Loan Prediction

March 23, 2022

[ ]:
```
%%time
import warnings
warnings.filterwarnings('ignore')

import datatable as dt
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

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

```
Wall time: 1.04 s
```

use datatable to fast load the dataset

[ ]:
```
%%time
train = dt.fread('train.csv').to_pandas()

pd.set_option('display.max_columns', None)
train.head(3)
```

```
Wall time: 205 ms
```

[ ]:

	UNIQUEID	DISBURSED_AMOUNT	ASSET_COST	LTV	BRANCH_ID	SUPPLIER_ID	MANUFACTURER_ID	CURRENT_PINCODE_ID	DATE_OF_BIRTH	EMPLOYMENT_TYPE	DISBURSAL_DATE	STATE_ID	EMPLOYEE_CODE_ID	MOBILENO_AVL_FLAG	AADHAR_FLAG
0	420825	50578	58400	89.55	67	22807	45	1441	01-01-1984	Salaried	03-08-2018	6	1998	True	True
1	537409	47145	65550	73.23	67	22807	45	1502	31-07-1985	Self employed	26-09-2018	6	1998	True	True
2	417566	53278	61360	89.63	67	22807	45	1497	24-08-1985	Self employed	01-08-2018	6	1998	True	True

```
   PAN_FLAG  VOTERID_FLAG  DRIVING_FLAG  PASSPORT_FLAG  PERFORM_CNS_SCORE  \
0     False         False         False          False                  0
1     False         False         False          False                598
2     False         False         False          False                  0

  PERFORM_CNS_SCORE_DESCRIPTION  PRI_NO_OF_ACCTS  PRI_ACTIVE_ACCTS  \
0   No Bureau History Available                0                 0
1                 I-Medium Risk                1                 1
2   No Bureau History Available                0                 0

   PRI_OVERDUE_ACCTS  PRI_CURRENT_BALANCE  PRI_SANCTIONED_AMOUNT  \
0                  0                    0                      0
1                  1                27600                  50200
2                  0                    0                      0

   PRI_DISBURSED_AMOUNT  SEC_NO_OF_ACCTS  SEC_ACTIVE_ACCTS  SEC_OVERDUE_ACCTS  \
0                     0                0                 0                  0
1                 50200                0                 0                  0
2                     0                0                 0                  0

   SEC_CURRENT_BALANCE  SEC_SANCTIONED_AMOUNT  SEC_DISBURSED_AMOUNT  \
0                    0                      0                     0
1                    0                      0                     0
2                    0                      0                     0

   PRIMARY_INSTAL_AMT  SEC_INSTAL_AMT  NEW_ACCTS_IN_LAST_SIX_MONTHS  \
0                   0               0                             0
1                1991               0                             0
2                   0               0                             0

   DELINQUENT_ACCTS_IN_LAST_SIX_MONTHS AVERAGE_ACCT_AGE CREDIT_HISTORY_LENGTH  \
0                                    0        0yrs 0mon            0yrs 0mon
1                                    1       1yrs 11mon           1yrs 11mon
2                                    0        0yrs 0mon            0yrs 0mon

   NO_OF_INQUIRIES  LOAN_DEFAULT
0                0         False
1                0          True
2                0         False
```

[ ]:
```
# drop ID columns and passwords
train.drop(columns = ['UNIQUEID', 'EMPLOYEE_CODE_ID', 'CURRENT_PINCODE_ID',␣
 ↪'BRANCH_ID', 'SUPPLIER_ID', 'MANUFACTURER_ID'], inplace = True)
print('Name of columns:', list(train.columns))
```

```
Name of columns: ['DISBURSED_AMOUNT', 'ASSET_COST', 'LTV', 'DATE_OF_BIRTH',
'EMPLOYMENT_TYPE', 'DISBURSAL_DATE', 'STATE_ID', 'MOBILENO_AVL_FLAG',
```

```
'AADHAR_FLAG', 'PAN_FLAG', 'VOTERID_FLAG', 'DRIVING_FLAG', 'PASSPORT_FLAG',
'PERFORM_CNS_SCORE', 'PERFORM_CNS_SCORE_DESCRIPTION', 'PRI_NO_OF_ACCTS',
'PRI_ACTIVE_ACCTS', 'PRI_OVERDUE_ACCTS', 'PRI_CURRENT_BALANCE',
'PRI_SANCTIONED_AMOUNT', 'PRI_DISBURSED_AMOUNT', 'SEC_NO_OF_ACCTS',
'SEC_ACTIVE_ACCTS', 'SEC_OVERDUE_ACCTS', 'SEC_CURRENT_BALANCE',
'SEC_SANCTIONED_AMOUNT', 'SEC_DISBURSED_AMOUNT', 'PRIMARY_INSTAL_AMT',
'SEC_INSTAL_AMT', 'NEW_ACCTS_IN_LAST_SIX_MONTHS',
'DELINQUENT_ACCTS_IN_LAST_SIX_MONTHS', 'AVERAGE_ACCT_AGE',
'CREDIT_HISTORY_LENGTH', 'NO_OF_INQUIRIES', 'LOAN_DEFAULT']
```

[ ]:
```
from datetime import datetime, date

# This function converts given date to age
def age(born):
    born = datetime.strptime(born, "%d-%m-%Y").date()
    today = date.today()
    return today.year - born.year - ((today.month,
                                      today.day) < (born.month,
                                                    born.day))

for i in train[['DATE_OF_BIRTH', 'DISBURSAL_DATE']].columns:
    train[i] = train[i].apply(age)
```

[ ]:
```
train.rename(columns = {'DATE_OF_BIRTH':'Age', 'DISBURSAL_DATE':'DISBURSAL␣
 ↪Years'}, inplace=True)
train.head(3)
```

[ ]:

	DISBURSED_AMOUNT	ASSET_COST	LTV	Age	EMPLOYMENT_TYPE	DISBURSAL Years	\
0	50578	58400	89.55	38	Salaried	3	
1	47145	65550	73.23	36	Self employed	3	
2	53278	61360	89.63	36	Self employed	3	

	STATE_ID	MOBILENO_AVL_FLAG	AADHAR_FLAG	PAN_FLAG	VOTERID_FLAG	\
0	6	True	True	False	False	
1	6	True	True	False	False	
2	6	True	True	False	False	

	DRIVING_FLAG	PASSPORT_FLAG	PERFORM_CNS_SCORE	\
0	False	False	0	
1	False	False	598	
2	False	False	0	

	PERFORM_CNS_SCORE_DESCRIPTION	PRI_NO_OF_ACCTS	PRI_ACTIVE_ACCTS	\
0	No Bureau History Available	0	0	
1	I-Medium Risk	1	1	
2	No Bureau History Available	0	0	

```
   PRI_OVERDUE_ACCTS  PRI_CURRENT_BALANCE  PRI_SANCTIONED_AMOUNT  \
0                  0                    0                      0
1                  1                27600                  50200
2                  0                    0                      0

   PRI_DISBURSED_AMOUNT  SEC_NO_OF_ACCTS  SEC_ACTIVE_ACCTS  SEC_OVERDUE_ACCTS  \
0                     0                0                 0                  0
1                 50200                0                 0                  0
2                     0                0                 0                  0

   SEC_CURRENT_BALANCE  SEC_SANCTIONED_AMOUNT  SEC_DISBURSED_AMOUNT  \
0                    0                      0                     0
1                    0                      0                     0
2                    0                      0                     0

   PRIMARY_INSTAL_AMT  SEC_INSTAL_AMT  NEW_ACCTS_IN_LAST_SIX_MONTHS  \
0                   0              0                             0
1                1991              0                             0
2                   0              0                             0

   DELINQUENT_ACCTS_IN_LAST_SIX_MONTHS AVERAGE_ACCT_AGE CREDIT_HISTORY_LENGTH  \
0                                    0        0yrs 0mon             0yrs 0mon
1                                    1       1yrs 11mon            1yrs 11mon
2                                    0        0yrs 0mon             0yrs 0mon

