BUSINESS REPORT

NBFC Foreclosure Prediction Notes 1

Abstract

Highlighting the Important driving factors which can help NBFC 's to take a prior action to avoid foreclosure and thereby reducing the cost incurred by the Foreclosure Process.

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Batch 1 - April 2020

Table of Contents

I. Introduction of the Business Problem

Problem Statement:

A Non-Banking Financial Company (NBFC) is a company engaged in the business of loans and advances etc.

Foreclosure is a legal process in which a lender attempts to recover the balance of a loan from a borrower who has stopped making payments to the lender by forcing the sale of the asset used as the collateral for the loan.

Because of the High Foreclosures costs, the lenders are looking forward to a solution in which they can avoid the cumbersome process.

Business Implications of the Study:

Prediction of driving factors leading to 'FORECLOSURE' of the loan will help the NBFC to take prior actions while sanctioning and during payment tenure, thereby ensuring to avoid a Foreclosure process.

By identifying and implementing measures from the study, the business outcome of an NBFC is far more beneficial in cutting down the cost and at the same time retaining the customers in the long run.

Utilization of funds are more directed to the right customers.

Profitability of the NBFC is increased and there by keeping a tab on Non-Performing assets (NPA).

II. Data Report

Data Dictionary:

<u>Variables are sorted as per understanding</u>.

COLUMN NAME	DESCRIPTION
AGREEMENTID	Agreement ID of the loan account (a customer can have multiple loans)
CUSTOMERID	Unique Customer ID given to each customer
SCHEMEID	Scheme ID under which loan was given
MOB	Internal code
AUTHORIZATIONDATE	Authorization date of the loan
INTEREST_START_DATE	Interest start date on the loan
DIFF_AUTH_INT_DATE	Difference between authorization and interest start date
DUEDAY	Next due date of the loan
ORIGNAL_TENOR	Original tenor of the loan (when the loan was sanctioned)
CURRENT_TENOR	Current tenor of the loan
DIFF_ORIGINAL_CURRENT_TENOR	Difference in original and current tenor (ORIGNAL_TENOR - CURRENT_TENOR)
COMPLETED_TENURE	Completed tenure
BALANCE_TENURE	Remaining tenure
DPD	Days past due
ORIGNAL_INTEREST_RATE	Original rate of interest on the loan (when the loan was sanctioned). Renamed field (Old Name: ORIGNAL_ROI)
CURRENT_INTEREST_RATE	Current rate of interest on the loan. Renamed field (Old Name: CURRENT_ROI)
DIFF_ORIGINAL_CURRENT_INTEREST_RATE	Difference in original ROI and current ROI (ORIGNAL_ROI - CURRENT_ROI)
CURRENT_INTEREST_RATE_MAX	Maximum value of the CURRENT ROI across transactions
CURRENT_INTEREST_RATE_MIN	Minimum value of the CURRENT ROI across transactions
DIFF_CURRENT_INTEREST_RATE_MAX_MIN	Difference between the maximum and minimum interest rate per agreement
CURRENT_INTEREST_RATE_CHANGES	Number of times the CURRENT ROI has changed
LOAN_AMT	Loan amount which was sanctioned
NET_DISBURSED_AMT	Amount that was disbursed
OUTSTANDING_PRINCIPAL	Outstanding principal
PAID_INTEREST	Paid interst
PAID_PRINCIPAL	Paid principal
PRE_EMI_DUEAMT	Pre EMI due amount for the loan
PRE_EMI_RECEIVED_AMT	Pre EMI that was received
PRE_EMI_OS_AMOUNT	Pre EMI Outstanding amount
NUM_EMI_CHANGES	Number of different values in the receipts amount
NUM_LOW_FREQ_TRANSACTIONS	Number of transactions done in less than 28 days

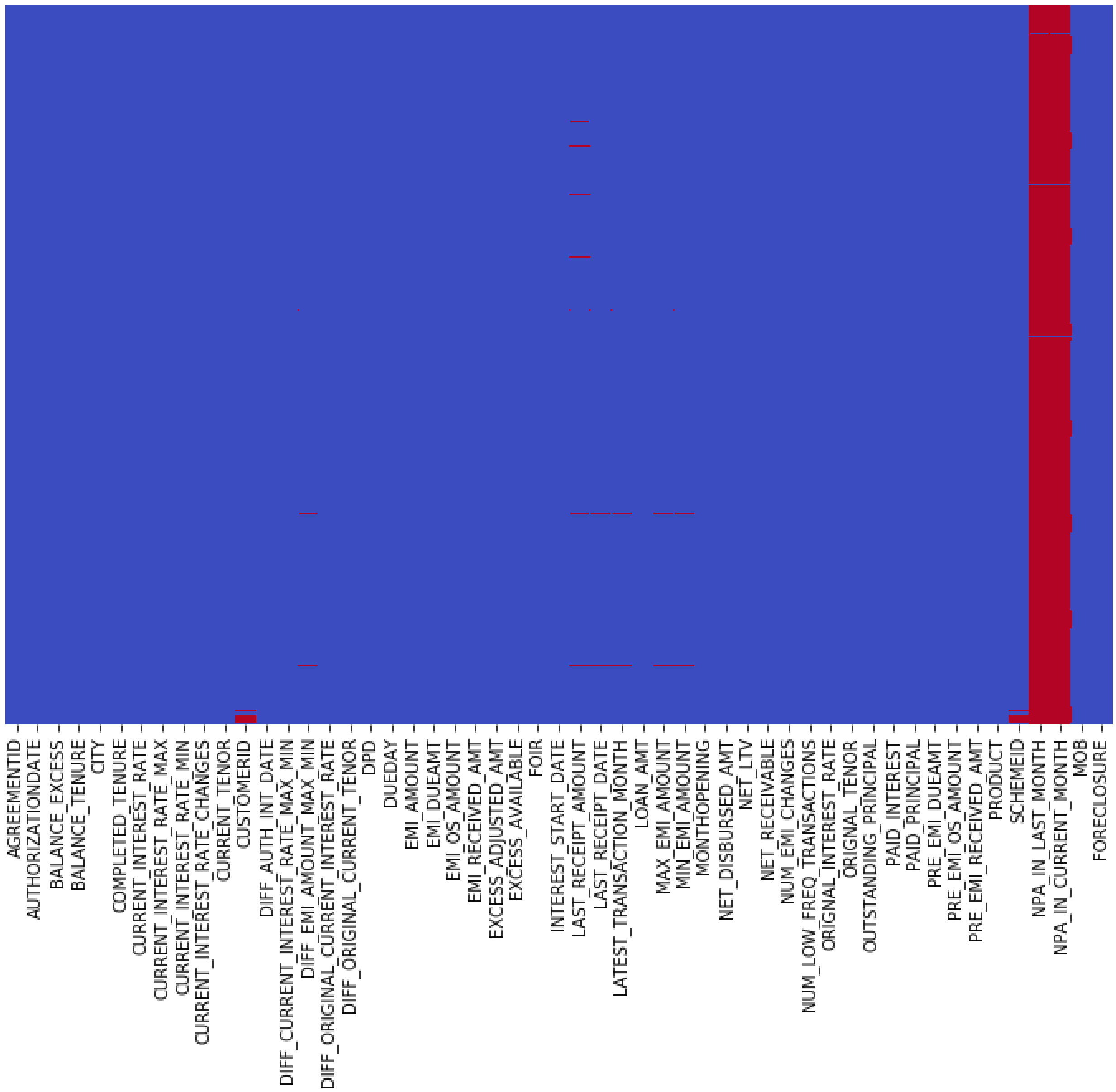
BALANCE_EXCESS	Balance of excess amount
EMI_AMOUNT	Mode of the receipt amount
MAX_EMI_AMOUNT	Maximum receipt amount
MIN_EMI_AMOUNT	Minimum receipt amount
DIFF_EMI_AMOUNT_MAX_MIN	Difference between maximum and minimum EMI AMOUNT
EMI_DUEAMT	EMI due amount
EMI_RECEIVED_AMT	EMI received amount
EMI_OS_AMOUNT	EMI outstanding amount
EXCESS_ADJUSTED_AMT	Excess adjusted amount
EXCESS_AVAILABLE	Excess received
NET_RECEIVABLE	Net receivable (EMI_DUEAMT - EMI_RECEIVED_AMT = EMI_OS_AMOUNT) + (EXCESS_AVAILABLE - EXCESS_ADJUSTED_AMT = BALANCE_EXCESS) = NET_RECEIVABLE)
LATEST_TRANSACTION_MONTH	Month of last receipt date. In case account is Foreclosed, it will be month of Foreclosure
LAST_RECEIPT_DATE	Last receipt date
LAST_RECEIPT_AMOUNT	Last receipt amount
FOIR	Fixed obligation to income ratio (Value should range from 0-1 – Derived variable)
NET_LTV	Net Loan to Value ratio (Value ranges from 0-100 (in %) – Derived variable)
MONTHOPENING	Month of opening
CITY	City of origination
PRODUCT	Loan product
NPA_IN_LAST_MONTH	Whether NPA in last month
NPA_IN_CURRENT_MONTH	Whether NPA in current month
FORECLOSURE	Labelled Field

