Loan Defaulter Prediction

Problem Statement

- The Bank Indessa has not done well in last 3 quarters. Their NPAs (Non Performing Assets) have reached all time high. It is starting to lose confidence of its investors. As a result, it's stock has fallen by 20% in the previous quarter alone.
- After careful analysis, it was found that the majority of NPA was contributed by loan defaulters. With the messy data collected
 over all the years, this bank has decided to use machine learning to figure out a way to find these defaulters and devise a plan to
 reduce them.
- This bank uses a pool of investors to sanction their loans. For example: If any customer has applied for a loan of \$20000, along with bank, the investors perform a due diligence on the requested loan application. Keep this in mind while understanding data.
- In this challenge, you will help this bank by predicting the probability that a member will default.

Data Acquisition:

Download the dataset from the following link: https://drive.google.com/drive/folders/15rWe7Mq7BgEyTQ7OZKLK-avJ0L9oveXP? usp=sharing

Machine Learning task:

• Binary Classification (Defaulter:1, Non- Defaulter:0)

Evaluation Metric:

• Since the data was imbalanced, So , metric used is ROC-AUC

Approach

- Load data
- · Exploratory Data Analysis
- · Transform data (data cleansing)
- · Handling Missing value
- Categorize/Dummify
- Split train and cross validation sets
- · Modelling using different models
- Predict

In [1]:

cd drive/My\ Drive/Artivatic

/content/drive/My Drive/Artivatic

In [2]:

```
!pip install catboost
```

```
Requirement already satisfied: catboost in /usr/local/lib/python3.6/dist-packages (0.23.2)
Requirement already satisfied: plotly in /usr/local/lib/python3.6/dist-packages (from catboost)
(4.4.1)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.6/dist-packages (from
catboost) (3.2.2)
Requirement already satisfied: numpy>=1.16.0 in /usr/local/lib/python3.6/dist-packages (from
catboost) (1.18.5)
Requirement already satisfied: pandas>=0.24.0 in /usr/local/lib/python3.6/dist-packages (from
catboost) (1.0.5)
Requirement already satisfied: scipy in /usr/local/lib/python3.6/dist-packages (from catboost)
(1.4.1)
Requirement already satisfied: six in /usr/local/lib/python3.6/dist-packages (from catboost)
(1.12.0)
Requirement already satisfied: graphviz in /usr/local/lib/python3.6/dist-packages (from catboost)
(0.10.1)
```

```
Requirement aiready satisfied: retrying>=1.3.3 in /usr/local/lib/python3.6/dist-packages (from plotly->catboost) (1.3.3)

Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.6/dist-packages (from matplotlib->catboost) (0.10.0)

Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python3.6/dist-packages (from matplotlib->catboost) (2.8.1)

Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /usr/local/lib/python3.6/dist-packages (from matplotlib->catboost) (2.4.7)

Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.6/dist-packages (from matplotlib->catboost) (1.2.0)

Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.6/dist-packages (from pandas>=0.24.0->catboost) (2018.9)
```

In [3]:

```
import nltk
nltk.download('stopwords')
import numpy as np
import pandas as pd
from sklearn.model selection import train test split
from sklearn.preprocessing import StandardScaler
\# Using GridSearchCV to find the best algorithm for this problem
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import ShuffleSplit
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.metrics import confusion matrix, classification report, accuracy score
# Importing essential libraries for visualization
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import pandas as pd
import seaborn as sns
import numpy as np
import xgboost as xgb
from tqdm import tqdm
from sklearn.svm import SVC
from keras.models import Sequential
from keras.layers.recurrent import LSTM, GRU
from keras.layers.core import Dense, Activation, Dropout
from keras.layers.embeddings import Embedding
from keras.layers.normalization import BatchNormalization
from keras.utils import np utils
from sklearn import preprocessing, decomposition, model selection, metrics, pipeline
from sklearn.model_selection import GridSearchCV
from sklearn.feature extraction.text import TfidfVectorizer, CountVectorizer
from sklearn.decomposition import TruncatedSVD
from sklearn.linear_model import LogisticRegression
from sklearn.model selection import train test split
from sklearn.naive_bayes import MultinomialNB
from keras.layers import GlobalMaxPooling1D, Conv1D, MaxPooling1D, Flatten, Bidirectional, SpatialD
from keras.preprocessing import sequence, text
from keras.callbacks import EarlyStopping
from nltk import word tokenize
from nltk.corpus import stopwords
stop words = stopwords.words('english')
from sklearn.metrics import roc curve, auc
# Configure visualisations
%matplotlib inline
sns.set style('white')
```

[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk data] Package stopwords is already up-to-date!