   NO_OF_INQUIRIES  LOAN_DEFAULT
0                0         False
1                0          True
2                0         False
```

convert two datastamp columns to years

[ ]:
```
train[['AVERAGE_ACCT_Yr','AVERAGE_ACCT_Month']] = train['AVERAGE_ACCT_AGE'].str.
 ↪split("yrs",expand=True)
train[['AVERAGE_ACCT_Month','AVERAGE_ACCT_Month1']] =␣
 ↪train['AVERAGE_ACCT_Month'].str.split("mon",expand=True)
train["AVERAGE_ACCT_AGE"]= train["AVERAGE_ACCT_Yr"].astype(str).
 ↪astype(int)+((train["AVERAGE_ACCT_Month"].astype(str).astype(int))/12)
train= train.drop(columns=␣
 ↪["AVERAGE_ACCT_Yr","AVERAGE_ACCT_Month",'AVERAGE_ACCT_Month1'])
train[['CREDIT_HISTORY_LENGTH_Yr','CREDIT_HISTORY_LENGTH_Month']] =␣
 ↪train['CREDIT_HISTORY_LENGTH'].str.split("yrs",expand=True)
train[['CREDIT_HISTORY_LENGTH_Month','CREDIT_HISTORY_LENGTH_Month1']] =␣
 ↪train['CREDIT_HISTORY_LENGTH_Month'].str.split("mon",expand=True)
train["CREDIT_HISTORY_LENGTH"]= train["CREDIT_HISTORY_LENGTH_Yr"].astype(str).
 ↪astype(int)+((train["CREDIT_HISTORY_LENGTH_Month"].astype(str).astype(int))/
 ↪12)
```

```
train= train.drop(columns=␣
 ↪["CREDIT_HISTORY_LENGTH_Yr","CREDIT_HISTORY_LENGTH_Month",'CREDIT_HISTORY_LENGTH_Month1'])
```

cut the two string columns into numeric columns that indicates the time

[ ]:
```
train.describe()
```

[ ]:

	DISBURSED_AMOUNT	ASSET_COST	LTV	Age	\
count	233154.000000	2.331540e+05	233154.000000	233154.000000	
mean	54356.993528	7.586507e+04	74.746530	37.508016	
std	12971.314171	1.894478e+04	11.456636	9.834623	
min	13320.000000	3.700000e+04	10.030000	21.000000	
25%	47145.000000	6.571700e+04	68.880000	29.000000	
50%	53803.000000	7.094600e+04	76.800000	36.000000	
75%	60413.000000	7.920175e+04	83.670000	44.000000	
max	990572.000000	1.628992e+06	95.000000	72.000000	

	DISBURSAL Years	STATE_ID	PERFORM_CNS_SCORE	PRI_NO_OF_ACCTS	\
count	233154.0	233154.000000	233154.000000	233154.000000	
mean	3.0	7.262243	289.462994	2.440636	
std	0.0	4.482230	338.374779	5.217233	
min	3.0	1.000000	0.000000	0.000000	
25%	3.0	4.000000	0.000000	0.000000	
50%	3.0	6.000000	0.000000	0.000000	
75%	3.0	10.000000	678.000000	3.000000	
max	3.0	22.000000	890.000000	453.000000	

	PRI_ACTIVE_ACCTS	PRI_OVERDUE_ACCTS	PRI_CURRENT_BALANCE	\
count	233154.000000	233154.000000	2.331540e+05	
mean	1.039896	0.156549	1.659001e+05	
std	1.941496	0.548787	9.422736e+05	
min	0.000000	0.000000	-6.678296e+06	
25%	0.000000	0.000000	0.000000e+00	
50%	0.000000	0.000000	0.000000e+00	
75%	1.000000	0.000000	3.500650e+04	
max	144.000000	25.000000	9.652492e+07	

	PRI_SANCTIONED_AMOUNT	PRI_DISBURSED_AMOUNT	SEC_NO_OF_ACCTS	\
count	2.331540e+05	2.331540e+05	233154.000000	
mean	2.185039e+05	2.180659e+05	0.059081	
std	2.374794e+06	2.377744e+06	0.626795	
min	0.000000e+00	0.000000e+00	0.000000	
25%	0.000000e+00	0.000000e+00	0.000000	
50%	0.000000e+00	0.000000e+00	0.000000	
75%	6.250000e+04	6.080000e+04	0.000000	
max	1.000000e+09	1.000000e+09	52.000000	

	SEC_ACTIVE_ACCTS	SEC_OVERDUE_ACCTS	SEC_CURRENT_BALANCE	\
count	233154.000000	233154.000000	2.331540e+05	
mean	0.027703	0.007244	5.427793e+03	
std	0.316057	0.111079	1.702370e+05	
min	0.000000	0.000000	-5.746470e+05	
25%	0.000000	0.000000	0.000000e+00	
50%	0.000000	0.000000	0.000000e+00	
75%	0.000000	0.000000	0.000000e+00	
max	36.000000	8.000000	3.603285e+07	

	SEC_SANCTIONED_AMOUNT	SEC_DISBURSED_AMOUNT	PRIMARY_INSTAL_AMT	\
count	2.331540e+05	2.331540e+05	2.331540e+05	
mean	7.295923e+03	7.179998e+03	1.310548e+04	
std	1.831560e+05	1.825925e+05	1.513679e+05	
min	0.000000e+00	0.000000e+00	0.000000e+00	
25%	0.000000e+00	0.000000e+00	0.000000e+00	
50%	0.000000e+00	0.000000e+00	0.000000e+00	
75%	0.000000e+00	0.000000e+00	1.999000e+03	
max	3.000000e+07	3.000000e+07	2.564281e+07	

	SEC_INSTAL_AMT	NEW_ACCTS_IN_LAST_SIX_MONTHS	\
count	2.331540e+05	233154.000000	
mean	3.232684e+02	0.381833	
std	1.555369e+04	0.955107	
min	0.000000e+00	0.000000	
25%	0.000000e+00	0.000000	
50%	0.000000e+00	0.000000	
75%	0.000000e+00	0.000000	
max	4.170901e+06	35.000000	

	DELINQUENT_ACCTS_IN_LAST_SIX_MONTHS	AVERAGE_ACCT_AGE	\
count	233154.000000	233154.000000	
mean	0.097481	0.742980	
std	0.384439	1.258868	
min	0.000000	0.000000	
25%	0.000000	0.000000	
50%	0.000000	0.000000	
75%	0.000000	1.083333	
max	20.000000	30.750000	

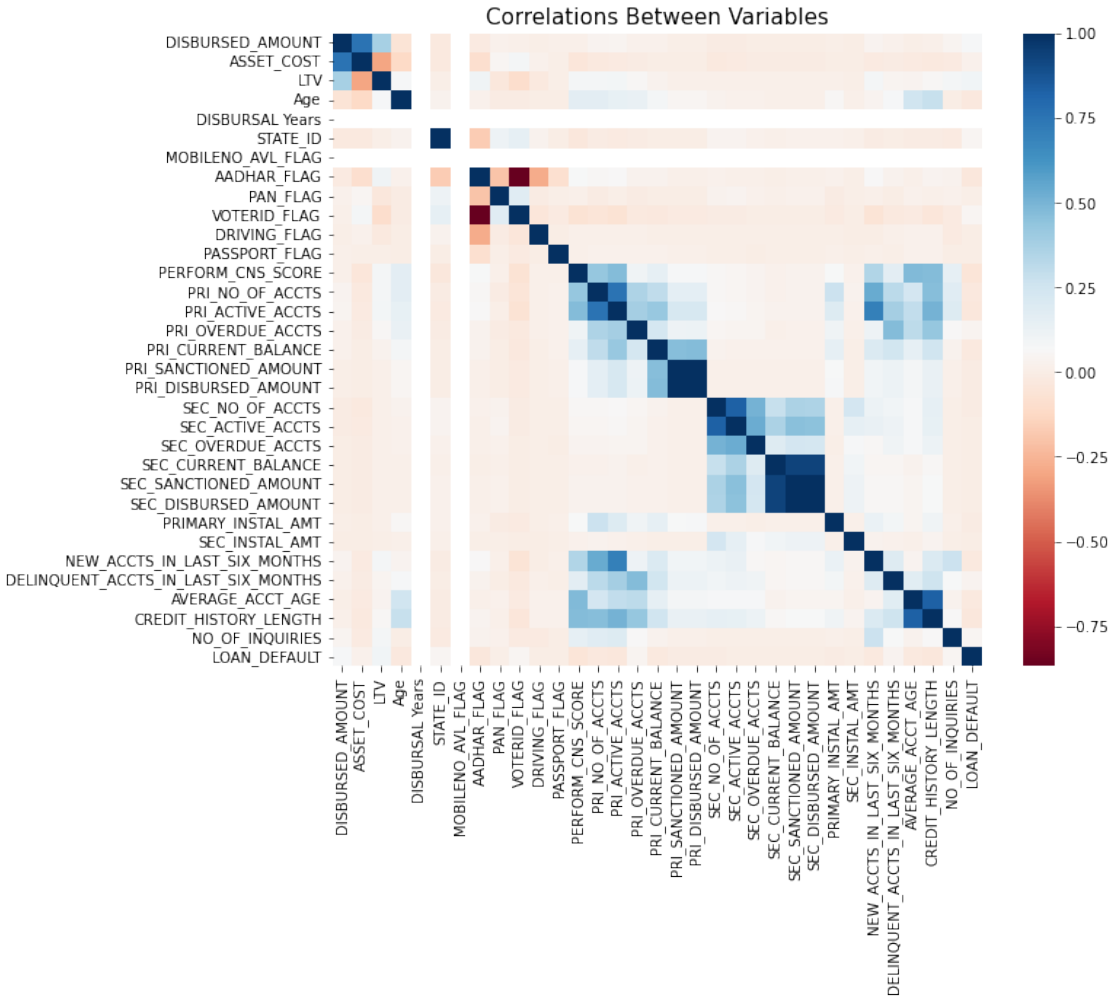
	CREDIT_HISTORY_LENGTH	NO_OF_INQUIRIES
count	233154.000000	233154.000000
mean	1.354367	0.206615
std	2.381771	0.706498
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	0.000000

