filterwarnings("ignore")

import sqlite3
import pandas as pd
import numpy as np
import nltk
import string
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer

from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve, auc
from nltk.stem.porter import PorterStemmer
from sklearn.impute import SimpleImputer
```

```
import re
# Tutorial about Python regular expressions: https://pymotw.com/2/re/
import string
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer

from gensim.models import Word2Vec
from gensim.models import KeyedVectors
import pickle

from tqdm import tqdm
import os

from chart_studio.plotly import plotly
import plotly.offline as offline
import plotly.graph_objs as go
offline.init_notebook_mode()
from collections import Counter
```

```
Collecting chart-studio
  Downloading chart_studio-1.1.0-py3-none-any.whl (64 kB)
     |                 | 64 kB 1.9 MB/s
Requirement already satisfied: plotly in /usr/local/lib/python3.7/dist-
packages (from chart-studio) (4.4.1)
Requirement already satisfied: six in /usr/local/lib/python3.7/dist-packages
(from chart-studio) (1.15.0)
Requirement already satisfied: requests in /usr/local/lib/python3.7/dist-
packages (from chart-studio) (2.23.0)
Requirement already satisfied: retrying>=1.3.3 in /usr/local/lib/python3.7/dist-
packages (from chart-studio) (1.3.3)
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.7/dist-
packages (from requests->chart-studio) (2.10)
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in
/usr/local/lib/python3.7/dist-packages (from requests->chart-studio) (1.24.3)
Requirement already satisfied: chardet<4,>=3.0.2 in
/usr/local/lib/python3.7/dist-packages (from requests->chart-studio) (3.0.4)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.7/dist-packages (from requests->chart-studio) (2021.5.30)
Installing collected packages: chart-studio
Successfully installed chart-studio-1.1.0
```

[ ]:
```
train_data = pd.read_csv('train_indessa.csv')
test_data = pd.read_csv('test_indessa.csv')
```

[ ]:
```
train_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 532428 entries, 0 to 532427
Data columns (total 45 columns):
 #   Column                       Non-Null Count   Dtype
---  ------                       --------------   -----
 0   member_id                    532428 non-null  int64
 1   loan_amnt                    532428 non-null  int64
 2   funded_amnt                  532428 non-null  int64
 3   funded_amnt_inv              532428 non-null  float64
 4   term                         532428 non-null  object
 5   batch_enrolled               447279 non-null  object
 6   int_rate                     532428 non-null  float64
 7   grade                        532428 non-null  object
 8   sub_grade                    532428 non-null  object
 9   emp_title                    501595 non-null  object
 10  emp_length                   505537 non-null  object
 11  home_ownership               532428 non-null  object
 12  annual_inc                   532425 non-null  float64
 13  verification_status          532428 non-null  object
 14  pymnt_plan                   532428 non-null  object
 15  desc                         75599 non-null   object
 16  purpose                      532428 non-null  object
 17  title                        532338 non-null  object
 18  zip_code                     532428 non-null  object
 19  addr_state                   532428 non-null  object
 20  dti                          532428 non-null  float64
 21  delinq_2yrs                  532412 non-null  float64
 22  inq_last_6mths               532412 non-null  float64
 23  mths_since_last_delinq       259874 non-null  float64
 24  mths_since_last_record       82123 non-null   float64
 25  open_acc                     532412 non-null  float64
 26  pub_rec                      532412 non-null  float64
 27  revol_bal                    532428 non-null  float64
 28  revol_util                   532141 non-null  float64
 29  total_acc                    532412 non-null  float64
 30  initial_list_status          532428 non-null  object
 31  total_rec_int                532428 non-null  float64
 32  total_rec_late_fee           532428 non-null  float64
 33  recoveries                   532428 non-null  float64
 34  collection_recovery_fee      532428 non-null  float64
 35  collections_12_mths_ex_med   532333 non-null  float64
 36  mths_since_last_major_derog  132980 non-null  float64
 37  application_type             532428 non-null  object
 38  verification_status_joint    305 non-null     object
 39  last_week_pay                532428 non-null  object
 40  acc_now_delinq               532412 non-null  float64
 41  tot_coll_amt                 490424 non-null  float64
 42  tot_cur_bal                  490424 non-null  float64
```

```
 43  total_rev_hi_lim              490424 non-null  float64
 44  loan_status                   532428 non-null  int64
dtypes: float64(23), int64(4), object(18)
memory usage: 182.8+ MB
```

[ ]:
```
dtypes = train_data.dtypes
categorical = dtypes[dtypes=='object']
print('following are categorical features')
catgs = np.array(categorical.keys())
cat_feature = catgs[catgs != 'desc']
print(cat_feature)
```

```
following are categorical features
['term' 'batch_enrolled' 'grade' 'sub_grade' 'emp_title' 'emp_length'
 'home_ownership' 'verification_status' 'pymnt_plan' 'purpose' 'title'
 'zip_code' 'addr_state' 'initial_list_status' 'application_type'
 'verification_status_joint' 'last_week_pay']
```

[ ]:
```
print('desc is text feature')
```

```
desc is text feature
```

[ ]:
```
dtypes = train_data.dtypes
categorical = dtypes[dtypes!='object']
print('following are numeric features')
int_features = np.array(categorical.keys())

print(int_features , int_features.shape[0])
```

```
following are numeric features
['member_id' 'loan_amnt' 'funded_amnt' 'funded_amnt_inv' 'int_rate'
 'annual_inc' 'dti' 'delinq_2yrs' 'inq_last_6mths'
 'mths_since_last_delinq' 'mths_since_last_record' 'open_acc' 'pub_rec'
 'revol_bal' 'revol_util' 'total_acc' 'total_rec_int' 'total_rec_late_fee'
 'recoveries' 'collection_recovery_fee' 'collections_12_mths_ex_med'
 'mths_since_last_major_derog' 'acc_now_delinq' 'tot_coll_amt'
 'tot_cur_bal' 'total_rev_hi_lim' 'loan_status'] 27
```

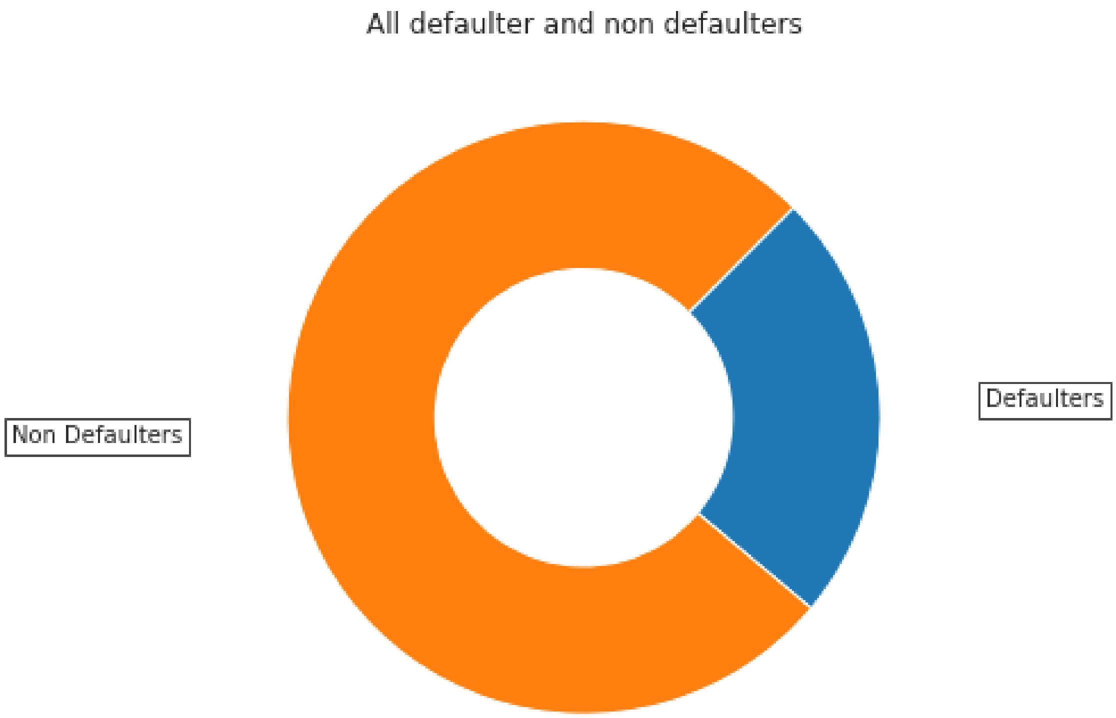
[ ]:
```
print("Number of data points in train data", train_data.shape)
print('-'*50)
print("The attributes of data :", train_data.columns.values)
```

```
Number of data points in train data (532428, 45)
--------------------------------------------------
The attributes of data : ['member_id' 'loan_amnt' 'funded_amnt'
'funded_amnt_inv' 'term'
 'batch_enrolled' 'int_rate' 'grade' 'sub_grade' 'emp_title' 'emp_length'
 'home_ownership' 'annual_inc' 'verification_status' 'pymnt_plan' 'desc'
```

```
'purpose' 'title' 'zip_code' 'addr_state' 'dti' 'delinq_2yrs'
'inq_last_6mths' 'mths_since_last_delinq' 'mths_since_last_record'
'open_acc' 'pub_rec' 'revol_bal' 'revol_util' 'total_acc'
'initial_list_status' 'total_rec_int' 'total_rec_late_fee' 'recoveries'
'collection_recovery_fee' 'collections_12_mths_ex_med'
'mths_since_last_major_derog' 'application_type'
'verification_status_joint' 'last_week_pay' 'acc_now_delinq'
'tot_coll_amt' 'tot_cur_bal' 'total_rev_hi_lim' 'loan_status']
```

[ ]:
```
y_value_counts = train_data['loan_status'].value_counts()
print("Number of members thar are Defaulters ", y_value_counts[1], ", (",␣
↪(y_value_counts[1]/(y_value_counts[1]+y_value_counts[0]))*100,"%)")
print("Number of projects thar are non defaulters ", y_value_counts[0], ", (",␣
↪(y_value_counts[0]/(y_value_counts[1]+y_value_counts[0]))*100,"%)")

fig, ax = plt.subplots(figsize=(6, 6), subplot_kw=dict(aspect="equal"))
recipe = ["Defaulters", "Non Defaulters"]

data = [y_value_counts[1], y_value_counts[0]]

wedges, texts = ax.pie(data, wedgeprops=dict(width=0.5), startangle=-40)

bbox_props = dict(boxstyle="square,pad=0.3", fc="w", ec="k", lw=0.72)
kw = dict(xycoords='data', textcoords='data', arrowprops=dict(arrowstyle="-"),
          bbox=bbox_props, zorder=0, va="center")

for i, p in enumerate(wedges):
    ang = (p.theta2 - p.theta1)/2. + p.theta1
    y = np.sin(np.deg2rad(ang))
    x = np.cos(np.deg2rad(ang))
    horizontalalignment = {-1: "right", 1: "left"}[int(np.sign(x))]
    connectionstyle = "angle,angleA=0,angleB={}".format(ang)
    kw["arrowprops"].update({"connectionstyle": connectionstyle})
    ax.annotate(recipe[i], xy=(x, y), xytext=(1.35*np.sign(x), 1.4*y),
                horizontalalignment=horizontalalignment, **kw)

ax.set_title("All defaulter and non defaulters")

plt.show()
```

```
Number of members thar are Defaulters  125827 , ( 23.632678972555915 %)
Number of projects thar are non defaulters  406601 , ( 76.36732102744409 %)
```



1.0.1 we can say that data is imbalence data

1. we will chosse to understamplig to deal with an imbalence dataset
2. we will choose over sampling to deal with imbalence data because with undersampling we dont want to loose the information
3. we will goin to do oversampling of minority class upto 2:3 ration

[ ]:
```
blank_spaces = train_data.eq(' ').sum()
blank_spaces
```

[ ]:
```
member_id                    0
loan_amnt                    0
funded_amnt                  0
funded_amnt_inv              0
term                         0
batch_enrolled          106079
int_rate                     0
grade                        0
sub_grade                    0
emp_title                    0
emp_length                   0
```

```
home_ownership                    0
annual_inc                        0
verification_status               0
pymnt_plan                        0
desc                              0
purpose                           0
title                             0
zip_code                          0
addr_state                        0
dti                               0
delinq_2yrs                       0
inq_last_6mths                    0
mths_since_last_delinq            0
mths_since_last_record            0
open_acc                          0
pub_rec                           0
revol_bal                         0
revol_util                        0
total_acc                         0
initial_list_status               0
total_rec_int                     0
total_rec_late_fee                0
recoveries                        0
collection_recovery_fee           0
collections_12_mths_ex_med        0
mths_since_last_major_derog       0
application_type                  0
verification_status_joint         0
last_week_pay                     0
acc_now_delinq                    0
tot_coll_amt                      0
tot_cur_bal                       0
total_rev_hi_lim                  0
loan_status                       0
dtype: int64
```

[ ]:
```
# we will check nan values in overall dataset
# review the columns with heighest amount of nan values
na_values = train_data.isna().sum()
na_values
```

[ ]:
```
member_id                         0
loan_amnt                         0
funded_amnt                       0
funded_amnt_inv                   0
term                              0
batch_enrolled                85149
```

```
int_rate                           0
grade                              0
sub_grade                          0
emp_title                      30833
emp_length                     26891
home_ownership                     0
annual_inc                         3
verification_status                0
pymnt_plan                         0
desc                          456829
purpose                            0
title                             90
zip_code                           0
addr_state                         0
dti                                0
delinq_2yrs                       16
inq_last_6mths                    16
mths_since_last_delinq        272554
mths_since_last_record        450305
open_acc                          16
pub_rec                           16
revol_bal                          0
revol_util                       287
total_acc                         16
initial_list_status                0
total_rec_int                      0
total_rec_late_fee                 0
recoveries                         0
collection_recovery_fee            0
collections_12_mths_ex_med        95
mths_since_last_major_derog   399448
application_type                   0
verification_status_joint     532123
last_week_pay                      0
acc_now_delinq                    16
tot_coll_amt                   42004
tot_cur_bal                    42004
total_rev_hi_lim               42004
loan_status                        0
dtype: int64
```

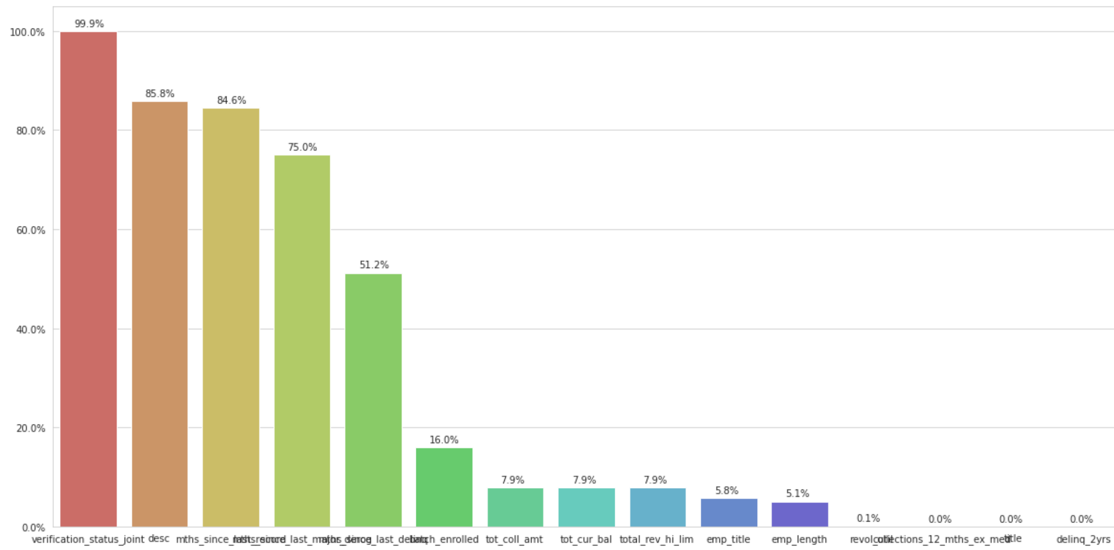
[ ]:
```
#columns with nan value
train_data.isna().any(axis=0).sum().sum()
```

[ ]:
```
21
```

- so we can find there are huge no of nan values in some columns so we will going to exclude

those columns whose contains more that 50 % of nan values
- for features whose are beetwen 0 to 50 % of nan values we will going replace them with median if they are numerical features and if they are categorical then we will going to replace them by most occuring category

[ ]:
```
# Creating a dictionary whose keys are the column names and values are the␣
↪percentage of missing values
x = train_data
nan_count = {k:list(x.isna().sum()*100/x.shape[0])[i] for i,k in enumerate(x.
↪columns)}

# Sorting the dictionary in descending order based on the percentage of missing␣
↪values
nan_count = {k: v for k, v in sorted(nan_count.items(), key=lambda item:␣
↪item[1],reverse=True)}

# Plotting a graph showing the top 15 features having highest percentage of␣
↪missing values
sns.set_style(style="whitegrid")
plt.figure(figsize=(20,10))

# Bar Plot
plot = sns.barplot(x= list(nan_count.keys())[:15],y = list(nan_count.values())[:
↪15],palette="hls")

# Add annotations above each bar signifying their value
for p in plot.patches:
        plot.annotate('{:.1f}%'.format(p.get_height()), (p.get_x()+0.2, p.
↪get_height()+1))