/usr/local/lib/python3.6/dist-packages/statsmodels/tools/_testing.py:19: FutureWarning: pandas.util.testing is deprecated. Use the functions in the public API at pandas.testing instead. import pandas.util.testing as tm
Using TensorFlow backend.

```
In [4]:
train = pd.read csv('train indessa.csv')
test= pd.read csv('test indessa.csv')
submission = pd.read csv('sample submission.csv')
In [5]:
test_member_id = pd.DataFrame(test['member_id'])
In [6]:
# Class Label : Binary Classification
train target = pd.DataFrame(train['loan status'])
In [7]:
train target['loan status'].value counts()
Out[7]:
0
      406601
     125827
Name: loan status, dtype: int64
In [8]:
train.head()
Out[8]:
   member id loan amnt funded amnt funded amnt inv
                                                           term batch enrolled int rate grade sub grade
                                                                                                                emp title emp leng
     58189336
 0
                    14350
                                 14350
                                                 14350.0
                                                                                   19.19
                                                                                             Ε
                                                                                                       E3
                                                                                                                    clerk
                                                                                                                              9 ye
                                                                                                                  Human
                                                             36
     70011223
                     4800
                                                  4800.0
                                                                    BAT1586599
                                  4800
                                                                                   10.99
                                                                                             В
                                                                                                       B4
                                                                                                               Resources
                                                                                                                              < 1 y
                                                                                                                Specialist
                                                 10000.0 months
     70255675
                    10000
                                 10000
                                                                    BAT1586599
                                                                                    7.26
                                                                                                                   Driver
                                                                                                        A4
                                                                                                                              2 ye
                                                                                                              Us office of
                                                 15000.0 months
      1893936
                    15000
                                 15000
                                                                    BAT4808022
                                                                                   19.72
                                                                                                               Personnel
                                                                                                                            10+ ye
                                                                                                             Management
                                                                                                                 LAUSD-
                                                 16000.0 months
                                                             36
                                                                                                           HOLLYWOOD
      7652106
                                                                    BAT2833642
                                                                                             В
                                                                                                       B2
                    16000
                                 16000
                                                                                   10 64
                                                                                                                            10+ ye
                                                                                                                   HIGH
                                                                                                                SCHOOL
In [9]:
train.columns
Out[9]:
Index(['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', 'deling 2yrs', 'ing_last_6mths', 'mths_since_last_deling',
         '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_deling', 'tot_coll_amt', 'tot_cur_bal', 'total_rev_hi_lim',
         'loan_status'],
```

```
dtype= object')
```

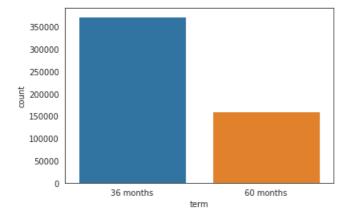
DATA PREPROCESSING

Term feature

```
In [10]:
```

```
ax = sns.countplot(x=train['term'], data=train)
print(train['term'].value_counts())
```

36 months 372793 60 months 159635 Name: term, dtype: int64



In [11]:

```
train['term'].replace(to_replace=' months', value='', regex=True, inplace=True)
test['term'].replace(to_replace=' months', value='', regex=True, inplace=True)

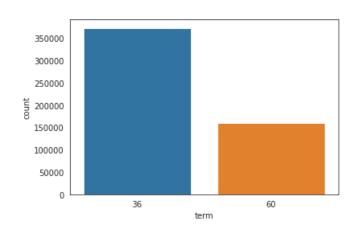
# Convert it to numeric
train['term'] = pd.to_numeric(train['term'], errors='coerce')
test['term'] = pd.to_numeric(test['term'], errors='coerce')
```

In [12]:

```
ax = sns.countplot(x=train['term'], data=train)
print(train['term'].value_counts())
```

36 372793 60 159635

Name: term, dtype: int64



.

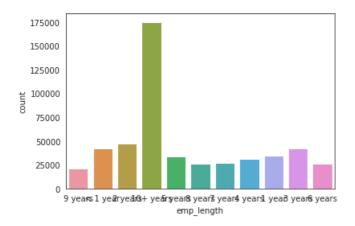
Emp length feature

• employment length, where 0 means less than one year and 10 means ten or more years

In [13]:

```
ax = sns.countplot(x=train['emp_length'], data=train)
print(train['emp_length'].value_counts())
```

```
10+ years 175105
            47276
2 years
            42253
< 1 year
            42175
3 vears
1 year
             34202
            33393
5 years
4 years
            31581
            26680
7 years
            26443
8 years
             25741
6 years
            20688
9 years
Name: emp length, dtype: int64
```



In [14]:

```
train['emp_length'].replace('n/a', '0', inplace=True)
train['emp_length'].replace(to_replace='\+ years', value='', regex=True, inplace=True)
train['emp_length'].replace(to_replace=' years', value='0', regex=True, inplace=True)
train['emp_length'].replace(to_replace='< 1 year', value='0', regex=True, inplace=True)
train['emp_length'].replace(to_replace=' year', value='', regex=True, inplace=True)

test['emp_length'].replace(to_replace='\+ years', value='', regex=True, inplace=True)
test['emp_length'].replace(to_replace=' years', value='', regex=True, inplace=True)
test['emp_length'].replace(to_replace='< 1 year', value='0', regex=True, inplace=True)
test['emp_length'].replace(to_replace=' year', value='', regex=True, inplace=True)

# Convert it to numeric
train['emp_length'] = pd.to_numeric(train['emp_length'], errors='coerce')
test['emp_length'] = pd.to_numeric(test['emp_length'], errors='coerce')</pre>
```

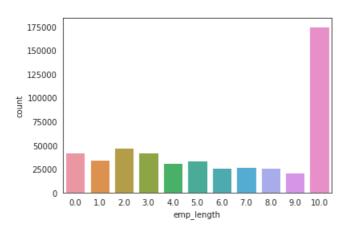
In [15]:

9.0

20688

```
ax = sns.countplot(x=train['emp_length'], data=train)
print(train['emp length'].value counts())
10.0 175105
2.0
       47276
0.0
        42253
3.0
        42175
1.0
        34202
       33393
5.0
       31581
4.0
       26680
7.0
8.0
       26443
6.0
        25741
```