```
75%                2.000000          0.000000
max               39.000000         36.000000
```

[ ]:
```
# check if there is missing value in any column
train[train.columns[train.isnull().any()]].isnull().sum()
```

[ ]:
```
Series([], dtype: float64)
```

[ ]:
```
plt.figure(figsize=(10,8))
sns.heatmap(train.corr(), cmap="RdBu")
plt.title("Correlations Between Variables", size=15)
plt.show()
```



Most variables are not highly correlated.

[ ]:
```
train['LOAN_DEFAULT'] = np.where((train.LOAN_DEFAULT == False), 0, train.
 ↪LOAN_DEFAULT)
train['LOAN_DEFAULT'] = np.where((train.LOAN_DEFAULT == True), 1, train.
 ↪LOAN_DEFAULT)
train.head()
# change the outcome variable into numeric binary form
```

[ ]:

	DISBURSED_AMOUNT	ASSET_COST	LTV	Age	EMPLOYMENT_TYPE	DISBURSAL Years
0	50578	58400	89.55	38	Salaried	3
1	47145	65550	73.23	36	Self employed	3
2	53278	61360	89.63	36	Self employed	3
3	57513	66113	88.48	28	Self employed	3
4	52378	60300	88.39	44	Self employed	3

	STATE_ID	MOBILENO_AVL_FLAG	AADHAR_FLAG	PAN_FLAG	VOTERID_FLAG
0	6	True	True	False	False
1	6	True	True	False	False
2	6	True	True	False	False
3	6	True	True	False	False
4	6	True	True	False	False

	DRIVING_FLAG	PASSPORT_FLAG	PERFORM_CNS_SCORE
0	False	False	0
1	False	False	598
2	False	False	0
3	False	False	305
4	False	False	0

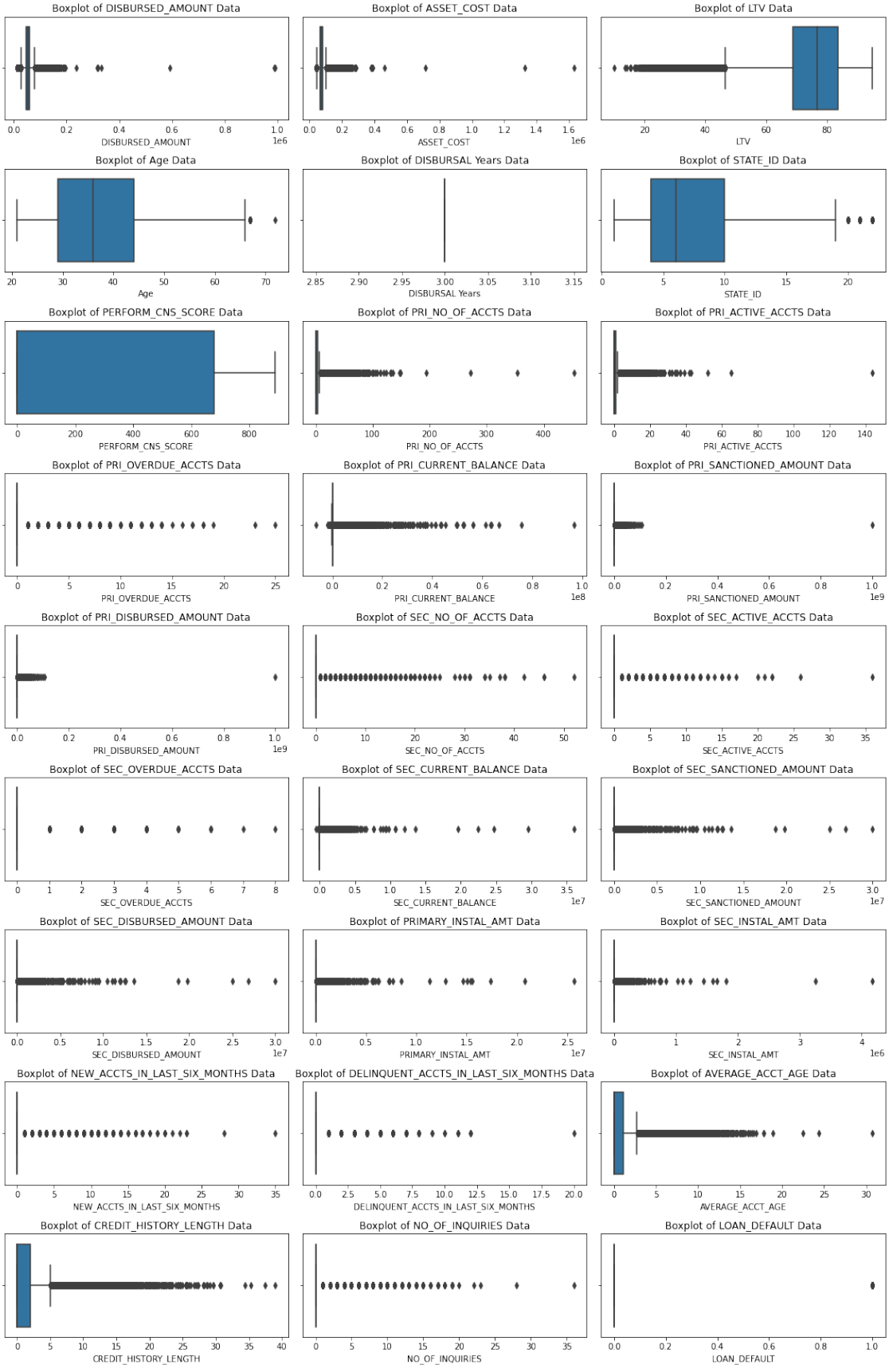
	PERFORM_CNS_SCORE_DESCRIPTION	PRI_NO_OF_ACCTS	PRI_ACTIVE_ACCTS
0	No Bureau History Available	0	0
1	I-Medium Risk	1	1
2	No Bureau History Available	0	0
3	L-Very High Risk	3	0
4	No Bureau History Available	0	0

	PRI_OVERDUE_ACCTS	PRI_CURRENT_BALANCE	PRI_SANCTIONED_AMOUNT
0	0	0	0
1	1	27600	50200
2	0	0	0
3	0	0	0
4	0	0	0

	PRI_DISBURSED_AMOUNT	SEC_NO_OF_ACCTS	SEC_ACTIVE_ACCTS	SEC_OVERDUE_ACCTS
0	0	0	0	0
1	50200	0	0	0
2	0	0	0	0
3	0	0	0	0