<u>**Data consists of aggregated loan transactions data of the customers and below are the observations.**</u>

- There are 20012 rows and 53 columns
- There are no duplicated rows
- Float – 32 Variables
- Integer – 14 Variables
- Date Time – 3 variables
- Object – 4 variables
- Methodology of collected data – Aggregated loan transaction data
- Time - (August 2010 – December 2018) – 8 Years 4 months loan data
- Frequency – The loan data narrowed down to daily date wise.
- Renaming not required for this dataset.
- There are missing values in the dataset. Below data is expressed in Percentage Missing values. Both NPA in last month and current month has 99.41% missing values. Rest all variables are negligible. Ie < 2%

CUSTOMERID	1.4000
DIFF_EMI_AMOUNT_MAX_MIN	0.4400
LAST_RECEIPT_AMOUNT	1.2300
LAST_RECEIPT_DATE	0.3700
LATEST_TRANSACTION_MONTH	0.3700
MAX_EMI_AMOUNT	0.4400
MIN_EMI_AMOUNT	0.4400
SCHEMEID	1.4000
NPA_IN_LAST_MONTH	99.4100
NPA_IN_CURRENT_MONTH	99.4100

Figure 1 : Visual Presentation of missing values



III. Missing value Treatment & Dropping variables

- **Agreement Id** variable is retained because it holds the distinct count of Foreclosure accounts.
- **Customer Id** has few missing values and the data is unique at an agreement id level which will not help in foreclosure prediction, which is dropped.
- **Scheme Id** has few missing values and the data has no extra information, which will not help in foreclosure prediction, which is dropped.
- **MOB** is an internal code and the data has no extra information, which will not help in foreclosure prediction, which is dropped.
- **NPA_IN_LAST_MONTH** variable has 99.41 missing values and only 2 Foreclosures of 15 NPA's, which is not a good predictor will drop this variable. Refer Below table: **<u>Table 1:</u>**

FORECLOSURE	0	1	All
NPA_IN_LAST_MONTH			
0	69	33	102
#N/	2	0	2
Yes	13	2	15
All	84	35	119

- **NPA_IN_CURRENT_MONTH** variable has 99.41 missing values and only 2 Foreclosures of 16 NPA's, which is not a good predictor will drop this variable. Refer Below table: **<u>Table 2:</u>**

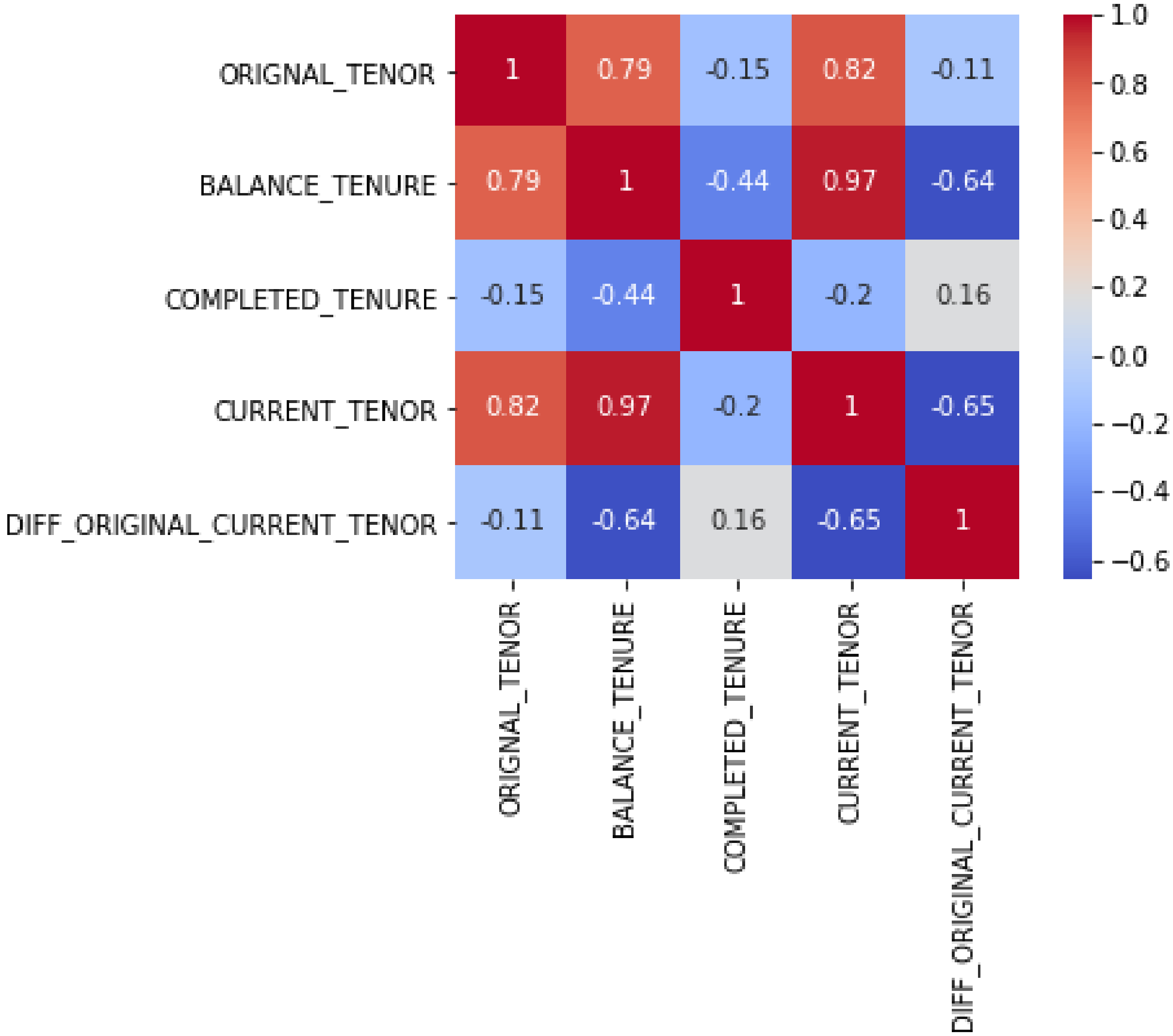
FORECLOSURE	0	1	All
NPA_IN_CURRENT_MONTH			
0	70	33	103
Yes	14	2	16
All	84	35	119

- **Min & Max & Min Max Difference Emi Amount, Latest transaction month, Last received amount** Variables imputed with median as these have extreme values.
- **Last receipt date** Variable imputed with mode as it has high frequency.

