BUSINESS REPORT

NBFC Default Prediction Final notes

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Batch 1 - April 2020

Contents

1. Introduction of the Business Problem

1.1 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.

- Ultimate problem – High Foreclosure Costs, Legal Hassle & Loss of Customers
- The Penultimate problem is the losing customers defaults which is resulting to the foreclosure process which is costing the NBFC and thereby.
- Defaults is a Core problem.

1.2 Business Implications of the Study:

- Highlighting the driving factors leading to 'FORECLOSURE' of the loan will help the NBFC to take prior actions while sanctioning the loan and during payment tenure.
- 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).

1.3 Objective:

Achieve a Best Model to predict the probability of default of the existing loan accounts. Recommend important variables for NBFC to take prior action to avoid foreclosures, save costs from legal hassle and thereby avoid losing customers.

2. EDA – Univariate / Bi-Variate / Multi-Variate

Data consists of aggregated loan transactions data of the customers and below are the observations.

- 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.

2.1 Visual Presentation of missing values

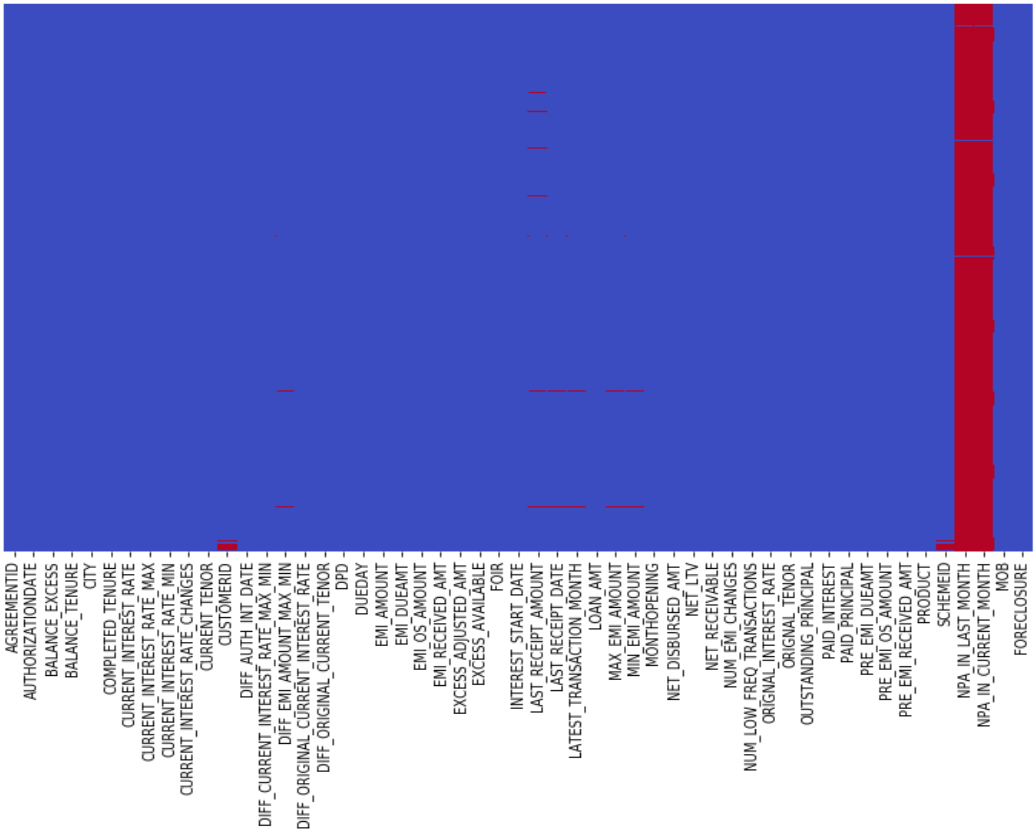
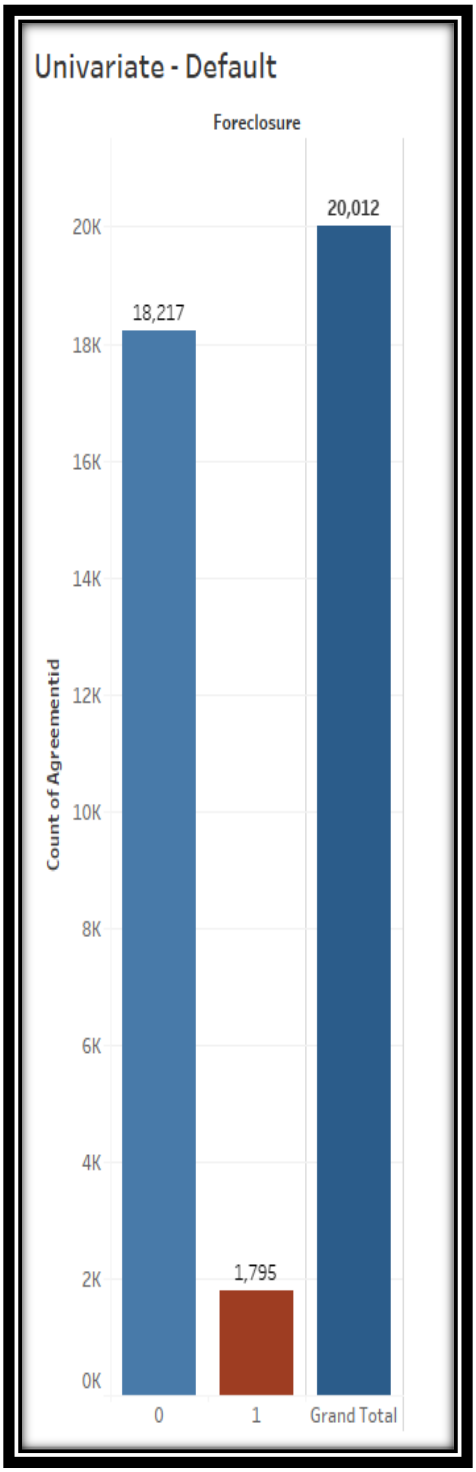


Figure 1: Visual presentation of missing variables

- 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. I.e., < 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**

2.2 Univariate – Default rate



- Default rate @ 8.9%
- Data is imbalanced.

Figure 2: Default Rate

2.3 Univariate – NET_LTV

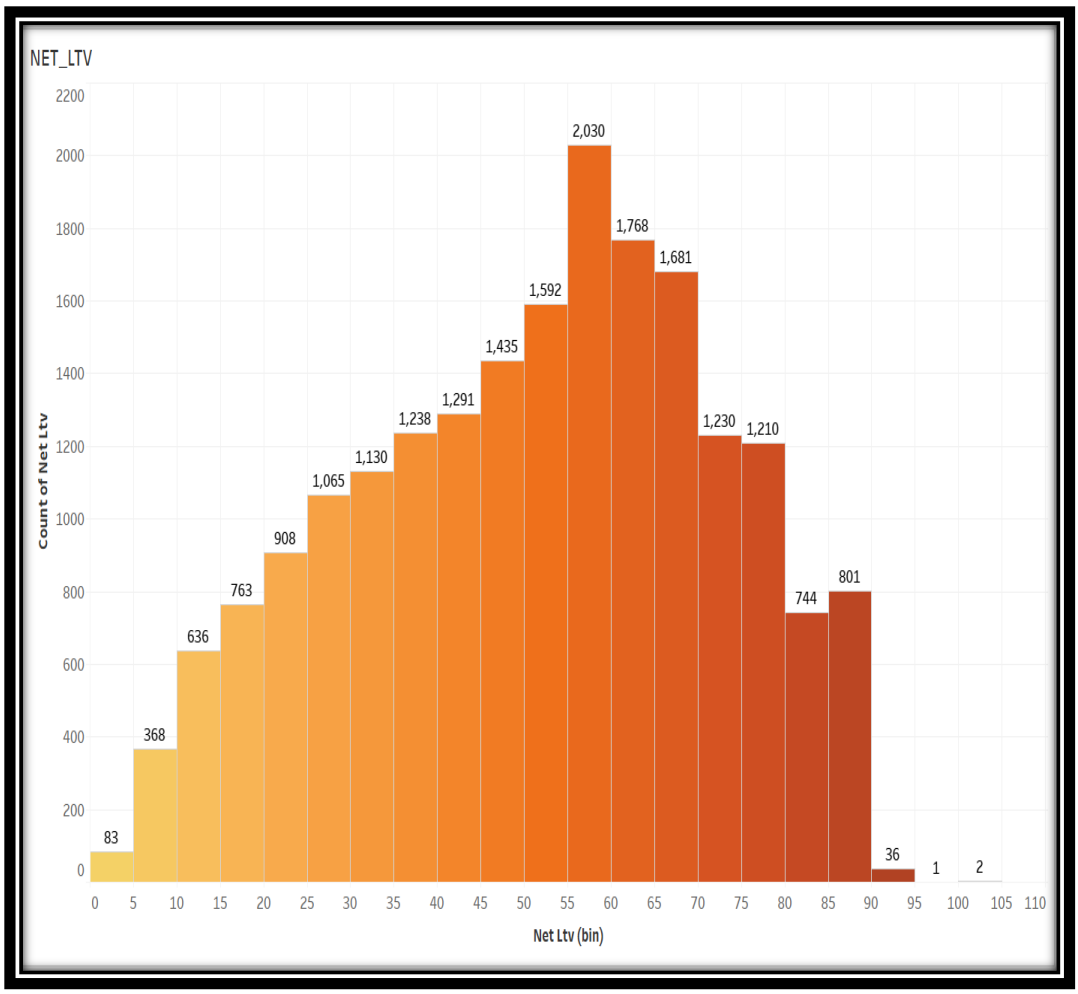


Figure 3: Net – Loan to Value (LTV)

- From Histogram Plot, the most of the NET_LTV lies between 30 – 75 %.

2.4 Product / Loan amount / Default

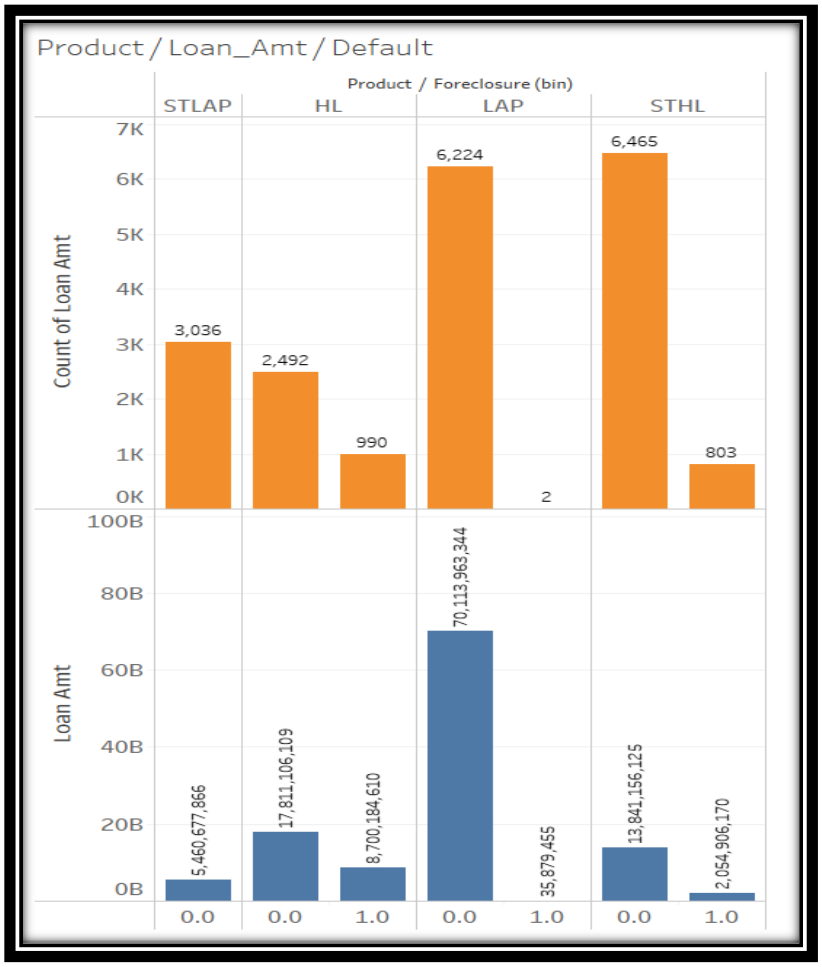


Figure 4. Product / Loan Amount vs. Default

- Highest selling product is STHL -Small Ticket Home loans, Followed by LAP – loan against property, HL – Home loan & STLAP – Small ticket loan against property.
- HL – Highest defaults.
- LAP – Highest loan amounts disbursed.

2.5 City / Defaults

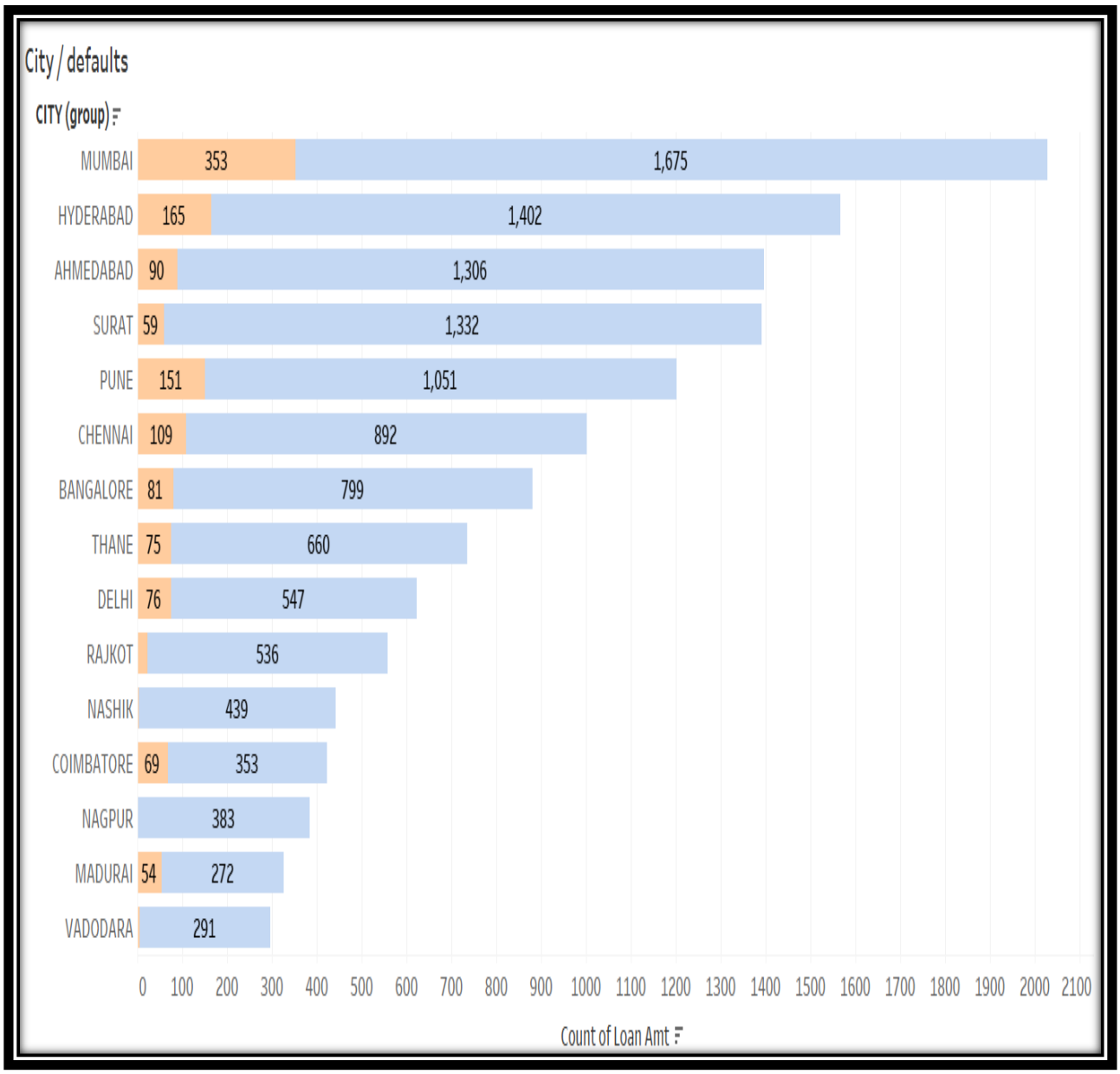


Figure 5. City vs. Default

- Mumbai – Highest loan disbursements and Highest defaults @ 353.
- Top 15 cities and their Defaults Vs Non- Defaults.