```
4                     0                 0                 0                     0

   SEC_CURRENT_BALANCE  SEC_SANCTIONED_AMOUNT  SEC_DISBURSED_AMOUNT  \
0                    0                      0                     0
1                    0                      0                     0
2                    0                      0                     0
3                    0                      0                     0
4                    0                      0                     0

   PRIMARY_INSTAL_AMT  SEC_INSTAL_AMT  NEW_ACCTS_IN_LAST_SIX_MONTHS  \
0                   0               0                             0
1                1991               0                             0
2                   0               0                             0
3                  31               0                             0
4                   0               0                             0

   DELINQUENT_ACCTS_IN_LAST_SIX_MONTHS  AVERAGE_ACCT_AGE  \
0                                    0          0.000000
1                                    1          1.916667
2                                    0          0.000000
3                                    0          0.666667
4                                    0          0.000000

   CREDIT_HISTORY_LENGTH  NO_OF_INQUIRIES  LOAN_DEFAULT
0               0.000000                0             0
1               1.916667                0             1
2               0.000000                0             0
3               1.250000                1             1
4               0.000000                1             1
```

[ ]:
```python
df_numeric = train.select_dtypes(include = np.number)
plt.figure(figsize=(15,25))
for i,col in enumerate(df_numeric.columns,1):
    plt.subplot(10,3,i)
    plt.title(f"Boxplot of {col} Data")
    sns.boxplot(train[col])
    plt.tight_layout()
    plt.plot()

# use boxplot to further investigate the numerical variables
```


Boxplot of DISBURSED_AMOUNT Data
DISBURSED_AMOUNT
1e6
Boxplot of ASSET_COST Data
ASSET_COST
1e6
Boxplot of LTV Data
LTV
Boxplot of Age Data
Age
Boxplot of DISBURSAL Years Data
DISBURSAL Years
Boxplot of STATE_ID Data
STATE_ID
Boxplot of PERFORM_CNS_SCORE Data
PERFORM_CNS_SCORE
Boxplot of PRI_NO_OF_ACCTS Data
PRI_NO_OF_ACCTS
Boxplot of PRI_ACTIVE_ACCTS Data
PRI_ACTIVE_ACCTS
Boxplot of PRI_OVERDUE_ACCTS Data
PRI_OVERDUE_ACCTS
Boxplot of PRI_CURRENT_BALANCE Data
PRI_CURRENT_BALANCE
1e8
Boxplot of PRI_SANCTIONED_AMOUNT Data
PRI_SANCTIONED_AMOUNT
1e9
Boxplot of PRI_DISBURSED_AMOUNT Data
PRI_DISBURSED_AMOUNT
1e9
Boxplot of SEC_NO_OF_ACCTS Data
SEC_NO_OF_ACCTS
Boxplot of SEC_ACTIVE_ACCTS Data
SEC_ACTIVE_ACCTS
Boxplot of SEC_OVERDUE_ACCTS Data
SEC_OVERDUE_ACCTS
Boxplot of SEC_CURRENT_BALANCE Data
SEC_CURRENT_BALANCE
1e7
Boxplot of SEC_SANCTIONED_AMOUNT Data
SEC_SANCTIONED_AMOUNT
1e7
Boxplot of SEC_DISBURSED_AMOUNT Data
SEC_DISBURSED_AMOUNT
1e7
Boxplot of PRIMARY_INSTAL_AMT Data
PRIMARY_INSTAL_AMT
1e7
Boxplot of SEC_INSTAL_AMT Data
SEC_INSTAL_AMT
1e6
Boxplot of NEW_ACCTS_IN_LAST_SIX_MONTHS Data
NEW_ACCTS_IN_LAST_SIX_MONTHS
Boxplot of DELINQUENT_ACCTS_IN_LAST_SIX_MONTHS Data
DELINQUENT_ACCTS_IN_LAST_SIX_MONTHS
Boxplot of AVERAGE_ACCT_AGE Data
AVERAGE_ACCT_AGE
Boxplot of CREDIT_HISTORY_LENGTH Data
CREDIT_HISTORY_LENGTH
Boxplot of NO_OF_INQUIRIES Data
NO_OF_INQUIRIES
Boxplot of LOAN_DEFAULT Data
LOAN_DEFAULT

Standardize the dataset

[ ]:
```
from sklearn.preprocessing import StandardScaler
scaler_data = StandardScaler()
def scaleColumns(df, cols_to_scale):

    for col in cols_to_scale:

        df[col] = pd.DataFrame(scaler_data.fit_transform(pd.
 ↪DataFrame(train[col])),columns=[col])

    return df

train = scaleColumns(train,['PERFORM_CNS_SCORE','PRI_ACTIVE_ACCTS',␣
 ↪'PRI_CURRENT_BALANCE',
                                'PRI_DISBURSED_AMOUNT', 'SEC_NO_OF_ACCTS',␣
 ↪'SEC_OVERDUE_ACCTS',
                                'SEC_CURRENT_BALANCE', 'PRIMARY_INSTAL_AMT',␣
 ↪'SEC_INSTAL_AMT',
                                'DELINQUENT_ACCTS_IN_LAST_SIX_MONTHS',␣
 ↪'CREDIT_HISTORY_LENGTH',
                                'NO_OF_INQUIRIES', 'Age', 'DISBURSAL Years'])

train.head()
```

[ ]:
```
   DISBURSED_AMOUNT  ASSET_COST    LTV       Age EMPLOYMENT_TYPE  \
0             50578       58400  89.55  0.050026        Salaried
1             47145       65550  73.23 -0.153338   Self employed
2             53278       61360  89.63 -0.153338   Self employed
3             57513       66113  88.48 -0.966792   Self employed
4             52378       60300  88.39  0.660117   Self employed

   DISBURSAL Years  STATE_ID  MOBILENO_AVL_FLAG  AADHAR_FLAG  PAN_FLAG  \
0              0.0         6               True         True     False
1              0.0         6               True         True     False
2              0.0         6               True         True     False
3              0.0         6               True         True     False
4              0.0         6               True         True     False

   VOTERID_FLAG  DRIVING_FLAG  PASSPORT_FLAG  PERFORM_CNS_SCORE  \
0         False         False          False          -0.855453
1         False         False          False           0.911822
2         False         False          False          -0.855453
3         False         False          False           0.045917
4         False         False          False          -0.855453
```

```
  PERFORM_CNS_SCORE_DESCRIPTION  PRI_NO_OF_ACCTS  PRI_ACTIVE_ACCTS  \
0   No Bureau History Available                0         -0.535617
1                 I-Medium Risk                1         -0.020549
2   No Bureau History Available                0         -0.535617
3              L-Very High Risk                3         -0.535617
4   No Bureau History Available                0         -0.535617

   PRI_OVERDUE_ACCTS  PRI_CURRENT_BALANCE  PRI_SANCTIONED_AMOUNT  \
0                  0            -0.176064                      0
1                  1            -0.146773                  50200
2                  0            -0.176064                      0
3                  0            -0.176064                      0
4                  0            -0.176064                      0

   PRI_DISBURSED_AMOUNT  SEC_NO_OF_ACCTS  SEC_ACTIVE_ACCTS  SEC_OVERDUE_ACCTS  \
0             -0.091711        -0.094259                 0          -0.065216
1             -0.070599        -0.094259                 0          -0.065216
2             -0.091711        -0.094259                 0          -0.065216
3             -0.091711        -0.094259                 0          -0.065216
4             -0.091711        -0.094259                 0          -0.065216