IV. Correlation Plot & Dropping variables

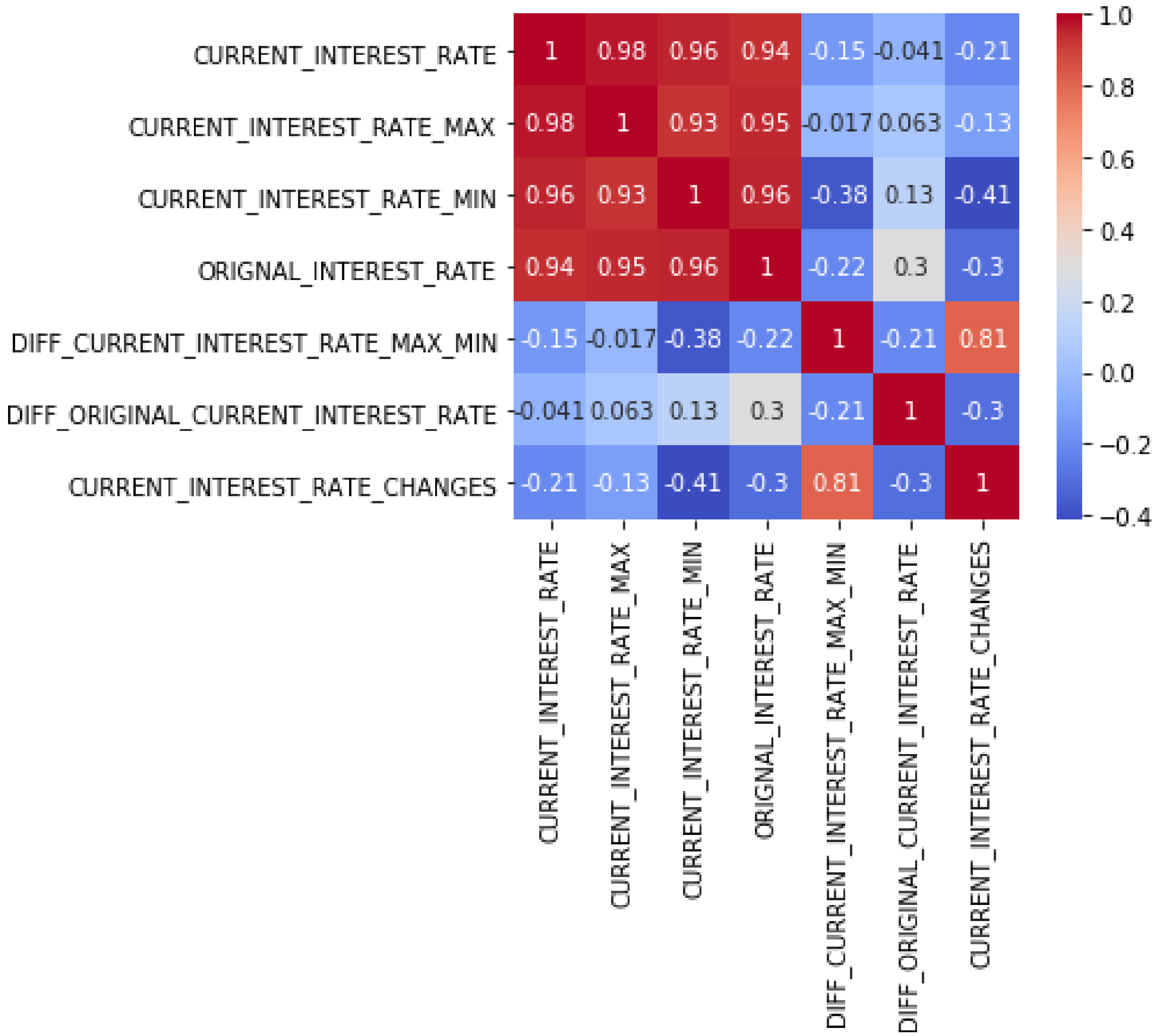
- From the below correlation graph Figure 2, Original Tenor, Balance Tenor and Current Tenor are highly correlated, Balance Tenor will be retained along with Completed Tenor, with domain understanding. Dropping Original Tenor, Current Tenor & difference between original and current tenor.

Figure 2 :



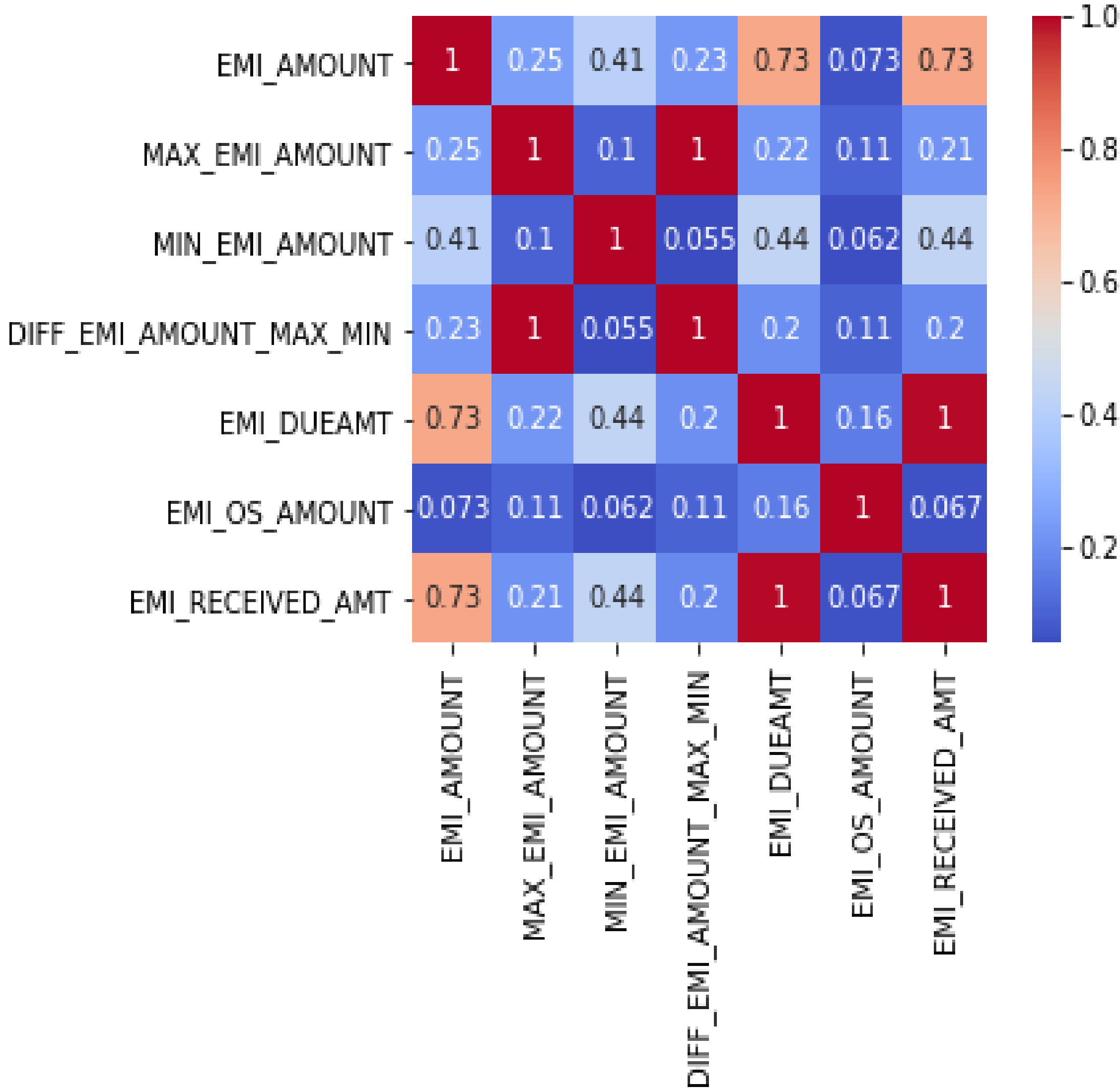
- From Below **Figure 3 :** Current Interest rate is highly correlated with other version of available interest rates(Max, Min & Original), Current Interest rate will be retained, others dropped.
- Difference between Current max and Current min, Difference between Original and Current Interest Rate & Current interest rate changes dropped as no insights derived from it.