2.6 Trend of Defaults

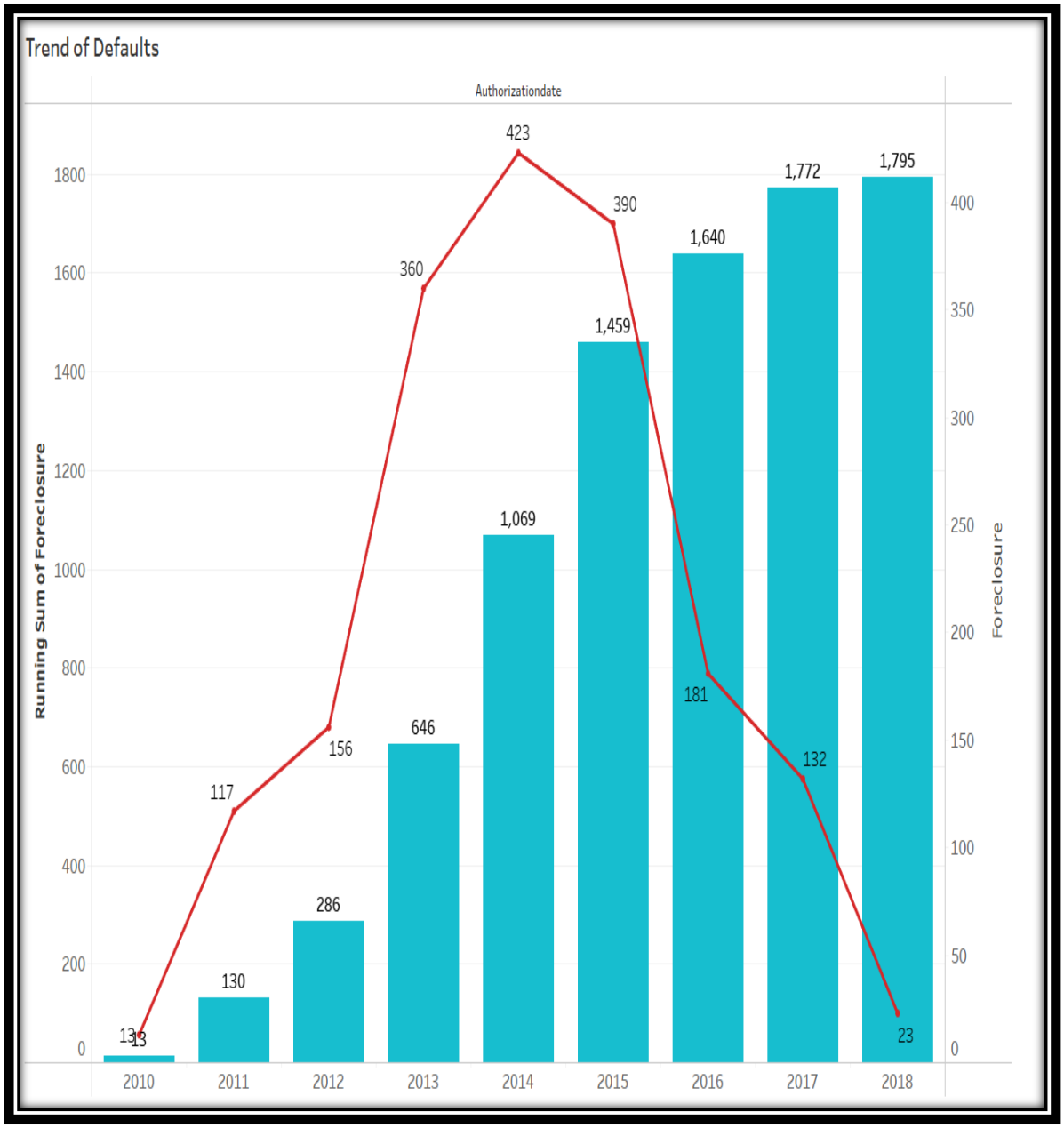


Figure 6. Default Trend

- The Trend of Foreclosures are trending up from 2010 to 2014 & trending down from 2014 to 2018.
- Year 2014 recorded highest number of Foreclosures.

2.7 Bivariate/Multivariate Analysis

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

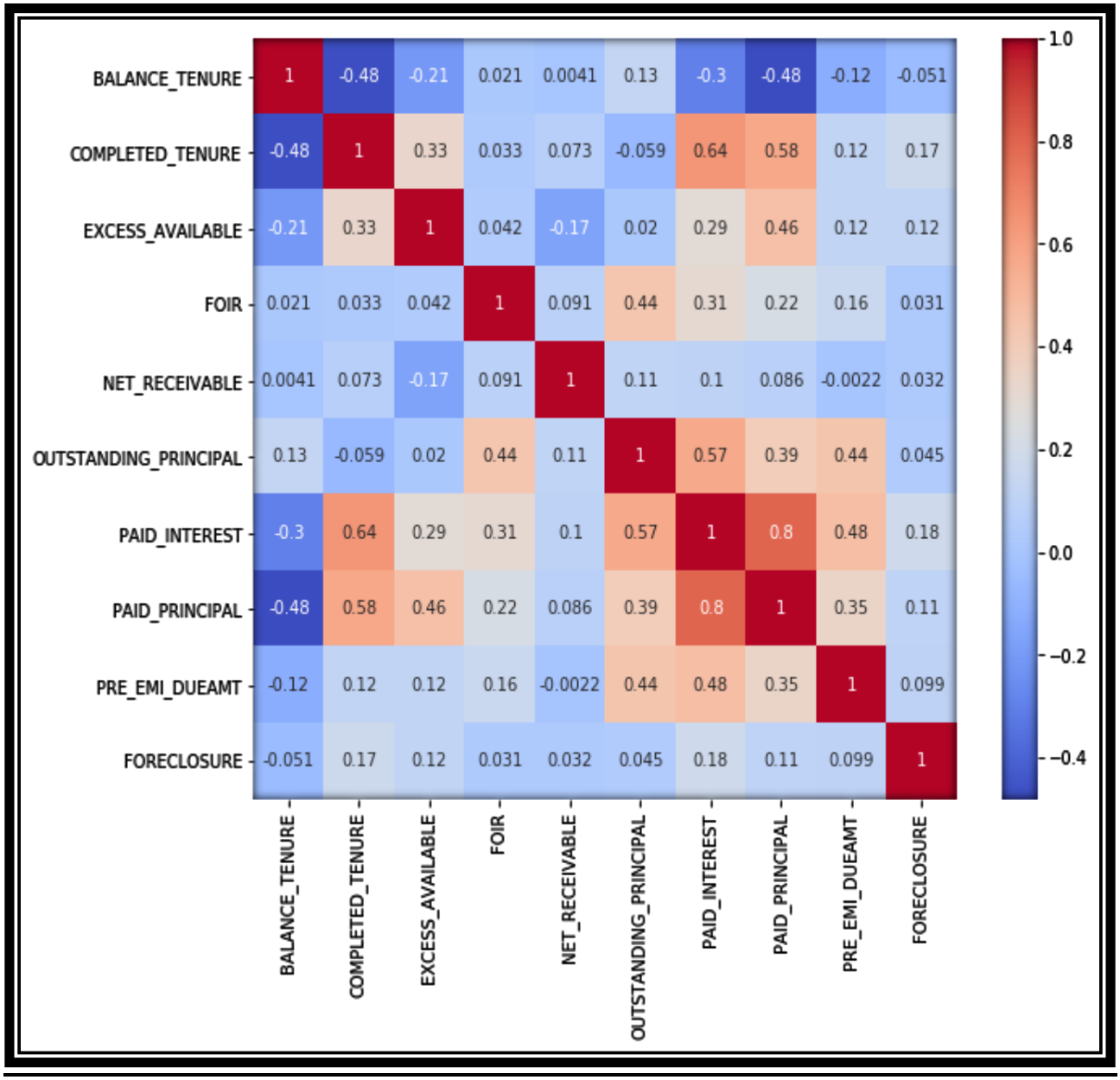


Figure 7: Pair Plot of Significant variables

2.7.1 Balance Tenure vs Foreclosure

- Median of foreclosure is less than non-foreclosure median with less margin. Balance Tenure, Unlikely to be a strong predictor.

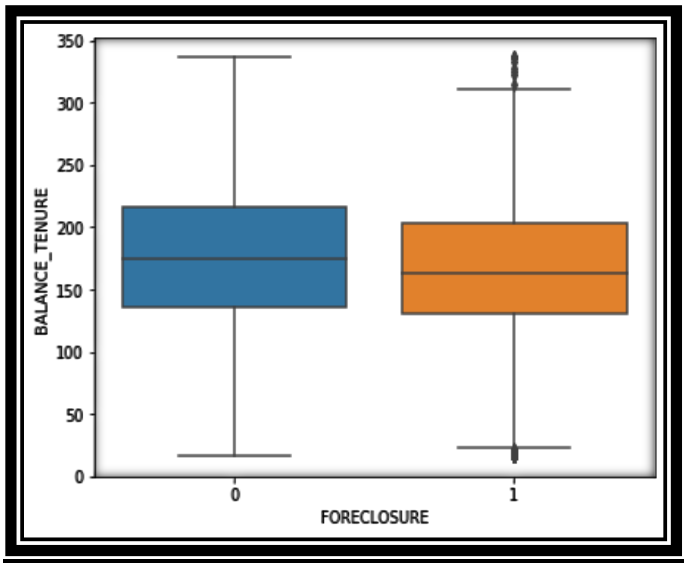


Figure 8 – Balance Tenure vs. Foreclosure

2.7.2 Completed Tenure vs Foreclosure

- Foreclosure and Non-Foreclosure population distribution is different and distinct, completed tenure likely to be a Strong Predictor.

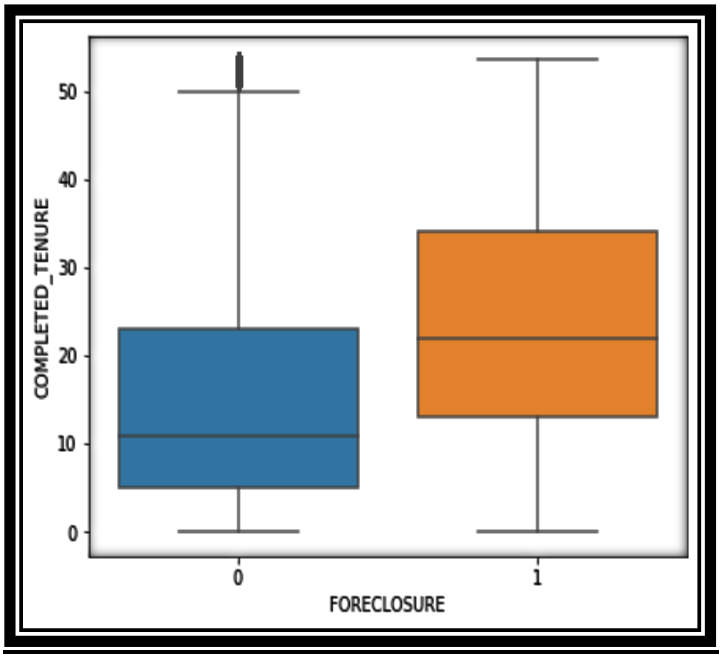


Figure 9 – Completed Tenure vs. Foreclosure

2.7.3 Excess Available vs Foreclosure

- Distributions are not similar, excess available highly likely to be strong predictor.

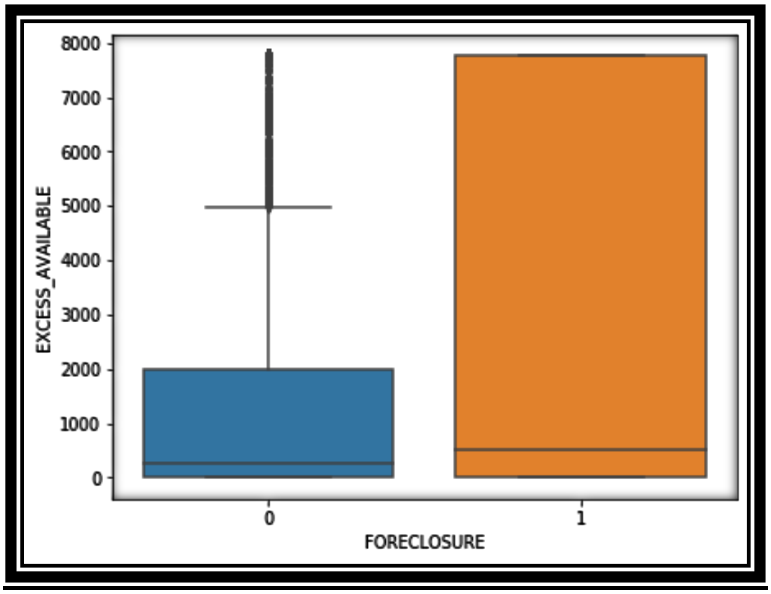


Figure 10 – Excess Available vs Foreclosure

2.7.4 FOIR vs Foreclosure

- Distributions are similar like to be a weak predictor.

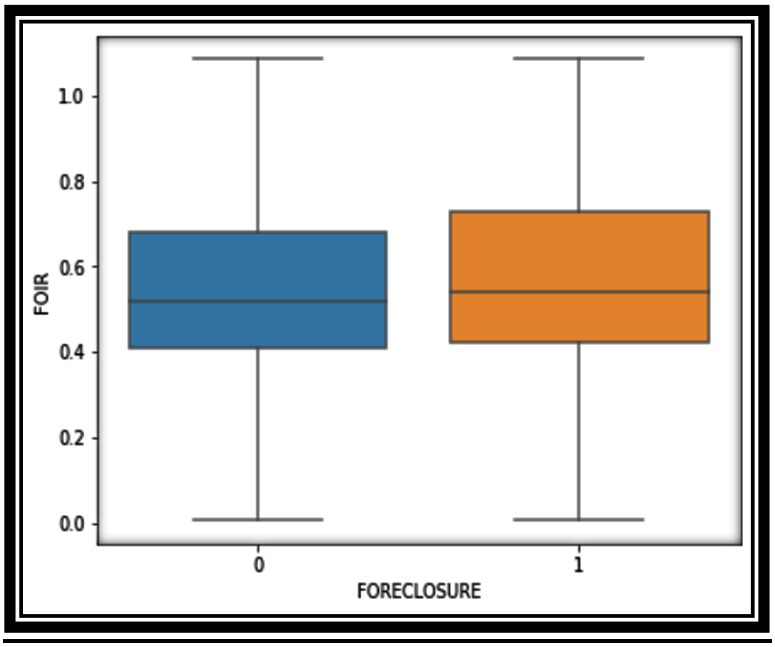


Figure 11 – FOIR vs. Foreclosure

2.7.5 Net-Receivable vs Foreclosure

- Distribution between foreclosure and non-foreclosure distributions are not similar, likely to be strong predictor.

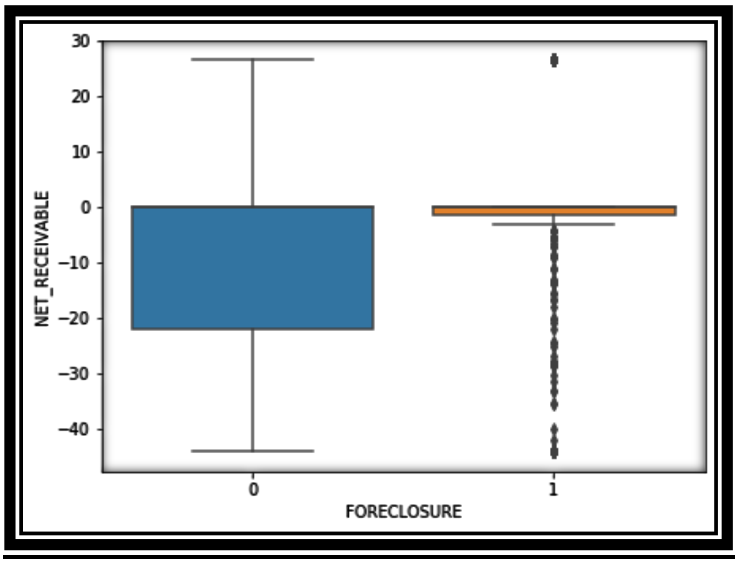


Figure 12 – Net-Receivable vs Foreclosure

2.7.6 Outstanding Principal vs Foreclosure

- Higher outstanding principle are likely head to Foreclosure, likely to be a strong predictor.