Name: emp_length, dtype: int64



sub grade feature

• grade assigned by the bank

In [16]:

```
ax = sns.countplot(x=train['sub_grade'], data=train)
print(train['sub_grade'].value_counts())
вз
      33844
В4
      33198
C1
      31975
C2
      31356
СЗ
      30080
В2
      29390
В5
      29313
C4
      29103
A5
      27016
В1
      26968
C5
      24985
      21712
D1
Α4
      20823
      17991
D2
D3
      15771
D4
      15226
АЗ
      14082
Α1
      13653
Α2
      13533
D5
      12867
E1
      10928
      10255
E2
E3
       8488
E4
       7051
E5
       5773
F1
       4350
F2
       3196
       2708
F3
F4
       2056
F5
       1516
G1
       1112
G2
        824
G3
        559
G4
        391
G5
        335
Name: sub_grade, dtype: int64
  35000
  30000
  25000
  20000
```

```
15000

10000

5000

EB4ADBABIAD4CDAACDEBAXXEDBF#EEF4F54G55G52

sub_grade
```

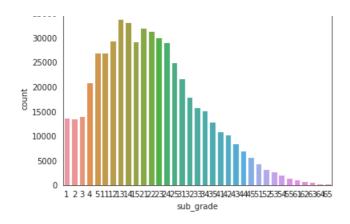
In [17]:

```
train['sub grade'].replace(to replace='A', value='0', regex=True, inplace=True)
train['sub_grade'].replace(to_replace='B', value='1', regex=True, inplace=True)
train['sub_grade'].replace(to_replace='C', value='2', regex=True, inplace=True)
train['sub grade'].replace(to replace='D', value='3', regex=True, inplace=True)
train['sub grade'].replace(to replace='E', value='4', regex=True, inplace=True)
train['sub grade'].replace(to replace='F', value='5', regex=True, inplace=True)
train['sub grade'].replace(to replace='G', value='6', regex=True, inplace=True)
test['sub grade'].replace(to replace='A', value='0', regex=True, inplace=True)
test['sub_grade'].replace(to_replace='B', value='1', regex=True, inplace=True)
test['sub_grade'].replace(to_replace='C', value='2', regex=True, inplace=True)
test['sub_grade'].replace(to_replace='D', value='3', regex=True, inplace=True)
test['sub_grade'].replace(to_replace='E', value='4', regex=True, inplace=True)
test['sub_grade'].replace(to_replace='F', value='5', regex=True, inplace=True)
test['sub grade'].replace(to replace='G', value='6', regex=True, inplace=True)
# Convert it to numeric
train['sub grade'] = pd.to numeric(train['sub grade'], errors='coerce')
test['sub grade'] = pd.to numeric(test['sub grade'], errors='coerce')
```

In [18]:

Name: sub grade, dtype: int64

35000 Г



last_week_pay feature

```
In [19]:
```

```
train['last_week_pay'].replace(to_replace='th week', value='', regex=True, inplace=True)
test['last_week_pay'].replace(to_replace='th week', value='', regex=True, inplace=True)

train['last_week_pay'].replace(to_replace='NA', value='', regex=True, inplace=True)
test['last_week_pay'].replace(to_replace='NA', value='', regex=True, inplace=True)

# Convert it to numeric
train['last_week_pay'] = pd.to_numeric(train['last_week_pay'], errors='coerce')
test['last_week_pay'] = pd.to_numeric(test['last_week_pay'], errors='coerce')
```

Handling Missing Values or NaN's

In [20]:

```
train.isnull().sum()
```

Out[20]:

```
0
member id
loan amnt
                                     0
funded amnt
                                     0
funded_amnt_inv
                                     0
                                     0
                                85149
batch enrolled
int rate
grade
                                     0
sub grade
                                    0
                                30833
emp title
                                26891
emp length
home_ownership
                                    0
annual inc
                                     3
verification_status
                                    0
pymnt_plan
                                    0
desc
                               456829
purpose
                                    Ω
                                   90
title
zip code
                                    0
addr_state
                                    Ω
dti
deling 2yrs
                                   16
ing last 6mths
                                   16
mths since last delinq
                               272554
mths_since_last_record
                               450305
open acc
                                   16
pub rec
                                   16
revol_bal
                                    Ω
                                   287
revol_util
total_acc
                                   16
initial_list_status
                                    0
total_rec_int
total_rec_late_fee
                                     0
recoveries
                                     0
```

```
0
collection_recovery_fee
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
                                  10614
acc now deling
                                       16
tot coll amt
                                   42004
tot cur bal
                                   42004
total_rev_hi_lim
                                   42004
loan_status
                                       0
dtype: int64
```

In [21]:

```
test.isnull().sum()
```

Out[21]:

Out[21]:	
member id	0
loan_amnt	0
funded amnt	0
funded amnt inv	0
term	0
batch enrolled	45599
int rate	0
grade	0
sub_grade	0
emp_title	20629
emp length	17934
home ownership	0
annual inc	1
verification status	0
pymnt_plan	0
desc	304770
purpose	0
title	62
zip code	0
addr state	0
dti	0
delinq 2yrs	13
inq_last_6mths	13
mths_since_last_delinq	181758
mths since last record	300021
open acc	13
pub rec	13
revol_bal	0
revol util	215
total_acc	13
initial list status	0
total rec int	0
total rec late fee	0
recoveries	0
collection recovery fee	0
collections_12_mths_ex_med	50
mths since last major derog	266228
application type	0
verification status joint	354745
last week pay	7045
acc_now_delinq	13
tot_coll_amt	28272
tot cur bal	28272
total_rev_hi_lim	28272
dtype: int64	20212
aclbe. THEOA	