<u>Figure 3 :</u>



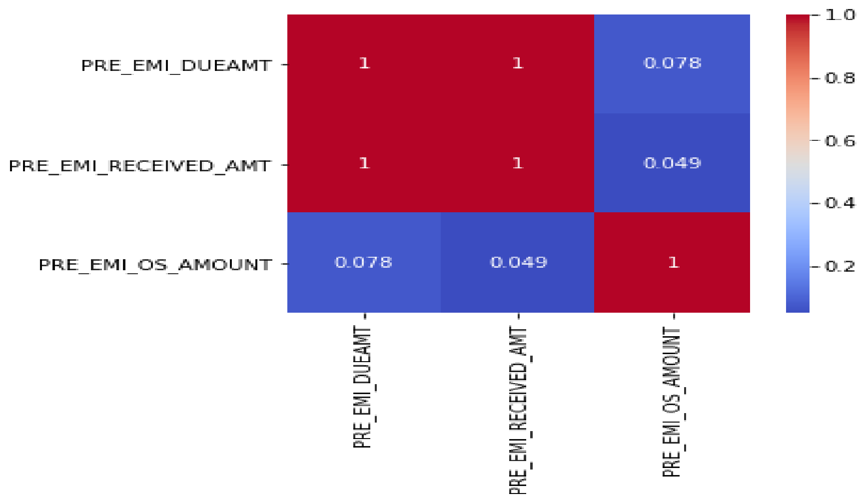
- From **Figure 4:** EMI Amount and Outstanding EMI amount and Received amount are more intuitive to use when compared to other variation of EMI variables. Rest other variables dropped.

Figure 4:



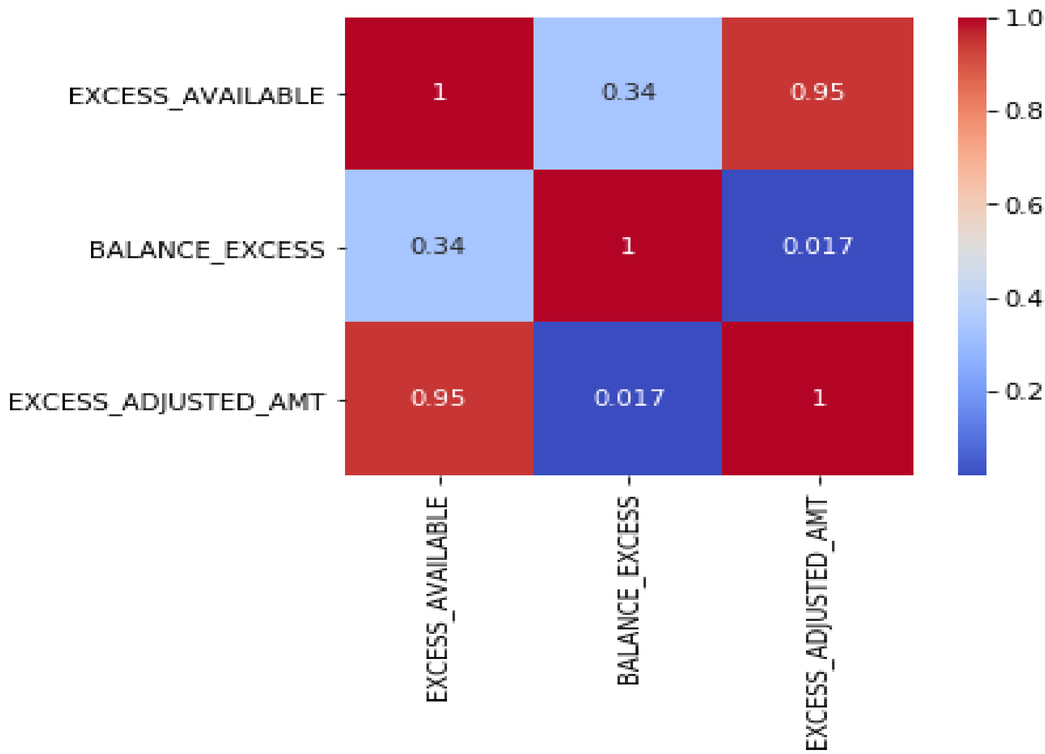
- From **Figure 5:** Pre-EMI Due amount & Pre EMI Received Amount are perfectly highly correlated, in the context of foreclosure the 'pre emi due amount' will be retained along with 'Pre Emi OS amount'.

Figure 5:



- From **Figure 6:** Excess Available and Excess Adjusted Amount are highly correlated, 'Excess Available' will be retained along with 'Balance Excess'.

Figure 6:



V. Applying VIF & Dropping variables

- Variance inflation factor applied to 26 variables with a cut off below 5 , dropped to 12 significant variables excluding the target variable Foreclosure.
  Table 3 :

	variables	VIF
1	COMPLETED_TENURE	2.5744
7	NUM_EMI_CHANGES	2.4403
9	PAID_INTEREST	2.2720
0	BALANCE_TENURE	2.1057
11	PRE_EMI_DUEAMT	2.0887
8	OUTSTANDING_PRINCIPAL	2.0731
10	PAID_PRINCIPAL	2.0575
4	EXCESS_AVAILABLE	1.8810
3	EMI_OS_AMOUNT	1.6284
2	DPD	1.5743
6	NET_RECEIVABLE	1.2846
12	FORECLOSURE	1.1291
5	FOIR	1.0007

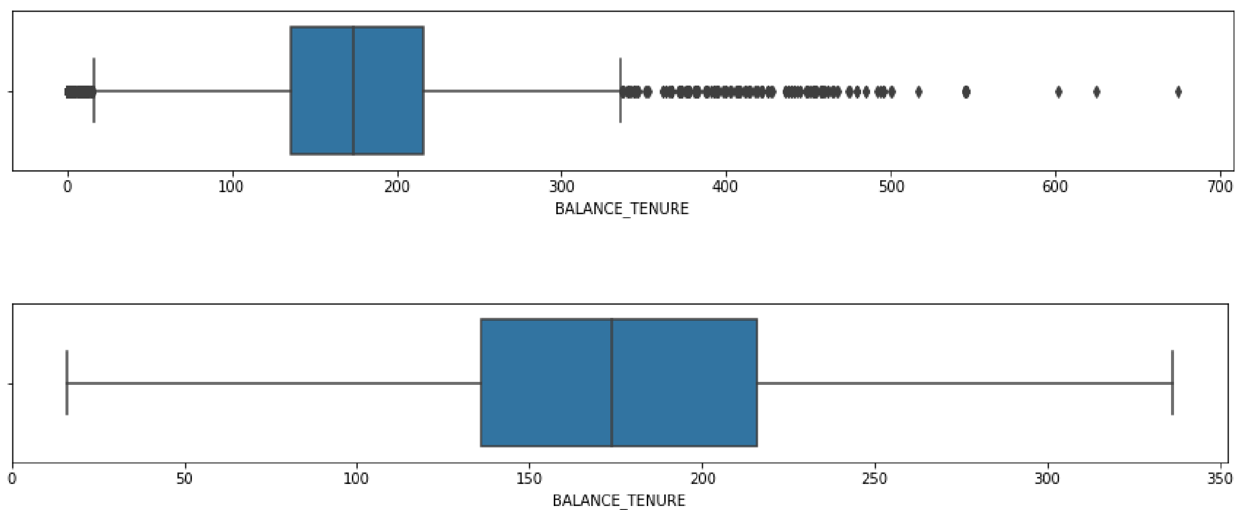
- From the below descriptive statistics of the significant variables, To increase the discriminatory power DPD,EMI OS amt & Number of Emi Changes will be binned and rest continuous variables will do outlier treatment.
  Table 4 :