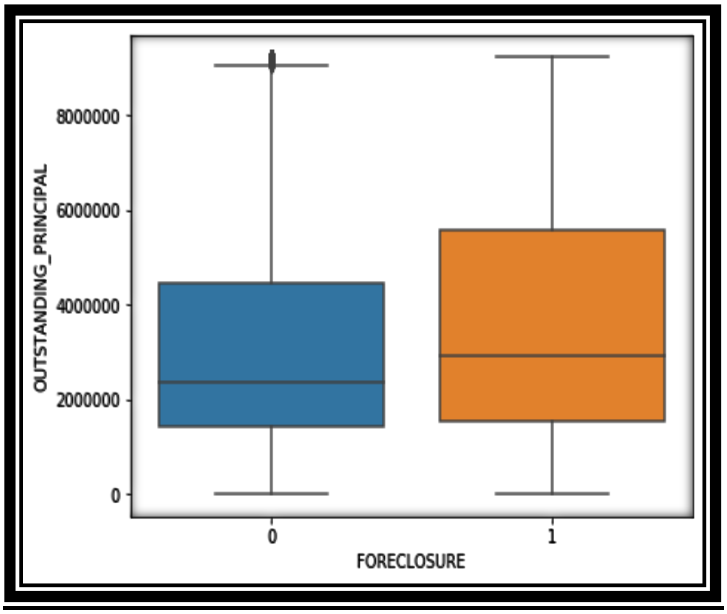


Figure 13 – Outstanding Principal vs Foreclosure

2.7.7 Paid Principal vs Foreclosure

- Customer paying more interest are likely to Foreclosure, could be an important variable in the final model.

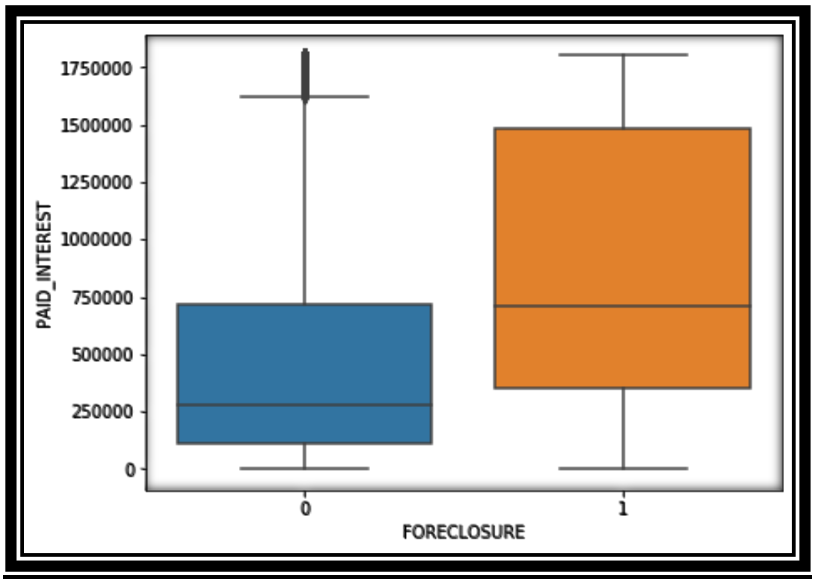


Figure 14 – Paid Interest vs Foreclosure

2.7.8 Paid Principal vs Foreclosure

- Paid Principal variable is contrary to business understanding, as per the distributions.

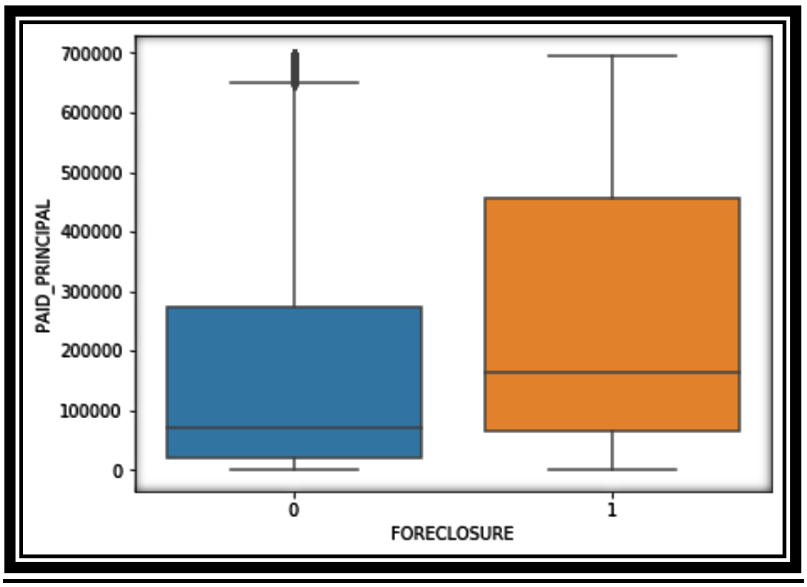


Figure 15 – Paid Interest vs Foreclosure

2.7.9 Pre EMI-Due Amount vs Foreclosure

- Distribution is quite distinctive in nature; Pre Emi-Due amount likely to be a strong predictor.

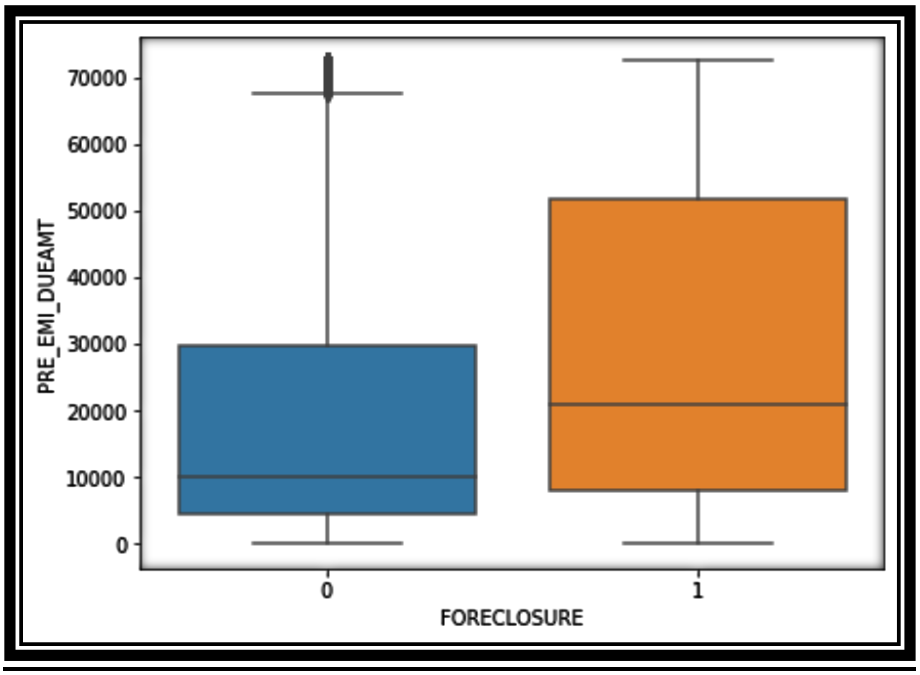


Figure 16 – Pre EMI-Due Amount vs Foreclosure

3. Data Cleaning & Preprocessing

3.1 Dropping variables

The variables are dropped based on data understanding

- **Agreement Id** variable holds the distinct count of Foreclosure accounts. It is dropped.
- **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 default prediction, which is dropped.
- **MOB** is an internal code, and the data has no extra information, which will not help in default prediction, which is dropped.

➢ The dataset has variables explaining the same subject which requires to be dropped by domain understanding.

➢ Dropping variables as per high number of missing values and treatment for the missing variables.

➢ **NPA_IN_LAST_MONTH** variable has 99.41 missing values and only 2 Foreclosures of 15 NPA's, which is not a good predictor thereby this variable is dropped.
Refer Below table 1:

FORECLOSURE	**0**	**1**	**All**
NPA_IN_LAST_MONTH			
0	69	33	102
#N/A	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 2:

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.

3.2 Correlation Plot & Dropping variables

- From the below correlation graph Figure 17, 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.

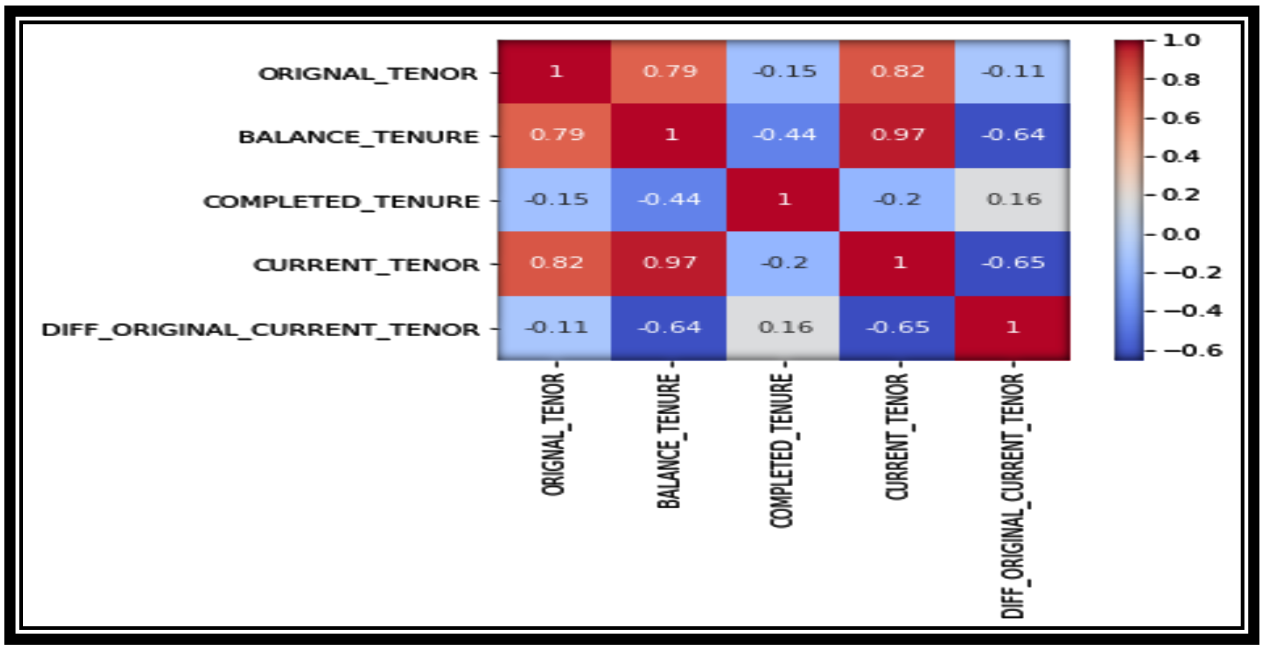


Figure 17 – Correlation Plot

- From Below **Figure 18:** 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.

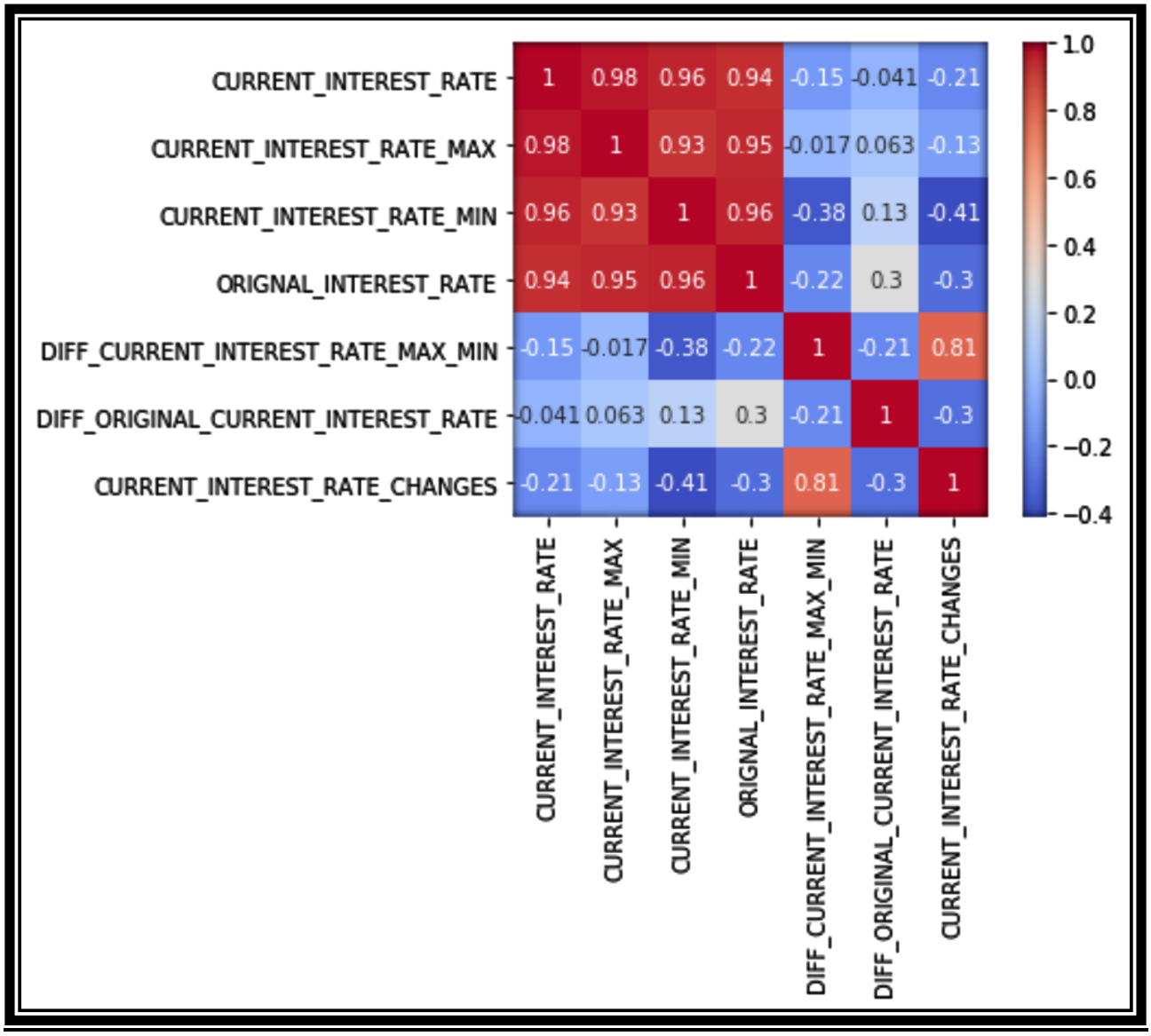


Figure 18 – Correlation Plot

- From **Figure 19:** 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.

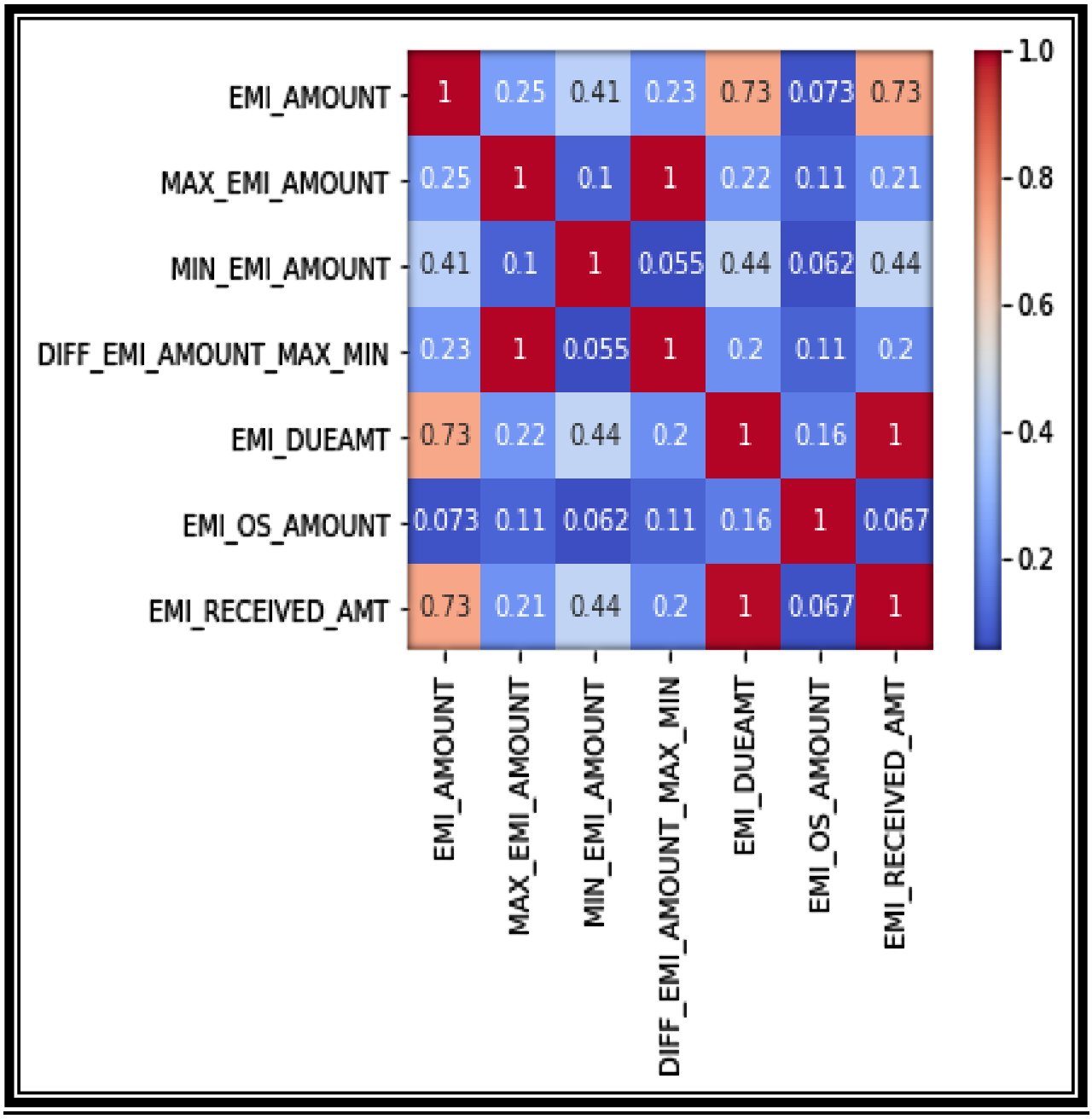


Figure 19 – Correlation Plot

- From **Figure 20:** 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'.