   SEC_CURRENT_BALANCE  SEC_SANCTIONED_AMOUNT  SEC_DISBURSED_AMOUNT  \
0            -0.031884                      0                     0
1            -0.031884                      0                     0
2            -0.031884                      0                     0
3            -0.031884                      0                     0
4            -0.031884                      0                     0

   PRIMARY_INSTAL_AMT  SEC_INSTAL_AMT  NEW_ACCTS_IN_LAST_SIX_MONTHS  \
0           -0.086581       -0.020784                             0
1           -0.073427       -0.020784                             0
2           -0.086581       -0.020784                             0
3           -0.086376       -0.020784                             0
4           -0.086581       -0.020784                             0

   DELINQUENT_ACCTS_IN_LAST_SIX_MONTHS  AVERAGE_ACCT_AGE  \
0                            -0.253566          0.000000
1                             2.347632          1.916667
2                            -0.253566          0.000000
3                            -0.253566          0.666667
4                            -0.253566          0.000000

   CREDIT_HISTORY_LENGTH  NO_OF_INQUIRIES  LOAN_DEFAULT
0              -0.568640        -0.292450             0
1               0.236085        -0.292450             1
2              -0.568640        -0.292450             0
```

```
3              -0.043819         1.122986              1
4              -0.568640         1.122986              1
```

[ ]:
```
# create dummy variables for the categorical variables
train_dummy = pd.get_dummies(train, prefix_sep='_', drop_first=True)
train_dummy.columns
```

[ ]:
```
Index(['DISBURSED_AMOUNT', 'ASSET_COST', 'LTV', 'Age', 'DISBURSAL Years',
       'STATE_ID', 'MOBILENO_AVL_FLAG', 'AADHAR_FLAG', 'PAN_FLAG',
       'VOTERID_FLAG', 'DRIVING_FLAG', 'PASSPORT_FLAG', 'PERFORM_CNS_SCORE',
       'PRI_NO_OF_ACCTS', 'PRI_ACTIVE_ACCTS', 'PRI_OVERDUE_ACCTS',
       'PRI_CURRENT_BALANCE', 'PRI_SANCTIONED_AMOUNT', 'PRI_DISBURSED_AMOUNT',
       'SEC_NO_OF_ACCTS', 'SEC_ACTIVE_ACCTS', 'SEC_OVERDUE_ACCTS',
       'SEC_CURRENT_BALANCE', 'SEC_SANCTIONED_AMOUNT', 'SEC_DISBURSED_AMOUNT',
       'PRIMARY_INSTAL_AMT', 'SEC_INSTAL_AMT', 'NEW_ACCTS_IN_LAST_SIX_MONTHS',
       'DELINQUENT_ACCTS_IN_LAST_SIX_MONTHS', 'AVERAGE_ACCT_AGE',
       'CREDIT_HISTORY_LENGTH', 'NO_OF_INQUIRIES', 'LOAN_DEFAULT',
       'EMPLOYMENT_TYPE_Salaried', 'EMPLOYMENT_TYPE_Self employed',
       'PERFORM_CNS_SCORE_DESCRIPTION_B-Very Low Risk',
       'PERFORM_CNS_SCORE_DESCRIPTION_C-Very Low Risk',
       'PERFORM_CNS_SCORE_DESCRIPTION_D-Very Low Risk',
       'PERFORM_CNS_SCORE_DESCRIPTION_E-Low Risk',
       'PERFORM_CNS_SCORE_DESCRIPTION_F-Low Risk',
       'PERFORM_CNS_SCORE_DESCRIPTION_G-Low Risk',
       'PERFORM_CNS_SCORE_DESCRIPTION_H-Medium Risk',
       'PERFORM_CNS_SCORE_DESCRIPTION_I-Medium Risk',
       'PERFORM_CNS_SCORE_DESCRIPTION_J-High Risk',
       'PERFORM_CNS_SCORE_DESCRIPTION_K-High Risk',
       'PERFORM_CNS_SCORE_DESCRIPTION_L-Very High Risk',
       'PERFORM_CNS_SCORE_DESCRIPTION_M-Very High Risk',
       'PERFORM_CNS_SCORE_DESCRIPTION_No Bureau History Available',
       'PERFORM_CNS_SCORE_DESCRIPTION_Not Scored: More than 50 active Accounts
found',
       'PERFORM_CNS_SCORE_DESCRIPTION_Not Scored: No Activity seen on the
customer (Inactive)',
       'PERFORM_CNS_SCORE_DESCRIPTION_Not Scored: No Updates available in last
36 months',
       'PERFORM_CNS_SCORE_DESCRIPTION_Not Scored: Not Enough Info available on
the customer',
       'PERFORM_CNS_SCORE_DESCRIPTION_Not Scored: Only a Guarantor',
       'PERFORM_CNS_SCORE_DESCRIPTION_Not Scored: Sufficient History Not
Available'],
      dtype='object')
```

[ ]:
```
feature = ['DISBURSED_AMOUNT', 'ASSET_COST', 'LTV', 'Age', 'DISBURSAL Years',
       'STATE_ID', 'MOBILENO_AVL_FLAG', 'AADHAR_FLAG', 'PAN_FLAG',
       'VOTERID_FLAG', 'DRIVING_FLAG', 'PASSPORT_FLAG', 'PERFORM_CNS_SCORE',
```

```
       'PRI_NO_OF_ACCTS', 'PRI_ACTIVE_ACCTS', 'PRI_OVERDUE_ACCTS',
       'PRI_CURRENT_BALANCE', 'PRI_SANCTIONED_AMOUNT', 'PRI_DISBURSED_AMOUNT',
       'SEC_NO_OF_ACCTS', 'SEC_ACTIVE_ACCTS', 'SEC_OVERDUE_ACCTS',
       'SEC_CURRENT_BALANCE', 'SEC_SANCTIONED_AMOUNT', 'SEC_DISBURSED_AMOUNT',
       'PRIMARY_INSTAL_AMT', 'SEC_INSTAL_AMT', 'NEW_ACCTS_IN_LAST_SIX_MONTHS',
       'DELINQUENT_ACCTS_IN_LAST_SIX_MONTHS', 'AVERAGE_ACCT_AGE',
       'CREDIT_HISTORY_LENGTH', 'NO_OF_INQUIRIES',
       'EMPLOYMENT_TYPE_Salaried', 'EMPLOYMENT_TYPE_Self employed',
       'PERFORM_CNS_SCORE_DESCRIPTION_B-Very Low Risk',
       'PERFORM_CNS_SCORE_DESCRIPTION_C-Very Low Risk',
       'PERFORM_CNS_SCORE_DESCRIPTION_D-Very Low Risk',
       'PERFORM_CNS_SCORE_DESCRIPTION_E-Low Risk',
       'PERFORM_CNS_SCORE_DESCRIPTION_F-Low Risk',
       'PERFORM_CNS_SCORE_DESCRIPTION_G-Low Risk',
       'PERFORM_CNS_SCORE_DESCRIPTION_H-Medium Risk',
       'PERFORM_CNS_SCORE_DESCRIPTION_I-Medium Risk',
       'PERFORM_CNS_SCORE_DESCRIPTION_J-High Risk',
       'PERFORM_CNS_SCORE_DESCRIPTION_K-High Risk',
       'PERFORM_CNS_SCORE_DESCRIPTION_L-Very High Risk',
       'PERFORM_CNS_SCORE_DESCRIPTION_M-Very High Risk',
       'PERFORM_CNS_SCORE_DESCRIPTION_No Bureau History Available',
       'PERFORM_CNS_SCORE_DESCRIPTION_Not Scored: More than 50 active Accounts␣
 ↪found',
       'PERFORM_CNS_SCORE_DESCRIPTION_Not Scored: No Activity seen on the␣
 ↪customer (Inactive)',
       'PERFORM_CNS_SCORE_DESCRIPTION_Not Scored: No Updates available in last␣
 ↪36 months',
       'PERFORM_CNS_SCORE_DESCRIPTION_Not Scored: Not Enough Info available on␣
 ↪the customer',
       'PERFORM_CNS_SCORE_DESCRIPTION_Not Scored: Only a Guarantor',
       'PERFORM_CNS_SCORE_DESCRIPTION_Not Scored: Sufficient History Not␣
 ↪Available']
X = train_dummy[feature]
Y  = train_dummy['LOAN_DEFAULT']
```

Use Boruta-shap function, combines the bortuta feature selection algorithm with shapley values to pick the features for our model, catboosting was combined for faster computating purpose.

[ ]:
```
# Use catboost model to perform Boruta feature selection algorithm
from BorutaShap import BorutaShap
from catboost import CatBoostClassifier
model = CatBoostClassifier(task_type="GPU")