	count	mean	std	min	25%	50%	75%	max
BALANCE_TENURE	20012.0000	172.8246	64.0045	0.0000	136.0000	174.0000	216.0000	674.0000
COMPLETED_TENURE	20012.0000	17.2691	16.4863	0.0000	6.0000	12.0000	25.0000	98.0000
DPD	20012.0000	7.5741	66.0989	0.0000	0.0000	0.0000	0.0000	2054.0000
EMI_OS_AMOUNT	20012.0000	33297.3485	656131.1347	0.0000	0.0000	0.0000	0.0000	58995308.7953
EXCESS_AVAILABLE	20012.0000	438896.1929	4169759.3531	0.0000	0.0000	260.6091	3105.0088	284164207.0655
FOIR	20012.0000	27.9600	3871.0648	-170.3300	0.4100	0.5200	0.6800	547616.0000
NET_RECEIVABLE	20012.0000	-45439.1533	1348502.3128	-75345537.7245	-17.6684	0.0000	0.0000	38643502.1153
NUM_EMI_CHANGES	20012.0000	2.9498	2.6355	-1.0000	2.0000	2.0000	4.0000	33.0000
OUTSTANDING_PRINCIPAL	20012.0000	5212982.4025	11521352.5645	-0.7506	1428919.4555	2394655.3775	4551203.7397	381836715.3048
PAID_INTEREST	20012.0000	989054.6886	3026052.5285	0.0000	125331.9266	309724.8300	795467.9601	123036220.6464
PAID_PRINCIPAL	20012.0000	866763.7301	34697580.7923	0.0000	23418.3379	78786.5023	291780.9673	4885216533.2000
PRE_EMI_DUEAMT	20012.0000	57804.4696	377664.7415	0.0000	4768.2638	10696.0173	31878.7917	31775396.1356
FORECLOSURE	20012.0000	0.0897	0.2858	0.0000	0.0000	0.0000	0.0000	1.0000

VI. Outlier Treatment / Univariate Analysis

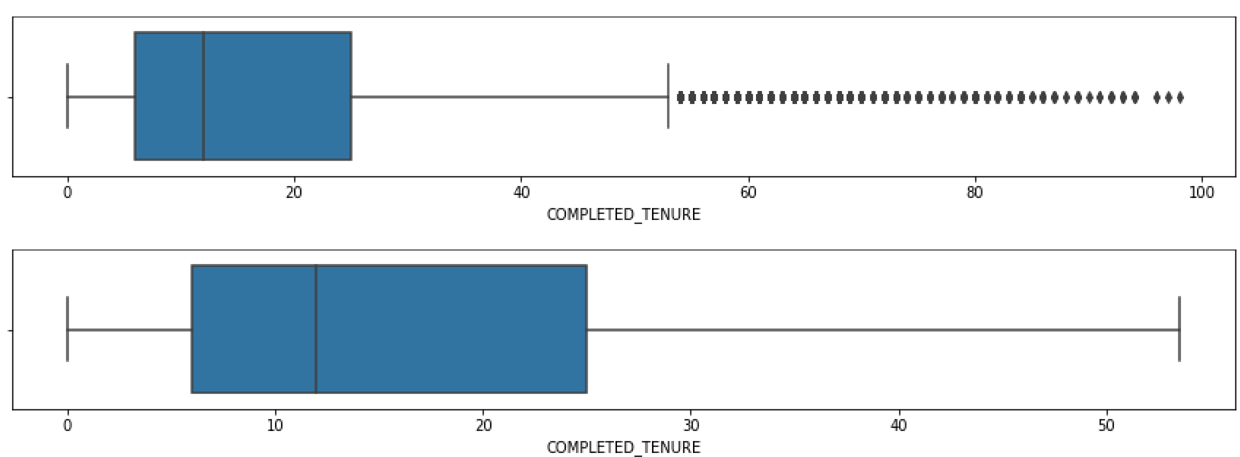
- Outlier treatment applied to 9 variables.
- Balance tenure – Before outlier treatment, balance tenure had extreme outliers to 674 months. After treatment most of the values lie approximately between130 to 220 months.

Figure 7:



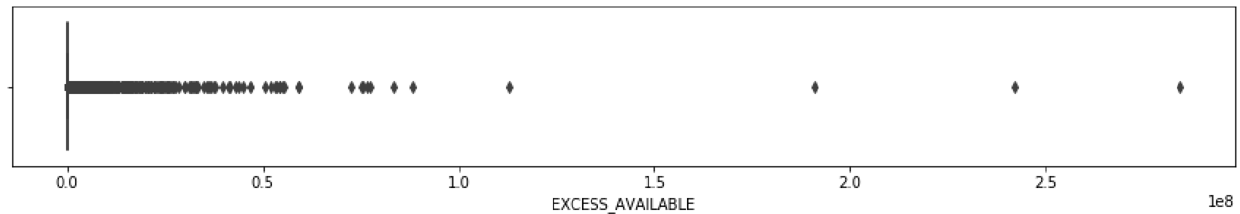
- Completed tenure – Before outlier treatment, completed tenure had extreme outliers to 98 months. After treatment most of the values lie approximately between 7 to 25 months.

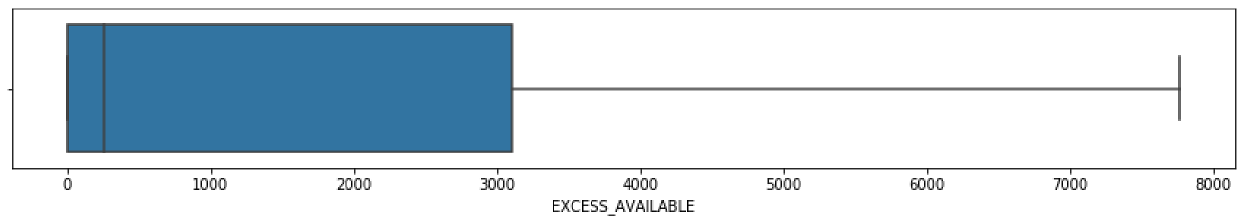
Figure 8:



- Excess available – Before outlier treatment, Excess available had extreme outliers to 28 cr odd. After treatment most of the values lie approximately between 0 to 3k.

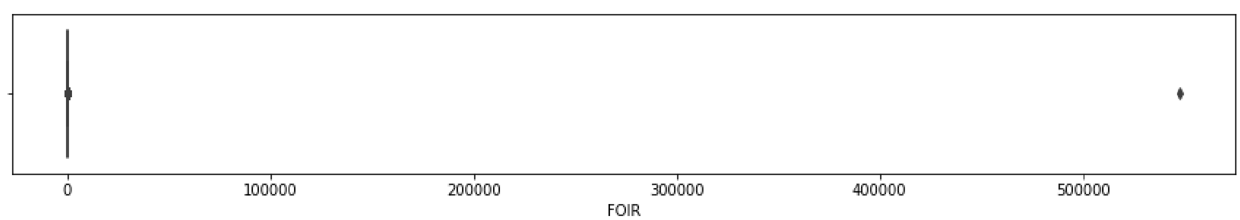
Figure 9:

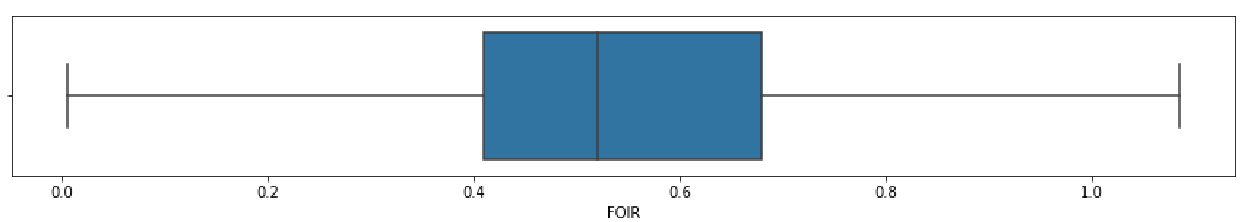




- FOIR – Before outlier treatment, FOIR available had negative value. After treatment most of the values lie approximately between 0.4 to 0.7 which is ideal range (0 – 1).