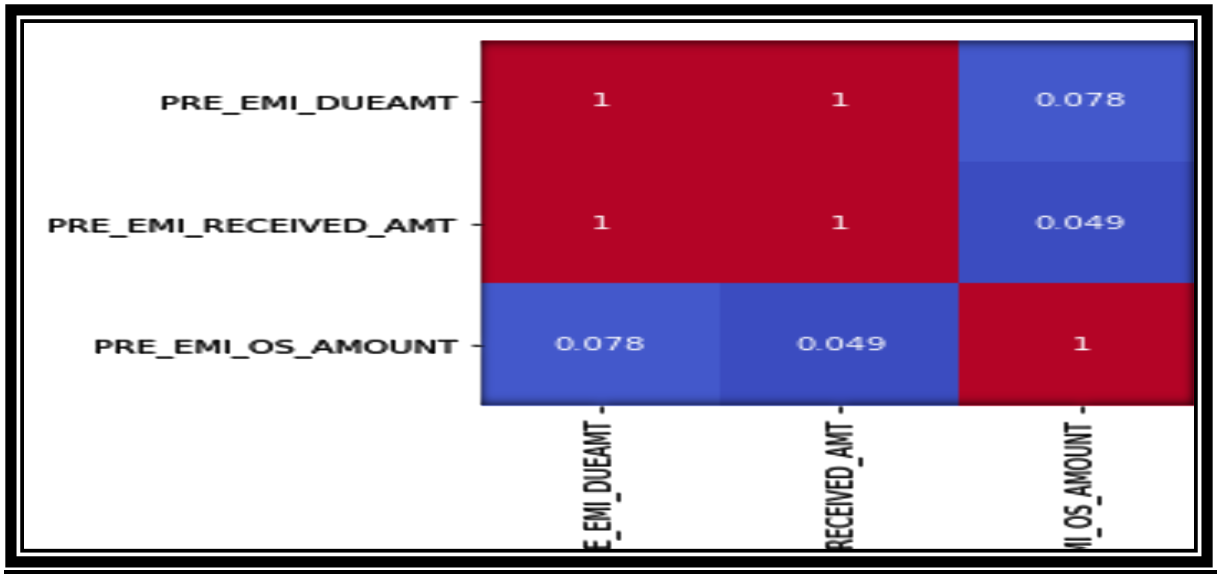


Figure 20 – Correlation Plot

- From **Figure 21:** Excess Available and Excess Adjusted Amount are highly correlated, 'Excess Available' will be retained along with 'Balance Excess'.

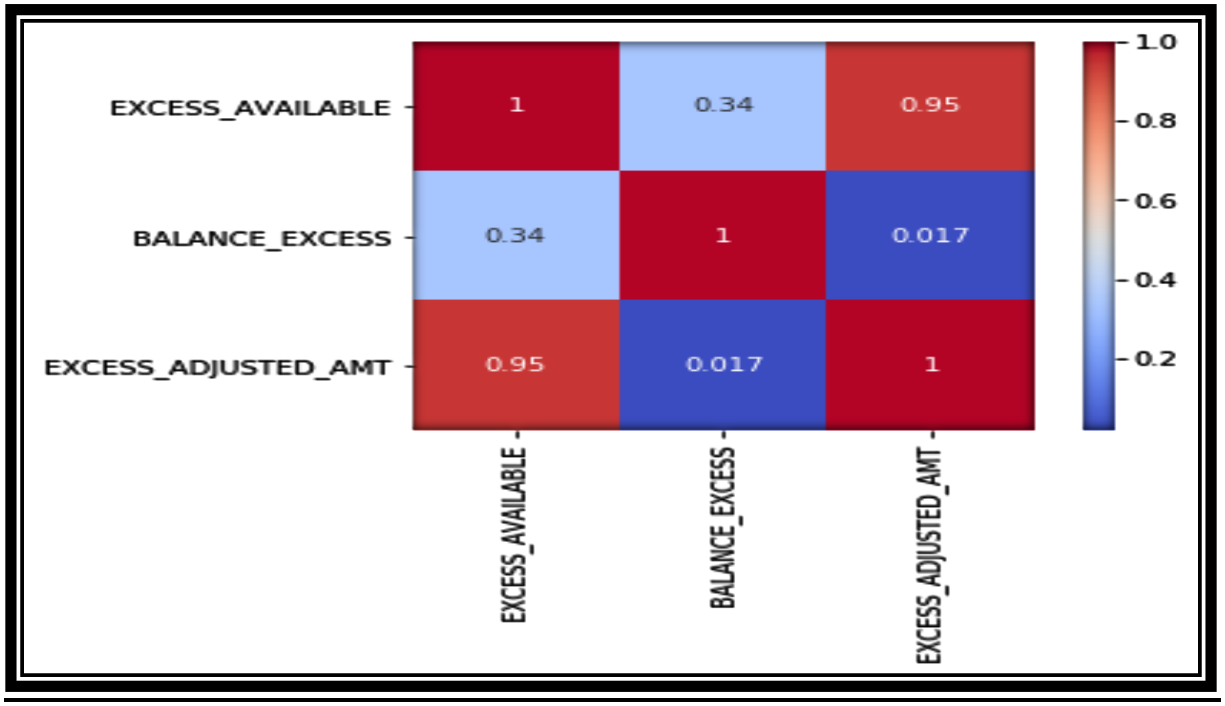


Figure 21 – Correlation Plot

3.3 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

- Refer **Table 4** in Appendix, 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.

3.4 Outlier Treatment / Univariate Analysis

- Outlier treatment applied to 9 variables.
- Refer Figure 22,23,24,25,26,27,28,29,30 in Appendix.

3.5 Derived Metrics & Insights

- Refer Table 5,6 & 7 in Appendix.
- Included City & Product categorical variables – Converted to integers using cat codes.

Note: Finally, 16 variables are selected to run the appropriate models.

4. Model Building & Model Validation

Supervised Learning Approach is used as the labels are provided.

- As it's a Binary Classification problem, under Classification – linear models such as Logistic regression & Linear Discriminant analysis is carried out.
- Under Non-Linear Classification Models Random Forest is Chosen.
- As the data is imbalanced, Smote was used to improve the metrics.
- The overall accuracy will give a wrong picture. Rather Recall and Precision of that class needs attention and tuned to get a best Model.
- 16 Significant variables were applied to logistic regression, 3 variables were dropped as "P" value being greater than significance value.
- One Variable NET_LTV, though the P value is greater, retained as per domain understanding.
- The List is arrived Basis Domain Knowledge, Correlation Plots, Variation inflation factor and finally on the P-values.
- Stas Model Library was used to build a logistic model.
- Logit Regression Results – Refer - **Table 8** in Appendix.

4.1 Models Comparison

Models	Dataset	Precision	Recall	F1-Score	Accuracy	AUC
Logistic Regression with Default Cut-Off	Train	0.46	0.05	0.09	0.91	0.52
Logistic Regression with Optimal Cut-Off	Train	0.19	0.69	0.30	0.72	0.70
Logistic Regression with Optimal Cut-Off	Test	0.19	0.66	0.30	0.72	0.69
Logistic Regression on SMOTE Train data	SMOTE Train	0.66	0.74	0.70	0.72	0.81
Logistic Regression on SMOTE Test data	SMOTE Test	0.66	0.73	0.69	0.72	0.81
Linear Discriminant Analysis - LDA	Train	0.39	0.12	0.18	0.90	0.79
Linear Discriminant Analysis - LDA	Test	0.37	0.10	0.16	0.90	0.77
Linear Discriminant Analysis with Optimal Cut-Off	Train	0.17	0.79	0.28	0.64	0.71
Linear Discriminant Analysis with Optimal Cut-Off	Test	0.17	0.75	0.27	0.64	0.69
Linear Discriminant Analysis - LDA on SMOTE	SMOTE Train	0.63	0.84	0.72	0.72	0.74
Random Forest Model on Train	Train	0.84	0.38	0.52	0.94	0.69
Random Forest Model on Test	Test	0.77	0.31	0.44	0.93	0.65
Random Forest Model on SMOTE	SMOTE Train	0.94	0.92	0.93	0.94	0.94

Table 8.1: Comparison of Models

- Random forest is a high-performance model, but it is a black box model lacking insight. Though the variable importance is achieved it lacks magnitude unlike logistic regression.
- SMOTE was used to balance the data and thereby it helped to fine tune the model. By fine Tuning, Random forest model achieved the maximum accuracy compared to all the models.
- Logistic Regression Model is preferred over other models, as it give enormous information on the variables which could easily be interpreted and understood by probabilities.
- Random Forest only helps in identifying the order of Importance among the variables but not the magnitude. Refer Table 8.2.

5. Final Interpretation

Table 8.3

VARIABLES	COEFFICENT	Exp (Coeff) - ODD ratio	Percent
Intercept	-0.285200000000	0.751863867	-24.81%
NUM_EMI_CHANGES_RANGE_CAT	0.130300000000	1.139170083	13.92%
NET_RECEIVABLE	0.003000000000	1.003004505	0.30%
NET_LTV	0.002300000000	1.002302647	0.23%
EXCESS_AVAILABLE	0.000060840000	1.000060842	0.01%
PRE_EMI_DUEAMT	0.000011210000	1.00001121	0.00%
PAID_INTEREST	0.000001540000	1.00000154	0.00%
LOAN_AMT	-0.000000025480	0.999999975	0.00%
OUTSTANDING_PRINCIPAL	-0.000000116700	0.999999883	0.00%
PAID_PRINCIPAL	-0.000002954000	0.999997046	0.00%
BALANCE_TENURE	-0.003900000000	0.996107595	-0.39%
CITY_NEW	-0.017700000000	0.982455725	-1.75%
FOIR	-0.868400000000	0.419622408	-58.04%
PRODUCT	-0.982800000000	0.374261698	-62.57%

- For a unit change in No. EMI Changes, the odds ratio for an account to default is 1.13.
- For a unit change in No EMI Changes, there is 13 percent increase in odds for an account to default.

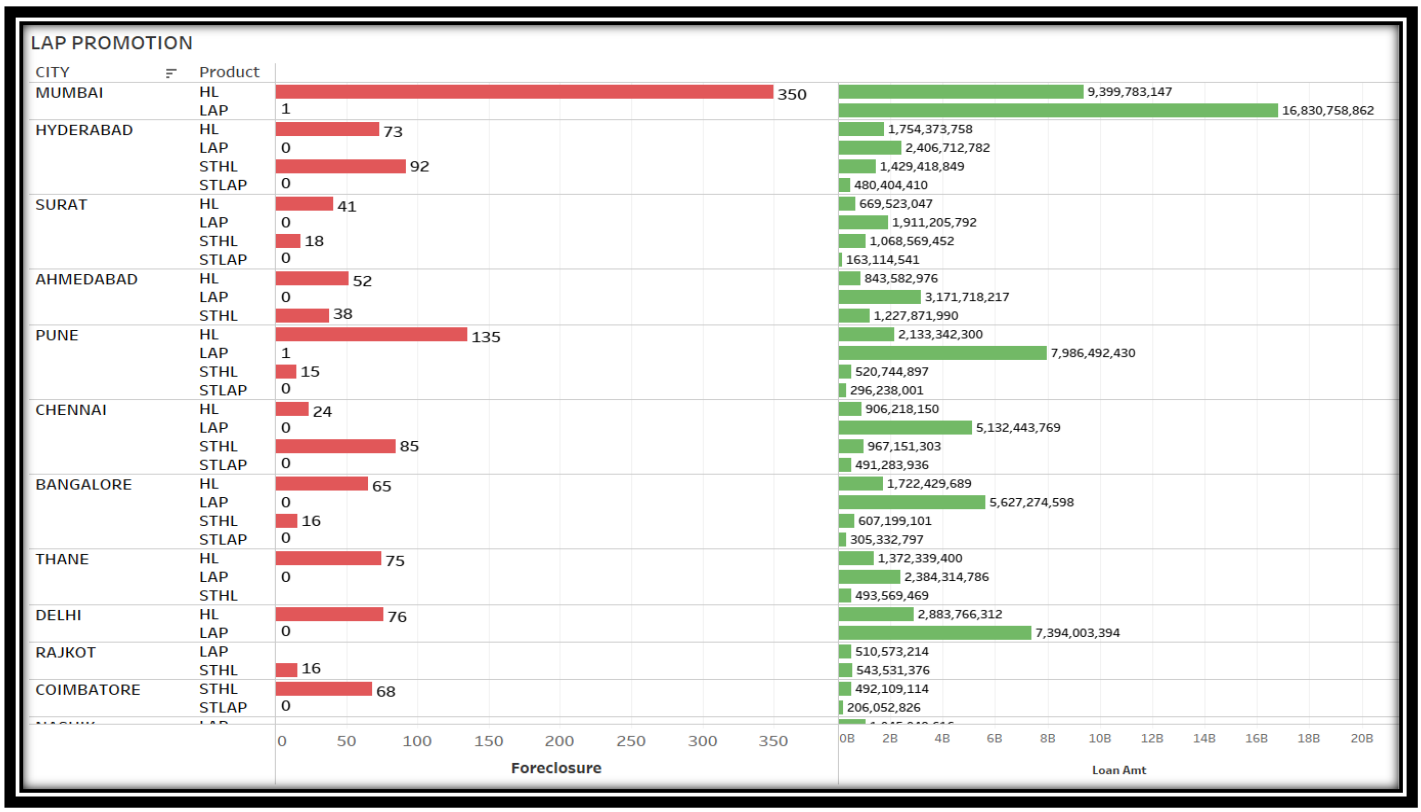
Table 8.4

PRODUCT	CAT	# COUNT		PRODUCT	# DEFAULTS	# COUNT	% DEFAULT
STHL	2	7,268		STHL	803	7,268	11%
LAP	1	6,226		LAP	2	6,226	0%
HL	0	3,482		HL	990	3,482	28%
STLAP	3	3,036		STLAP	0	3,036	0%
TOTAL		20,012		TOTAL	1,795	20,012	9%

- For a unit change in product i.e., HL to LAP, LAP to STHL, STHL to STLAP there is a 62 percent decrease in odd for an account to default.

6. Final Recommendation

Figure 41:



- High Defaults are seen in Home loan category.
- When customer opts for an EMI change in Home Loan category there is 13% chance that an account might default.
- The NBFC should have a dedicated follow up on customers who opt for EMI change.
- High value ticket HL loans are seen in Mumbai, Hyderabad, Pune, The NBFC Should be more vigilant in these cities for EMI changes.
- Promote more LAP loans as there are less defaults observed.
- Promote more LAP loans in Hyderabad, Surat, Ahmedabad, Rajkot, Coimbatore.

7. Appendix

7.1 Data Dictionary:

Variables are sorted as per understanding.