feature_selector = BorutaShap(model = model, importance_measure = 'shap',␣
 ↪classification=True)
```

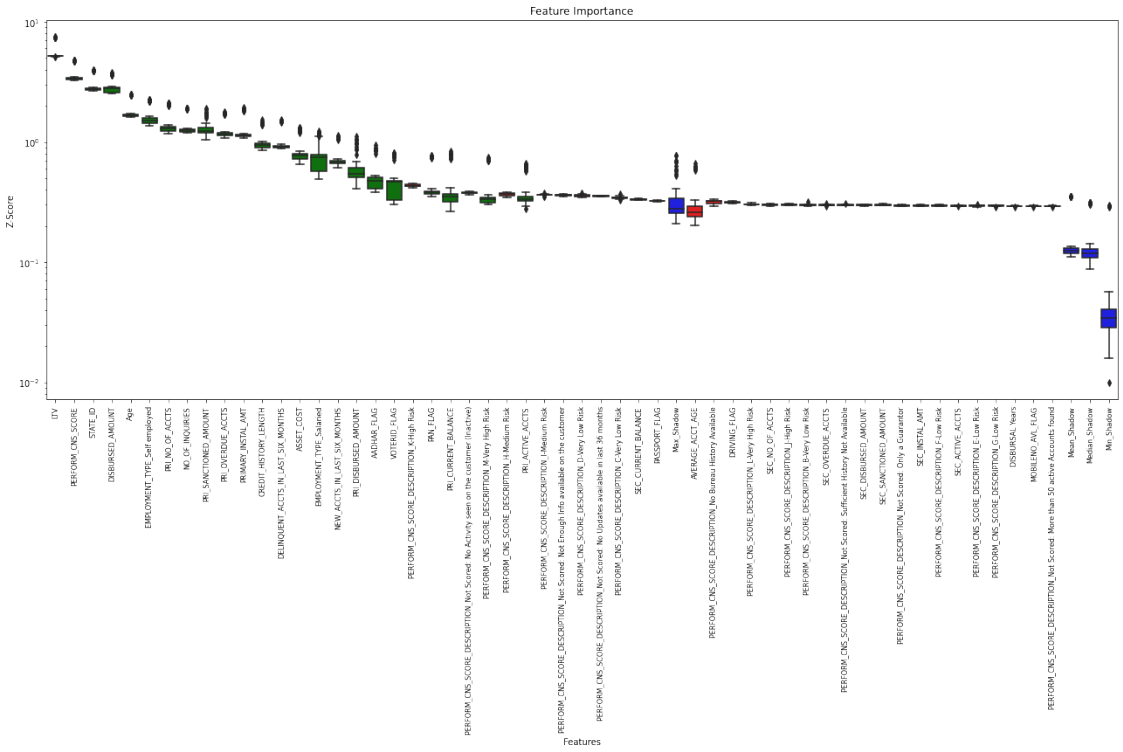
```
feature_selector.fit(X = train_dummy[feature], y = train_dummy['LOAN_DEFAULT'],␣
 ↪n_trials= 100)
```

```
100%|      | 100/100 [25:16<00:00, 15.16s/it]
```

```
23 attributes confirmed important: ['PRI_CURRENT_BALANCE', 'DISBURSED_AMOUNT',
'Age', 'NEW_ACCTS_IN_LAST_SIX_MONTHS', 'NO_OF_INQUIRIES', 'AADHAR_FLAG',
'EMPLOYMENT_TYPE_Salaried', 'PRI_ACTIVE_ACCTS', 'STATE_ID',
'PRI_SANCTIONED_AMOUNT', 'PERFORM_CNS_SCORE_DESCRIPTION_M-Very High Risk',
'CREDIT_HISTORY_LENGTH', 'ASSET_COST', 'PERFORM_CNS_SCORE', 'PRI_OVERDUE_ACCTS',
'LTV', 'DELINQUENT_ACCTS_IN_LAST_SIX_MONTHS', 'PRIMARY_INSTAL_AMT', 'PAN_FLAG',
'PRI_NO_OF_ACCTS', 'EMPLOYMENT_TYPE_Self employed', 'PRI_DISBURSED_AMOUNT',
'VOTERID_FLAG']
30 attributes confirmed unimportant: ['AVERAGE_ACCT_AGE',
'PERFORM_CNS_SCORE_DESCRIPTION_H-Medium Risk', 'SEC_SANCTIONED_AMOUNT',
'SEC_DISBURSED_AMOUNT', 'PERFORM_CNS_SCORE_DESCRIPTION_I-Medium Risk',
'PERFORM_CNS_SCORE_DESCRIPTION_J-High Risk', 'PERFORM_CNS_SCORE_DESCRIPTION_G-
Low Risk', 'PERFORM_CNS_SCORE_DESCRIPTION_E-Low Risk',
'PERFORM_CNS_SCORE_DESCRIPTION_K-High Risk', 'PERFORM_CNS_SCORE_DESCRIPTION_Not
Scored: Not Enough Info available on the customer',
'PERFORM_CNS_SCORE_DESCRIPTION_F-Low Risk', 'PERFORM_CNS_SCORE_DESCRIPTION_Not
Scored: More than 50 active Accounts found', 'PERFORM_CNS_SCORE_DESCRIPTION_No
Bureau History Available', 'PERFORM_CNS_SCORE_DESCRIPTION_B-Very Low Risk',
'PERFORM_CNS_SCORE_DESCRIPTION_Not Scored: Sufficient History Not Available',
'SEC_INSTAL_AMT', 'PERFORM_CNS_SCORE_DESCRIPTION_D-Very Low Risk', 'DISBURSAL
Years', 'SEC_CURRENT_BALANCE', 'PERFORM_CNS_SCORE_DESCRIPTION_Not Scored: No
Activity seen on the customer (Inactive)', 'PERFORM_CNS_SCORE_DESCRIPTION_Not
Scored: No Updates available in last 36 months', 'SEC_NO_OF_ACCTS',
'PASSPORT_FLAG', 'DRIVING_FLAG', 'PERFORM_CNS_SCORE_DESCRIPTION_Not Scored: Only
a Guarantor', 'MOBILENO_AVL_FLAG', 'PERFORM_CNS_SCORE_DESCRIPTION_C-Very Low
Risk', 'SEC_OVERDUE_ACCTS', 'PERFORM_CNS_SCORE_DESCRIPTION_L-Very High Risk',
'SEC_ACTIVE_ACCTS']
0 tentative attributes remains: []
```

23 features are confirmed important, 30 other attributes are abandoned. Catboosting with GPU task tpye reduced the training time to 24 minutes for a dataset with 233 thousand rows and 53 columns.

[ ]:
```
# plot features based their importance
feature_selector.plot(which_features='all', figsize=(22,8))
```



[ ]:
```
features = ['DISBURSED_AMOUNT', 'AADHAR_FLAG', 'CREDIT_HISTORY_LENGTH', 'Age',␣
 ↪'PRI_NO_OF_ACCTS', 'VOTERID_FLAG', 'PAN_FLAG', 'ASSET_COST',␣
 ↪'PRI_SANCTIONED_AMOUNT', 'NO_OF_INQUIRIES',␣
 ↪'DELINQUENT_ACCTS_IN_LAST_SIX_MONTHS', 'PRIMARY_INSTAL_AMT',␣
 ↪'PRI_ACTIVE_ACCTS', 'PRI_OVERDUE_ACCTS', 'PRI_DISBURSED_AMOUNT', 'LTV',␣
 ↪'EMPLOYMENT_TYPE_Salaried', 'NEW_ACCTS_IN_LAST_SIX_MONTHS',␣
 ↪'PERFORM_CNS_SCORE', 'EMPLOYMENT_TYPE_Self employed',␣
 ↪'PERFORM_CNS_SCORE_DESCRIPTION_M-Very High Risk', 'STATE_ID',␣
 ↪'PRI_CURRENT_BALANCE']
```

[ ]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(train_dummy[features],␣
 ↪train_dummy['LOAN_DEFAULT'], test_size = 0.2)

from sklearn.linear_model import LogisticRegression
logmodel = LogisticRegression()
logmodel.fit(X_train,y_train)
logpred = logmodel.predict(X_test)

from sklearn.metrics import accuracy_score, confusion_matrix,␣
 ↪classification_report

print(confusion_matrix(y_test, logpred))
```

```
print(classification_report(y_test, logpred))
```

```
[[36438     0]
 [10193     0]]
              precision    recall  f1-score   support

           0       0.78      1.00      0.88     36438
           1       0.00      0.00      0.00     10193

    accuracy                           0.78     46631
   macro avg       0.39      0.50      0.44     46631
weighted avg       0.61      0.78      0.69     46631
```