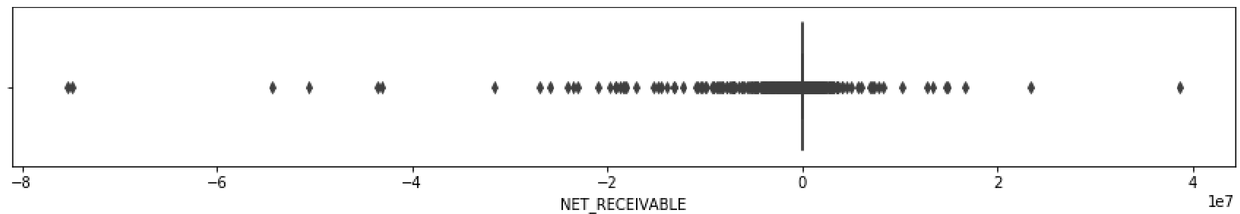
Figure 10:

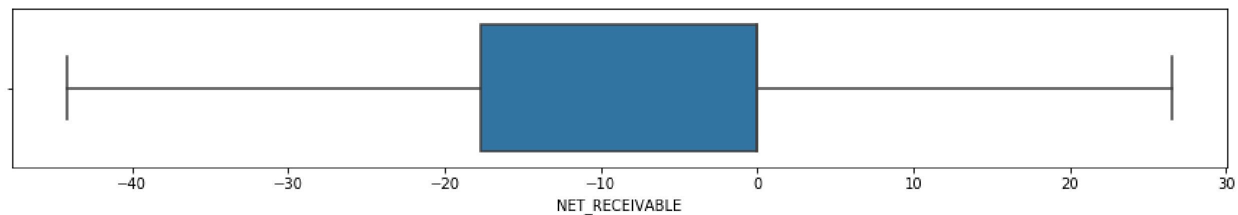




- Net receivable – Before outlier treatment, Net receivable had extreme outliers on both positive and negative ends. After treatment most of the values lie approximately between -18 to 0 lacs(mostly on the negative end). Which is good predictor for foreclosure.

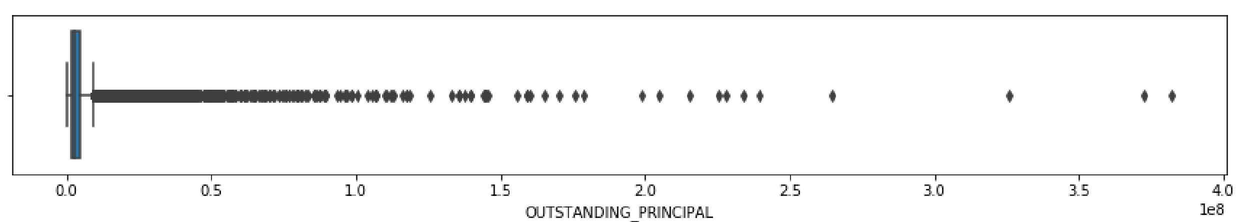
Figure 11:

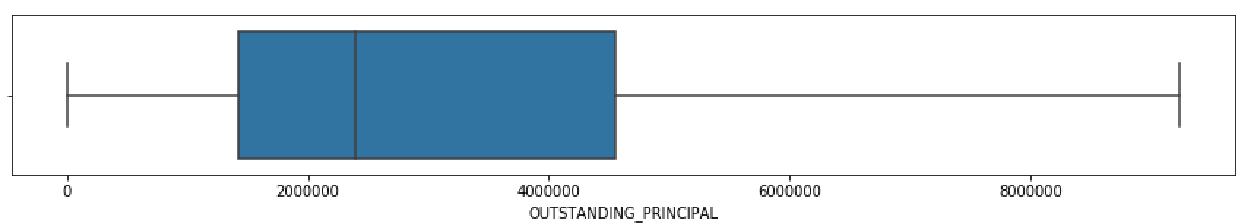




- Outstanding principal – Before outlier treatment, outstanding principal had extreme outliers to 38 cr. After treatment most of the values lie approximately between 17 to 45 lacs.

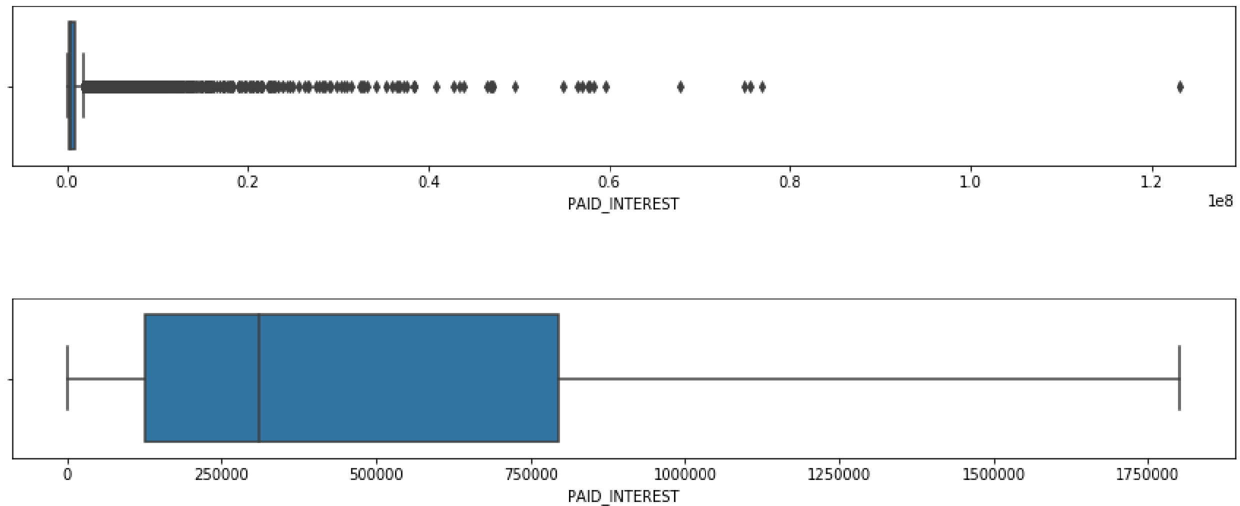
Figure 12:





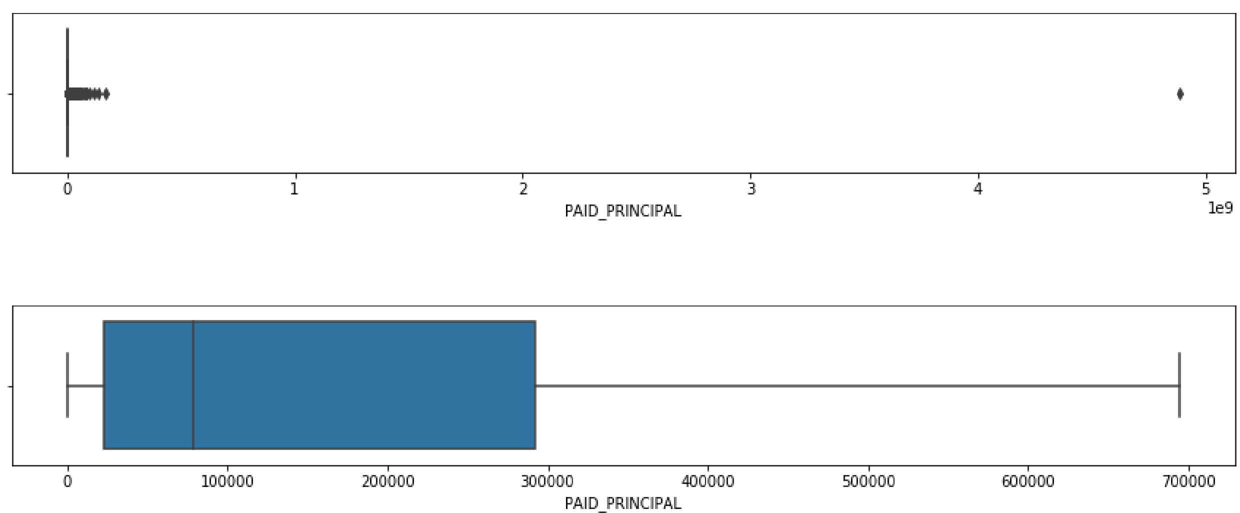
- Paid Interest – Before outlier treatment, paid interest had extreme outliers to 12.3 cr. After treatment most of the values lie approximately between 2 to 7.7 lacs.

Figure 13:



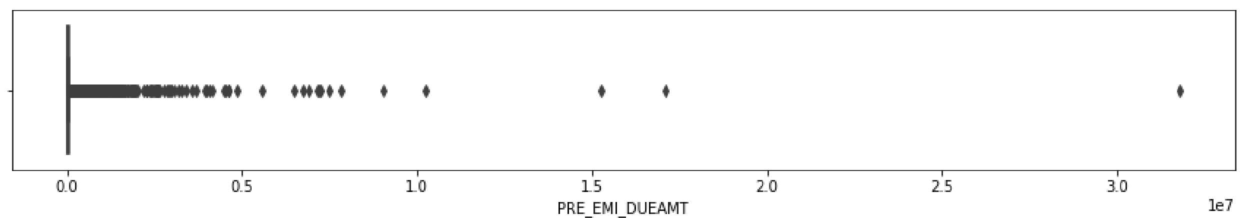
- Paid Principal – Before outlier treatment, Paid principal had extreme outliers to 488 cr. After treatment most of the values lie approximately between 40k to 2.9 lacs.

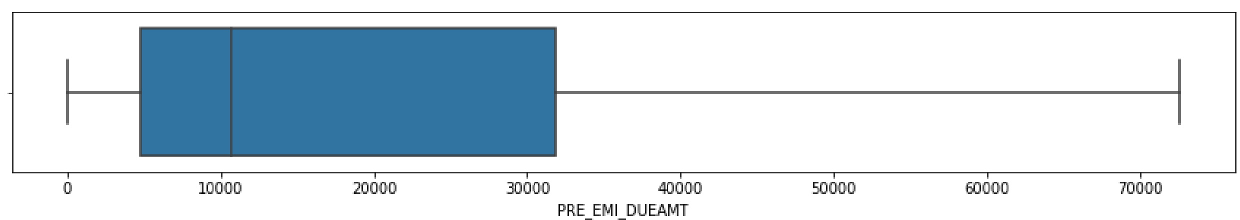
Figure 14:



- Pre Emi Due amt – Before outlier treatment, Pre Emi Due amt had extreme outliers to 3.1 cr. After treatment most of the values lie approximately between 5k to 32k.

<u>Figure 15:</u>





VII. Derived Metrics & Insights

- To increase the discriminatory power of the model, variables DPD,EMI OS amt & Number of Emi Changes was binned.
  New variable names – DPD_RANGE, EMI_OSAMT_RANGE & NUM_EMI_CHANGES_RANGE.

Table 5 : As days past due increases the probability of foreclosure is high. The binning technique will help us assign more Foreclosure weights to the higher segment.

FORECLOSURE	0	1	All	Per %
DPD_RANGE				
0-1	17113	1657	18770	9
1-30	546	59	605	10
30-60	217	22	239	9
60-90	148	26	174	15
90 and above	193	31	224	14
All	18217	1795	20012	

Table 6 : The % Foreclosure seen across for EMI OS bins are distinctive, hence would improve the discriminatory power of the model.

FORECLOSURE	0	1	All	Per %
EMI_OSAMT_RANGE				
0-10k	17153	1623	18776	5
10k-50k	346	62	408	15.2
50k-300K	492	79	571	13.8
300k and above	226	31	257	12.1
All	18217	1795	20012	14.0

Table 7 : The %Foreclosures have a monotonically increasing trend as customers opt for more EMI changes

FORECLOSURE	0	1	All	Per %
NUM_EMI_CHANGES_RANGE				
-5-2#	10880	916	11796	8
2-5#	5276	583	5859	10
5 and above	2061	296	2357	13
All	18217	1795	20012	

VIII. Bivariate/Multivariate Analysis

- Below is the pair plot of the significant variables which clearly shows that there is no clear relationship between each other, ie. There is no Multicollinearity

Figure 16:

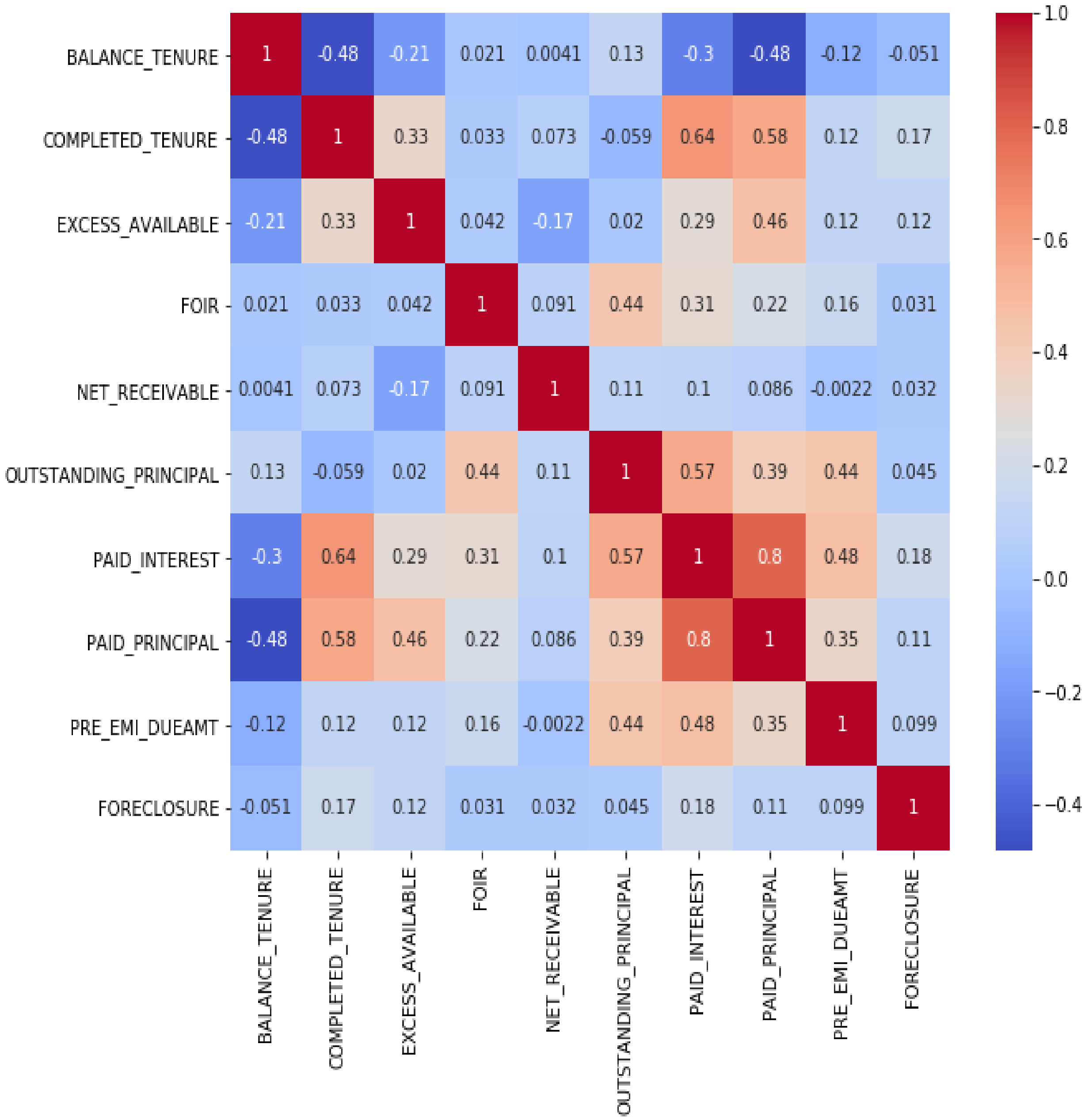


Figure 17: Foreclosure and non-foreclosure distribution is similar. Unlikely to be a strong predictor.

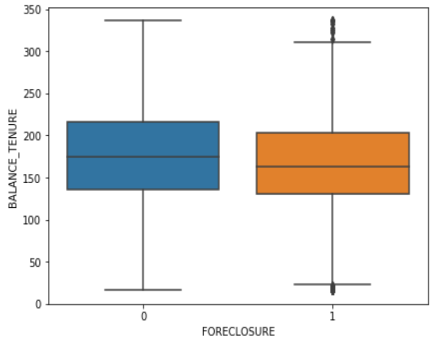


Figure 18: Foreclosure and Non-Foreclosure population distribution is different and distinct, likely to be a Strong Predictor

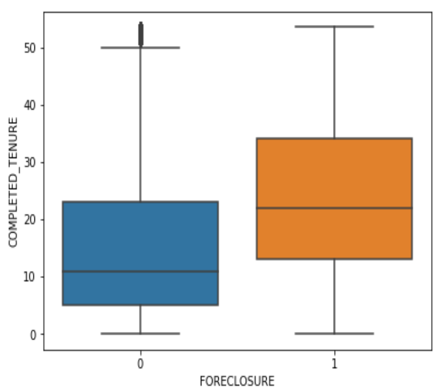


Figure 19: Distributions are not similar and very likely to be strong predictor

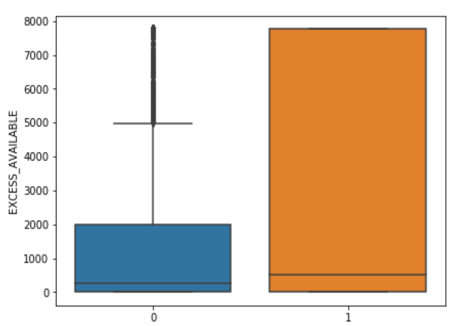


Figure 20: FOIR – distributions are fairly similar like to be a weak predictor

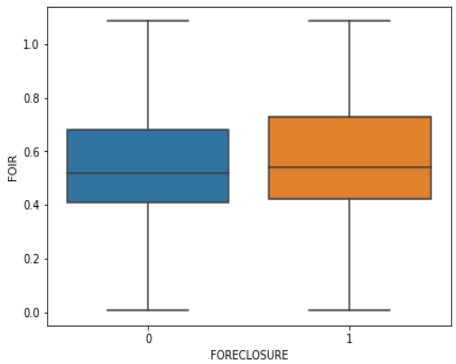


Figure 21: Net-Receivable distribution between foreclosure and non-foreclosure distributions are not similar, likely to be strong predictor

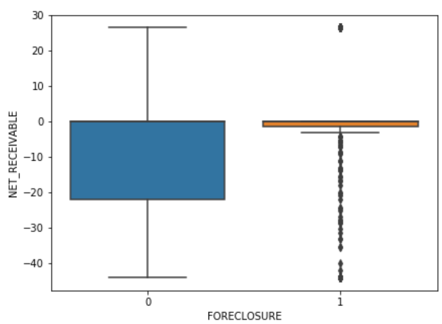


Figure 22: Higher the outstanding principal likely the customers to foreclose, likely to be a strong predictor

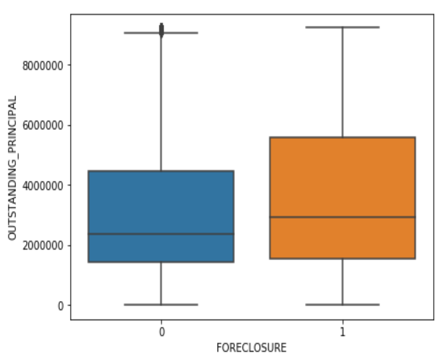


Figure 23 : Customer paying more interest are likely to Foreclose, could be an important variable in the final model

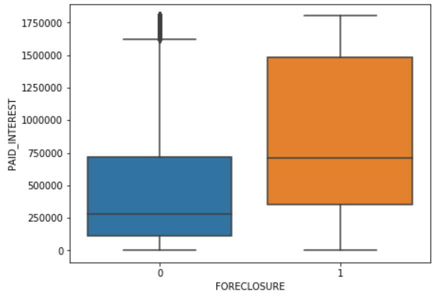


Figure 24: This variable is contrary to business understanding; yet the distributions are different. Likely to be removed in further analysis

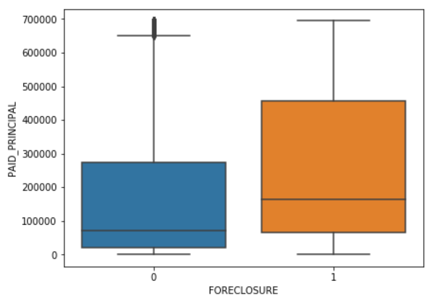
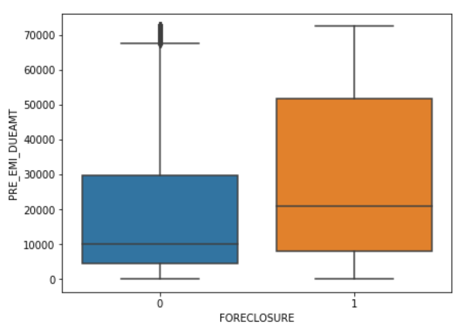


Figure 25: Distribution are quite distinctive in nature; likely to be a strong predictor



X. Business Insights from EDA

a) Is the data unbalanced? If so, what can be done? Please explain in the context of the business

Yes, the data is unbalanced.

Smote is a technique which can done to regularize the data. Imbalance of data will create a biased model. Best technique to avoid the curse of imbalanced data is by under-sampling the larger classified dataset and by oversampling the less classified dataset. So that, the final dataset will have a balanced/equal amount of data among all the labels

In the Context of business, the model created for the NBFC should neither be underfit or overfit as to generalize in real world conditions as we are in state of flux. ie. Constantly changing.

b) Any business insights using clustering (if applicable)

The clustering was performed on scaled and unscaled data on the final variables after exploratory data analysis (12 variables), the clustering results are not definitive, and the scree plot are not helpful in identifying the number of clusters required. However, predictive modelling solution is the advised here with the given data of 9% foreclosures.

c) Any other business insights

As observed in the derived variables section,

- As the days past due increases the probability of foreclosures are high. The binning technique will help us assign more Foreclosure weights to the higher DPD segments as we observe a slight monotonically increasing trend
- The % of Foreclosure seen across for EMI OS bins are quite distinctive, hence the binning would improve the discriminatory power of the model
- The % of Foreclosures have a monotonically increasing trend as customers opt for more EMI changes are vulnerable to foreclosure behavior