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

7.2 Descriptive Statistics – Significant Variables:

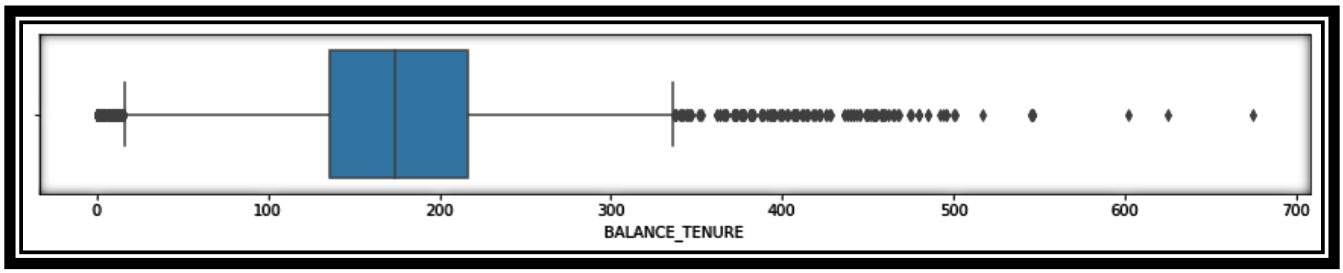
Table 4:

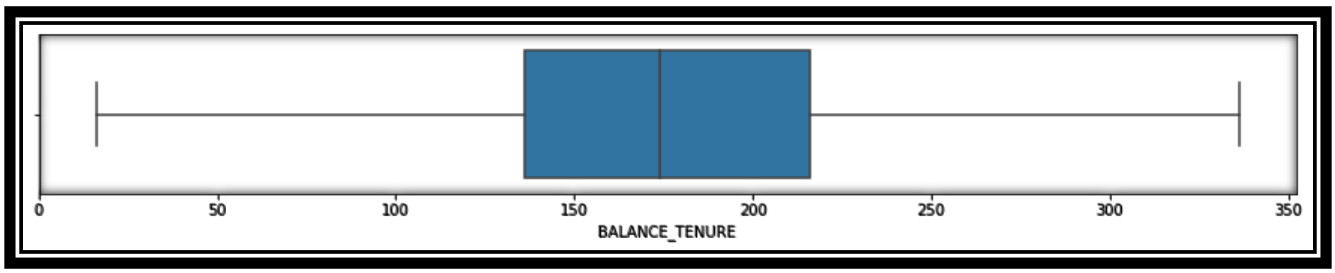
	count	mean	std	min	25%	50%	75%	max
BALANCE_TENURE	20012.0000	172.8246	64.0045	0.0000	136.0000	174.0000	216.0000	674.0000
COMPLETED_TENURE	20012.0000	17.2691	16.4863	0.0000	6.0000	12.0000	25.0000	98.0000
DPD	20012.0000	7.5741	66.0989	0.0000	0.0000	0.0000	0.0000	2054.0000
EMI_OS_AMOUNT	20012.0000	33297.3485	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

7.3 Outlier Treatment / Univariate Analysis

- 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.

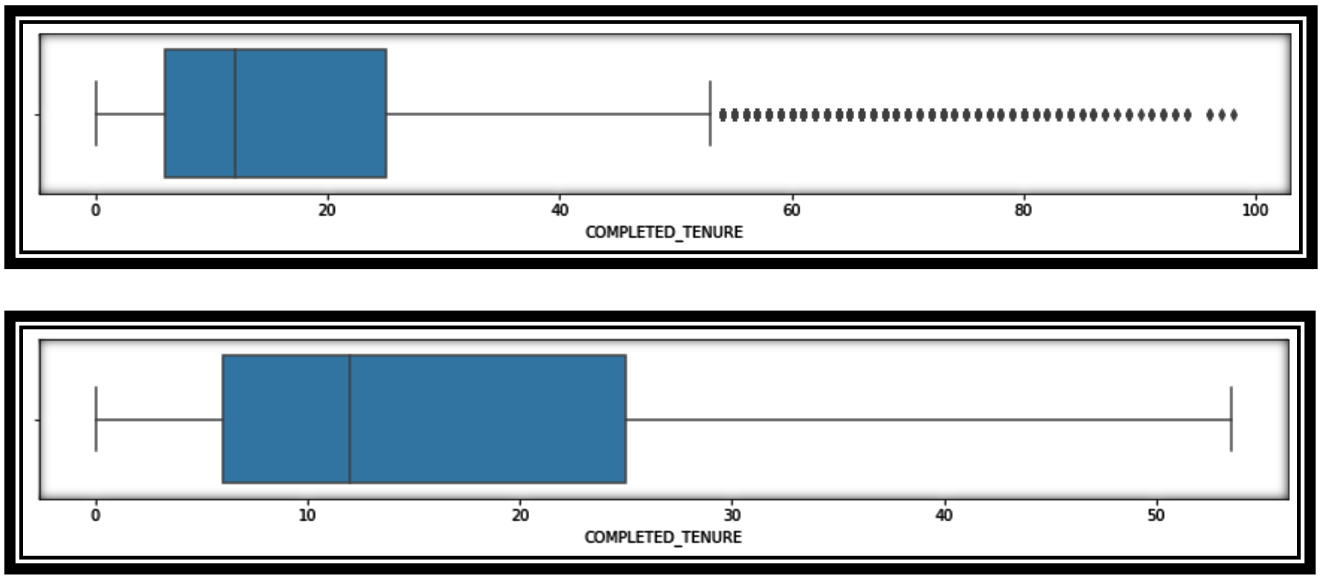
Figure 22:





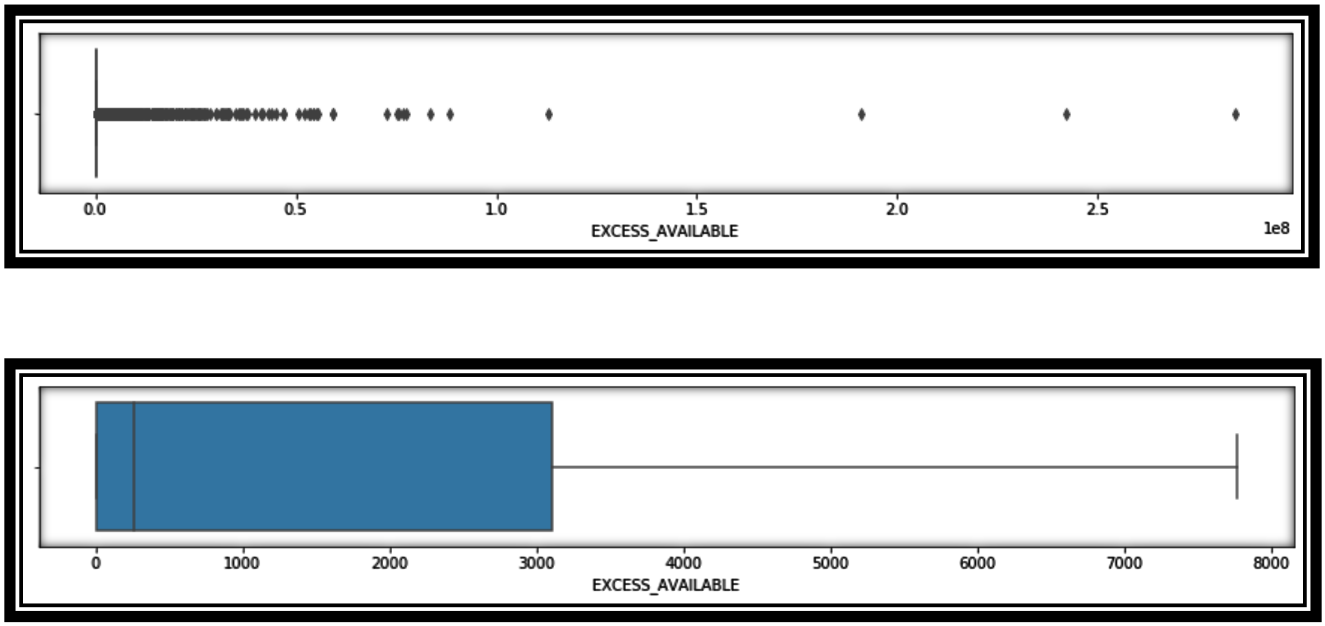
- Completed tenure – Before outlier treatment, completed tenure had extreme outliers to 98 months. After treatment most of the values lie approximately between 7 to 25 months.

Figure 23:



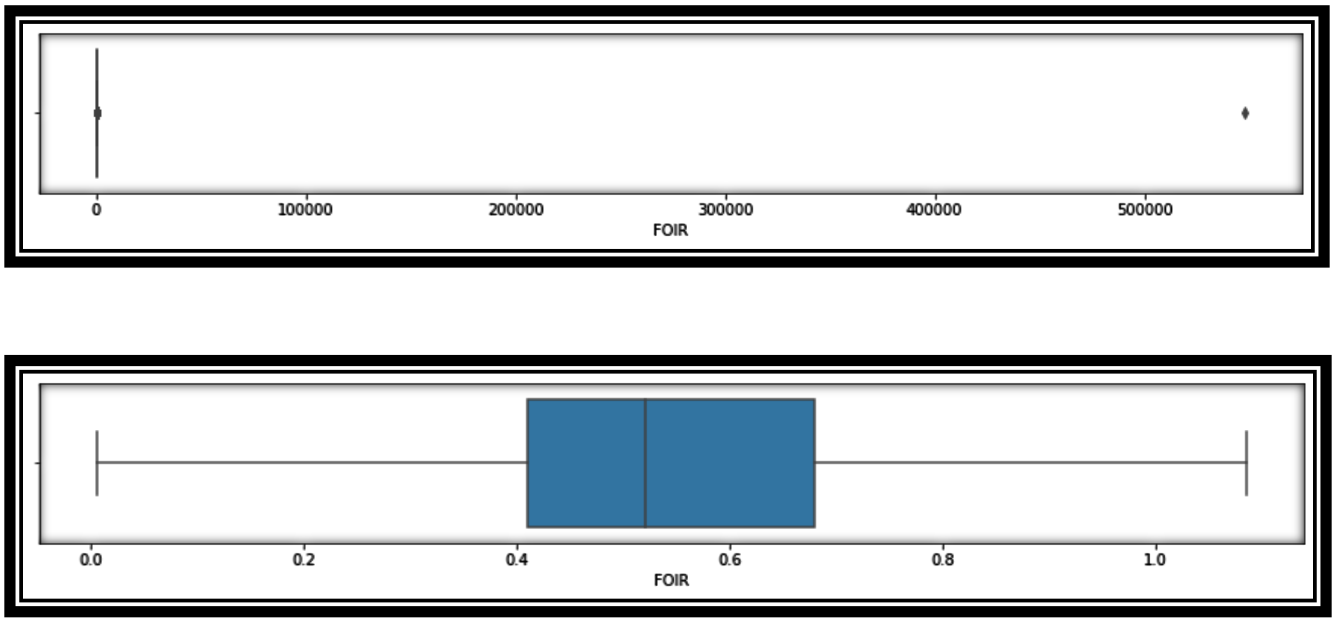
- Excess available – Before outlier treatment, Excess available had extreme outliers to 28 cr odd. After treatment most of the values lie approximately between 0 to 3k.

Figure 24:



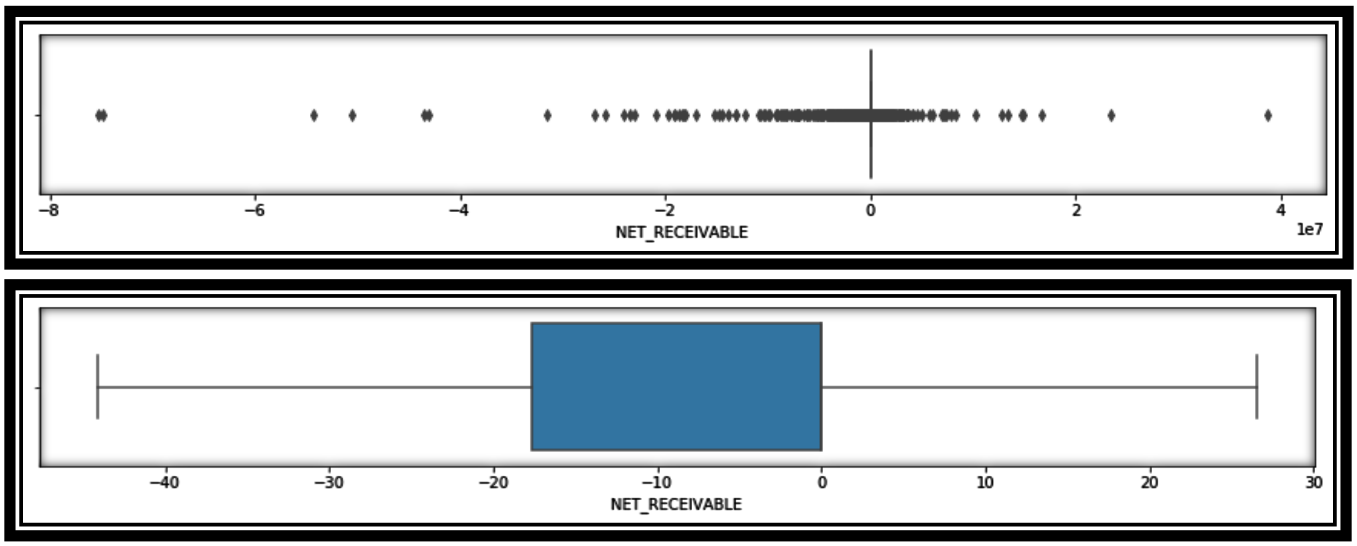
- FOIR – Before outlier treatment, FOIR available had negative value. After treatment most of the values lie approximately between 0.4 to 0.7 which is ideal range (0 – 1).

Figure 25:



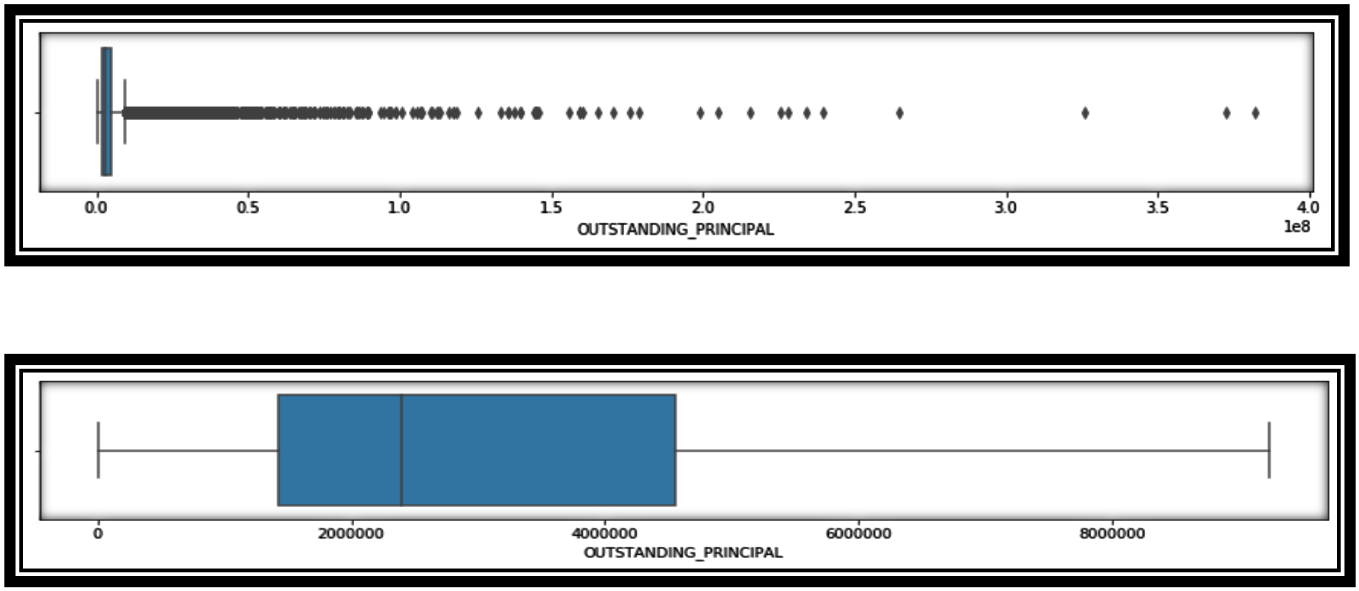
- Net receivable – Before outlier treatment, Net receivable had extreme outliers on both positive and negative ends. After treatment most of the values lie approximately between -18 to 0 lacs(mostly on the negative end). Which is good predictor for foreclosure.