Getting the columns having nulls

In [22]:

```
#Droping columns based on number of empty values
#for TRAINING data
colsDropped = []
for col_names in train.columns:
```

```
if(train[col names].isnull().sum() > 0):
        colsDropped.append(col_names)
print(colsDropped)
['batch_enrolled', 'emp_title', 'emp_length', 'annual_inc', 'desc', 'title', 'delinq_2yrs',
'inq_last_6mths', 'mths_since_last_delinq', 'mths_since_last_record', 'open_acc', 'pub_rec',
'revol util', 'total acc', 'collections 12 mths ex med', 'mths since last major derog',
'verification_status_joint', 'last_week_pay', 'acc_now_delinq', 'tot_coll_amt', 'tot_cur_bal', 'to
tal rev hi lim']
In [23]:
#Droping columns based on number of empty values
#for TESTING data
colsDropped = []
for col_names in test.columns:
    if(train[col names].isnull().sum() > 0):
        colsDropped.append(col_names)
print(colsDropped)
['batch enrolled', 'emp title', 'emp length', 'annual inc', 'desc', 'title', 'deling 2yrs',
'inq_last_6mths', 'mths_since_last_delinq', 'mths_since_last_record', 'open_acc', 'pub_rec',
'revol_util', 'total_acc', 'collections_12_mths_ex_med', 'mths_since_last_major_derog',
'verification status joint', 'last week pay', 'acc now deling', 'tot coll amt', 'tot cur bal', 'to
tal rev hi lim']
In [24]:
cate_cols = ['term', 'loan_amnt', 'funded_amnt', 'last_week_pay', 'int_rate', 'sub_grade', 'annual_
inc', 'dti', 'mths since last delinq', 'mths since last record', 'open acc', 'revol bal', 'revol ut
il', 'total_acc', 'total_rec_int', 'mths_since_last_major_derog', 'tot_coll_amt', 'tot_cur_bal', 't
otal_rev_hi_lim', 'emp_length']
for col in cate_cols:
    train[col].fillna(train[col].median(), inplace=True)
    test[col].fillna(test[col].median(), inplace=True)
num cols = ['acc now deling', 'total rec late fee', 'recoveries', 'collection recovery fee', 'colle
ctions 12 mths ex med']
for col in num_cols:
    train[col].fillna(0, inplace=True)
    test[col].fillna(0, inplace=True)
In [25]:
cat attr = ['home ownership', 'purpose']
for cat in cat attr:
   df col = [cat]
   train[cat] = train[cat].astype("category")
   train[cat] = pd.get dummies(train, columns=df col)
   test[cat] = test[cat].astype("category")
   test[cat] = pd.get dummies(test, columns=df col)
Feature Enginering
In [26]:
train.columns
Out[26]:
Index(['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_deling', 'tot_coll_amt', 'tot_cur_bal', 'total_rev_hi_lim',
               'loan status'],
            dtype='object')
In [27]:
finalTrain=train.copy()
finalTrain = finalTrain.drop(['loan_status'],axis=1)
finalTest=test.copy()
In [28]:
finalTrain.shape , finalTest.shape
Out[28]:
((532428, 44), (354951, 44))
In [29]:
import math
# How big the loan a person has taken with respect to his earnings, annual income to fund by bank
ratio
finalTrain['income to loan'] =
np.round (finalTrain['annual inc']/finalTrain['funded amnt'], decimals = 2)
finalTest['income_to_loan'] = np.round_(finalTest['annual_inc']/finalTest['funded_amnt'], decimals
# How big the loan a person has taken with respect to his earnings, annual income to fund by inves
tors ratio
finalTrain['income to loan inv'] = np.round (finalTrain['annual inc']/finalTrain['funded amnt inv']
], decimals = 2)
finalTest['income to loan inv'] = np.round (finalTest['annual inc']/finalTest['funded amnt inv'],d
ecimals = 2)
# Interest paid so far = interest received till date + Late fee received till date
finalTrain['total_int_paid'] = finalTrain['total_rec_int'] + finalTrain['total_rec_late_fee']
finalTest['total_int_paid'] = finalTest['total_rec_int'] + finalTest['total_rec_late_fee']
# Calculating EMIs (monthly)
\#EMI = [P \times R \times (1+R)^N]/[(1+R)^N-1]
P_tr=finalTrain['loan_amnt']
r_tr=finalTrain['int_rate'] /(100*12)
n tr=finalTrain['term']
P te=finalTest['loan amnt']
r te=finalTest['int rate'] /(100*12)
n te=finalTest['term']
\label{eq:finalTrain['emi_per_month'] = np.round_((P_tr * r_tr * (1+r_tr)**n_tr)/((1+r_tr)**(n_tr)-1), decimal Train['emi_per_month'] = np.round_((P_tr * r_tr * (1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+r_tr)**n_tr)/((1+
final Test['emi per month'] = np.round ((P te * r te * (1+r te)**n te)/((1+r te)**(n te)-1), decimals
```

In [30]:

)*100.decimals = 2)

0), decimals = 2)

```
finalTrain.shape, finalTest.shape
```

finalTrain['emi paid perc'] = np.round (((finalTrain['last week pay'])/(finalTrain['term']/12*52+1)

finalTest['emi paid perc'] = np.round (((finalTest['last week pay']/(finalTest['term']/12*52+1))*10