# Make y-axis more interpretable
plot.set_yticklabels(map('{:.1f}%'.format, plot.yaxis.get_majorticklocs()))
plt.show()
```



[ ]:
```
print('columns whose having nan values more than 50% ')
x = nan_count
sorted_x = sorted(x.items(), key=lambda kv: kv[1], reverse=True)
heigh_na_features = {i:j for i,j in sorted_x if j > 50}
print(heigh_na_features)
print('columns whose having nan values less than 50%')
medium_na_features = {i:j for i,j in sorted_x if j <= 50 and j > 0}
print(medium_na_features)
```

```
columns whose having nan values more than 50%
{'verification_status_joint': 99.94271525915241, 'desc': 85.80108484151847,
'mths_since_last_record': 84.57575484384743, 'mths_since_last_major_derog':
75.02385299045129, 'mths_since_last_delinq': 51.19077133434004}
columns whose having nan values less than 50%
{'batch_enrolled': 15.99258491288963, 'tot_coll_amt': 7.889141818236457,
'tot_cur_bal': 7.889141818236457, 'total_rev_hi_lim': 7.889141818236457,
'emp_title': 5.791017752635098, 'emp_length': 5.05063595453282, 'revol_util':
0.05390400204346879, 'collections_12_mths_ex_med': 0.017842788132855524,
'title': 0.01690369402059997, 'delinq_2yrs': 0.0030051011592177723,
'inq_last_6mths': 0.0030051011592177723, 'open_acc': 0.0030051011592177723,
'pub_rec': 0.0030051011592177723, 'total_acc': 0.0030051011592177723,
'acc_now_delinq': 0.0030051011592177723, 'annual_inc': 0.0005634564673533323}
```

[ ]:
```
train_data_preprocessed = train_data
test_data_preprocessed = test_data
```

[ ]:
```
#drop the columns having missing values rate > 50%
```

```
train_data_preprocessed = train_data_preprocessed.
↪drop(columns=['verification_status_joint', 'desc', 'mths_since_last_record',␣
↪'mths_since_last_major_derog', 'mths_since_last_delinq'])
```

[ ]:
```
train_data_preprocessed.shape
```

[ ]:
```
(532428, 40)
```

[ ]:
```

```

2 Handle missing values

- batch batch_enrolled feature contains nan values + blank spaces
- this is total nearly 35.9 % of total rows
- as we are not domain expert we cant tell values whcih are missing are missing reandomly or the missing value have its own meaning
- there are three options in this case
  - remove column
  - replace spaces and nan with most frequest value
  - conside blank space and nan as new categories
- we will choose third option

[ ]:
```
(blank_spaces['batch_enrolled']+na_values['batch_enrolled'])/train_data.shape[0]
```

[ ]:
```
0.3591621777968101
```

[ ]:
```
train_data_preprocessed['batch_enrolled'] =␣
↪train_data_preprocessed['batch_enrolled'].fillna('unknown')
```

[ ]:
```
train_data_preprocessed['batch_enrolled'] =␣
↪train_data_preprocessed['batch_enrolled'].map(lambda x: 'blank' if x == ' '␣
↪else x)
```

[ ]:
```
batch_enrolled = train_data_preprocessed['batch_enrolled']
print(batch_enrolled[batch_enrolled=='blank'].shape ,␣
↪batch_enrolled[batch_enrolled=='unknown'].shape)
```

```
(106079,) (85149,)
```

[ ]:
```
train_data_preprocessed['batch_enrolled']
```

[ ]:
```
0              blank
1         BAT1586599
2         BAT1586599
3         BAT4808022
4         BAT2833642
```

```
            …
532423        blank
532424    BAT2003848
532425       unknown
532426    BAT3193689
532427    BAT4136152
Name: batch_enrolled, Length: 532428, dtype: object
```

[ ]:
```
medium_na_features
categorical_na_features = list(filter(lambda x: x in␣
↪cat_feature,list(medium_na_features.keys())))
int_na_features = list(filter(lambda x: x in␣
↪int_features,list(medium_na_features.keys())))
```

[ ]:
```
categorical_na_features
```

[ ]:
```
['batch_enrolled', 'emp_title', 'emp_length', 'title']
```

[ ]:
```
int_na_features
```

[ ]:
```
['tot_coll_amt',
 'tot_cur_bal',
 'total_rev_hi_lim',
 'revol_util',
 'collections_12_mths_ex_med',
 'delinq_2yrs',
 'inq_last_6mths',
 'open_acc',
 'pub_rec',
 'total_acc',
 'acc_now_delinq',
 'annual_inc']
```

[ ]:
```
def replace_with_most_frequent (feature):
   values_data = train_data_preprocessed[feature].value_counts()
   max_value = values_data[values_data == values_data.max()].index[0]
   return train_data_preprocessed[feature].fillna(max_value[0]) , max_value
```

[ ]:
```
def fill_cat_na(categorical_na_features):
  save_feature_max_value = dict({})
  for i in categorical_na_features:
    feature , val =  replace_with_most_frequent(i)
    train_data_preprocessed[i] = feature
    save_feature_max_value[i] = val
  pickle.dump(save_feature_max_value, file = open("save_feature_max_value.
↪pickle", "wb"))
```

```
  save_feature_max_value = pickle.load(open("save_feature_max_value.pickle",␣
↪"rb"))
  return save_feature_max_value
```

[ ]:
```
fill_cat_na(categorical_na_features)
```

[ ]:
```
{'batch_enrolled': 'blank',
 'emp_length': '10+ years',
 'emp_title': 'Teacher',
 'title': 'Debt consolidation'}
```

[ ]:
```
save_feature_max_value = pickle.load(open("save_feature_max_value.pickle",␣
↪"rb"))
save_feature_max_value
```

[ ]:
```
{'batch_enrolled': 'blank',
 'emp_length': '10+ years',
 'emp_title': 'Teacher',
 'title': 'Debt consolidation'}
```

[ ]:
```
def replace_with_median (feature):
    median_value =  train_data_preprocessed[feature].median()
    train_feature = train_data_preprocessed[feature].fillna(median_value)
    return train_feature , median_value
```

[ ]:
```
def fill_int_na(int_na_features):
  save_feature_median_value = dict({})
  for i in int_na_features:
    feature , val =  replace_with_median(i)
    train_data_preprocessed[i] = feature
    save_feature_median_value[i] = val
  pickle.dump(save_feature_median_value, file = open("save_feature_median_value.
↪pickle", "wb"))
  save_feature_median_value = pickle.load(open("save_feature_median_value.
↪pickle", "rb"))
  return save_feature_median_value
```

[ ]:
```
fill_int_na(int_na_features)
```

[ ]:
```
{'acc_now_delinq': 0.0,
 'annual_inc': 65000.0,
 'collections_12_mths_ex_med': 0.0,
 'delinq_2yrs': 0.0,
 'inq_last_6mths': 0.0,
 'open_acc': 11.0,
 'pub_rec': 0.0,
 'revol_util': 56.0,
```

```
 'tot_coll_amt': 0.0,
 'tot_cur_bal': 80669.5,
 'total_acc': 24.0,
 'total_rev_hi_lim': 23700.0}
```

[ ]:
```
train_data_preprocessed.isna().sum()
```

[ ]:
```
member_id                      0
loan_amnt                      0
funded_amnt                    0
funded_amnt_inv                0
term                           0
batch_enrolled                 0
int_rate                       0
grade                          0
sub_grade                      0
emp_title                      0
emp_length                     0
home_ownership                 0
annual_inc                     0
verification_status            0
pymnt_plan                     0
purpose                        0
title                          0
zip_code                       0
addr_state                     0
dti                            0
delinq_2yrs                    0
inq_last_6mths                 0
open_acc                       0
pub_rec                        0
revol_bal                      0
revol_util                     0
total_acc                      0
initial_list_status            0
total_rec_int                  0
total_rec_late_fee             0
recoveries                     0
collection_recovery_fee        0
collections_12_mths_ex_med     0
application_type               0
last_week_pay                  0
acc_now_delinq                 0
tot_coll_amt                   0
tot_cur_bal                    0
total_rev_hi_lim               0
loan_status                    0
```

```
dtype: int64
```

#Basic EDA

```
[ ]: dtypes = train_data_preprocessed.dtypes
categorical = dtypes[dtypes=='object']
print('following are categorical features')
catgs = np.array(categorical.keys())
preprocess_cat_feature = catgs[catgs != 'desc']
print(preprocess_cat_feature ,preprocess_cat_feature.shape)
```

```
following are categorical features
['term' 'batch_enrolled' 'grade' 'sub_grade' 'emp_title' 'emp_length'
 'home_ownership' 'verification_status' 'pymnt_plan' 'purpose' 'title'
 'zip_code' 'addr_state' 'initial_list_status' 'application_type'
 'last_week_pay'] (16,)
```

```
[ ]: dtypes = train_data_preprocessed.dtypes
categorical = dtypes[dtypes!='object']
print('following are numerical features')
catgs = np.array(categorical.keys())
preprocess_int_feature = catgs[np.logical_and(catgs != 'member_id', catgs !=␣
 ↪'loan_status') ]
print(preprocess_int_feature.shape)
preprocess_int_feature
```

```
following are numerical features
(22,)
```

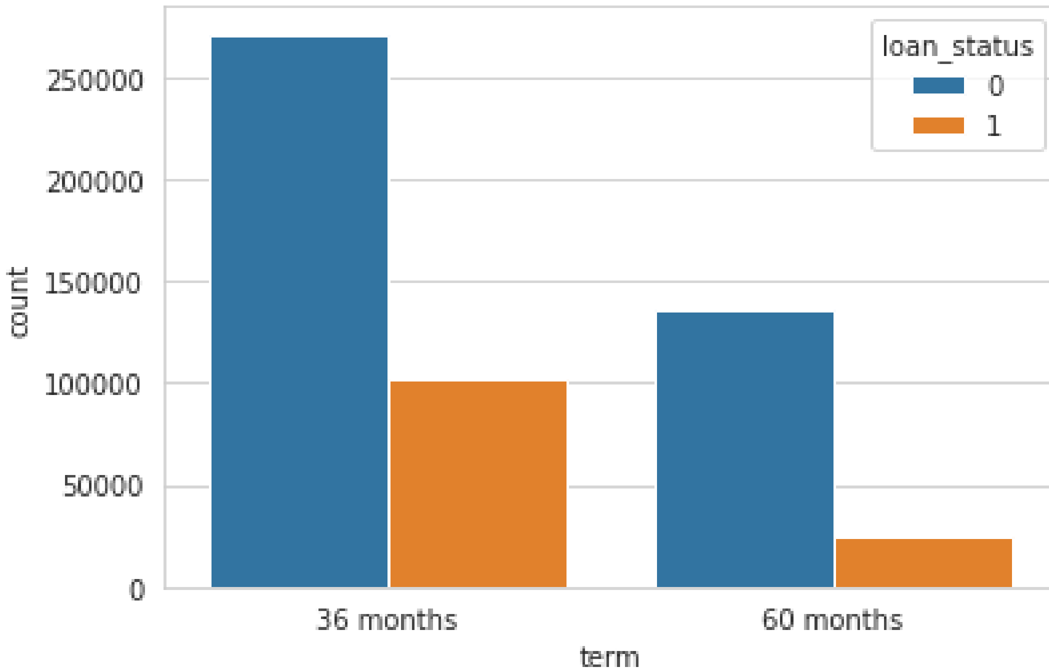
```
[ ]: array(['loan_amnt', 'funded_amnt', 'funded_amnt_inv', 'int_rate',
       'annual_inc', 'dti', 'delinq_2yrs', 'inq_last_6mths', 'open_acc',
       'pub_rec', 'revol_bal', 'revol_util', 'total_acc', 'total_rec_int',
       'total_rec_late_fee', 'recoveries', 'collection_recovery_fee',
       'collections_12_mths_ex_med', 'acc_now_delinq', 'tot_coll_amt',
       'tot_cur_bal', 'total_rev_hi_lim'], dtype=object)
```

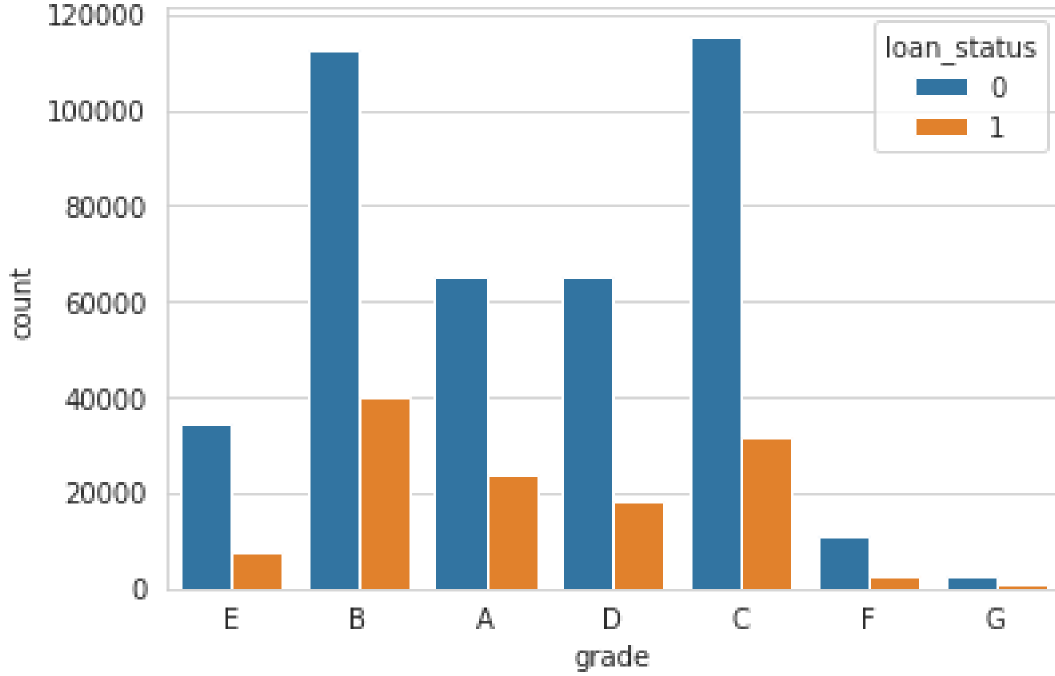
```
[ ]: def printCounterPlot(feature , row):
  # count plot on two categorical variable
  if train_data_preprocessed[feature].value_counts().shape[0] > 30:
    return
  sns.countplot(x = feature, hue = "loan_status", data =␣
 ↪train_data_preprocessed)
  plt.show()
```

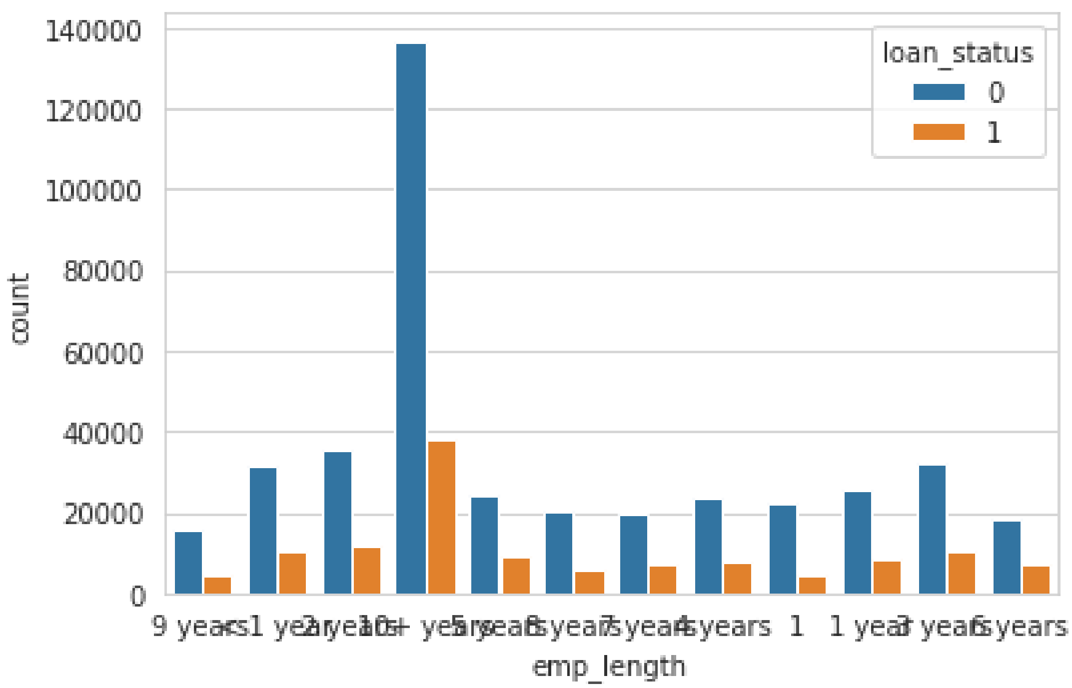
```
[ ]: train_data_preprocessed.loan_status.value_counts()
```

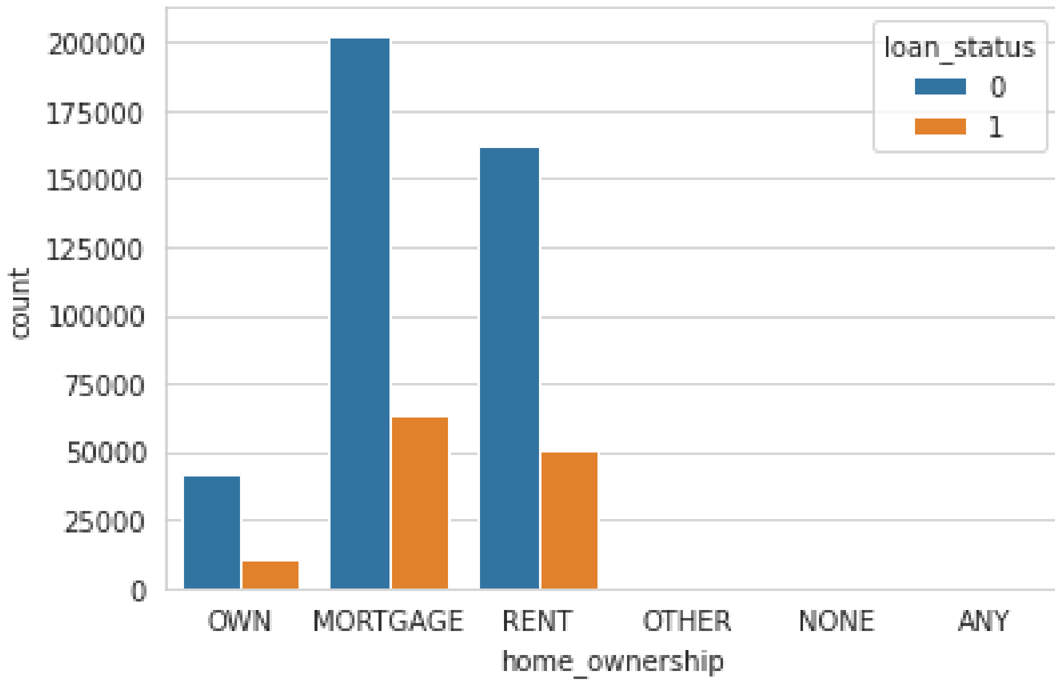
```
[ ]: 0    406601
     1    125827
     Name: loan_status, dtype: int64
```