Accuracy inherited the precision of 0 (since y_train has way more 0 than 1), however, our target should be precision of 1, since our target is to maximize the predictive power of revealing customers that would default their loan instead of 'will not'. I will use other ML models to acheive it, and oversampling method to maximize the precision of 1.

[ ]:
```
# use xgboost algorithm to predict the outcome
from xgboost import XGBClassifier

# train model
xgb = XGBClassifier().fit(X_train[features], y_train)

# predict on test set
xgb_pred = xgb.predict(X_test[features])
print(confusion_matrix(y_test, xgb_pred))
print(round(accuracy_score(y_test, xgb_pred),2)*100)
print(classification_report(y_test, xgb_pred))
```

```
[20:55:12] WARNING: C:/Users/Administrator/workspace/xgboost-
win64_release_1.5.1/src/learner.cc:1115: Starting in XGBoost 1.3.0, the default
evaluation metric used with the objective 'binary:logistic' was changed from
'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
[[45357   342]
 [12326   264]]
78.0
              precision    recall  f1-score   support

           0       0.79      0.99      0.88     45699
           1       0.44      0.02      0.04     12590

    accuracy                           0.78     58289
   macro avg       0.61      0.51      0.46     58289
weighted avg       0.71      0.78      0.70     58289
```

[ ]:
```
train_dummy.LOAN_DEFAULT.value_counts()
```

[ ]:
```
0    182543
1     50611
Name: LOAN_DEFAULT, dtype: int64
```

xgboost classifer increased the precision of 1 to 44%, (was 0 by logistic). Now I will perform oversampling to increase the precison of 1

[ ]:
```
from imblearn.over_sampling import SMOTE
# setting up testing and training sets
sm = SMOTE()
X_train, y_train = sm.fit_resample(train_dummy[features],␣
 ↪train_dummy['LOAN_DEFAULT'])
```

[ ]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X_train, y_train, test_size␣
 ↪= 0.2)
```

[ ]:
```
from xgboost import XGBClassifier
from sklearn.metrics import classification_report , confusion_matrix ,␣
 ↪accuracy_score

model_xg = XGBClassifier()
model_xg.fit(X_train, y_train)
xgb_pred = model_xg.predict(X_test)


print(classification_report(xgb_pred, y_test))
accuracy_score(xgb_pred, y_test)
```

```
[22:18:44] WARNING: C:/Users/Administrator/workspace/xgboost-
win64_release_1.5.1/src/learner.cc:1115: Starting in XGBoost 1.3.0, the default
evaluation metric used with the objective 'binary:logistic' was changed from
'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
              precision    recall  f1-score   support

           0       0.98      0.78      0.87     45796
           1       0.72      0.97      0.83     27222

    accuracy                           0.85     73018
   macro avg       0.85      0.88      0.85     73018
weighted avg       0.88      0.85      0.85     73018
```

[ ]:
```
0.8509682544030239
```

Precision of predicting '1' - customer default on their loan increased from 61% -> 72% by 11%, recall of predicting 1 also increased from 2% to 97% (95%)

[ ]:
```
from eli5.sklearn import PermutationImportance
import eli5
xgb_model = model_xg.fit(X_train, y_train)
perm = PermutationImportance(xgb_model, random_state=1).fit(X_train, y_train)
eli5.show_weights(perm, feature_names = X_train.columns.tolist())
```

```
[20:58:37] WARNING: C:/Users/Administrator/workspace/xgboost-
win64_release_1.5.1/src/learner.cc:1115: Starting in XGBoost 1.3.0, the default
evaluation metric used with the objective 'binary:logistic' was changed from
'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
```

[ ]:
```
<IPython.core.display.HTML object>
```

Most important features are: 1. age 2. count of total loans taken by the customer at hte time of disbursement 3. bereau score 4. employment type

Now I use optuna to optimize the hyperparameter for catboost classifer.

[ ]:
```
%%time

import optuna

sm = SMOTE()
X_smote, y_smote = sm.fit_resample(train_dummy[features],␣
 ↪train_dummy['LOAN_DEFAULT'])

def objective(trial):
    X= X_smote
    y= y_smote
    categorical_features_indices = np.where(X.dtypes != np.float)[0]

    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)

    param = {
        "objective": trial.suggest_categorical("objective", ["Logloss",␣
 ↪"CrossEntropy"]),
        "colsample_bylevel": trial.suggest_float("colsample_bylevel", 0.01, 0.
 ↪1),
        "depth": trial.suggest_int("depth", 1, 12),
        "boosting_type": trial.suggest_categorical("boosting_type", ["Ordered",␣
 ↪"Plain"]),
        "bootstrap_type": trial.suggest_categorical(
            "bootstrap_type", ["Bayesian", "Bernoulli", "MVS"]
```

```
        ),
        "used_ram_limit": "24gb",
    }

    if param["bootstrap_type"] == "Bayesian":
        param["bagging_temperature"] = trial.
 ↪suggest_float("bagging_temperature", 0, 10)
    elif param["bootstrap_type"] == "Bernoulli":
        param["subsample"] = trial.suggest_float("subsample", 0.1, 1)

    cat_cls = CatBoostClassifier(**param)

    cat_cls.fit(X_train, y_train, eval_set=[(X_test, y_test)],␣
 ↪cat_features=categorical_features_indices,verbose=0,␣
 ↪early_stopping_rounds=100)

    preds = cat_cls.predict(X_test)
    pred_labels = np.rint(preds)
    accuracy = accuracy_score(y_test, pred_labels)
    return accuracy


if __name__ == "__main__":
    study = optuna.create_study(direction="maximize")
    study.optimize(objective, n_trials=100, timeout=600)

    print("Number of finished trials: {}".format(len(study.trials)))

    print("Best trial:")
    trial = study.best_trial

    print("  Value: {}".format(trial.value))

    print("  Params: ")
    for key, value in trial.params.items():
        print("    {}: {}".format(key, value))
```

```
[I 2022-03-22 22:44:07,739] A new study created in memory with name:
no-name-0add6e9d-50a4-4cff-a537-98fbc220badc
[I 2022-03-22 22:44:58,268] Trial 0 finished with value:
0.8036374592566217 and parameters: {'objective': 'Logloss', 'colsample_bylevel':
0.021040395700456026, 'depth': 3, 'boosting_type': 'Ordered', 'bootstrap_type':
'Bernoulli', 'subsample': 0.8911112525068823}. Best is trial 0 with value:
0.8036374592566217.
[I 2022-03-22 22:45:25,005] Trial 1 finished with value:
0.8015009997534854 and parameters: {'objective': 'Logloss', 'colsample_bylevel':
0.01505332282285357, 'depth': 4, 'boosting_type': 'Plain', 'bootstrap_type':
```