Calculating EMIs paid (in terms of percent)np.round (in array, decimals = 3)

Vectorising 'batch_enrolled' feature

In [31]:

In [32]:

```
# x_tr.shape , x_te.shape
```

In [33]:

```
# df_tr = pd.DataFrame(x_tr.toarray(), columns=v.get_feature_names())
# df_te = pd.DataFrame(x_te.toarray(), columns=v.get_feature_names())
# res_train = pd.concat([finalTrain, df_tr], axis=1)
# res_test = pd.concat([finalTest, df_te], axis=1)
# res_train.drop('batch_enrolled',axis=1,inplace=True)
# res_test.drop('batch_enrolled',axis=1,inplace=True)
```

In [34]:

```
cols = ['grade','emp_title','verification_status_joint','verification_status','pymnt_plan','desc',
'purpose','title','zip_code','addr_state','initial_list_status', 'application_type']

for col in cols:
    finalTrain[col].fillna('missing', inplace=True)
    finalTest[col].fillna('missing', inplace=True)
```

In [35]:

```
finalTrain.fillna(0)
finalTest.fillna(0)
```

Out[35]:

	member_id	loan_amnt	funded_amnt	funded_amnt_inv	term	batch_enrolled	int_rate	grade	sub_grade	emp_title	emp_
0	11937648	14000	14000	14000.0	60	BAT4711174	16.24	С	25	Data Analyst	
1	38983318	16000	16000	16000.0	60	BAT4318899	9.49	В	12	Senior Database Administrator	
2	27999917	11050	11050	11050.0	60	BAT446479	15.61	D	31	Customer service representative	
3	61514932	35000	35000	34700.0	60	BAT4664105	12.69	С	22	ACCT OFFICER	
4	59622821	6500	6500	6500.0	36		6.89	Α	3	Paralegal	
354946	19145105	15000	15000	15000.0	36	BAT4217242	6.49	Α	2	Network administrator	

54949 53032475 20000 20000 20000.0 36 BAT3840785 7.26 A 4 Computer Engineer	354947	member_id	loan_amnt	funded_amnt	funded_amnt_inv	term	batch_enrolled	int ²⁵ rate	grade	sub_grade	emp _n atitle	emp
54950 994245 2700 2700 2450.0 60 0 7.49 A 4 Sandwiches 54951 rows × 49 columns	354948	903745	14000	14000	13975.0	60	BAT6117184	17.51	E	44		
54951 rows × 49 columns	354949	53032475	20000	20000	20000.0	36	BAT3840785	7.26	Α	4		
	354950	994245	2700	2700	2450.0	60	0	7.49	Α	4		
			olumns									

Credit Kisk

vectorising grade feature

finalTest.reset_index(inplace=True)

```
In [37]:
```

```
from sklearn.feature extraction.text import TfidfVectorizer
v = TfidfVectorizer(min df=3, max features=None,
            strip_accents='unicode', analyzer='word',token_pattern=r'\w{1,}',
            ngram_range=(1, 3), use_idf=1,smooth_idf=1,sublinear_tf=1,
            stop words = 'english')
x_tr = v.fit_transform(finalTrain['grade'])
x te = v.transform(finalTest['grade'])
print(x_tr.shape , x_te.shape)
df_tr = pd.DataFrame(x_tr.toarray(), columns=v.get_feature_names())
df_te = pd.DataFrame(x_te.toarray(), columns=v.get_feature_names())
res_train = pd.concat([finalTrain, df_tr], axis=1)
res test = pd.concat([finalTest, df te], axis=1)
res train.drop('grade',axis=1,inplace=True)
res_test.drop('grade',axis=1,inplace=True)
print(res_train.shape , res_test.shape)
(532428, 6) (354951, 6)
(532428, 55) (354951, 55)
```

vectorising emp_title feature

```
In [38]:
```

```
# preprocessed_grade_tr = []
# for i in res_train['emp_title']:
# preprocessed_grade_tr.append(i.replace(' ','_'))

# preprocessed_grade_te = []
# for i in res_test['emp_title']:
# preprocessed_grade_te.append(i.replace(' ','_'))
```

```
In [39]:
```

```
# res_train['clean_emp_title'] = preprocessed_grade_tr
# res_train.drop(['emp_title'], axis=1)
```

```
# res_test['clean_emp_title'] = preprocessed_grade_te
# res_test.drop(['emp_title'], axis=1)
```

In [40]:

Vectorise verification status

In [41]:

```
from sklearn.feature_extraction.text import TfidfVectorizer
v = TfidfVectorizer(min df=3, max features=None,
            \verb|strip_accents='unicode'|, analyzer='word'|, token_pattern=r'\setminus w\{1,\}'|,
            ngram range=(1, 3), use idf=1, smooth idf=1, sublinear tf=1,
            stop words = 'english')
x tr = v.fit transform(res train['verification status'])
x te = v.transform(res test['verification status'])
print(x tr.shape , x te.shape)
df tr = pd.DataFrame(x tr.toarray(), columns=v.get feature names())
df_te = pd.DataFrame(x_te.toarray(), columns=v.get_feature_names())
res train = pd.concat([res train, df tr], axis=1)
res_test = pd.concat([res_test, df_te], axis=1)
res train.drop('verification status',axis=1,inplace=True)
res test.drop('verification status',axis=1,inplace=True)
print(res train.shape , res test.shape)
(532428, 3) (354951, 3)
(532428, 57) (354951, 57)
```