```
[ ]: ### Data Visualization libraries
     import seaborn as sns
     import matplotlib.pyplot as plt


     for idx,cat_col in enumerate(preprocess_cat_feature):
         printCounterPlot(cat_col,idx)
     #plt.subplots_adjust(hspace=1)
```

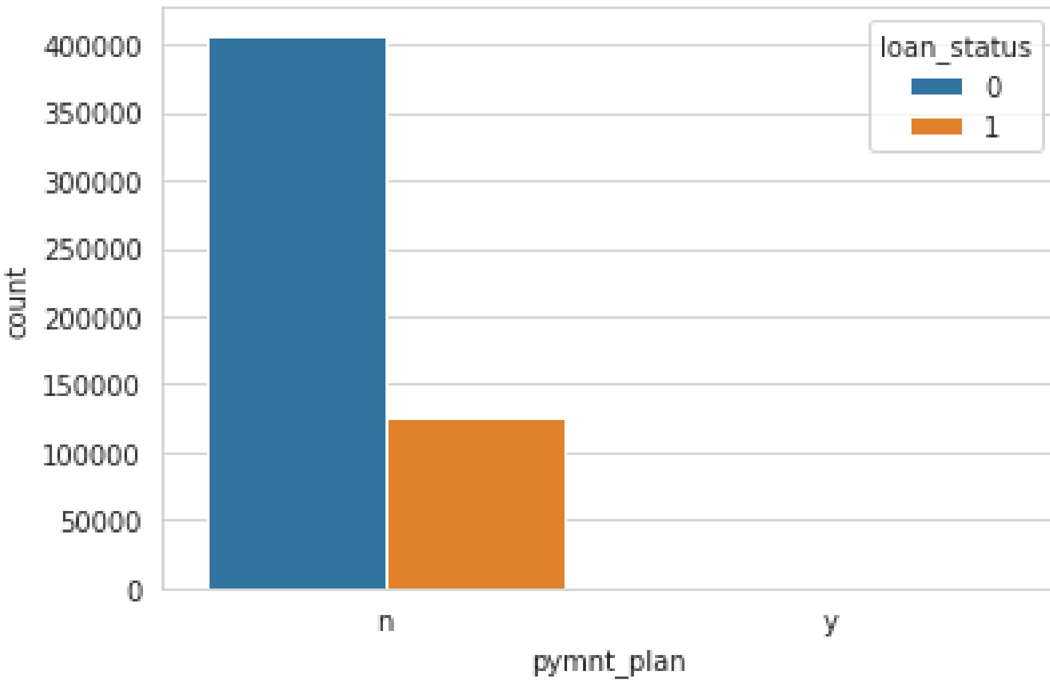



loan_status
0
1
count
120000
100000
80000
60000
40000
20000
0
E
B
A
D
C
F
G
grade

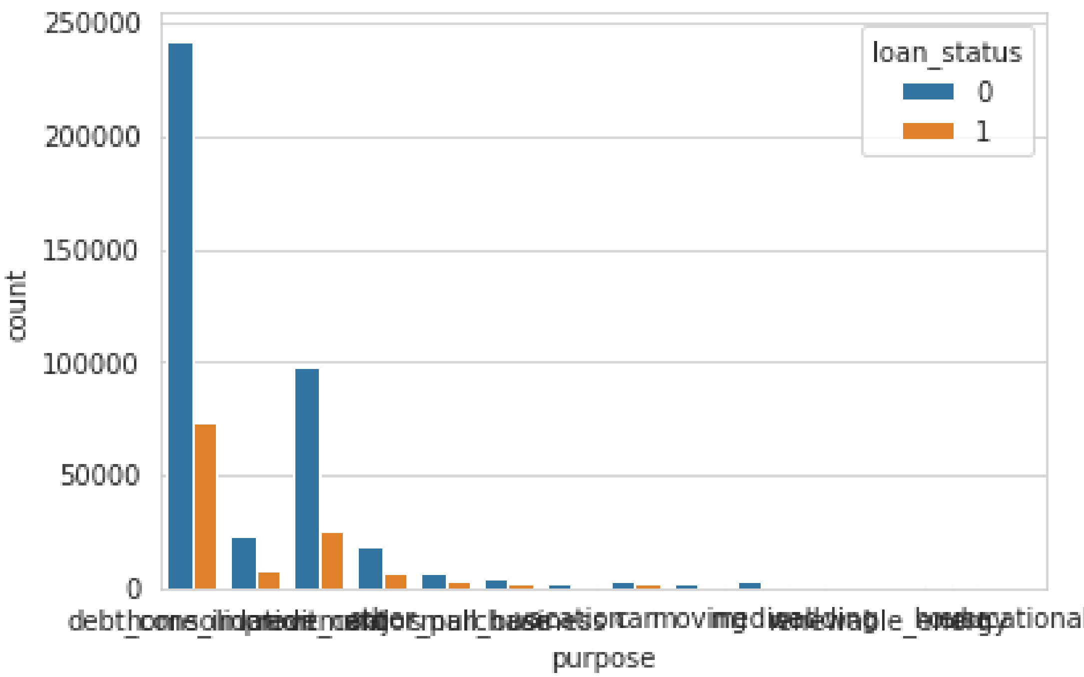

loan_status
0
1
count
140000
120000
100000
80000
60000
40000
20000
0
4 years
1
emp_length


loan_status
0
1
count
200000
175000
150000
125000
100000
75000
50000
25000
0
OWN
MORTGAGE
RENT
OTHER
NONE
ANY
home_ownership

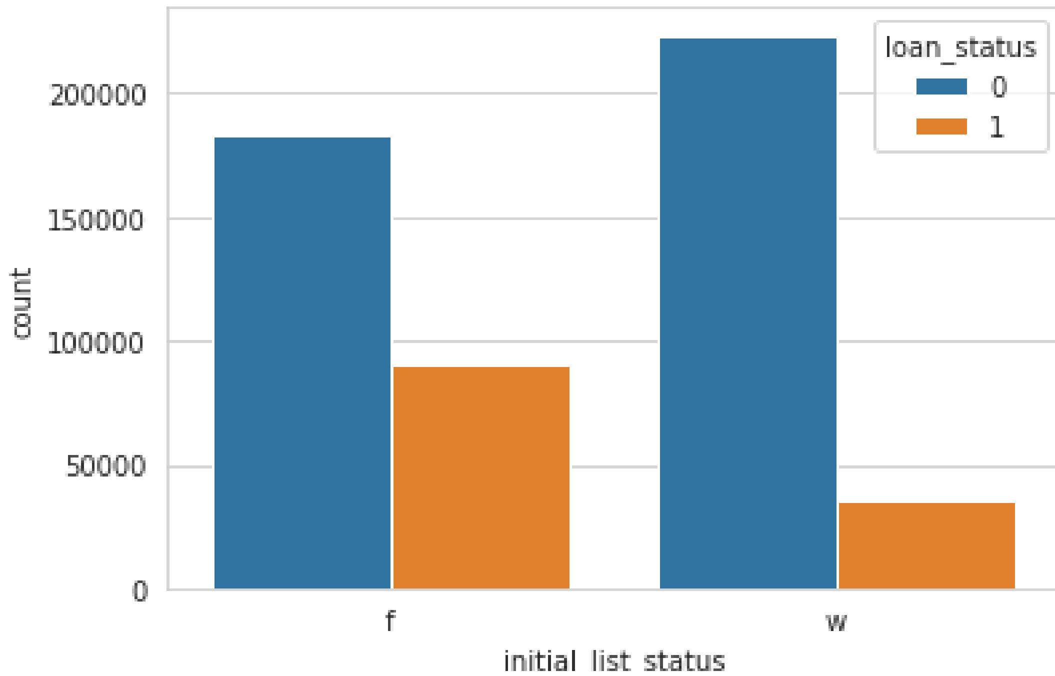

loan_status
0
1
count
160000
140000
120000
100000
80000
60000
40000
20000
0
Source Verified
Not Verified
Verified
verification_status

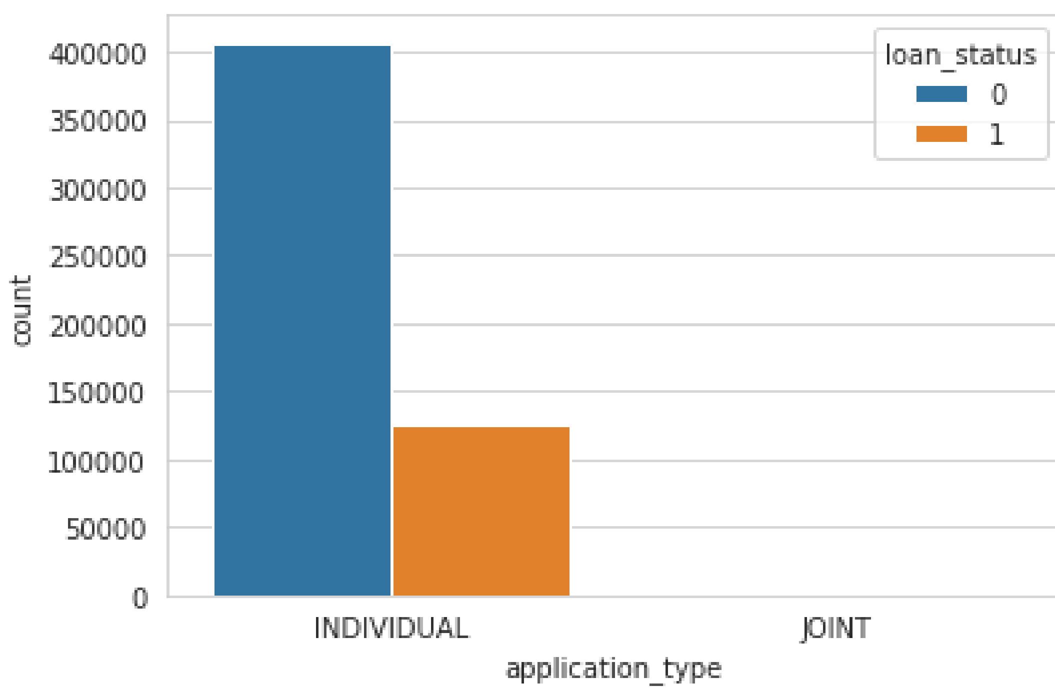


loan_status
0
1
count
400000
350000
300000
250000
200000
150000
100000
50000
0
n
y
pymnt_plan



loan_status
0
1
count
250000
200000
150000
100000
50000
0
purpose





[ ]:
```
train_data_preprocessed.application_type.value_counts()
```

```
[ ]: INDIVIDUAL    532123
     JOINT            305
     Name: application_type, dtype: int64
```

```
[ ]: application_type = train_data_preprocessed[train_data_preprocessed.loan_status␣
      ↪== 0].application_type
     application_type[application_type == 'JOINT'].shape[0]
```

```
[ ]: 304
```

```
[ ]: application_type = train_data_preprocessed[train_data_preprocessed.loan_status␣
      ↪== 1].application_type
     application_type[application_type == 'JOINT'].shape[0]
```

```
[ ]: 1
```

```
[ ]: train_data_preprocessed.pymnt_plan.value_counts()
```

```
[ ]: n    532420
     y         8
     Name: pymnt_plan, dtype: int64
```

```
[ ]: pymnt_plan = train_data_preprocessed[train_data_preprocessed.loan_status == 0].
      ↪pymnt_plan
     application_type[application_type == 'y'].shape[0]
```

```
[ ]: 0
```

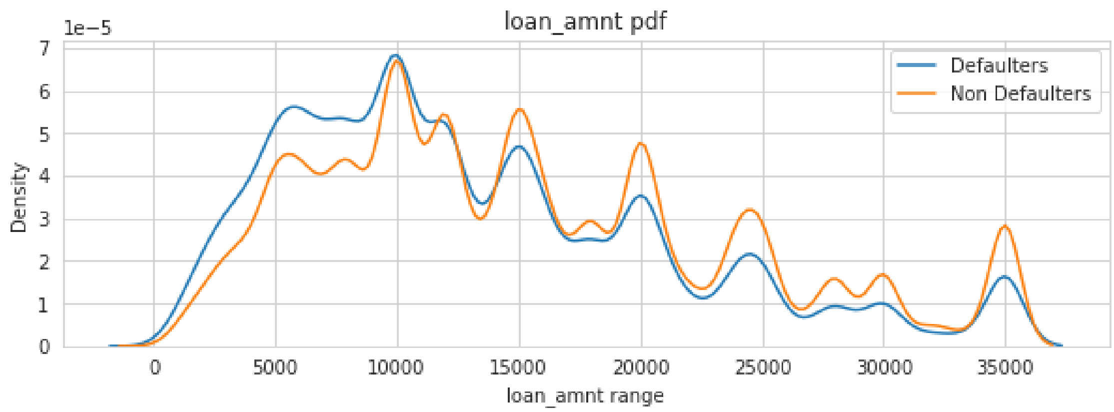
```
[ ]: train_data_preprocessed = train_data_preprocessed.
      ↪drop(columns=['application_type', 'pymnt_plan'])
```

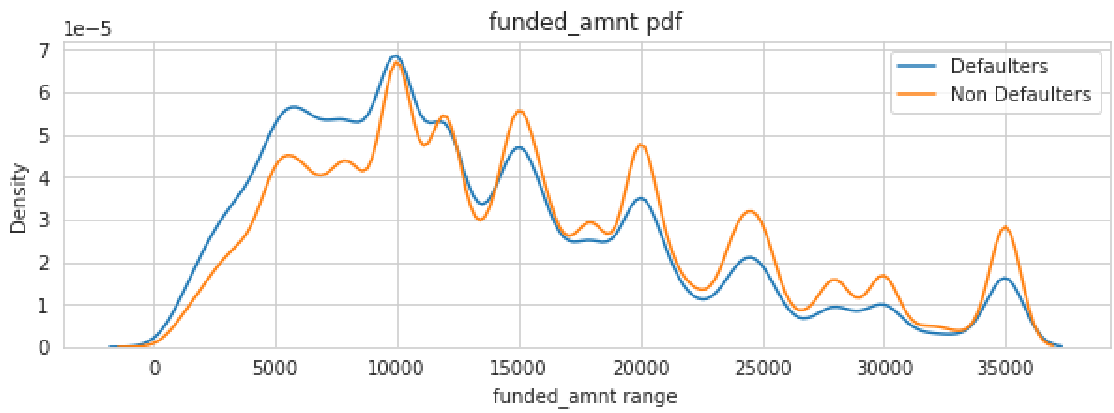
- in our dataset if we see mostly all members having individual application type we so if we drop this feature it will not affect result much
- same is about pymnt__plan feature almost all the members having pymnt__plan category n so this feature can misguide us
- we will drop this two features from categorical features

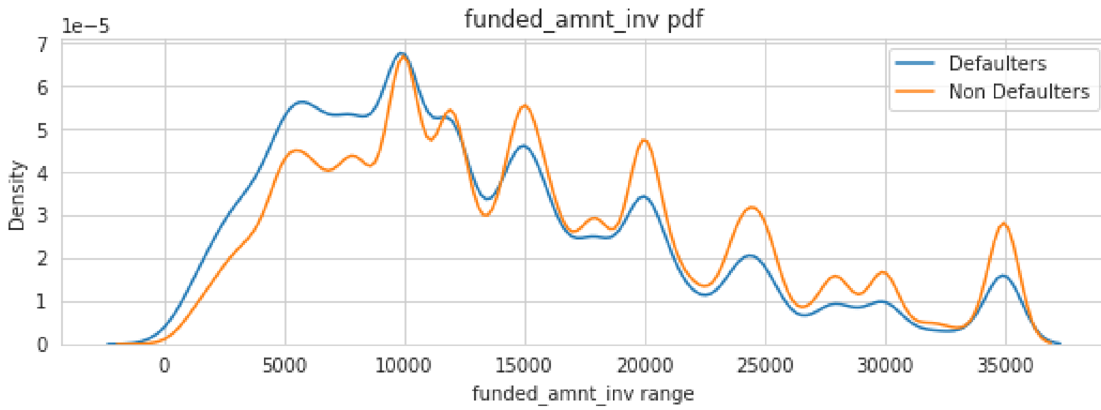
```
[ ]: def plotPdf(feature):
       defaulter =␣
      ↪train_data_preprocessed[train_data_preprocessed['loan_status']==1][feature].
      ↪values
       non_defaulter =␣
      ↪train_data_preprocessed[train_data_preprocessed['loan_status']==0][feature].
      ↪values
       plt.figure(figsize=(10,3))
       sns.distplot(defaulter, hist=False, label="Defaulters")
       sns.distplot(non_defaulter, hist=False, label="Non Defaulters")
```