Figure 26:



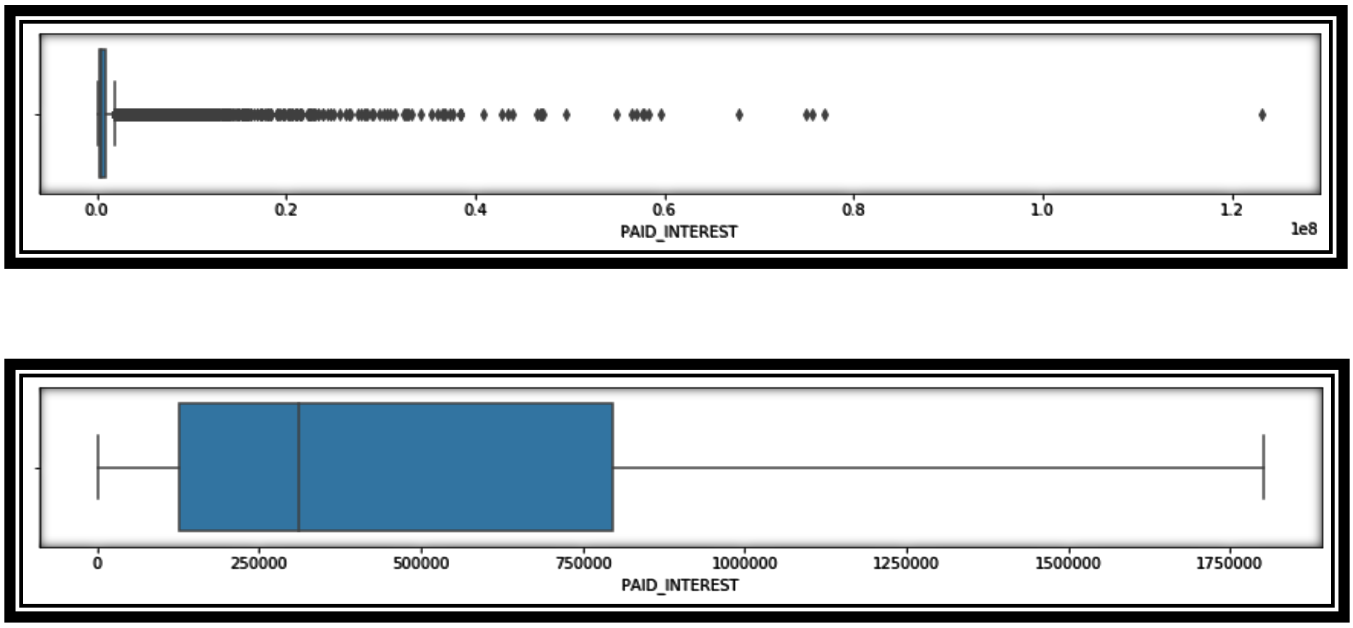
- Outstanding principal – Before outlier treatment, outstanding principal had extreme outliers to 38 cr. After treatment most of the values lie approximately between 17 to 45 lacs.

Figure 27:



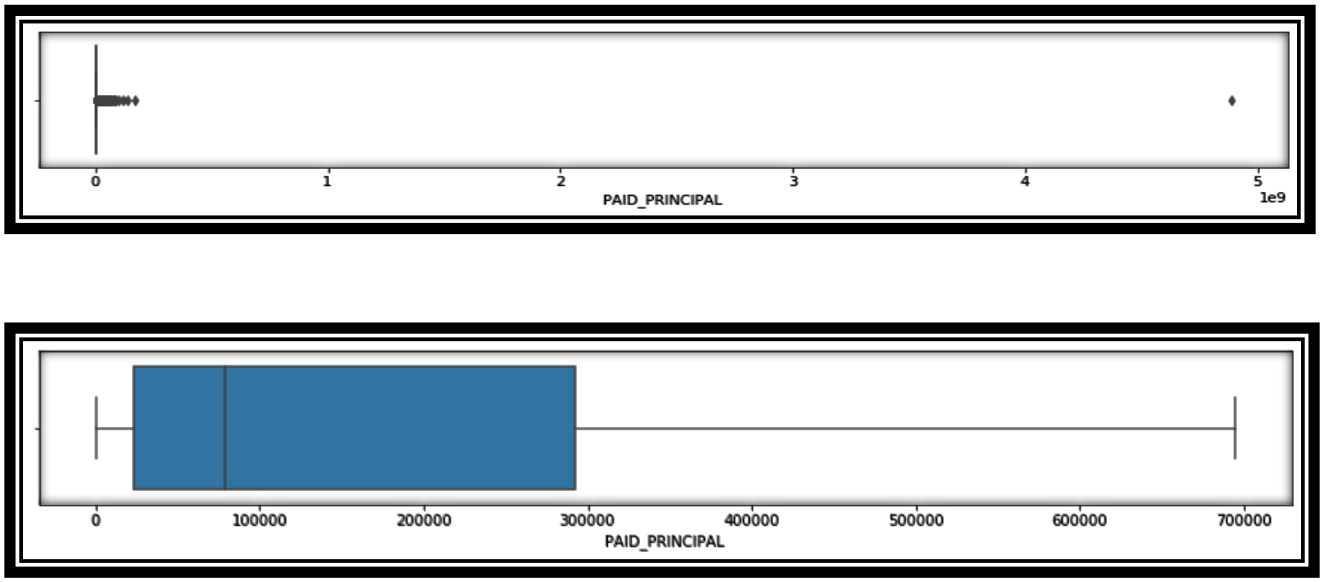
- Paid Interest – Before outlier treatment, paid interest had extreme outliers to 12.3 cr. After treatment most of the values lie approximately between 2 to 7.7 lacs.

Figure 28:



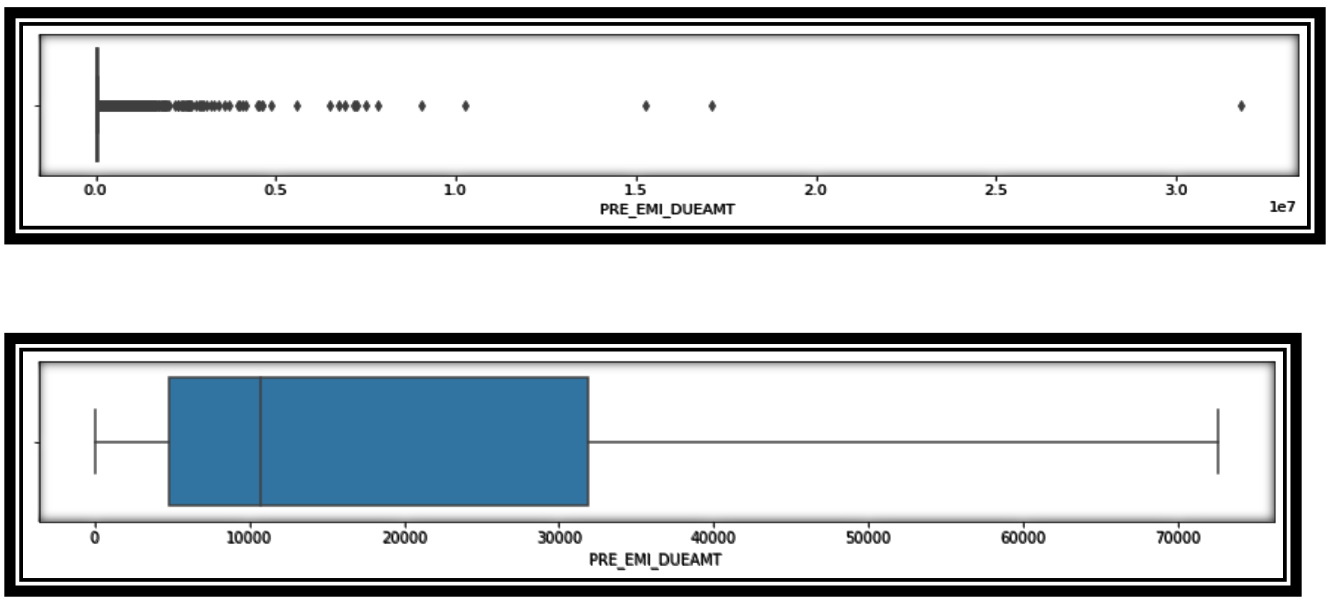
- Paid Principal – Before outlier treatment, Paid principal had extreme outliers to 488 cr. After treatment most of the values lie approximately between 40k to 2.9 lacs.

Figure 29:



- 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.

Figure 30:



7.4 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	

7.5 Logistic Regression Output – Model 4

Table 8

Logit Regression Results			
Dep. Variable:	FORECLOSURE	**No. Observations:**	13408
Model:	Logit	**Df Residuals:**	13394
Method:	MLE	**Df Model:**	13
Date:	Sun, 25 Apr 2021	**Pseudo R-squ.:**	0.1515
Time:	19:33:30	**Log-Likelihood:**	-3426.5
converged:	True	**LL-Null:**	-4038.5
Covariance Type:	nonrobust	**LLR p-value:**	1.172e-253

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	-0.2852	0.205	-1.390	0.164	-0.687	0.117
BALANCE_TENURE	-0.0039	0.001	-5.152	0.000	-0.005	-0.002
EXCESS_AVAILABLE	6.084e-05	1.04e-05	5.828	0.000	4.04e-05	8.13e-05
FOIR	-0.8684	0.149	-5.820	0.000	-1.161	-0.576
NET_RECEIVABLE	0.0030	0.002	1.791	0.073	-0.000	0.006
OUTSTANDING_PRINCIPAL	-1.167e-07	1.93e-08	-6.047	0.000	-1.55e-07	-7.89e-08
PAID_INTEREST	1.54e-06	9.8e-08	15.718	0.000	1.35e-06	1.73e-06
PAID_PRINCIPAL	-2.954e-06	2.92e-07	-10.133	0.000	-3.53e-06	-2.38e-06
PRE_EMI_DUEAMT	1.121e-05	1.5e-06	7.462	0.000	8.26e-06	1.42e-05
NUM_EMI_CHANGES_RANGE_CAT	0.1303	0.050	2.596	0.009	0.032	0.229

PRODUCT	-0.9828	0.045	-22.011	0.000	-1.070	-0.895
LOAN_AMT	-2.548e-08	5.89e-09	-4.327	0.000	-3.7e-08	-1.39e-08
NET_LTV	0.0023	0.002	1.423	0.155	-0.001	0.006
CITY_NEW	-0.0177	0.008	-2.202	0.028	-0.033	-0.002

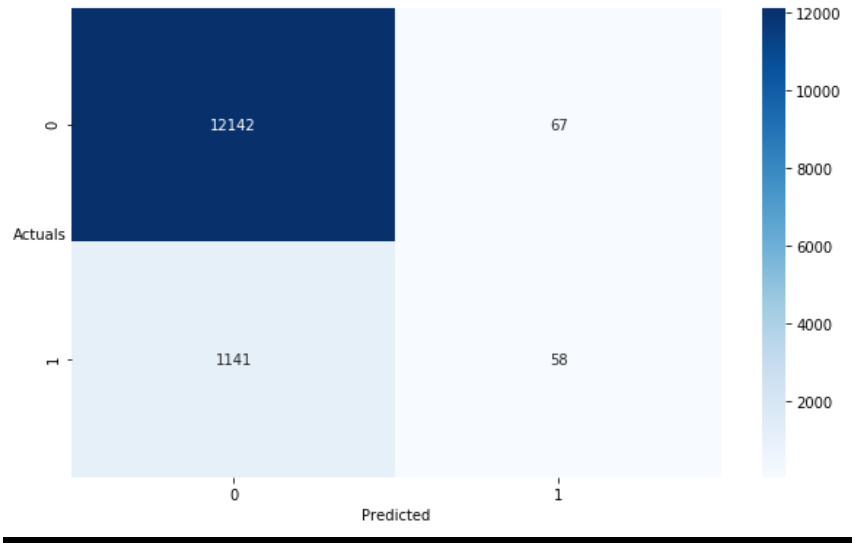
Table 8.2

Out[237]:

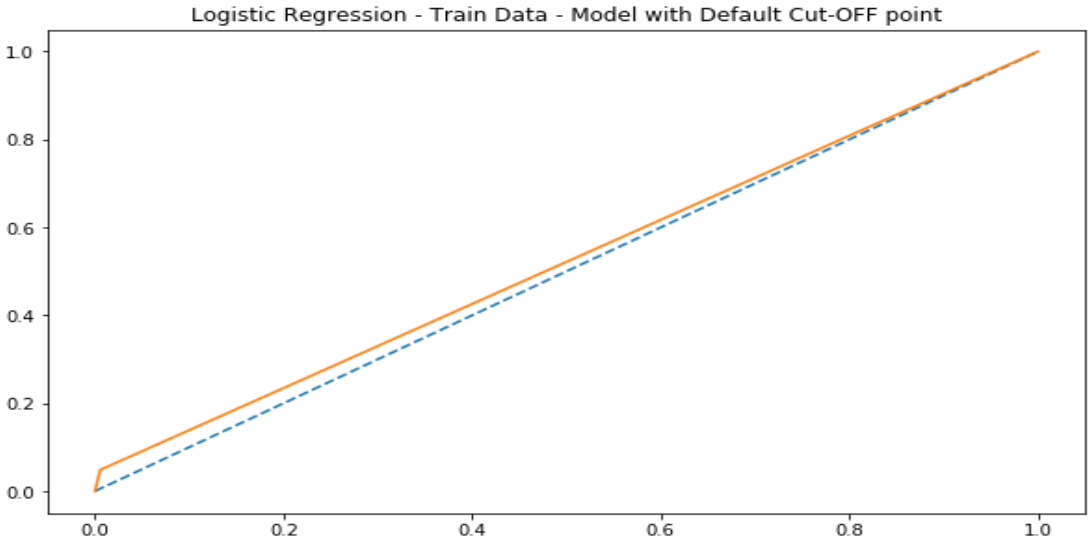
	Variable	Importance
12	PRODUCT	0.2749
4	NET_RECEIVABLE	0.1264
1	COMPLETED_TENURE	0.1165
2	EXCESS_AVAILABLE	0.1122
6	PAID_INTEREST	0.0794
0	BALANCE_TENURE	0.0512
8	PRE_EMI_DUEAMT	0.0462
13	LOAN_AMT	0.0377
15	CITY_NEW	0.0345
7	PAID_PRINCIPAL	0.0302
5	OUTSTANDING_PRINCIPAL	0.0278
3	FOIR	0.0253
11	NUM_EMI_CHANGES_RANGE_CAT	0.0208
14	NET_LTV	0.0108
10	EMI_OSAMT_RANGE_CAT	0.0036
9	DPD_RANGE_CAT	0.0025

7.5.1. LOGISTIC REGRESSION - WITH DEFAULT CUTOFF 0.5

Figure 31:



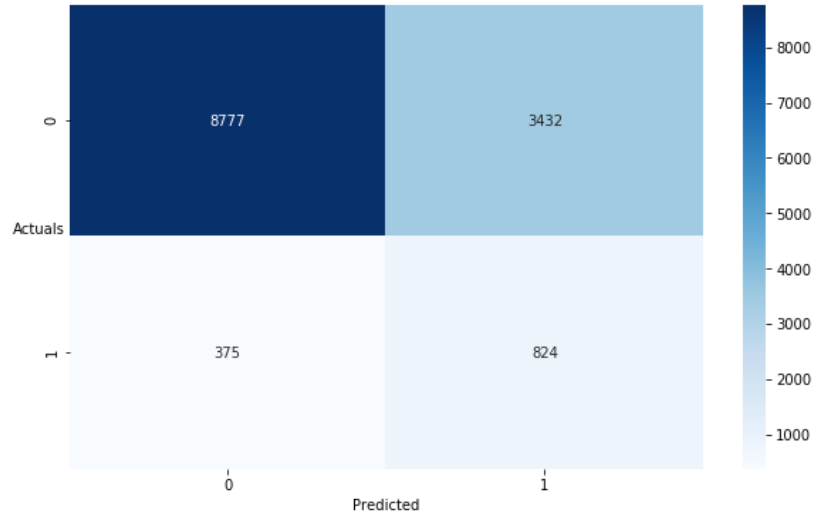
	precision	recall	f1-score	support
0	0.914	0.995	0.953	12209
1	0.464	0.048	0.088	1199
accuracy			0.910	13408
macro avg	0.689	0.521	0.520	13408
weighted avg	0.874	0.910	0.875	13408



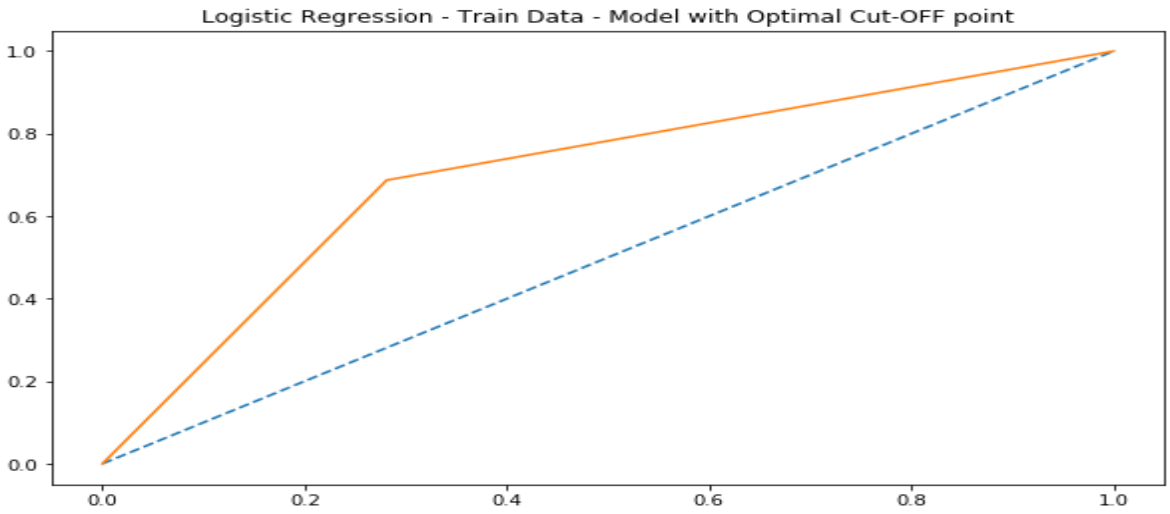
Inference : Recall at 4.8 percent and precision at 46.4 percent which only 4.8% defaults predicted correctly with a default cutoff 0.5. But Specificity 99 percent indicates that the most loan accounts are showing as non default. AUC – 52