Vectorising verification_status_joint

```
In [42]:
```

```
stop_words = 'english')

x_tr = v.fit_transform(res_train['verification_status_joint'])
x_te = v.transform(res_test['verification_status_joint'])

print(x_tr.shape , x_te.shape)

df_tr = pd.DataFrame(x_tr.toarray(), columns=v.get_feature_names())

df_te = pd.DataFrame(x_te.toarray(), columns=v.get_feature_names())

res_train = pd.concat([res_train, df_tr], axis=1)

res_test = pd.concat([res_test, df_te], axis=1)

res_test = pd.concat([res_test, df_te], axis=1)

res_test.drop('verification_status_joint',axis=1,inplace=True)

print(res_train.shape , res_test.shape)

(532428, 4) (354951, 4)
(532428, 60) (354951, 60)
```

Vectorise pymnt plan

In [43]:

```
from sklearn.feature_extraction.text import TfidfVectorizer
v = TfidfVectorizer(min df=3, max features=None,
            strip_accents='unicode', analyzer='word',token_pattern=r'\w{1,}',
            ngram_range=(1, 3), use_idf=1,smooth_idf=1,sublinear_tf=1,
            stop words = 'english')
x_tr = v.fit_transform(res_train['pymnt_plan'])
x te = v.transform(res test['pymnt plan'])
print(x tr.shape , x te.shape)
df_tr = pd.DataFrame(x_tr.toarray(), columns=v.get_feature_names())
df te = pd.DataFrame(x te.toarray(), columns=v.get feature names())
res train = pd.concat([res train, df tr], axis=1)
res test = pd.concat([res test, df te], axis=1)
res train.drop('pymnt plan',axis=1,inplace=True)
res_test.drop('pymnt_plan',axis=1,inplace=True)
print(res_train.shape , res_test.shape)
(532428, 2) (354951, 2)
(532428, 61) (354951, 61)
```

Vectorising title

In [44]:

```
# preprocessed_grade_tr = []
# for i in res_train['title']:
# preprocessed_grade_tr.append(i.replace(' ','_'))

# preprocessed_grade_te = []
# for i in res_test['title']:
# preprocessed_grade_te.append(i.replace(' ','_'))

# res_train['clean_title'] = preprocessed_grade_tr
# res_train.drop(['title'], axis=1)

# res_test['clean_title'] = preprocessed_grade_te
# res_test['clean_title'] = preprocessed_grade_te
```

```
# res_test.drop(['title'], axis=1)
```

In [45]:

In [46]:

```
# res_train.drop('title',axis=1,inplace=True)
# res_test.drop('title',axis=1,inplace=True)
```

Vectorising addr_state

In [47]:

```
from sklearn.feature_extraction.text import TfidfVectorizer
v = TfidfVectorizer(min df=3, max features=None,
            strip accents='unicode', analyzer='word', token pattern=r'\w{1,}',
            ngram_range=(1, 3), use_idf=1,smooth_idf=1,sublinear_tf=1,
            stop words = 'english')
x_tr = v.fit_transform(res_train['addr_state'])
x te = v.transform(res test['addr state'])
print(x tr.shape , x te.shape)
df_tr = pd.DataFrame(x_tr.toarray(), columns=v.get_feature_names())
df te = pd.DataFrame(x te.toarray(), columns=v.get feature names())
res train = pd.concat([res train, df tr], axis=1)
res_test = pd.concat([res_test, df_te], axis=1)
res train.drop('addr state',axis=1,inplace=True)
res test.drop('addr state',axis=1,inplace=True)
print(res train.shape , res test.shape)
(532428, 46) (354951, 46)
(532428, 106) (354951, 106)
```

Vectorising initial_list_status

```
In [48]:
```

```
from sklearn.feature_extraction.text import TfidfVectorizer
```

```
v = TfidfVectorizer(min df=3, max features=None,
            strip_accents='unicode', analyzer='word', token_pattern=r'\w{1,}',
            ngram_range=(1, 3), use_idf=1,smooth_idf=1,sublinear_tf=1,
            stop words = 'english')
x_tr = v.fit_transform(res_train['initial_list_status'])
x te = v.transform(res test['initial list status'])
print(x tr.shape , x te.shape)
df_tr = pd.DataFrame(x_tr.toarray(), columns=v.get_feature_names())
df te = pd.DataFrame(x te.toarray(), columns=v.get feature names())
res train = pd.concat([res train, df tr], axis=1)
res test = pd.concat([res test, df te], axis=1)
res_train.drop('initial_list_status',axis=1,inplace=True)
res_test.drop('initial_list_status',axis=1,inplace=True)
print(res_train.shape , res_test.shape)
(532428, 2) (354951, 2)
(532428, 107) (354951, 107)
```