```
    plt.title(feature+' pdf')
    plt.xlabel(feature+' range')
    plt.legend()
    plt.show()
```

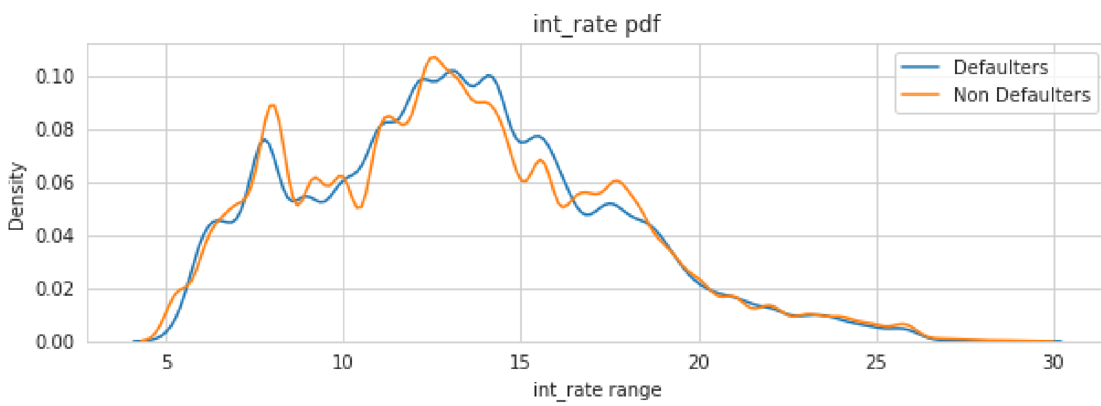
[ ]:
```
for idx,cat_col in enumerate(preprocess_int_feature):
    plotPdf(cat_col)
```



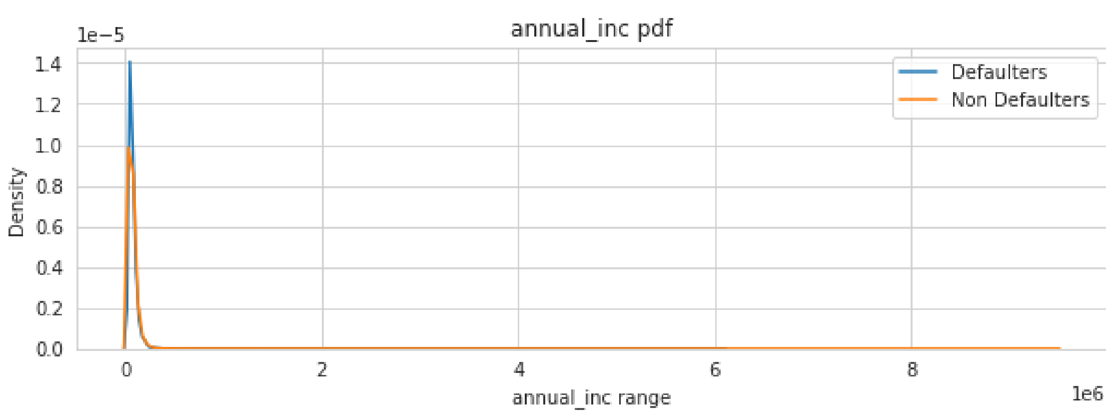




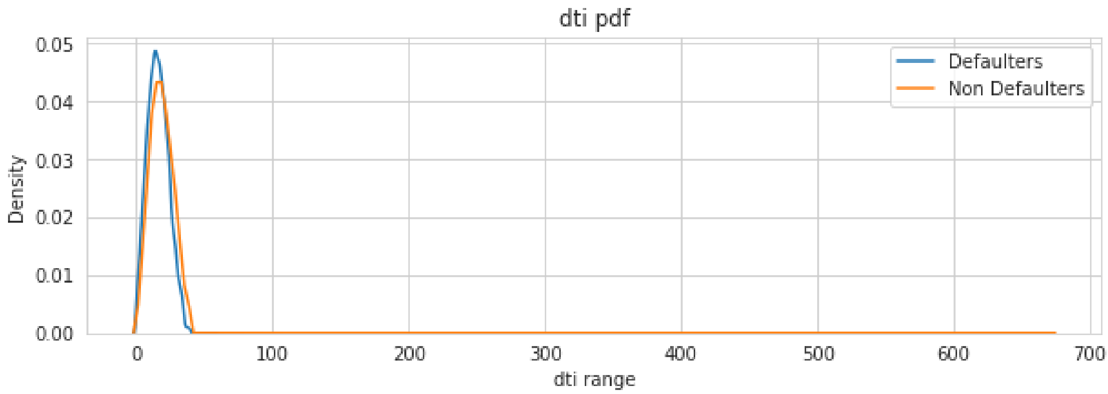
funded_amnt_inv pdf
1e−5
Density
Defaulters
Non Defaulters
0
1
2
3
4
5
6
7
0
5000
10000
15000
20000
25000
30000
35000
funded_amnt_inv range

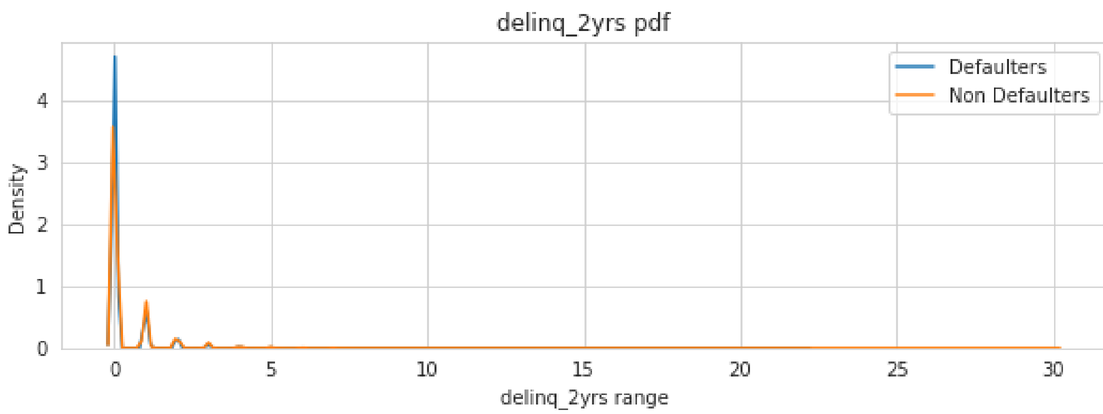


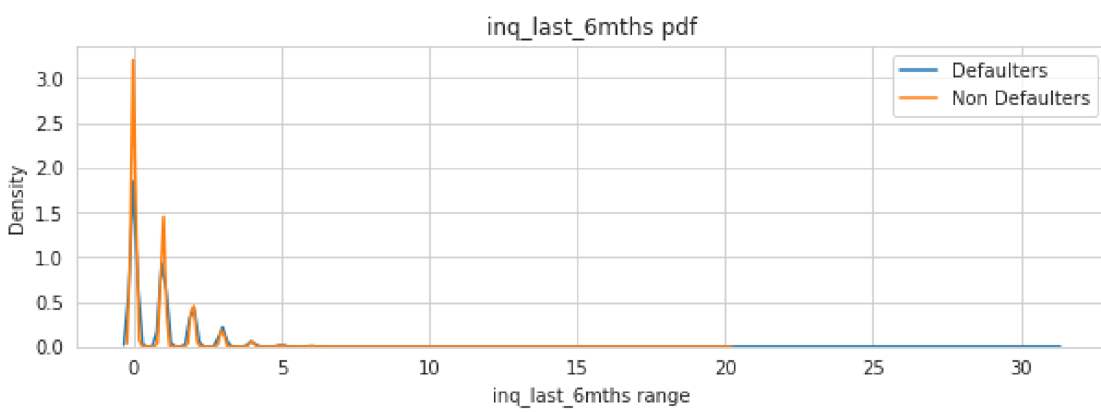
int_rate pdf
Density
Defaulters
Non Defaulters
0.00
0.02
0.04
0.06
0.08
0.10
5
10
15
20
25
30
int_rate range

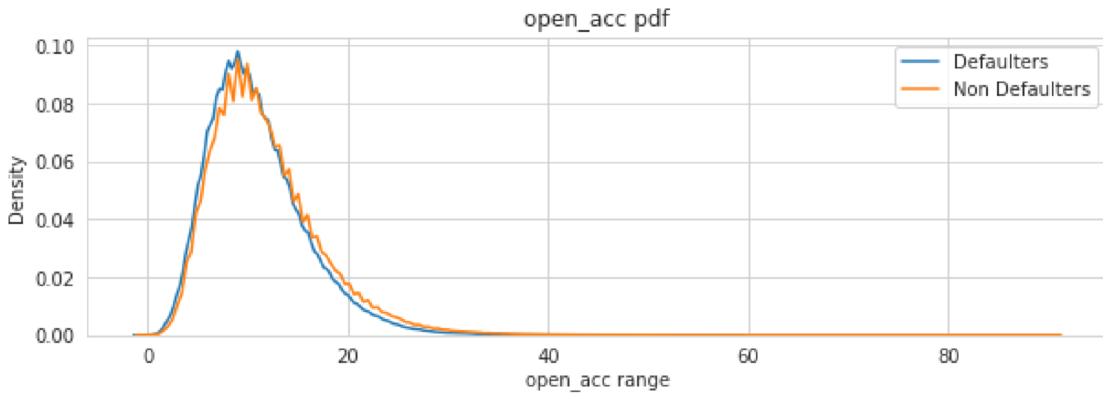


annual_inc pdf
1e−5
Density
Defaulters
Non Defaulters
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
0
2
4
6
8
1e6
annual_inc range

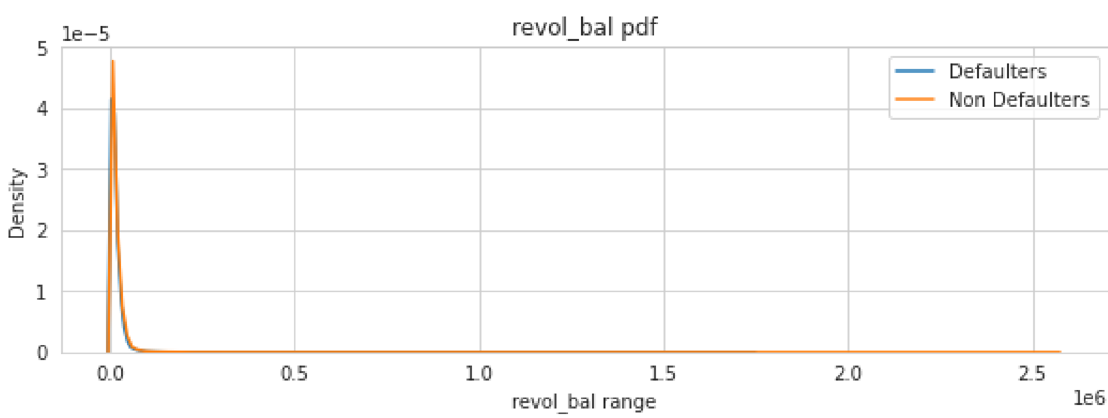

dti pdf
Density
0.05
0.04
0.03
0.02
0.01
0.00
0
100
200
300
400
500
600
700
dti range
Defaulters
Non Defaulters

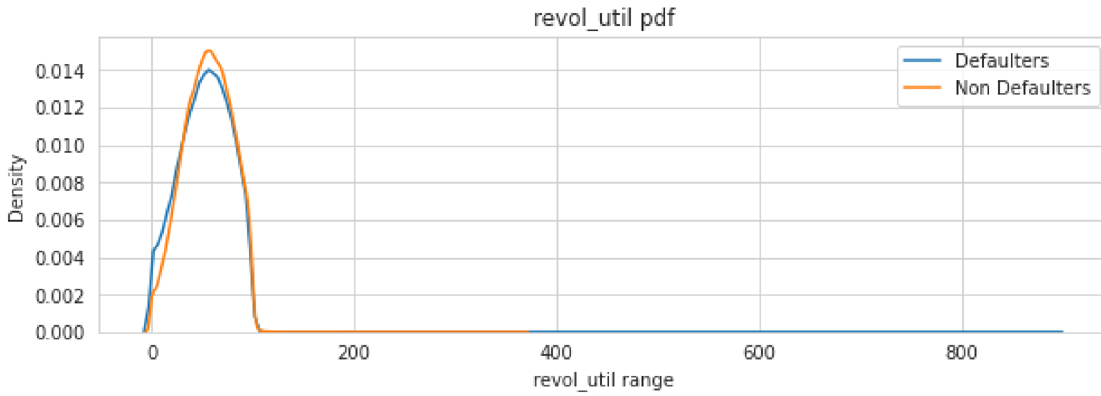

delinq_2yrs pdf
Density
4
3
2
1
0
0
5
10
15
20
25
30
delinq_2yrs range
Defaulters
Non Defaulters

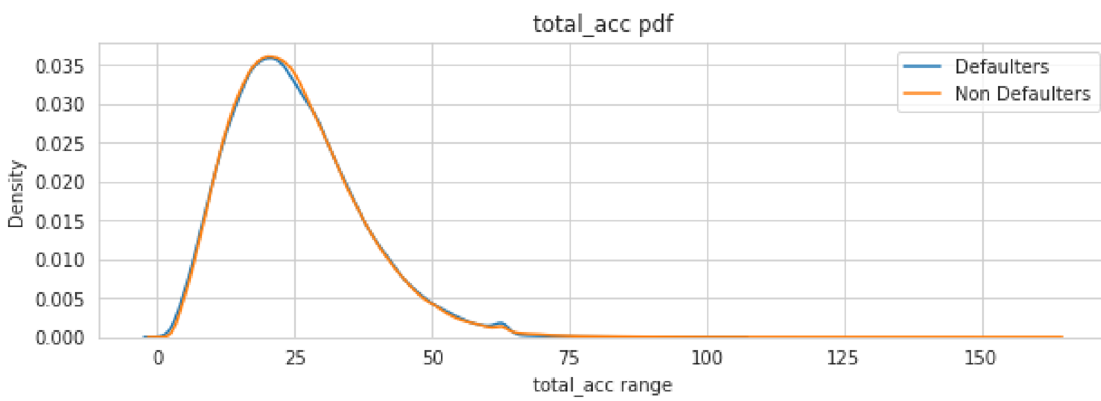

inq_last_6mths pdf
Density
3.0
2.5
2.0
1.5
1.0
0.5
0.0
0
5
10
15
20
25
30
inq_last_6mths range
Defaulters
Non Defaulters

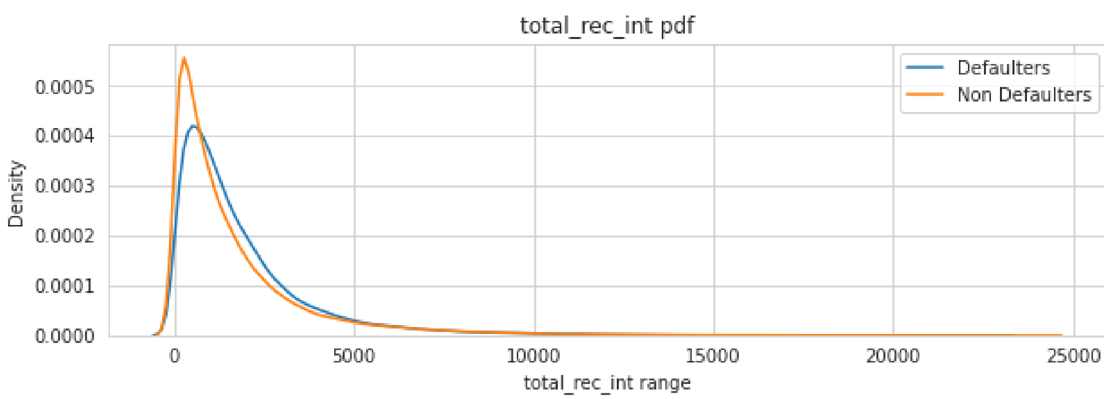

open_acc pdf
Defaulters
Non Defaulters
Density
open_acc range

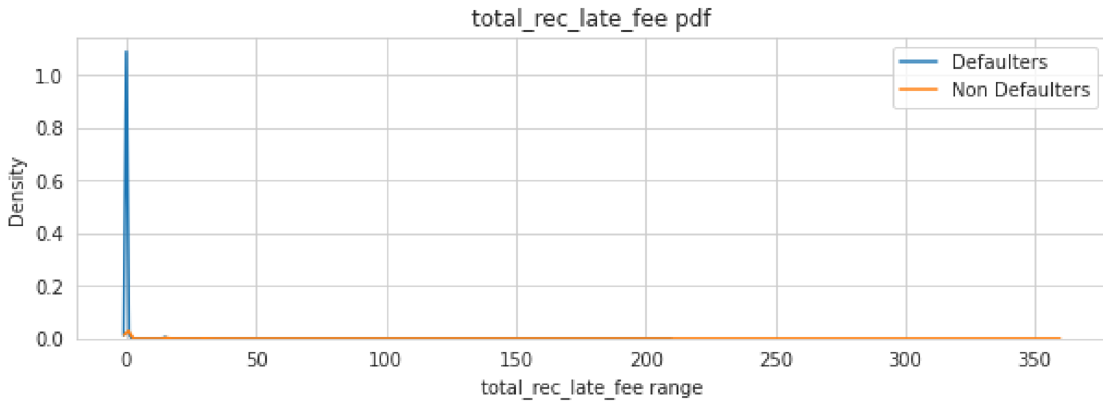

pub_rec pdf
Defaulters
Non Defaulters
Density
pub_rec range

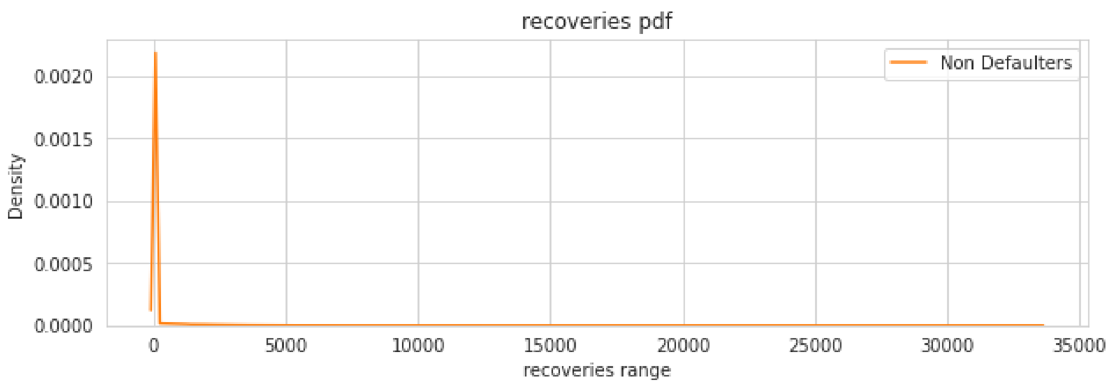

revol_bal pdf
Defaulters
Non Defaulters
Density
revol_bal range

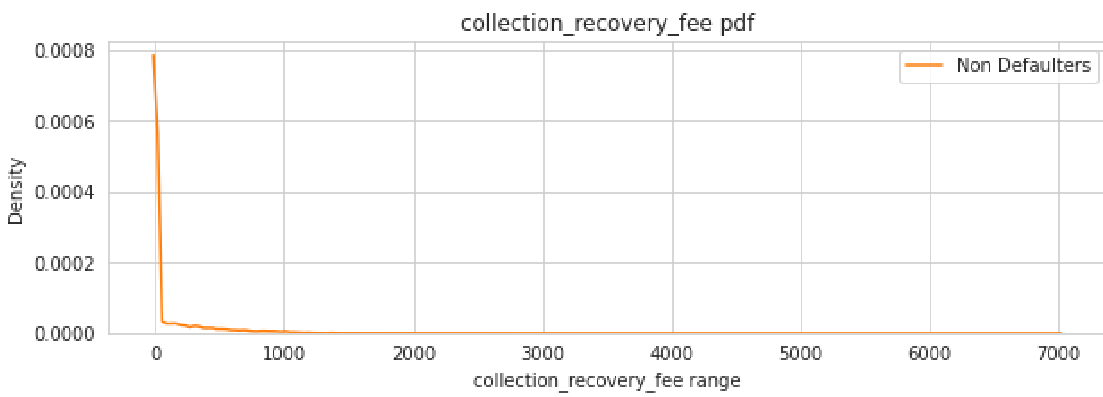

revol_util pdf
Density
0.014
0.012
0.010
0.008
0.006
0.004
0.002
0.000
0
200
400
600
800
revol_util range
Defaulters
Non Defaulters

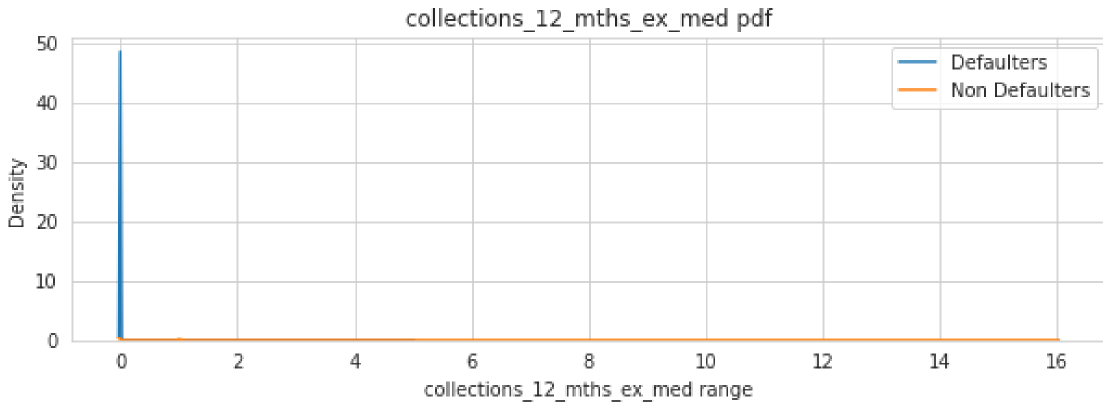

total_acc pdf
Density