7.5.2. LOGISTIC REGRESSION – TRAIN DATA - WITH OPTIMUM CUTOFF 0.09

Figure 32:



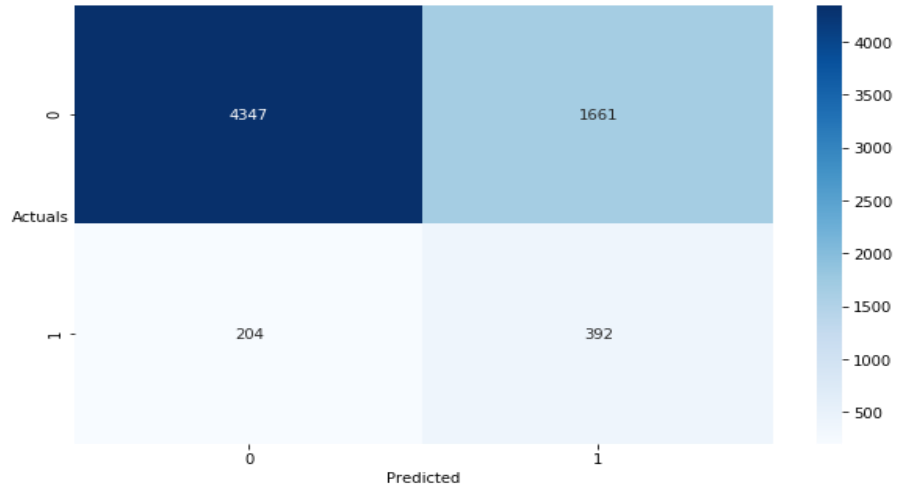
	precision	recall	f1-score	support
0	0.959	0.719	0.822	12209
1	0.194	0.687	0.302	1199
accuracy			0.716	13408
macro avg	0.576	0.703	0.562	13408
weighted avg	0.891	0.716	0.775	13408



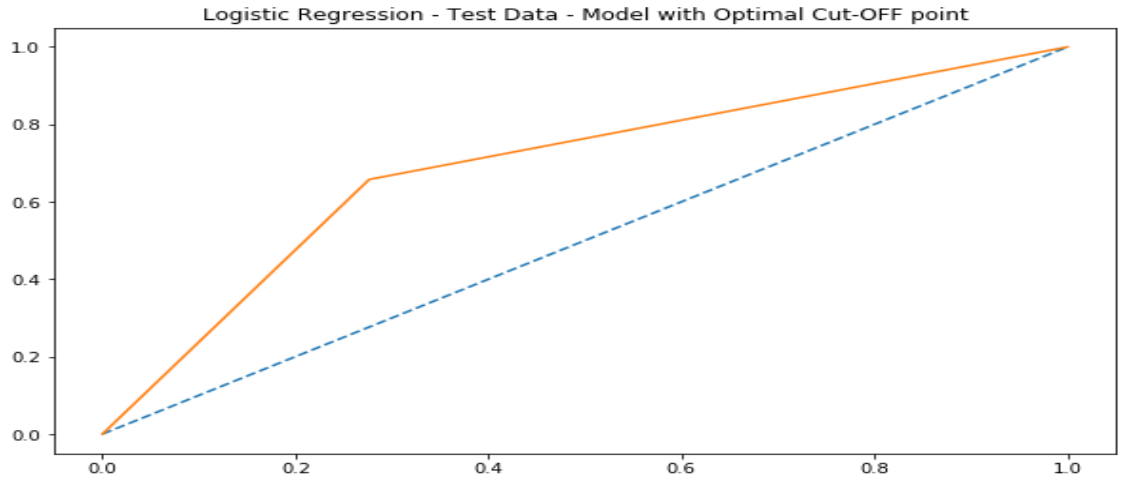
Inference : Recall at 68 percent and precision at 19.4 percent is lowest, with 68% defaults is predicted correctly with a optimum cutoff 0.09. Specificity 71.9 percent. AUC – 70

7.5.3. LOGISTIC REGRESSION – TEST DATA - WITH OPTIMUM CUTOFF 0.09

Figure 33:



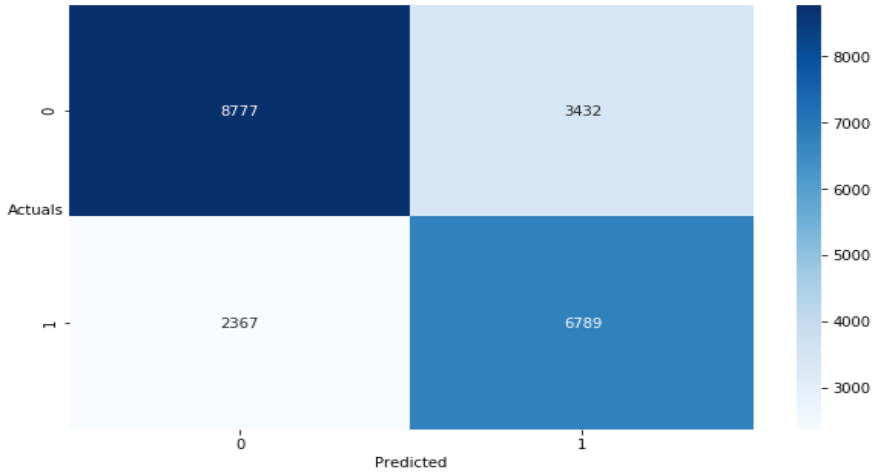
	precision	recall	f1-score	support
0	0.955	0.724	0.823	6008
1	0.191	0.658	0.296	596
accuracy			0.718	6604
macro avg	0.573	0.691	0.560	6604
weighted avg	0.886	0.718	0.776	6604



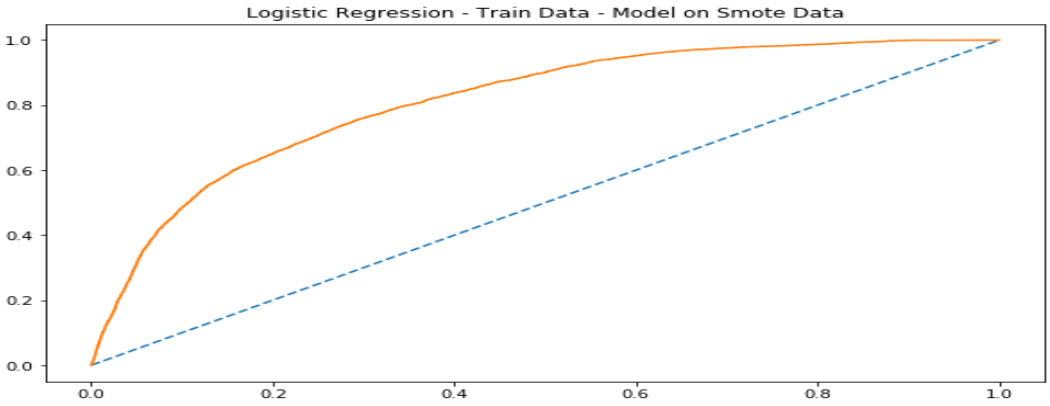
Inference : Test set Recall reduced to 65.8 percent and precision at 19.1 percent is lowest, with 65.8% defaults is predicted correctly with a optimum cutoff 0.09. Specificity 72.4 percent. AUC – 69

7.5.4. LOGISTIC REGRESSION – SMOTE DATA – TRAIN DATASET – CUTOFF – 0.09

Figure 34:



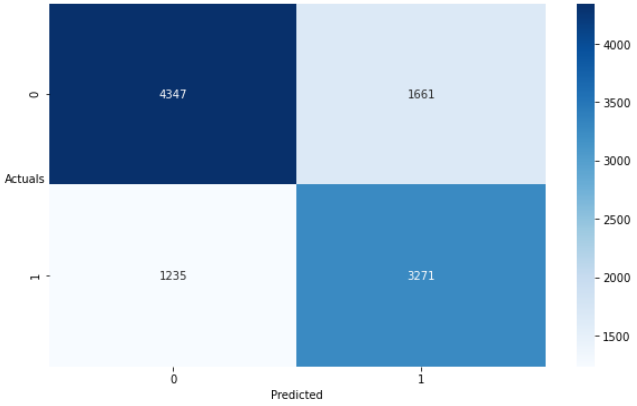
	precision	recall	f1-score	support
0	0.788	0.719	0.752	12209
1	0.664	0.741	0.701	9156
accuracy			0.729	21365
macro avg	0.726	0.730	0.726	21365
weighted avg	0.735	0.729	0.730	21365



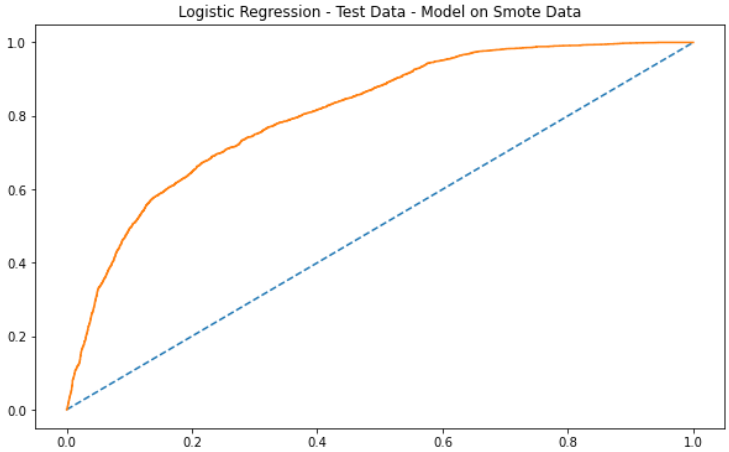
Inference: Recall at 74 percent and precision at 66 percent which 74% of defaults predicted correctly with a optimum cutoff 0.09 is a very good model when smote is applied. Recall is at maximum compared to past 3 summary of logistic regression. Both Recall and precision are high with a regularized data. AUC- 81.

7.5.5. LOGISTIC REGRESSION – SMOTE DATA – TEST DATASET – CUTOFF – 0.09

Figure 34.1



	precision	recall	f1-score	support
0	0.779	0.724	0.750	6008
1	0.663	0.726	0.693	4506
accuracy			0.725	10514
macro avg	0.721	0.725	0.722	10514
weighted avg	0.729	0.725	0.726	10514



Inference: Recall at 73 percent and precision at 66 percent which 73% of defaults predicted correctly with an optimum cutoff 0.09 is a very good model when smote is applied on test data. Recall is equal to the train data of logistic regression. Both Recall and precision are high with a regularized data.
AUC- 81.

Both Smote Train data and Smote Test Data have similar metrics, hence it is a good model.

7.6 LDA - LINEAR DISCRMINANT ANALYSIS

LDA With default values for both train and test datasets.

Table 9

	precision	recall	f1-score	support
0	0.92	0.98	0.95	12209
1	0.39	0.12	0.18	1199
accuracy			0.90	13408
macro avg	0.66	0.55	0.57	13408
weighted avg	0.87	0.90	0.88	13408

Table 10

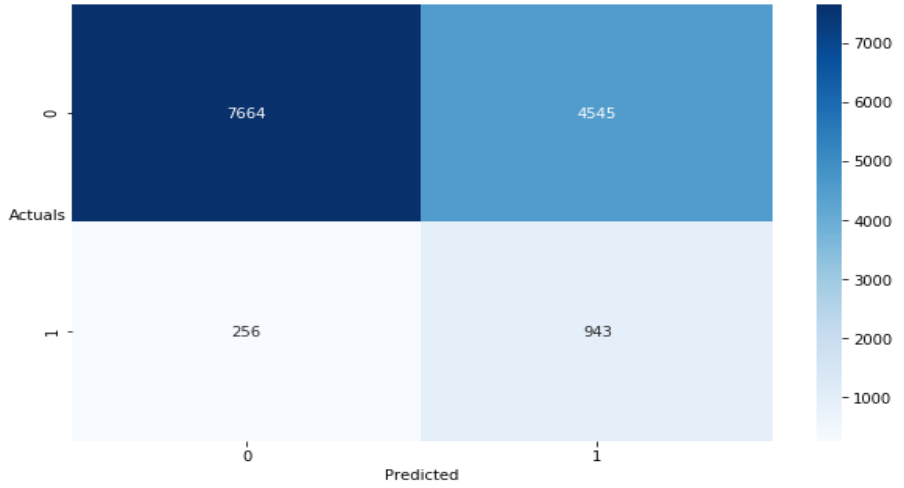
	precision	recall	f1-score	support
0	0.92	0.98	0.95	6008
1	0.37	0.10	0.16	596
accuracy			0.90	6604
macro avg	0.64	0.54	0.55	6604
weighted avg	0.87	0.90	0.88	6604

Inference:

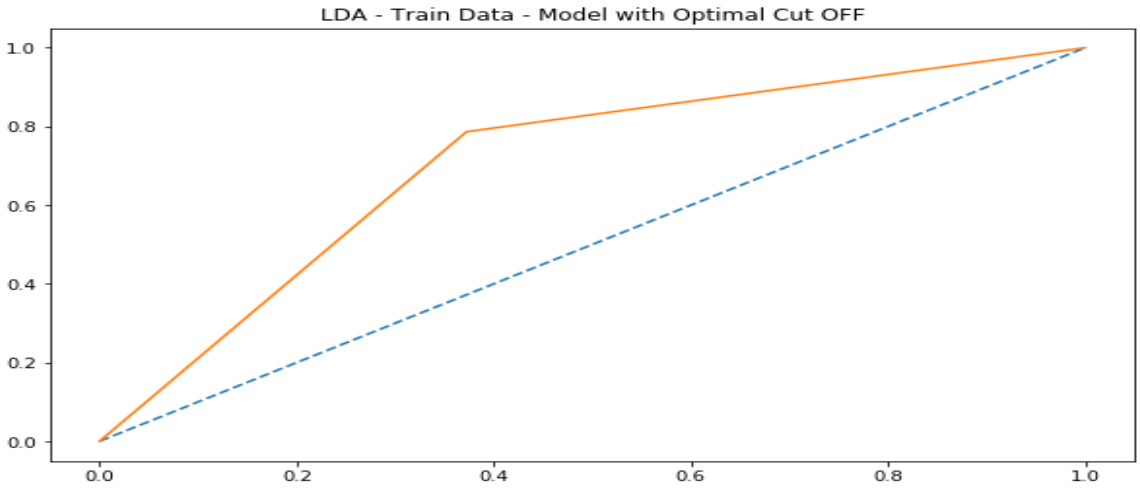
Recall for both train and test data for LDA model with default values show poor recall scores of 12 & 10 percent and having precision being lowest. Prediction of loan defaults correctly at 10 percent levels is very poor metrics.

7.6.1. LDA – TRAIN DATASET – CUTOFF – 0.06

Figure 35



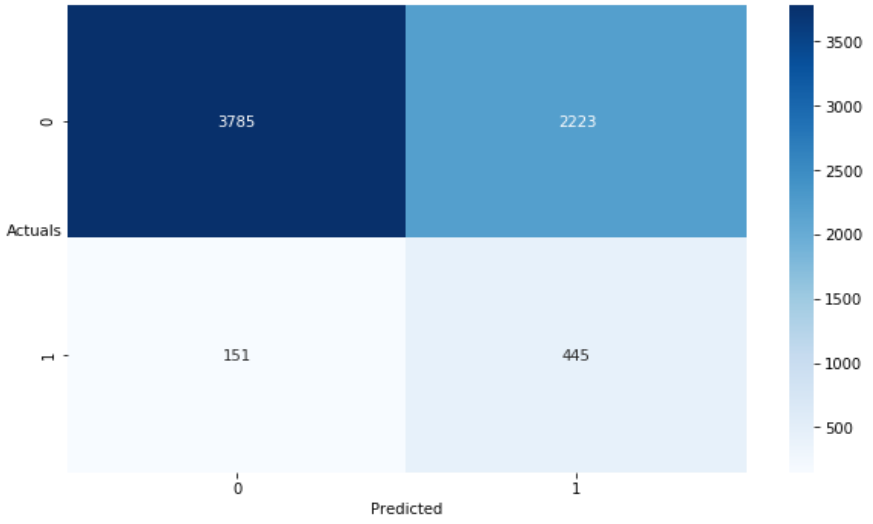
	precision	recall	f1-score	support
0	0.968	0.628	0.761	12209
1	0.172	0.786	0.282	1199
accuracy			0.642	13408
macro avg	0.570	0.707	0.522	13408
weighted avg	0.897	0.642	0.719	13408



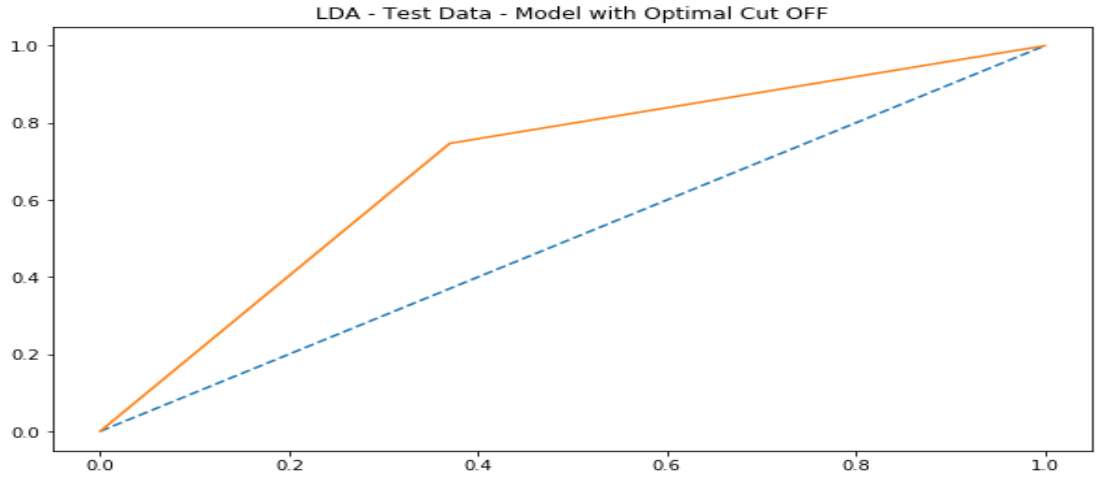
Inference: Recall at 78 percent and precision at 17 percent which 78% of defaults predicted correctly with a optimum cutoff 0.06 is a very good but precision being low. AUC- 70.

7.6.2. LDA – TEST DATASET – CUTOFF – 0.06

Figure 36



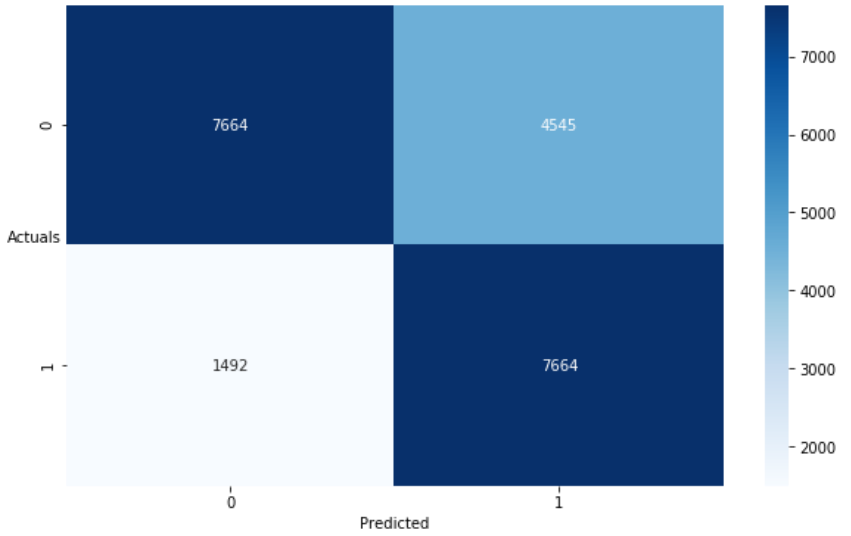
	precision	recall	f1-score	support
0	0.962	0.630	0.761	6008
1	0.167	0.747	0.273	596
accuracy			0.641	6604
macro avg	0.564	0.688	0.517	6604
weighted avg	0.890	0.641	0.717	6604



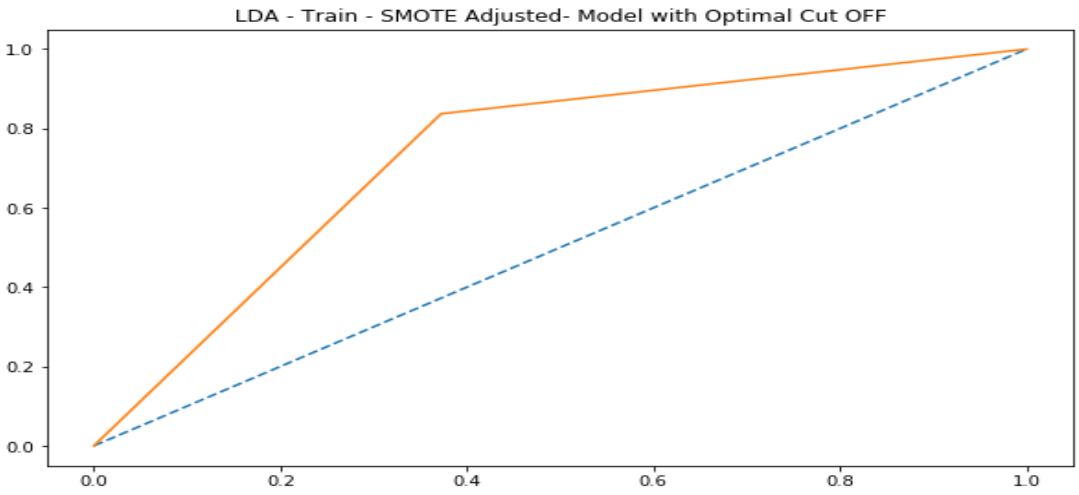
Inference: Recall reduced to 74 percent on test data and precision at 16 percent which 74% of defaults predicted correctly with a optimum cutoff 0.06 is a very good but precision being low. AUC- 68.

7.6.3. LDA – SMOTE DATASET – CUTOFF – 0.06

Figure 37



	precision	recall	f1-score	support
0	0.837	0.628	0.717	12209
1	0.628	0.837	0.717	9156
accuracy			0.717	21365
macro avg	0.732	0.732	0.717	21365
weighted avg	0.747	0.717	0.717	21365

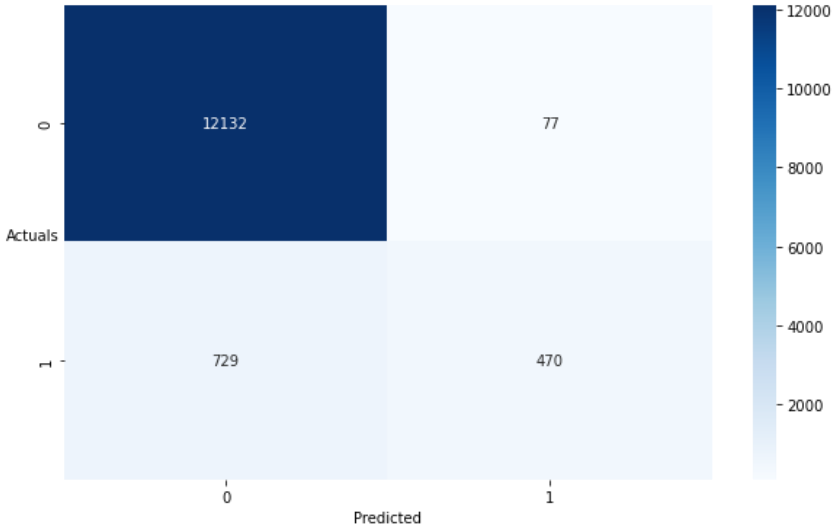


Inference: Recall at 83 percent and precision at 62 percent which 83% of loan defaults predicted correctly with a optimum cutoff 0.06 is a very good model when smote is applied. Recall is at maximum compared to past 3 summary of LDA. Both Recall and precision are high with a regularized data.
AUC- 73.

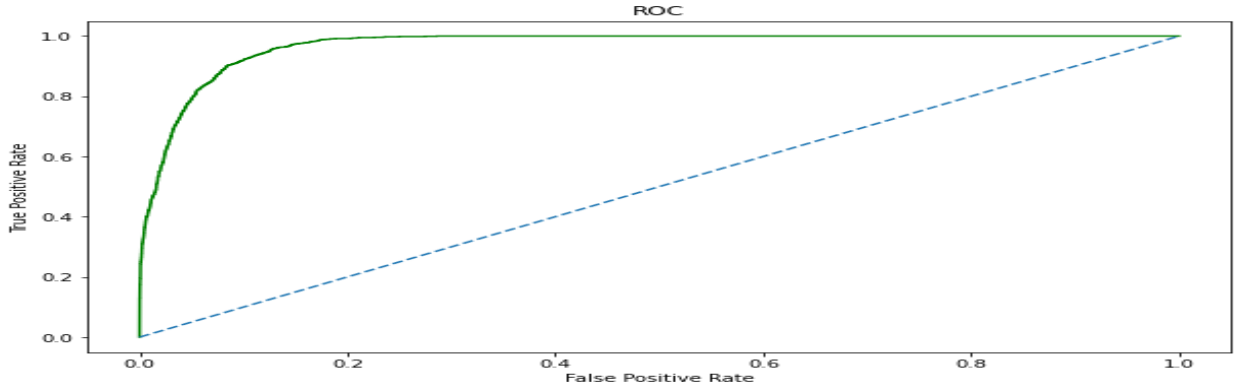
7.7. RANDOM FOREST MODEL

7.7.1. RANDOM FOREST – TRAIN DATASET

Figure 38



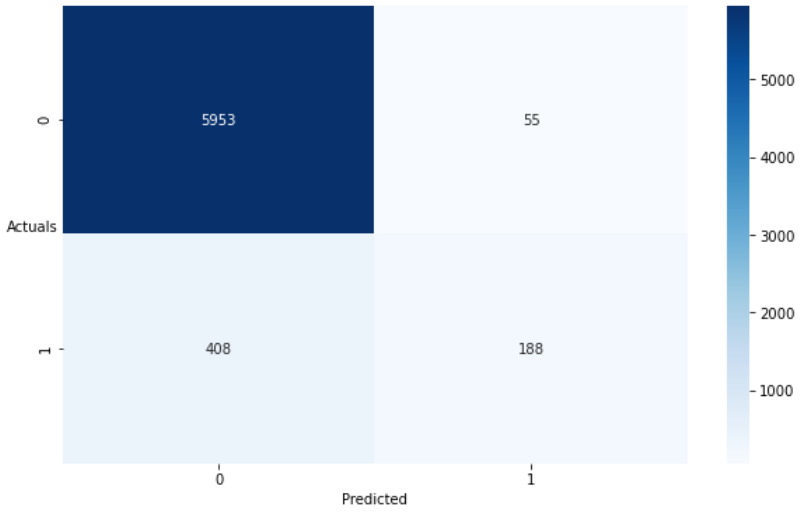
	precision	recall	f1-score	support
0	0.943	0.994	0.968	12209
1	0.859	0.392	0.538	1199
accuracy			0.940	13408
macro avg	0.901	0.693	0.753	13408
weighted avg	0.936	0.940	0.929	13408



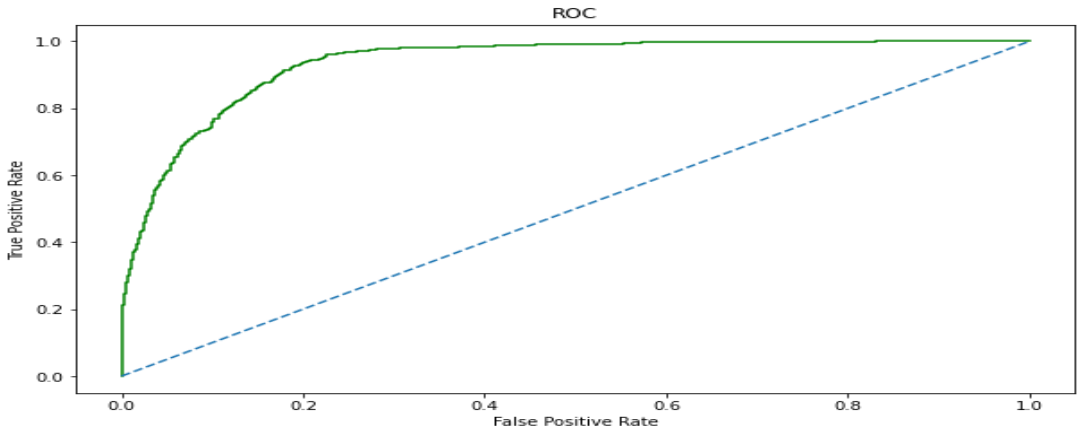
Inference: Recall at 39 percent and precision at 85 percent which 39% of loan defaults predicted correctly which is very low.
AUC- 69.

7.7.2. RANDOM FOREST – TEST DATASET

Figure 39



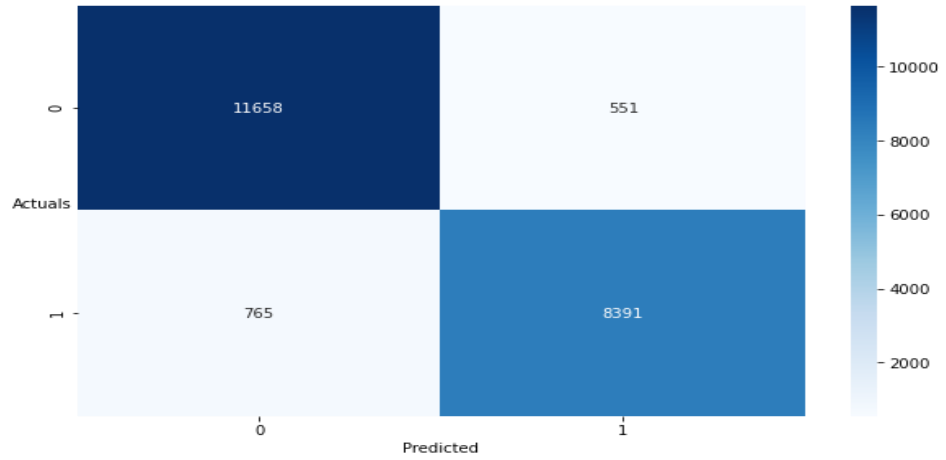
	precision	recall	f1-score	support
0	0.936	0.991	0.963	6008
1	0.774	0.315	0.448	596
accuracy			0.930	6604
macro avg	0.855	0.653	0.705	6604
weighted avg	0.921	0.930	0.916	6604



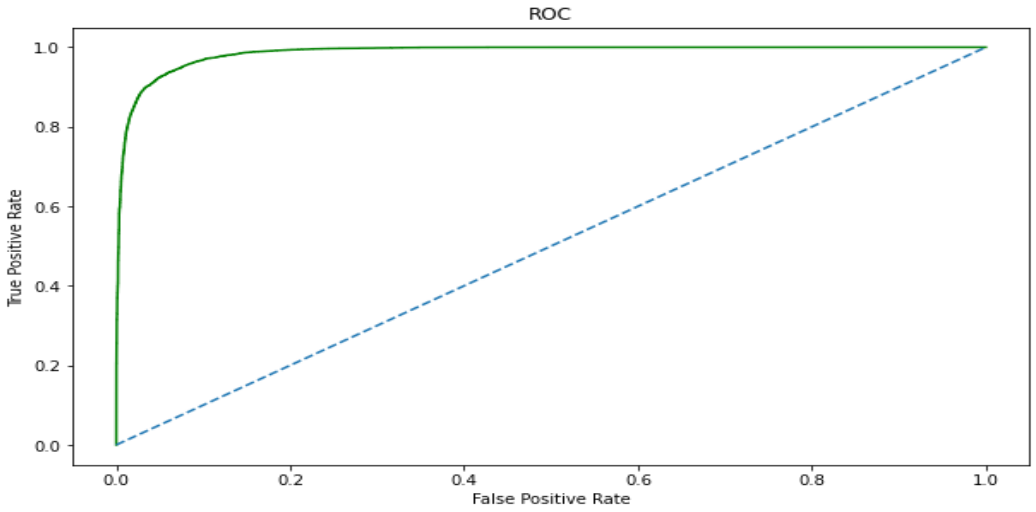
Inference: Recall reduced to 31 percent and precision at 77 percent which 31% of loan defaults predicted correctly which is very low.
AUC- 65.

7.7.3. RANDOM FOREST – SMOTE DATASET

Figure 40



	precision	recall	f1-score	support
0	0.938	0.955	0.947	12209
1	0.938	0.916	0.927	9156
accuracy			0.938	21365
macro avg	0.938	0.936	0.937	21365
weighted avg	0.938	0.938	0.938	21365



Inference: Recall drastically increased to 91 percent and precision at 93 percent which 91% of loan defaults predicted correctly with a optimum best

parameters is a very good model when smote is applied. Recall is at maximum compared to all models. Both Recall and precision are high with a regularized data. AUC- 93.