Vectorising application_type

```
In [49]:
```

```
from sklearn.feature_extraction.text import TfidfVectorizer
v = TfidfVectorizer(min_df=3, max_features=None,
            strip_accents='unicode', analyzer='word',token_pattern=r'\w{1,}',
            ngram_range=(1, 3), use_idf=1,smooth_idf=1,sublinear_tf=1,
            stop words = 'english')
x_tr = v.fit_transform(res_train['application_type'])
x_te = v.transform(res_test['application_type'])
print(x tr.shape , x te.shape)
df tr = pd.DataFrame(x tr.toarray(), columns=v.get feature names())
df_te = pd.DataFrame(x_te.toarray(), columns=v.get_feature_names())
res train = pd.concat([res train, df tr], axis=1)
res test = pd.concat([res test, df te], axis=1)
res_train.drop('application_type',axis=1,inplace=True)
res test.drop('application type',axis=1,inplace=True)
print(res_train.shape , res_test.shape)
(532428, 2) (354951, 2)
(532428, 108) (354951, 108)
In [50]:
res_train.drop(['desc','zip_code','emp_title','title','batch_enrolled'], axis=1, inplace=True)
res_test.drop(['desc','zip_code','emp_title','title','batch_enrolled'], axis=1, inplace=True)
In [51]:
res train.tail()
Out[51]:
        index member_id loan_amnt funded_amnt_inv term int_rate sub_grade emp_length home_ownership ann
```

```
home_ownership
index
532424 532424
                       loan_amnt funded_amnt inv term int_rate sub_grade emp_length
532425 532425
                7357607
                           18725
                                      18725
                                                           60
                                                                20.80
                                                   18725.0
                                                                            41
                                                                                     8.0
                                                                                               7357607
532426 532426
               23182668
                           21000
                                      21000
                                                   21000.0
                                                                16.29
                                                                            32
                                                                                     1.0
                                                                                               23182668
532427 532427
                                                                            2
                                                                                     0.0
               46122259
                           10000
                                      10000
                                                   10000.0
                                                           36
                                                                 6.39
                                                                                               46122259
5 rows × 103 columns
In [52]:
def scaler():
    result = res train.copy()
    for feature name in res train.columns:
       max_value = res_train[feature_name].max()
        min_value = res_train[feature_name].min()
        result[feature_name] = (res_train[feature_name] - min_value) / (max_value - min_value)
    return result
In [53]:
def scaler te():
    result = res test.copy()
    for feature name in res test.columns:
        max_value = res_test[feature_name].max()
        min_value = res_test[feature_name].min()
        result[feature name] = (res test[feature name] - min value) / (max value - min value)
    return result
In [54]:
res_train_enc= scaler()
In [55]:
res test enc= scaler te()
Train-Test Split
In [56]:
from sklearn.model selection import train test split
# Split train and cross validation sets
X train, X test, y train, y test = train test split(np.array(res train enc), np.array(train target)
, test size=0.30)
eval set=[(X test, y test)]
In [57]:
X_train.shape, y_train.shape, X_test.shape, y_test.shape
Out [57]:
((372699, 103), (372699, 1), (159729, 103), (159729, 1))
In [126]:
#CATBoost
from sklearn.metrics import roc auc score
from catboost import CatBoostClassifier
cb clf = CatBoostClassifier(learning rate=0.1, n estimators=1000, subsample=0.70, max depth=5, scal
e pos weight=2.5, silent=True)
cb_clf.fit(X_train, y_train)
# evaluate predictions
v train predict ch = ch clf predict (Y train)
```

```
print('Train Accuracy %.3f' % metrics.accuracy_score(y_train, y_train_predict_cb))

# make predictions for test data
y_pred_cb = cb_clf.predict(X_test)
predictions = [round(value) for value in y_pred_cb]

accuracy_per_roc_auc = roc_auc_score(y_test, predictions)
print("ROC-AUC: %.10f%%" % (accuracy_per_roc_auc * 100))

print('Test Accuracy %.3f' % metrics.accuracy_score(y_test, predictions))
print(metrics.confusion_matrix(y_test, predictions))
print(metrics.classification_report(y_test, predictions))
print('Precision Score %.3f' % metrics.precision_score(y_test, predictions))
print('Recall Score %.3f' % metrics.recall_score(y_test, predictions))
print('Fl Score %.3f' % metrics.fl_score(y_test, predictions))
```

```
Train Accuracy 0.940
ROC-AUC: 93.3757372225%
Test Accuracy 0.939
[[115232 6919]
 [ 2850 34728]]
            precision
                       recall f1-score
                                        support
                0.98
                        0.94
                                  0.96
                                        122151
         1
                0.83
                        0.92
                                 0.88
                                          37578
                                  0.94
                                          159729
   accuracy
                                  0.92
                       0.93
  macro avg
                0.90
                                          159729
               0.94
                                 0.94
                         0.94
                                        159729
weighted avg
```

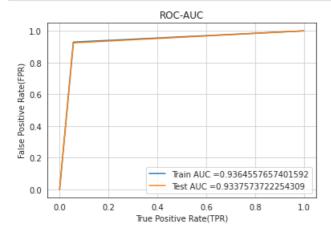
Precision Score 0.834 Recall Score 0.924 F1 Score 0.877

In [127]:

```
y_train_pred = cb_clf.predict(X_train)
y_test_pred = cb_clf.predict(X_test)

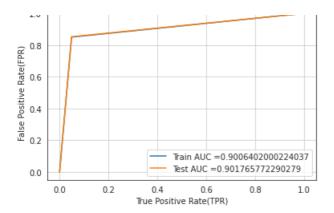
train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_pred)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_test_pred)

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("True Positive Rate(TPR)")
plt.ylabel("False Positive Rate(FPR)")
plt.title("ROC-AUC")
plt.grid()
plt.show()
```