0.035
0.030
0.025
0.020
0.015
0.010
0.005
0.000
0
25
50
75
100
125
150
total_acc range
Defaulters
Non Defaulters

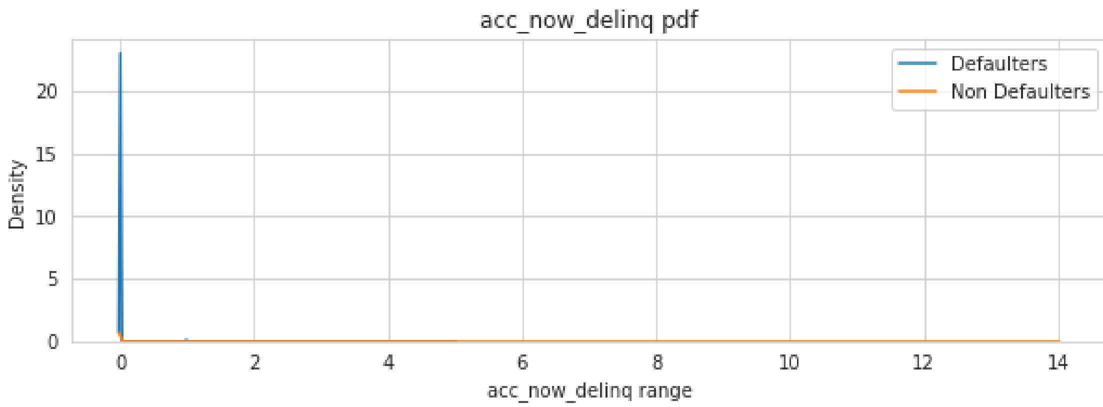

total_rec_int pdf
Density
0.0005
0.0004
0.0003
0.0002
0.0001
0.0000
0
5000
10000
15000
20000
25000
total_rec_int range
Defaulters
Non Defaulters

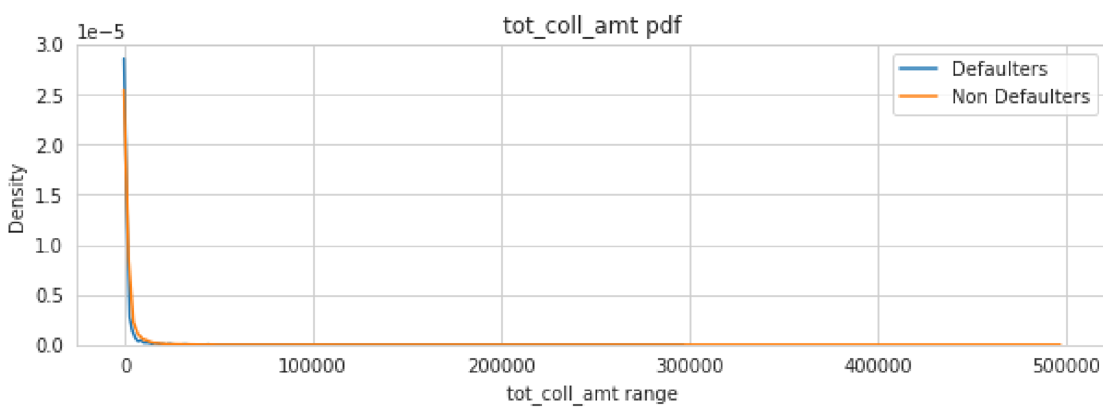

total_rec_late_fee pdf
Defaulters
Non Defaulters
Density
1.0
0.8
0.6
0.4
0.2
0.0
0
50
100
150
200
250
300
350
total_rec_late_fee range

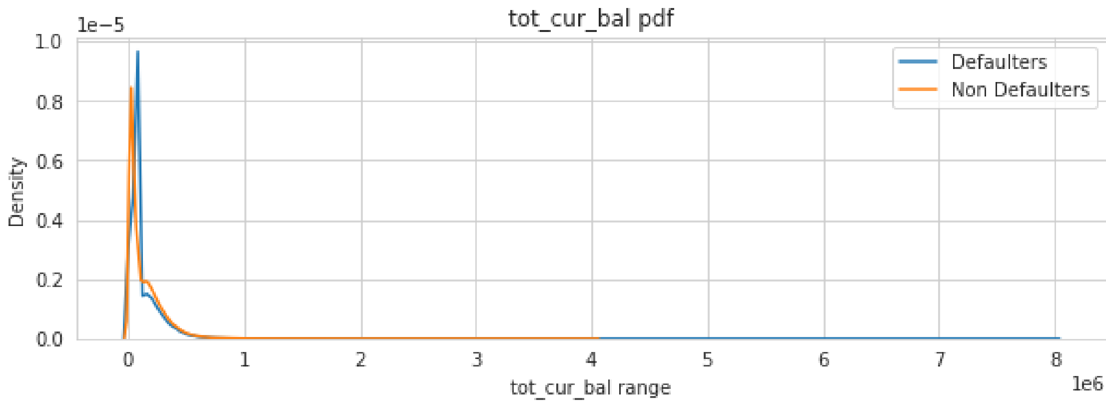

recoveries pdf
Non Defaulters
Density
0.0020
0.0015
0.0010
0.0005
0.0000
0
5000
10000
15000
20000
25000
30000
35000
recoveries range

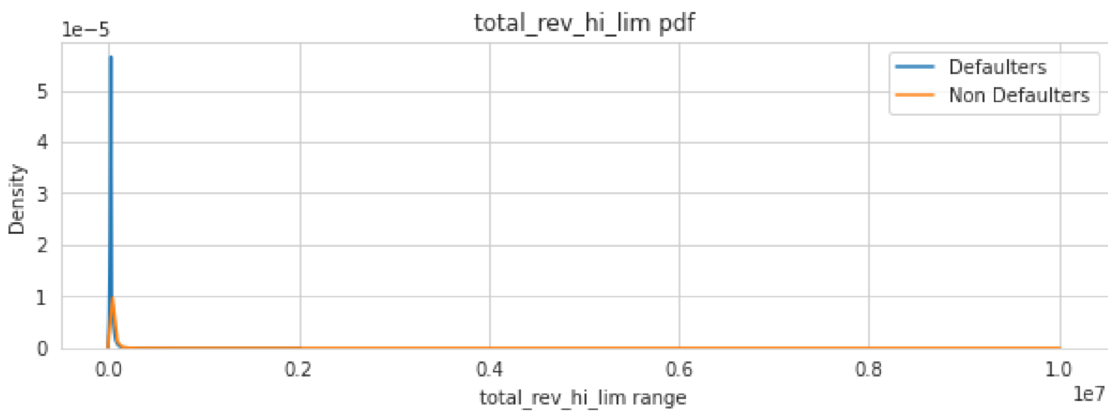

collection_recovery_fee pdf
Non Defaulters
Density
0.0008
0.0006
0.0004
0.0002
0.0000
0
1000
2000
3000
4000
5000
6000
7000
collection_recovery_fee range


collections_12_mths_ex_med pdf
Density
collections_12_mths_ex_med range
Defaulters
Non Defaulters


acc_now_delinq pdf
Density
acc_now_delinq range
Defaulters
Non Defaulters


tot_coll_amt pdf
Density
tot_coll_amt range
Defaulters
Non Defaulters





[ ]:
```
train_data_preprocessed[train_data_preprocessed.loan_status == 1].
↪collection_recovery_fee.value_counts()
```

[ ]:
```
0.0    125827
Name: collection_recovery_fee, dtype: int64
```

[ ]:
```
train_data_preprocessed[train_data_preprocessed.loan_status == 1].recoveries.
↪value_counts()
```

[ ]:
```
0.0    125827
Name: recoveries, dtype: int64
```

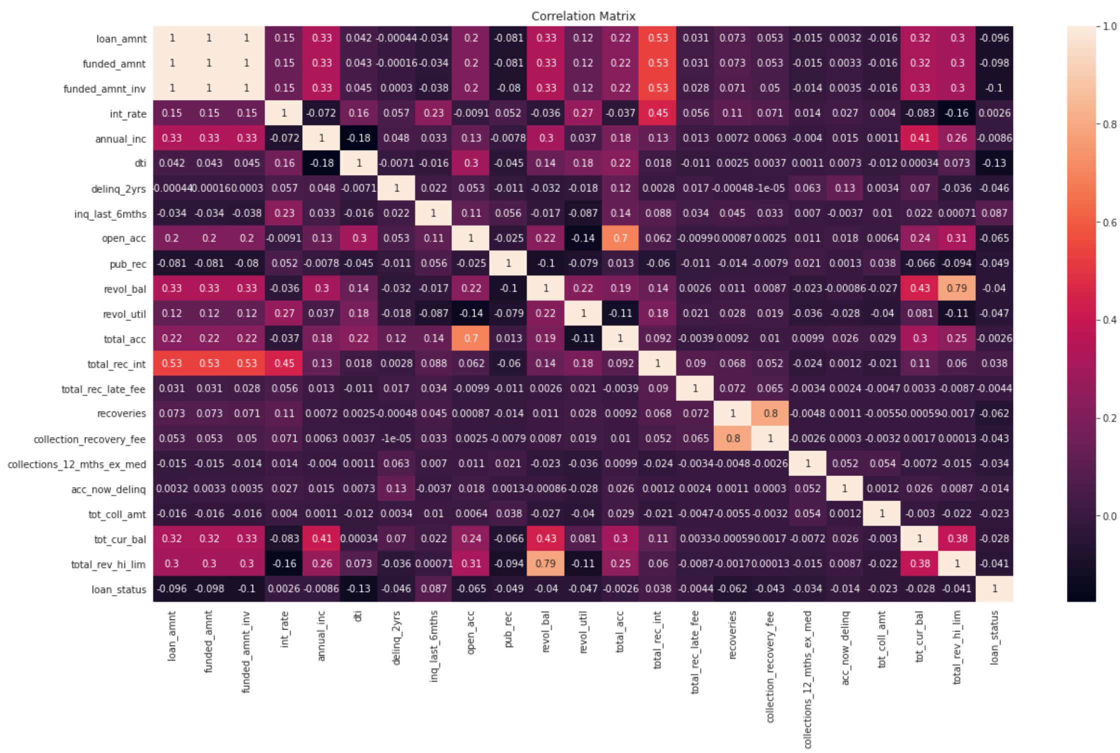
- from abouve analysis we can say that 'loan_amnt', 'funded_amnt', 'funded_amnt_inv', 'int_rate' these are some imp features becase they show quite good seperation of defaulter and no defaulter pdf areas
- collection_recovery_fee and recoveries having zero std deviation for defauters i.e all values for defauter cases for this two features are zero

```python
def text_operations(features):
  for i in features:
    train_data_preprocessed[i] = train_data_preprocessed[i].map(lambda x: x.lower().replace(' ','_'))
```

```python

```

```python
text_operations(['term','batch_enrolled','grade','sub_grade','emp_title','emp_length'
,'home_ownership','verification_status','purpose','title'
,'zip_code','addr_state','initial_list_status'
,'last_week_pay'])
```

```python
plt.figure(figsize=(20,11))
sns.heatmap(train_data_preprocessed.corr(),annot=True)
plt.title("Correlation Matrix")
plt.show()
```



1. loan amount , funded_amount and funded_amount_inv have correlation of 1 with each other that can will reduce model performence
2. we will drop funded_amount and funded_amount_inv

```python
train_data_preprocessed = train_data_preprocessed.drop(columns=['funded_amnt', 'funded_amnt_inv'])
```

3 create new feature

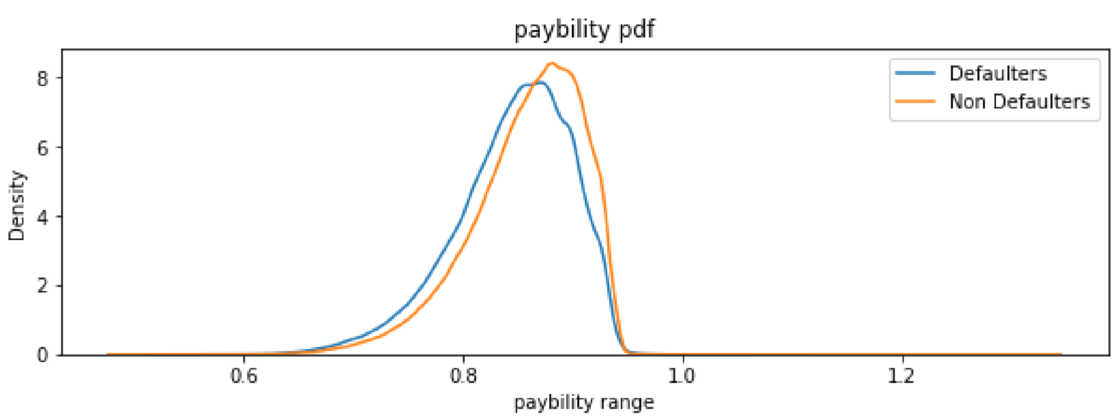
- we dont have experties in bank domain , generally we can see if there is to much of loan with respect to monthly income then person will no able to complete loan
- new feature = log(loan_amount + intrest_rate * term_of_loan)+0.00001/log(anual_income)+0.00001
- used log to reduce correlaiton and 0.00001 noice prevent us from devide by zero error
- if pdf of this feature will not show significant seperation then we will take this feature

[ ]:
```
import math
train_data_preprocessed['paybility'] = train_data_preprocessed.apply(lambda row:
↪ (math.log(row.loan_amnt + (float(row.term.split('_')[0]) * row.int_rate)) +␣
↪0.00001 )/math.log(row.annual_inc), axis=1)
```

[ ]:
```
train_data_preprocessed['paybility']
```

[ ]:
```
0         0.937054
1         0.772015
2         0.862030
3         0.835694
4         0.893638
            …
532423    0.884233
532424    0.861602
532425    0.929137
532426    0.924028
532427    0.848782
Name: paybility, Length: 532428, dtype: float64
```

[ ]:
```
plotPdf('paybility')
```



- its seperating regions cosiderable we will keep this feature

4 Modeling

- train test split
- oversampling of train dataset
- normalize numerical features as we dont want to loose original distribution of dataser
- one hot encoading of categorical features
- after dataset is ready load into model we will apply (Logistic regression , GBDT , Random-Forest)
  - cross validation using random serach
  - plot auc-roc value against epocs
  - draw roc cusrve on both train and test
  - draw confussion metrix in from best threshold
- we will also try small mlp nural network with dence layers
- compaire models and select model having heighest AUC-ROC score
- predict submission data

[ ]:
```
#train_data_preprocessed.to_pickle("train_data_preprocessed.pkl")
train_data_preprocessed = pd.read_pickle("train_data_preprocessed.pkl")
```

[ ]:
```
train_data_preprocessed.shape
```

[ ]:
```
(532428, 36)
```

[ ]:
```
y = train_data_preprocessed['loan_status']
X_data = train_data_preprocessed.drop(columns=['loan_status'])
```

[ ]:
```
from sklearn.model_selection import train_test_split
X_train_old, X_test, y_train_old, y_test = train_test_split(X_data, y,
                                                            stratify=y,
                                                            test_size=0.2,␣
 ↪random_state=42)
```

[ ]:
```
#!pip install -U imbalanced-learn
from imblearn.over_sampling import RandomOverSampler
from collections import Counter
```

[ ]:
```
print(Counter(y_train_old))
# define oversampling strategy
oversample = RandomOverSampler(sampling_strategy=0.5,random_state=42)
# fit and apply the transform
X_over, y_over = oversample.fit_resample(X_train_old, y_train_old)
# summarize class distribution
print(Counter(y_over))
```

```
Counter({0: 325280, 1: 100662})
Counter({0: 325280, 1: 162640})
```

[ ]:
```
X_train , y_train = X_over, y_over
```

5 normalizing numerical features

[ ]:
```
from sklearn.preprocessing import Normalizer

numerical_features = ['loan_amnt', 'int_rate',
       'annual_inc', 'dti', 'delinq_2yrs', 'inq_last_6mths', 'open_acc',
       'pub_rec', 'revol_bal', 'revol_util', 'total_acc', 'total_rec_int',
       'total_rec_late_fee', 'recoveries', 'collection_recovery_fee',
       'collections_12_mths_ex_med', 'acc_now_delinq', 'tot_coll_amt',
       'tot_cur_bal', 'total_rev_hi_lim','paybility']
```

[ ]:
```
X_test.shape
```

[ ]:
```
(106486, 35)
```

[ ]:
```
X_train.shape
```

[ ]:
```
(487920, 35)
```

[ ]:
```
X_train_numerical_features = X_train[numerical_features].values
X_test_numerical_features = X_test[numerical_features].values
```

[ ]:
```
X_train[numerical_features]
```

[ ]:
```
        loan_amnt  int_rate  …  total_rev_hi_lim  paybility
0            8950     15.99  …           21100.0   0.904719
1           11900     18.54  …           15900.0   0.919721
2            6000     12.49  …           15700.0   0.810718
3            5200      6.54  …           23700.0   0.766193
4           10675     20.99  …            5000.0   0.911511
…             …       …   …                 …        …
487915      10000      5.99  …           23700.0   0.861016
487916       8000     10.99  …           50100.0   0.791277
487917      21550     15.61  …           49700.0   0.867431
487918      15000     12.99  …           21200.0   0.854447
487919      10000     11.49  …           23700.0   0.865844

[487920 rows x 21 columns]
```

[ ]:
```
from sklearn.preprocessing import MinMaxScaler
def normalize_feature(nmumerical_fetures):
  X_train_numerical_features = X_train[nmumerical_fetures].values
  X_test_numerical_features = X_test[nmumerical_fetures].values
```

```
    data = X_train_numerical_features
    scaler = MinMaxScaler()
    scaler.fit(data)
    pickle.dump(scaler, open('normelizers_numeric.pkl', 'wb'))
    X_train_numerical = scaler.transform(X_train_numerical_features)
    X_test_numerical = scaler.transform(X_test_numerical_features)
    return X_train_numerical , X_test_numerical
```

[ ]:
```
X_train_numerical , X_test_numerical = normalize_feature(numerical_features)
```

[ ]:
```
X_train_numerical.shape
```

[ ]:
```
(487920, 21)
```

[ ]:
```
X_train.loan_amnt.value_counts()
```

[ ]:
```
10000    34360
12000    27810
15000    25783
20000    25199
35000    19220
         …
34700        1
29075        1
925          1
32575        1
33725        1
Name: loan_amnt, Length: 1368, dtype: int64
```

[ ]:
```
from sklearn.preprocessing import OneHotEncoder
def vectorize_feature(features):
  for i in features:
    vectorizer = OneHotEncoder(handle_unknown='ignore')
    vectorizer.fit(X_train[i].values.reshape(-1,1)) # fit has to happen only on␣
 ↪train data
    globals()[f"vectorizer_{i}"] = vectorizer
    pickle.dump(globals()[f"vectorizer_{i}"], open(f'vectorizers/vectorizer_{i}.
 ↪pkl', 'wb'))
    # we use the fitted OneHotEncoader to convert the text to vector
    X_train_vectors = vectorizer.transform(X_train[i].values.reshape(-1,1))
    X_test_vectors = vectorizer.transform(X_test[i].values.reshape(-1,1))

    globals()[f"X_train_{i}"] = X_train_vectors
    globals()[f"X_test_{i}"] = X_test_vectors
    print("After one hot encoading of "+i)
    print(X_train_vectors.shape, y_train.shape)
    print(X_test_vectors.shape, y_test.shape)
```

```
    print("="*100)
```

[ ]:
```
categorical_features_preprocessed =␣
 ↪['term','batch_enrolled','grade','sub_grade','emp_title','emp_length'
,'home_ownership','verification_status','purpose','title'
,'zip_code','addr_state','initial_list_status'
,'last_week_pay']
len(categorical_features_preprocessed)
```

[ ]: 14

[ ]:
```
vectorize_feature(categorical_features_preprocessed)
```

```
After one hot encoding of term
(487920, 2) (487920,)
(106486, 2) (106486,)
================================================================================
====================
After one hot encoding of batch_enrolled
(487920, 105) (487920,)
(106486, 105) (106486,)
================================================================================
====================
After one hot encoding of grade
(487920, 7) (487920,)
(106486, 7) (106486,)
================================================================================
====================
After one hot encoding of sub_grade
(487920, 35) (487920,)
(106486, 35) (106486,)
================================================================================
====================
After one hot encoding of emp_title
(487920, 138934) (487920,)
(106486, 138934) (106486,)
================================================================================
====================
After one hot encoding of emp_length
(487920, 12) (487920,)
(106486, 12) (106486,)
================================================================================
====================
After one hot encoding of home_ownership
(487920, 6) (487920,)
(106486, 6) (106486,)
================================================================================
```

```
====================
After one hot encoding of verification_status
(487920, 3) (487920,)
(106486, 3) (106486,)
================================================================================
====================
After one hot encoding of purpose
(487920, 14) (487920,)
(106486, 14) (106486,)
================================================================================
====================
After one hot encoding of title
(487920, 27853) (487920,)
(106486, 27853) (106486,)
================================================================================
====================
After one hot encoding of zip_code
(487920, 907) (487920,)
(106486, 907) (106486,)
================================================================================
====================
After one hot encoding of addr_state
(487920, 51) (487920,)
(106486, 51) (106486,)
================================================================================
====================
After one hot encoding of initial_list_status
(487920, 2) (487920,)
(106486, 2) (106486,)
================================================================================
====================
After one hot encoding of last_week_pay
(487920, 97) (487920,)
(106486, 97) (106486,)
================================================================================
====================
```

[ ]:
```python
from scipy.sparse import hstack
X_train_final = hstack((X_train_numerical , X_train_term␣
 ↪,X_train_batch_enrolled,X_train_grade,X_train_sub_grade,X_train_emp_title,X_train_emp_lengt
,X_train_home_ownership,X_train_verification_status,X_train_purpose,X_train_title
,X_train_zip_code,X_train_addr_state,X_train_initial_list_status
,X_train_last_week_pay ))
```

[ ]:
```python
pickle.dump(X_train_final, open('X_train_final.pkl', 'wb'))
```

```
[ ]: X_test_final = hstack((X_test_numerical , X_test_term␣
     ↪,X_test_batch_enrolled,X_test_grade,X_test_sub_grade,X_test_emp_title,X_test_emp_length
     ,X_test_home_ownership,X_test_verification_status,X_test_purpose,X_test_title
     ,X_test_zip_code,X_test_addr_state,X_test_initial_list_status
     ,X_test_last_week_pay ))
     pickle.dump(X_test_final, open('X_test_final.pkl', 'wb'))
```

```
[ ]: pickle.dump(y_train, open('y_train.pkl', 'wb'))
     pickle.dump(y_test, open('y_test.pkl', 'wb'))
```

```
[ ]: pickle.dump(X_train_numerical, open('X_train_numerical.pkl', 'wb'))
     pickle.dump(X_test_numerical, open('X_test_numerical.pkl', 'wb'))
```

```
[ ]: X_train_final = pickle.load(open('X_train_final.pkl', 'rb'))
     X_test_final = pickle.load(open('X_test_final.pkl', 'rb'))
```

```
[ ]: X_train_csr = X_train_final.tocsr()
     X_test_csr = X_test_final.tocsr()
```

```
[ ]: y_train = pickle.load(open('y_train.pkl', 'rb'))
     y_test = pickle.load(open('y_test.pkl', 'rb'))
```

```
[ ]: X_test_final
```

```
[ ]: <106486x168049 sparse matrix of type '<class 'numpy.float64'>'
             with 2836048 stored elements in COOrdinate format>
```

#Apply Model

- first we apply logistic regression becase Liniar model give good results when dimentions are heigh

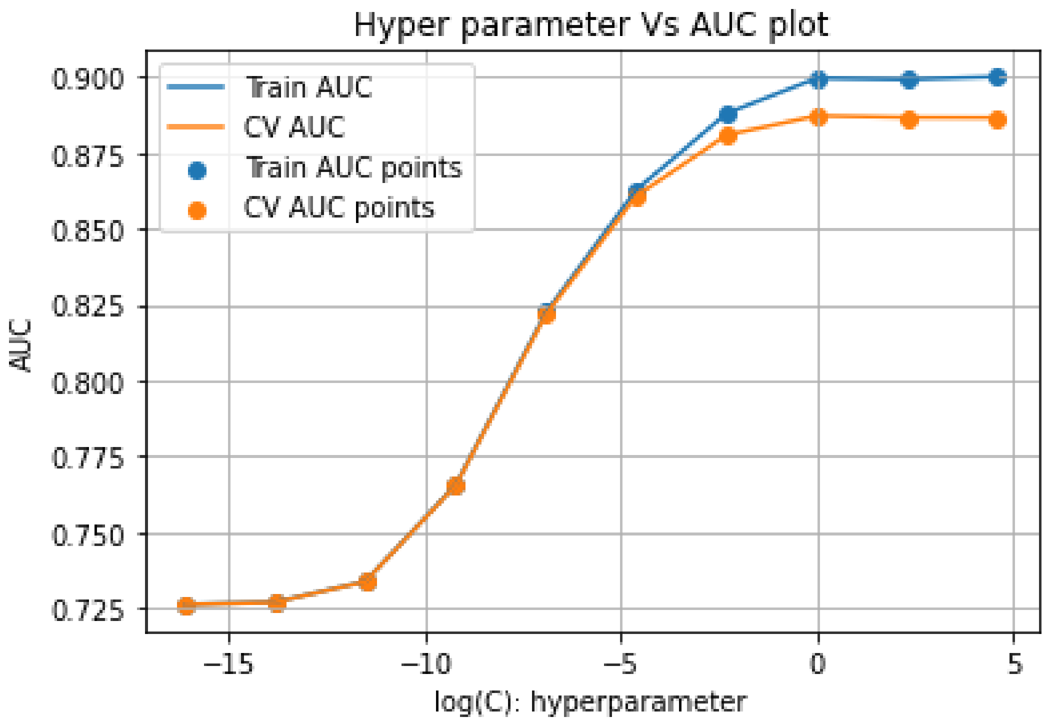
```
[ ]: def batch_predict(clf, data):
         """ this function predicts batch wise propablity
             for given data over given model
         """

         y_data_pred = []
         tr_loop = data.shape[0] - data.shape[0]%1000
         for i in range(0, tr_loop, 1000):
             y_data_pred.extend(clf.predict_proba(data[i:i+1000])[:,1])
         # we will be predicting for the last data points
         if data.shape[0]%1000 !=0:
             y_data_pred.extend(clf.predict_proba(data[tr_loop:])[:,1])

         return y_data_pred
```

```
[ ]: from sklearn.model_selection import RandomizedSearchCV
```

##Logistic Regression

```
[ ]: from sklearn.datasets import load_iris
from sklearn.linear_model import LogisticRegression
clf = LogisticRegression(random_state=15)
parameters = {'C':[1e-7,1e-6,1e-5, 1e-4, 1e-3, 1e-2, 1e-1, 1, 10, 100]}
clf = RandomizedSearchCV(clf, parameters, cv=3 ,scoring='roc_auc'␣
 ↪,return_train_score=True,random_state=15)

clf.fit(X_train_csr,y_train)

results = pd.DataFrame.from_dict(clf.cv_results_)
print(results.columns)
results = results.sort_values(['param_C'])

train_auc= results['mean_train_score']
train_auc_std= results['std_train_score']
cv_auc = results['mean_test_score']
cv_auc_std= results['std_test_score']
K =  list(map(lambda x: np.log(x) , results['param_C']))
#K = results['param_C']
plt.plot(K, train_auc, label='Train AUC')

plt.plot(K, cv_auc, label='CV AUC')

plt.scatter(K, train_auc, label='Train AUC points')
plt.scatter(K, cv_auc, label='CV AUC points')


plt.legend()
plt.xlabel("log(C): hyperparameter")
plt.ylabel("AUC")
plt.title("Hyper parameter Vs AUC plot")
plt.grid()
plt.show()

results
```

```
Index(['mean_fit_time', 'std_fit_time', 'mean_score_time', 'std_score_time',
       'param_C', 'params', 'split0_test_score', 'split1_test_score',
       'split2_test_score', 'mean_test_score', 'std_test_score',
       'rank_test_score', 'split0_train_score', 'split1_train_score',
       'split2_train_score', 'mean_train_score', 'std_train_score'],
      dtype='object')
```



[ ]:

	mean_fit_time	std_fit_time	…	mean_train_score	std_train_score
0	1.931660	0.041759	…	0.726235	0.000389
1	1.559254	0.073042	…	0.727051	0.000382
2	1.967143	0.039396	…	0.733847	0.000328
3	3.106050	0.016808	…	0.765705	0.000086
4	6.956268	0.078847	…	0.822467	0.000044
5	15.453114	0.261965	…	0.862777	0.000250
6	15.177733	0.358979	…	0.887906	0.001693
7	15.282248	0.173678	…	0.899523	0.001926
8	15.434415	0.144933	…	0.899126	0.001063
9	15.478861	0.116143	…	0.899997	0.002875

[10 rows x 17 columns]

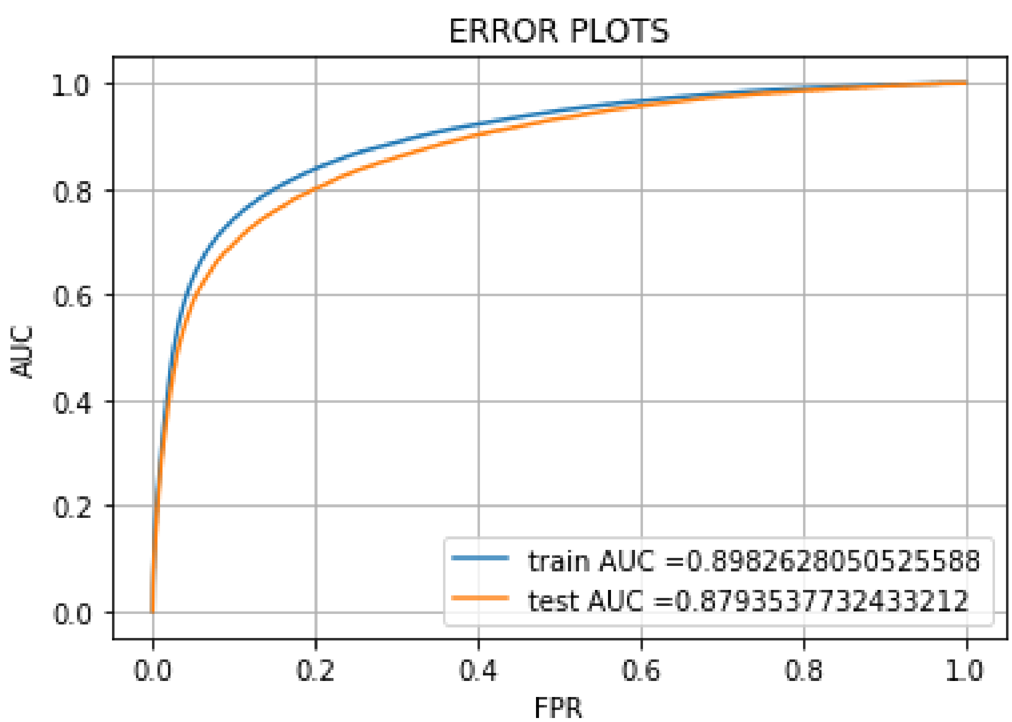
[ ]:

```

```

[ ]:

```
#best  C is 1
from sklearn.metrics import roc_curve, auc

lr_model = LogisticRegression(C=1, random_state=15)
lr_model.fit(X_train_csr, y_train)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probability␣
↪estimates of the positive class
```

```
# not the predicted outputs

y_train_pred = batch_predict(lr_model, X_train_csr)
y_test_pred = batch_predict(lr_model, X_test_csr)

train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_pred)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_test_pred)

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr,␣
 ↪train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("FPR")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.grid()
plt.show()
pickle.dump(lr_model, open('lr_model', 'wb'))
```



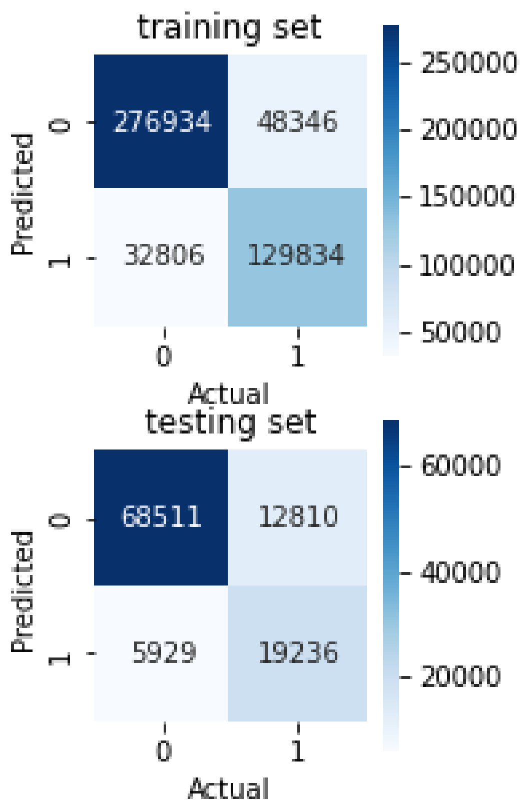
[ ]:
```
def find_best_threshold(threshould, fpr, tpr):
    t = threshould[np.argmax(tpr*(1-fpr))]
    # (tpr*(1-fpr)) will be maximum if your fpr is very low and tpr is very high
```

```
    print("the maximum value of tpr*(1-fpr)", max(tpr*(1-fpr)), "for␣
↪threshold", np.round(t,3))
    return t

def predict_with_best_t(proba, threshould):
    predictions = []
    for i in proba:
        if i>=threshould:
            predictions.append(1)
        else:
            predictions.append(0)
    return predictions
```

[ ]:
```
import seaborn as sns
import matplotlib.pyplot as plt
print("="*100)
from sklearn.metrics import confusion_matrix
best_t = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
print("Train confusion matrix")
train_predict = predict_with_best_t(y_train_pred, best_t)
cm_train = confusion_matrix(y_train, predict_with_best_t(y_train_pred, best_t))
#cm_train = confusion_matrix(y_train,train_predict)
#print(confusion_matrix(y_train, predict_with_best_t(y_train_pred, best_t)))
print("Test confusion matrix")
test_predict = predict_with_best_t(y_test_pred, best_t)
cm_test = confusion_matrix(y_test, predict_with_best_t(y_test_pred, best_t))
#cm_test = confusion_matrix(y_test, test_predict)
#print(confusion_matrix(y_test, predict_with_best_t(y_test_pred, best_t)))

fig = plt.figure(figsize = (5,5)) # width x height
ax1 = fig.add_subplot(2,2,1) # row, column, position
ax2 = fig.add_subplot(2,2,3)

ax1.set_title('training set')
cm_train = pd.DataFrame(cm_train)
cm_train['Predicted'] = [0,1]
cm_train.columns.name = 'Actual'
cm_train.set_index('Predicted',inplace=True)
sns.heatmap(cm_train,ax=ax1,square=True, annot=True,fmt="d",cmap='Blues')

ax2.set_title('testing set')
cm_test = pd.DataFrame(cm_test)
cm_test['Predicted'] = [0,1]
cm_test.columns.name = 'Actual'
cm_test.set_index('Predicted',inplace=True)
sns.heatmap(cm_test,ax=ax2,square=True, annot=True,fmt="d",cmap='Blues')
```

```
================================================================================
====================
the maximum value of tpr*(1-fpr) 0.679641655354506 for threshold 0.335
Train confusion matrix
Test confusion matrix
```

[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f277ff33250>



5.1 GBDT

[ ]:
```python
import xgboost as xgb
from xgboost.sklearn import XGBClassifier
```

[ ]:
```python
parameters = {
 'learning_rate':[0.05,0.1,0.2,0.3],
 'n_estimators':[10,50,120,200]
}
xgb = XGBClassifier(
 max_depth=3,
 subsample=0.8,
```

```
 colsample_bytree=0.8)

random_search =␣
 ↪RandomizedSearchCV(xgb,parameters,cv=3,return_train_score=True,random_state=15,scoring='roc
random_search.fit(X_train_csr,y_train)

results = pd.DataFrame.from_dict(random_search.cv_results_)

results
```

```
[ ]:    mean_fit_time  std_fit_time  …  mean_train_score  std_train_score
    0        9.667801      0.496915  …          0.764585         0.001853
    1       31.940976      0.431594  …          0.860757         0.004607
    2      117.651682      1.100278  …          0.858403         0.000115
    3       71.379337      0.822498  …          0.838266         0.000358
    4       71.361843      0.580145  …          0.907090         0.003358
    5       32.100068      0.288634  …          0.798859         0.001024
    6      117.399010      1.028311  …          0.938808         0.001881
    7       71.746024      0.644654  …          0.865048         0.000668
    8       31.915615      0.393351  …          0.879740         0.003140
    9      116.421143      1.177270  …          0.926831         0.002243

    [10 rows x 18 columns]
```

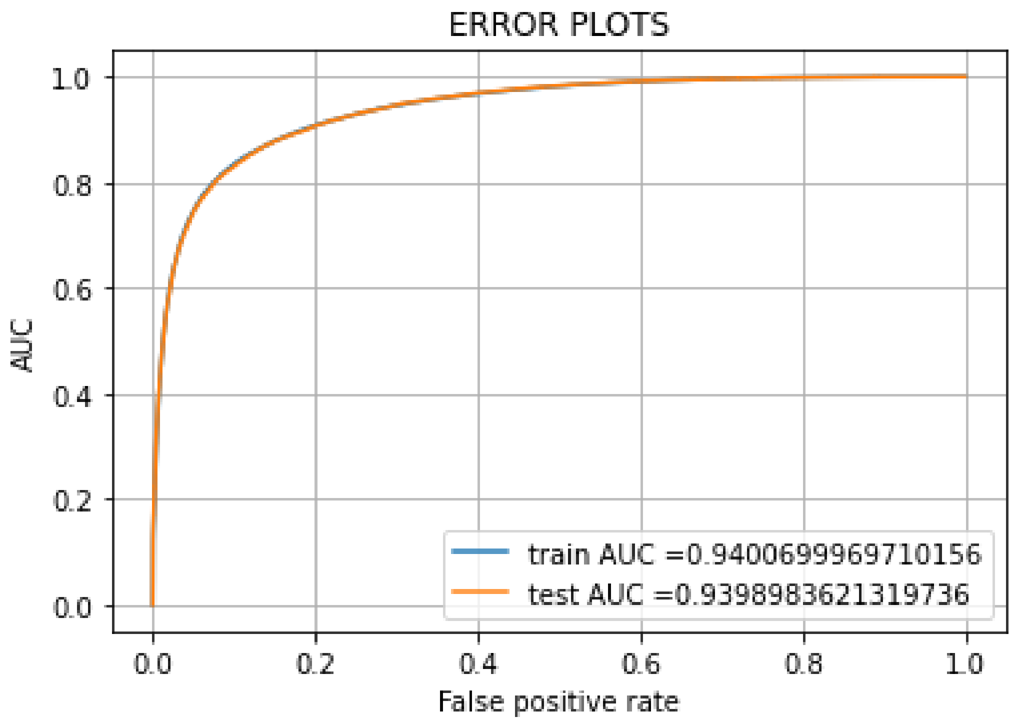
```
[ ]: import plotly.offline as offline
     import plotly.graph_objs as go
     offline.init_notebook_mode()
     import numpy as np
     import matplotlib.pyplot as plt
```

5.1.1 plese ensure you have installed plotly to see below 3d graph

```
[ ]: x1,y1,z1 = results['param_n_estimators'],results['param_learning_rate'],␣
      ↪results['mean_train_score']
     x2,y2,z2 = results['param_n_estimators'],results['param_learning_rate'],␣
      ↪results['mean_test_score']
     trace1 = go.Scatter3d(x=x1,y=y1,z=z1, name = 'train')
     trace2 = go.Scatter3d(x=x2,y=y2,z=z2, name = 'Cross validation')
     data = [trace1, trace2]

     layout = go.Layout(scene = dict(
             xaxis = dict(title='param_n_estimators'),
             yaxis = dict(title='param_learning_rate'),
             zaxis = dict(title='AUC'),))
```

```
fig = go.Figure(data=data, layout=layout)
offline.iplot(fig, filename='3d-scatter-colorscale')
fig.show(renderer="colab")
plt.show()
```

[ ]:
```
# {'n_estimators': 200, 'learning_rate': 0.3} these are our best params
from sklearn.metrics import roc_curve, auc
xgbClf = XGBClassifier(
 learning_rate = 0.3,
 n_estimators=200,
 max_depth=3,
 subsample=0.8,
 colsample_bytree=0.8)
xgbClf.fit(X_train_csr, y_train)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probability␣
↪estimates of the positive class
# not the predicted outputs

y_train_pred = batch_predict(xgbClf, X_train_csr)
y_test_pred = batch_predict(xgbClf, X_test_csr)

train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_pred)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_test_pred)

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr,␣
↪train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("False positive rate")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.grid()
plt.show()
```



[ ]:
```
from sklearn.externals import joblib

joblib_file = "xgb_model.joblib"
joblib.dump(xgbClf, joblib_file)
```

[ ]: ['xgb_model.joblib']

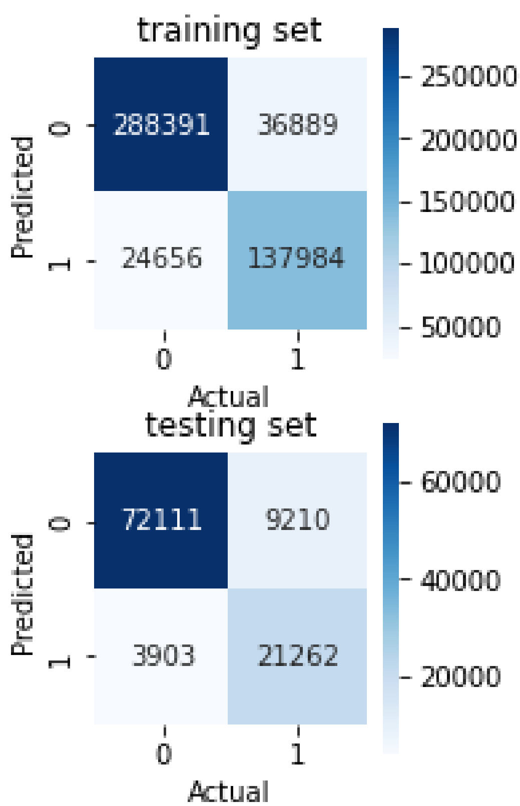
[ ]:
```
xgbClf = joblib.load('xgb_model.joblib')
```

[ ]:
```
print("="*100)
best_t = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
print("Train confusion matrix")
train_predict = predict_with_best_t(y_train_pred, best_t)
cm_train = confusion_matrix(y_train, predict_with_best_t(y_train_pred, best_t))
#cm_train = confusion_matrix(y_train,train_predict)
#print(confusion_matrix(y_train, predict_with_best_t(y_train_pred, best_t)))
print("Test confusion matrix")
test_predict = predict_with_best_t(y_test_pred, best_t)
cm_test = confusion_matrix(y_test, predict_with_best_t(y_test_pred, best_t))
#cm_test = confusion_matrix(y_test, test_predict)
#print(confusion_matrix(y_test, predict_with_best_t(y_test_pred, best_t)))

fig = plt.figure(figsize = (5,5)) # width x height
```

```
ax1 = fig.add_subplot(2,2,1) # row, column, position
ax2 = fig.add_subplot(2,2,3)

ax1.set_title('training set')
cm_train = pd.DataFrame(cm_train)
cm_train['Predicted'] = [0,1]
cm_train.columns.name = 'Actual'
cm_train.set_index('Predicted',inplace=True)
sns.heatmap(cm_train,ax=ax1,square=True, annot=True,fmt="d",cmap='Blues')

ax2.set_title('testing set')
cm_test = pd.DataFrame(cm_test)
cm_test['Predicted'] = [0,1]
cm_test.columns.name = 'Actual'
cm_test.set_index('Predicted',inplace=True)
sns.heatmap(cm_test,ax=ax2,square=True, annot=True,fmt="d",cmap='Blues',)
```

```
================================================================================
====================
the maximum value of tpr*(1-fpr) 0.7521867978163548 for threshold 0.342
Train confusion matrix
Test confusion matrix
```

[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5c2b0d7990>



5.2 Random Forest

[ ]:
```
from sklearn.ensemble import RandomForestClassifier
parameters={'n_estimators':[10,30,50,80,100],'max_depth': [1, 5, 10, 50]}
clf_tree=RandomForestClassifier()
random_search =␣
 ↪RandomizedSearchCV(clf_tree,parameters,cv=3,return_train_score=True,random_state=15,n_iter=
random_search.fit(X_train_csr,y_train)

results = pd.DataFrame.from_dict(random_search.cv_results_)
print(results.columns)
results = results.sort_values(['param_max_depth'])

results
```

```
Index(['mean_fit_time', 'std_fit_time', 'mean_score_time', 'std_score_time',
       'param_n_estimators', 'param_max_depth', 'params', 'split0_test_score',
       'split1_test_score', 'split2_test_score', 'mean_test_score',
       'std_test_score', 'rank_test_score', 'split0_train_score',
       'split1_train_score', 'split2_train_score', 'mean_train_score',
       'std_train_score'],
      dtype='object')
```

[ ]:

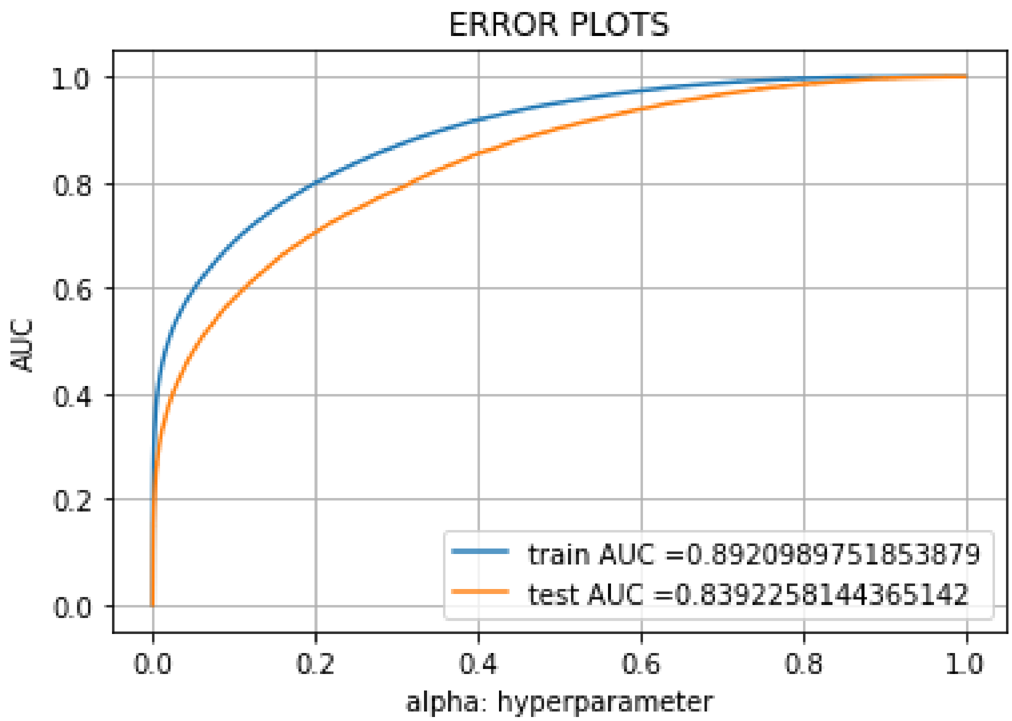
	mean_fit_time	std_fit_time	…	mean_train_score	std_train_score
2	8.053658	0.755660	…	0.710498	0.009089
4	9.820057	0.928637	…	0.691998	0.032478
5	5.109497	0.477210	…	0.637429	0.010957
9	3.221154	0.271778	…	0.618996	0.018599
3	35.680916	4.428566	…	0.791857	0.008366
10	10.799898	1.211847	…	0.721833	0.005188
13	17.858352	2.268550	…	0.757287	0.008296
6	7.153913	0.885289	…	0.724137	0.013648
8	54.829779	6.657790	…	0.809414	0.006388
12	68.294789	8.097947	…	0.808040	0.006578
14	21.078361	2.516116	…	0.788913	0.005481
0	452.040343	38.835618	…	0.900459	0.004362
1	44.561542	4.798198	…	0.848499	0.010950
7	134.166251	14.245967	…	0.883674	0.003985
11	224.039160	21.466611	…	0.892269	0.004467
15	363.562780	37.001578	…	0.897993	0.003660

[16 rows x 18 columns]

[ ]:

[ ]:
```python
x1,y1,z1 = results['param_n_estimators'],results['param_max_depth'],␣
↪results['mean_train_score']
x2,y2,z2 = results['param_n_estimators'],results['param_max_depth'],␣
↪results['mean_test_score']
trace1 = go.Scatter3d(x=x1,y=y1,z=z1, name = 'train')
trace2 = go.Scatter3d(x=x2,y=y2,z=z2, name = 'Cross validation')
data = [trace1, trace2]

layout = go.Layout(scene = dict(
        xaxis = dict(title='param_n_estimators'),
        yaxis = dict(title='param_max_depth'),
        zaxis = dict(title='AUC'),))

fig = go.Figure(data=data, layout=layout)
offline.iplot(fig, filename='3d-scatter-colorscale')
fig.show(renderer="colab")
plt.show()
```

[ ]:
```python
#{'n_estimators': 100, 'max_depth': 50} are the best parameters
dtree = RandomForestClassifier(n_estimators=100,max_depth=50,random_state=15)
dtree.fit(X_train_csr, y_train)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probability␣
↪estimates of the positive class
# not the predicted outputs

y_train_pred = batch_predict(dtree, X_train_csr)
y_test_pred = batch_predict(dtree, X_test_csr)

train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_pred)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_test_pred)

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr,␣
↪train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.grid()
plt.show()
```

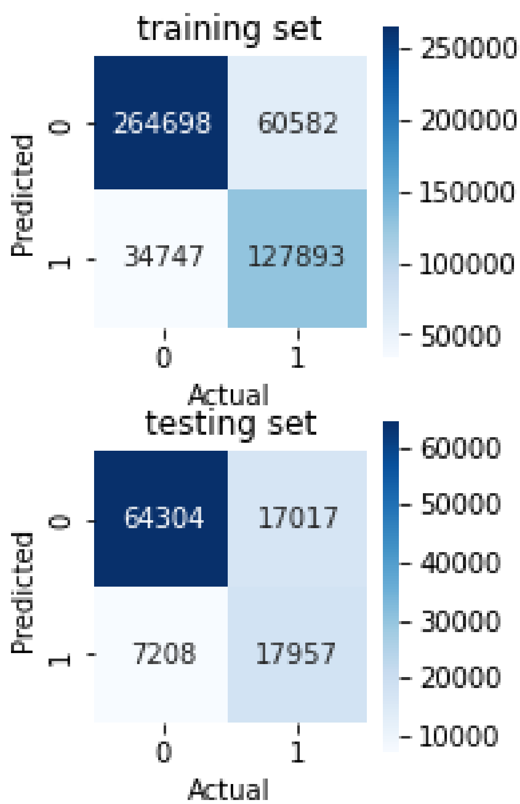


[ ]:
```
print("="*100)
from sklearn.metrics import confusion_matrix
best_t = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
print("Train confusion matrix w2v")
train_predict = predict_with_best_t(y_train_pred, best_t)
cm_train = confusion_matrix(y_train, predict_with_best_t(y_train_pred, best_t))
#cm_train = confusion_matrix(y_train,train_predict)
#print(confusion_matrix(y_train, predict_with_best_t(y_train_pred, best_t)))
print("Test confusion matrix w2v")
test_predict = predict_with_best_t(y_test_pred, best_t)
cm_test = confusion_matrix(y_test, predict_with_best_t(y_test_pred, best_t))
#cm_test = confusion_matrix(y_test, test_predict)
#print(confusion_matrix(y_test, predict_with_best_t(y_test_pred, best_t)))

fig = plt.figure(figsize = (5,5)) # width x height
ax1 = fig.add_subplot(2,2,1) # row, column, position
ax2 = fig.add_subplot(2,2,3)

ax1.set_title('training set')
cm_train = pd.DataFrame(cm_train)
cm_train['Predicted'] = [0,1]
cm_train.columns.name = 'Actual'
cm_train.set_index('Predicted',inplace=True)
```

```
sns.heatmap(cm_train,ax=ax1,square=True, annot=True,fmt="d",cmap='Blues')

ax2.set_title('testing set')
cm_test = pd.DataFrame(cm_test)
cm_test['Predicted'] = [0,1]
cm_test.columns.name = 'Actual'
cm_test.set_index('Predicted',inplace=True)
sns.heatmap(cm_test,ax=ax2,square=True, annot=True,fmt="d",cmap='Blues')
```

```
================================================================================
====================
the maximum value of tpr*(1-fpr) 0.6399008804688818 for threshold 0.341
Train confusion matrix w2v
Test confusion matrix w2v
```

[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5c2c488950>



[ ]:
```
joblib.dump(dtree, 'rdtree.joblib')
```

[ ]: ['rdtree.joblib']

[ ]:
```
import tensorflow as tf
import random as rn
from sklearn.model_selection import train_test_split
from tensorflow.keras.callbacks import Callback
from sklearn.metrics import confusion_matrix, f1_score, precision_score,␣
↪recall_score
from tensorflow.keras.callbacks import ModelCheckpoint
from tensorflow.keras.callbacks import EarlyStopping
import tensorflow.keras.layers as layers
from tensorflow.keras.layers import BatchNormalization
from tensorflow.keras.layers import Dense,Input,Dropout
from tensorflow.keras.models import Model
```

[ ]:
```
def aucroc(y_true, y_pred):
    m = tf.keras.metrics.AUC()
    m.update_state(y_true, y_pred)
    return m.result().numpy()
```

[ ]:
```
def chage_sparce_to_dence(sparce_mat):
  reaturn_mat = []
  for i in tqdm(range(0,sparce_mat.shape[0])):
    if reaturn_mat == []:
      reaturn_mat = sparce_mat[i,:].toarray()
      continue
    reaturn_mat = np.concatenate((reaturn_mat, sparce_mat[i,:].toarray() ),␣
↪axis=0)
  return reaturn_mat
```

[ ]:
```
X_train_dence = pd.DataFrame.sparse.from_spmatrix(X_train_csr)
X_test_dence = pd.DataFrame.sparse.from_spmatrix(X_test_csr)
```

[ ]:
```
X_train_dence
```

[ ]:
```
              0         1         2         3   …  168045  168046  168047
168048
0      0.244928  0.450782  0.002506  0.031404   …     0.0     0.0     0.0
0.0
1      0.330435  0.558513  0.003006  0.022795   …     0.0     0.0     0.0
0.0
2      0.159420  0.302915  0.005137  0.018988   …     0.0     0.0     0.0
0.0
3      0.136232  0.051542  0.007769  0.018394   …     0.0     0.0     0.0
0.0
4      0.294928  0.662019  0.002999  0.022111   …     0.0     0.0     1.0
0.0
…           …         …         …         …   …       …       …       …
…
```

```
487915  0.275362  0.028306  0.004646  0.007792  …     0.0     0.0     0.0
0.0
487916  0.217391  0.239544  0.009456  0.035657  …     0.0     0.0     0.0
0.0
487917  0.610145  0.434728  0.010822  0.010617  …     0.0     0.0     0.0
0.0
487918  0.420290  0.324039  0.008296  0.004238  …     0.0     0.0     0.0
0.0
487919  0.275362  0.260668  0.004611  0.015895  …     0.0     0.0     0.0
0.0

[487920 rows x 168049 columns]
```

#- Note i wrote a logic tried multiple times to run below nural network but because i was working on colab and its provide only 12gb ram it was got creashed during training so did not perform full training but i kept logic as it is

[ ]:
```
X_input =  Input(shape=(X_train_dence.shape[1]), name= 'X_input', sparse=True)
Dence0 =  Dense(32,activation="relu",kernel_initializer='he_uniform')(X_input)

Dence1 =  Dense(32,activation="relu",kernel_initializer='he_uniform')(Dence0)
Dropout1 = Dropout(0.1)(Dence1)
Dence2 = Dense(64,activation="relu",kernel_initializer='he_uniform')(Dropout1)
BnLayer =  BatchNormalization()(Dence2)
Dropout2 = Dropout(0.1)(BnLayer)
Dence3 = Dense(64,activation="relu",kernel_initializer='he_uniform')(Dropout2)

output = Dense(1,activation="sigmoid",kernel_initializer='he_uniform')(Dence3)
model = Model(inputs=X_input, outputs=output)

earlystop = EarlyStopping(monitor='aucroc', min_delta=0.0000001, patience=4,␣
 ↪verbose=2,mode='auto')

optimizer = tf.keras.optimizers.Adam(learning_rate=0.001,beta_1=0.9,beta_2=0.
 ↪999)

model.compile(loss='binary_crossentropy', optimizer=optimizer,␣
 ↪metrics=['accuracy',aucroc],run_eagerly=True)
save_model = model.fit(␣
 ↪x=X_train_dence,y=y_train,batch_size=100,epochs=25,validation_data=(X_test_dence,y_test),ca
```

#Load and Predict Funtions

[ ]:
```
train_data_preprocessed = pd.read_pickle("train_data_preprocessed.pkl")
train_data_preprocessed.columns
```

```
[ ]: Index(['loan_amnt', 'term', 'batch_enrolled', 'int_rate', 'grade', 'sub_grade',
        'emp_title', 'emp_length', 'home_ownership', 'annual_inc',
        'verification_status', 'purpose', 'title', 'zip_code', 'addr_state',
        'dti', 'delinq_2yrs', 'inq_last_6mths', 'open_acc', 'pub_rec',
        'revol_bal', 'revol_util', 'total_acc', 'initial_list_status',
        'total_rec_int', 'total_rec_late_fee', 'recoveries',
        'collection_recovery_fee', 'collections_12_mths_ex_med',
        'last_week_pay', 'acc_now_delinq', 'tot_coll_amt', 'tot_cur_bal',
        'total_rev_hi_lim', 'loan_status', 'paybility'],
       dtype='object')
```

6 Result summary in tabular form

Model

Hyperparameter

Validation Auc

Logistic regression classifier

C = 1

0.879

GBDT classifier

n_estimators = 200 , learning_rate = 0.3

0.9398

Random Forest

n_estimators = 100 , max_depth = 50

0.839

6.0.1 so gbdt shows best auc score of 0.9398 with least overfitting so we will choose gbdt model to predict our submissions

```
[ ]: def text_operations(features):
       for i in features:
         train_data_preprocessed[i] = train_data_preprocessed[i].map(lambda x: x.
      ↪lower().replace(' ','_'))
```

```
[ ]: text_operations(['term','batch_enrolled','grade','sub_grade','emp_title','emp_length'
     ,'home_ownership','verification_status','purpose','title'
     ,'zip_code','addr_state','initial_list_status'
     ,'last_week_pay'])
```

[ ]:
```
def predict_paybility(row):
  annual_inc = row.annual_inc
  if row.annual_inc == 0:
    #small value to ignore log(0) error
    annual_inc = 0.0001
  return (math.log(row.loan_amnt + (float(row.term.split('_')[0]) * row.
↪int_rate)) + 0.00001 )/math.log(annual_inc)
```

[ ]:
```
import math
from scipy.sparse import hstack
from sklearn.externals import joblib
def load_predict():
  test_data = pd.read_csv('test_indessa.csv')
  member_id = test_data.member_id

  # select selected features which is in train_preprocessing
  test_data = test_data[['loan_amnt', 'term', 'batch_enrolled', 'int_rate',␣
↪'grade', 'sub_grade',
        'emp_title', 'emp_length', 'home_ownership', 'annual_inc',
        'verification_status', 'purpose', 'title', 'zip_code', 'addr_state',
        'dti', 'delinq_2yrs', 'inq_last_6mths', 'open_acc', 'pub_rec',
        'revol_bal', 'revol_util', 'total_acc', 'initial_list_status',
        'total_rec_int', 'total_rec_late_fee', 'recoveries',
        'collection_recovery_fee', 'collections_12_mths_ex_med',
        'last_week_pay', 'acc_now_delinq', 'tot_coll_amt', 'tot_cur_bal',
        'total_rev_hi_lim']]

  #replace nan and black spaces in batch enrolled
  test_data['batch_enrolled'] = test_data['batch_enrolled'].fillna('unknown')
  test_data['batch_enrolled'] = test_data['batch_enrolled'].map(lambda x:␣
↪'blank' if x == ' ' else x)

  # fill nan values
  median_value_features = pickle.load(open('save_feature_median_value.pickle',␣
↪'rb'))
  max_value_features = pickle.load(open('save_feature_max_value.pickle', 'rb'))
  for i in median_value_features.keys():
    test_data[i] = test_data[i].fillna(median_value_features[i])
  for j in max_value_features.keys():
    test_data[j] = test_data[j].fillna(max_value_features[j])

  #preprocess categorica data
  cat_features =␣
↪['term','batch_enrolled','grade','sub_grade','emp_title','emp_length'
  ,'home_ownership','verification_status','purpose','title'
  ,'zip_code','addr_state','initial_list_status'
  ,'last_week_pay']
```

```python
for i in cat_features:
    test_data[i] = test_data[i].map(lambda x: x.lower().replace(' ','_'))

#create new feature
test_data['paybility'] =  test_data.apply(lambda row: predict_paybility(row),␣
↪axis=1)

#normalize numerical features
numerical_features = ['loan_amnt', 'int_rate',
      'annual_inc', 'dti', 'delinq_2yrs', 'inq_last_6mths', 'open_acc',
      'pub_rec', 'revol_bal', 'revol_util', 'total_acc', 'total_rec_int',
      'total_rec_late_fee', 'recoveries', 'collection_recovery_fee',
      'collections_12_mths_ex_med', 'acc_now_delinq', 'tot_coll_amt',
      'tot_cur_bal', 'total_rev_hi_lim','paybility']
normelizer_scaler = pickle.load(open('normelizers_numeric.pkl', 'rb'))
test_data_numerical_features = test_data[numerical_features].values
test_data_numerical = normelizer_scaler.
↪transform(test_data_numerical_features)

#one hot encode categorical features
categorical_features =␣
↪['term','batch_enrolled','grade','sub_grade','emp_title','emp_length'
,'home_ownership','verification_status','purpose','title'
,'zip_code','addr_state','initial_list_status'
,'last_week_pay']
for i in categorical_features:
  vector = pickle.load(open(f'vectorizers/vectorizer_{i}.pkl', 'rb'))
  test_feature = vector.transform(test_data[i].values.reshape(-1,1))
  globals()[f"test_feature_{i}"] = test_feature

test_data_final = hstack((test_data_numerical , test_feature_term␣
↪,test_feature_batch_enrolled,test_feature_grade,test_feature_sub_grade,test_feature_emp_tit
␣
↪,test_feature_home_ownership,test_feature_verification_status,test_feature_purpose,test_fea
␣
↪,test_feature_zip_code,test_feature_addr_state,test_feature_initial_list_status
,test_feature_last_week_pay )).tocsr()

#predict probablities
xgbClf = joblib.load('xgb_model.joblib')
y_probabilities = batch_predict(xgbClf , test_data_final )
test_submission_df = pd.DataFrame({'member_id':member_id, 'loan_status':
↪y_probabilities})
test_submission_df.to_csv('test_submission.csv')
test_submission_df.head()
```

```
load_predict()
```

[ ]:

	member_id	loan_status
0	11937648	0.410839
1	38983318	0.291551
2	27999917	0.164921
3	61514932	0.206364
4	59622821	0.304588

[ ]:

```
```