```
'Bernoulli', 'subsample': 0.6000634161183727}. Best is trial 0 with value:
0.8036374592566217.
[I 2022-03-22 22:46:12,331] Trial 2 finished with value:
0.7770549727464461 and parameters: {'objective': 'CrossEntropy',
'colsample_bylevel': 0.015878054237629887, 'depth': 4, 'boosting_type':
'Ordered', 'bootstrap_type': 'MVS'}. Best is trial 0 with value:
0.8036374592566217.
[I 2022-03-22 22:47:00,644] Trial 3 finished with value:
0.798994768413268 and parameters: {'objective': 'Logloss', 'colsample_bylevel':
0.01985298691507547, 'depth': 3, 'boosting_type': 'Ordered', 'bootstrap_type':
'MVS'}. Best is trial 0 with value: 0.8036374592566217.
[I 2022-03-22 22:47:26,747] Trial 4 finished with value:
0.7987482538552138 and parameters: {'objective': 'Logloss', 'colsample_bylevel':
0.035163053410174706, 'depth': 1, 'boosting_type': 'Plain', 'bootstrap_type':
'MVS'}. Best is trial 0 with value: 0.8036374592566217.
[I 2022-03-22 22:48:20,135] Trial 5 finished with value:
0.7971459092278617 and parameters: {'objective': 'CrossEntropy',
'colsample_bylevel': 0.04567074938752714, 'depth': 2, 'boosting_type':
'Ordered', 'bootstrap_type': 'MVS'}. Best is trial 0 with value:
0.8036374592566217.
[I 2022-03-22 22:51:02,866] Trial 6 finished with value:
0.8462707825467692 and parameters: {'objective': 'Logloss', 'colsample_bylevel':
0.06680053548183071, 'depth': 11, 'boosting_type': 'Plain', 'bootstrap_type':
'MVS'}. Best is trial 6 with value: 0.8462707825467692.
[I 2022-03-22 22:53:17,862] Trial 7 finished with value:
0.8255087786573174 and parameters: {'objective': 'Logloss', 'colsample_bylevel':
0.05842759077679999, 'depth': 11, 'boosting_type': 'Plain', 'bootstrap_type':
'Bayesian', 'bagging_temperature': 5.3258074626540175}. Best is trial 6 with
value: 0.8462707825467692.
[I 2022-03-22 22:54:35,755] Trial 8 finished with value:
0.841477443917938 and parameters: {'objective': 'Logloss', 'colsample_bylevel':
0.056653747173721486, 'depth': 8, 'boosting_type': 'Plain', 'bootstrap_type':
'Bernoulli', 'subsample': 0.7543322182216617}. Best is trial 6 with value:
0.8462707825467692.

Number of finished trials: 9
Best trial:
  Value: 0.8462707825467692
  Params:
    objective: Logloss
    colsample_bylevel: 0.06680053548183071
    depth: 11
    boosting_type: Plain
    bootstrap_type: MVS
Wall time: 11min 4s
```

[ ]:
```
X_smote['EMPLOYMENT_TYPE_Self employed'].dtype == 'uint8'
```

[ ]: False

[ ]:
```
for col_name in X_smote.columns:
    if(X_smote[col_name].dtype == 'int' or X_smote[col_name].dtype == 'uint8'):
        X_smote[col_name]= X_smote[col_name].astype('float')

pd.set_option('display.max_columns', None)
X_smote.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 365086 entries, 0 to 365085
Data columns (total 23 columns):
 #   Column                                        Non-Null Count   Dtype
---  ------                                        --------------   -----
 0   DISBURSED_AMOUNT                              365086 non-null  float64
 1   AADHAR_FLAG                                   365086 non-null  bool
 2   CREDIT_HISTORY_LENGTH                         365086 non-null  float64
 3   Age                                           365086 non-null  float64
 4   PRI_NO_OF_ACCTS                               365086 non-null  float64
 5   VOTERID_FLAG                                  365086 non-null  bool
 6   PAN_FLAG                                      365086 non-null  bool
 7   ASSET_COST                                    365086 non-null  float64
 8   PRI_SANCTIONED_AMOUNT                         365086 non-null  float64
 9   NO_OF_INQUIRIES                               365086 non-null  float64
 10  DELINQUENT_ACCTS_IN_LAST_SIX_MONTHS           365086 non-null  float64
 11  PRIMARY_INSTAL_AMT                            365086 non-null  float64
 12  PRI_ACTIVE_ACCTS                              365086 non-null  float64
 13  PRI_OVERDUE_ACCTS                             365086 non-null  float64
 14  PRI_DISBURSED_AMOUNT                          365086 non-null  float64
 15  LTV                                           365086 non-null  float64
 16  EMPLOYMENT_TYPE_Salaried                      365086 non-null  float64
 17  NEW_ACCTS_IN_LAST_SIX_MONTHS                  365086 non-null  float64
 18  PERFORM_CNS_SCORE                             365086 non-null  float64
 19  EMPLOYMENT_TYPE_Self employed                 365086 non-null  float64
 20  PERFORM_CNS_SCORE_DESCRIPTION_M-Very High Risk  365086 non-null  float64
 21  STATE_ID                                      365086 non-null  float64
 22  PRI_CURRENT_BALANCE                           365086 non-null  float64
dtypes: bool(3), float64(20)
memory usage: 56.8 MB
```

[ ]:
```
%%time
categorical_features_indices = np.where(train_dummy[features].dtypes != np.
 ↪number)[0]

sm = SMOTE()
X_smote, y_smote = sm.fit_resample(train_dummy[features],␣
 ↪train_dummy['LOAN_DEFAULT'])
```

```
X_train, X_test, y_train, y_test = train_test_split(X_smote, y_smote,␣
 ↪test_size=0.2, random_state=42)


model  = CatBoostClassifier(verbose=False,
    random_state=22,
    objective ='Logloss',
    colsample_bylevel= 0.06680053548183071,
    depth= 11,
    boosting_type = 'Plain',
    bootstrap_type = 'MVS')

model.fit(X_train, y_train, cat_features=categorical_features_indices)
y_pred = model.predict(X_test)
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.78      0.96      0.86     36374
           1       0.95      0.73      0.83     36644

    accuracy                           0.85     73018
   macro avg       0.86      0.85      0.84     73018
weighted avg       0.86      0.85      0.84     73018

Wall time: 3min 9s
```

Catboost after hyperparameter tune, shows pretty similar overall accuracy as previous xgboost model, however, this model has better precision on predicting 1 (True Positive) - the customers that default their loan, which helps better with the business problem.

[ ]:
```
from imblearn.over_sampling import SMOTENC

categorical_features_indices = np.where(train_dummy[features].dtypes != np.
 ↪number)[0]

sm = SMOTENC(categorical_features = [13, 16, 17, 19, 20, 21])
X_smote, y_smote = sm.fit_resample(train_dummy[features],␣
 ↪train_dummy['LOAN_DEFAULT'])

X_train, X_test, y_train, y_test = train_test_split(X_smote, y_smote,␣
 ↪test_size=0.2, random_state=42)


model  = CatBoostClassifier(verbose=False,
    random_state=22,
```

```
    objective ='Logloss',
    colsample_bylevel= 0.06680053548183071,
    depth= 11,
    boosting_type = 'Plain',
    bootstrap_type = 'MVS')

model.fit(X_train, y_train, cat_features=categorical_features_indices)
y_pred = model.predict(X_test)
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.78      0.94      0.85     36374
           1       0.93      0.74      0.82     36644

    accuracy                           0.84     73018
   macro avg       0.86      0.84      0.84     73018
weighted avg       0.86      0.84      0.84     73018
```

[ ]:
```
model  = CatBoostClassifier(verbose=False)

model.fit(X_train, y_train, cat_features=categorical_features_indices)
y_pred = model.predict(X_test)
print(classification_report(y_test, y_pred))
```

```
Custom logger is already specified. Specify more than one logger at same time is
not thread safe.
              precision    recall  f1-score   support

           0       0.78      0.99      0.87     36374
           1       0.98      0.73      0.83     36644

    accuracy                           0.85     73018
   macro avg       0.88      0.86      0.85     73018
weighted avg       0.88      0.85      0.85     73018
```