In [128]:

```
from xgboost import XGBClassifier
xg = XGBClassifier(scale pos weight=2.5 ,silent=True)
xg.fit(X train, y train)
# evaluate predictions
y_train_predict_xg = xg.predict(X_train)
print('Train Accuracy %.3f' % metrics.accuracy_score(y_train, y_train_predict_xg))
# make predictions for test data
y_pred_xg = xg.predict(X_test)
predictions = [round(value) for value in y pred xg]
accuracy_per_roc_auc = roc_auc_score(y_test, predictions)
print("ROC-AUC: %.10f%%" % (accuracy per roc auc * 100))
print('Test Accuracy %.3f' % metrics.accuracy score(y test, predictions))
print(metrics.confusion_matrix(y_test, predictions))
print(metrics.classification_report(y_test, predictions))
print('Precision Score %.3f' % metrics.precision_score(y_test, predictions))
print('Recall Score %.3f' % metrics.recall_score(y_test, predictions))
print('F1 Score %.3f' % metrics.f1 score(y test, predictions))
/usr/local/lib/python3.6/dist-packages/sklearn/preprocessing/ label.py:235: DataConversionWarning:
A column-vector y was passed when a 1d array was expected. Please change the shape of y to
(n samples, ), for example using ravel().
 y = column or_1d(y, warn=True)
/usr/local/lib/python3.6/dist-packages/sklearn/preprocessing/ label.py:268: DataConversionWarning:
A column-vector y was passed when a 1d array was expected. Please change the shape of y to
(n_samples, ), for example using ravel().
 y = column_or_1d(y, warn=True)
Train Accuracy 0.927
ROC-AUC: 90.1765772290%
Test Accuracy 0.928
[[116167 5984]
[ 5542 32036]]
             precision recall f1-score support
           0
                 0.95 0.95
                                    0.95 122151
           1
                  0.84
                           0.85
                                     0.85
                                              37578
   accuracy
                                      0.93
                                              159729
                  0.90
                           0.90
                                     0.90
                                              159729
   macro avg
weighted avg
                  0.93
                           0.93
                                     0.93 159729
Precision Score 0.843
Recall Score 0.853
F1 Score 0.848
In [129]:
y train pred = xg.predict(X train)
y_test_pred = xg.predict(X_test)
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("True Positive Rate(TPR)")
plt.ylabel("False Positive Rate(FPR)")
plt.title("ROC-AUC")
plt.grid()
plt.show()
```



In [61]:

```
from sklearn.metrics import roc_auc_score
from lightgbm import LGBMClassifier
lgbm = LGBMClassifier(objective ="binary", verbosity = -1, learning rate=0.1, n estimators=1000, sca
le pos weight=2.5)
lgbm.fit(X_train, y_train)
# evaluate predictions
y_train_predict_lgbm = lgbm.predict(X_train)
print('Train Accuracy %.3f' % metrics.accuracy score(y train, y train predict lgbm))
# make predictions for test data
y_pred_lgbm = lgbm.predict(X_test)
predictions = [round(value) for value in y pred lgbm]
accuracy per roc auc = roc auc score(y test, predictions)
print("ROC-AUC: %.10f%%" % (accuracy_per_roc_auc * 100))
print('Test Accuracy %.3f' % metrics.accuracy_score(y_test, predictions))
print(metrics.confusion matrix(y test, predictions))
\verb|print(metrics.classification_report(y_test, predictions))|\\
print('Precision Score %.3f' % metrics.precision_score(y_test, predictions))
print('Recall Score %.3f' % metrics.recall_score(y_test, predictions))
print('F1 Score %.3f' % metrics.f1_score(y_test, predictions))
Train Accuracy 0.951
```

```
ROC-AUC: 93.2427178211%
Test Accuracy 0.938
[[115255
          6888]
 [ 2960 34626]]
                        recall f1-score
             precision
                                           support
          0
                  0.97
                          0.94
                                    0.96
                                             122143
                  0.83
                           0.92
                                     0.88
                                             37586
                                     0.94
                                             159729
   accuracy
                  0.90
                           0.93
                                    0.92
                                             159729
  macro avg
                                    0.94
                                             159729
weighted avg
                 0.94
                           0.94
```

Precision Score 0.834 Recall Score 0.921 F1 Score 0.875

Pickle all the models

In [87]:

```
#from sklearn.externals import joblib
```

```
# Save the moder as a pickle in a life
#joblib.dump(xg, 'xgboost.pkl')
#joblib.dump(cb_clf, 'catboost.pkl')
#joblib.dump(lgbm, 'lgbm.pkl')
Out[87]:
['lgbm.pkl']
In [84]:
# Please compare all your models using Prettytable library
# http://zetcode.com/python/prettytable/
from prettytable import PrettyTable
#If you get a ModuleNotFoundError error , install prettytable using: pip3 install prettytable
x = PrettyTable()
x.field names = ["Model Used", "ROC-AUC", "Test Accuracy(%)"]
x.add_row(["CatBoost Classifier", 93.37,93.9])
x.add_row(["XGBoost Classifier", 90.17, 92.8])
x.add_row(["LGBM Classifier", 93.24, 93.8])
print(x)
   -----+
     Model Used | ROC-AUC | Test Accuracy(%) |
+----+
| CatBoost Classifier | 93.37 | 93.9 | | XGBoost Classifier | 90.17 | 92.8 | | LGBM Classifier | 93.24 | 93.8 |
```

CONCLUSION:

- CatBoost is the clear winner here and all the models have done a good job.
- Performance can be increaded further by considering text features too which I had to ignore since it would make the dimensions
 huge and since the number of data points were also large, the system was crashing.
- So, even with these features and few of engineered features , the model is performing very good.

In []: