BUSINESS REPORT

NBFC Foreclosure Prediction Notes 2

Abstract

Model Building, Tuning & Evaluating Using Performance metrics.
Interpretation of the Optimum Model.

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I. Model Building & interpretation

Logistics Regression

- List of Significant Variables used for model building are below :
- 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.
- The P value was obtained by the summary and insignificant predictors were removed one by one to get 13 predictors which are significant.
- One Variable NET_LTV , though the P value is greater, retained as per domain understanding.
- Below are the significant predictors which can predict Loan Default and output from Stats model.
- **The Coeffecients of "NET_RECEIVABLE" is positive to indicate the predictors are significant to predict the default of a loan.**

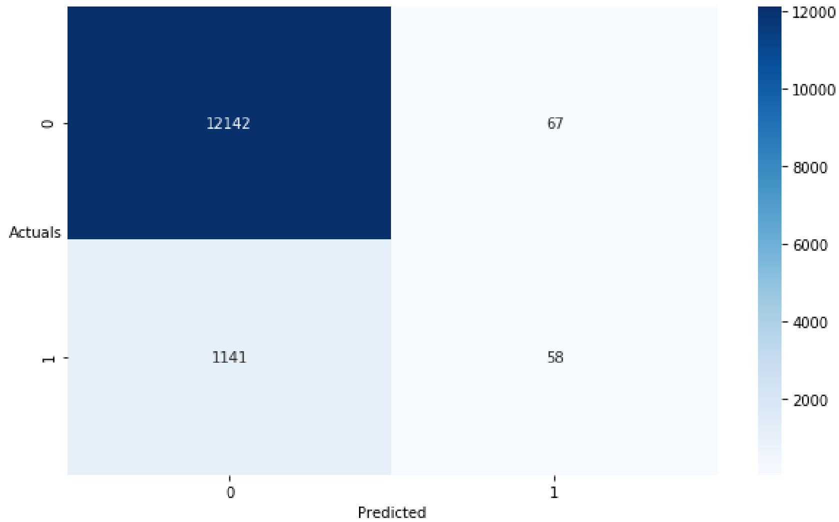
Table 1.1

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

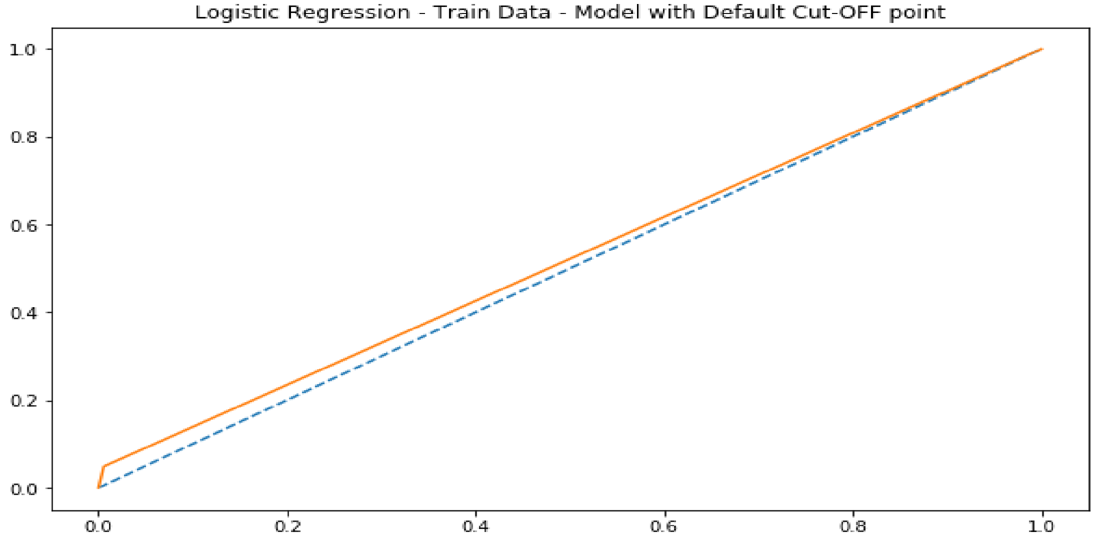
LOGISTIC REGRESSION - WITH DEFAULT CUTOFF 0.5

Figure 1.1



	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

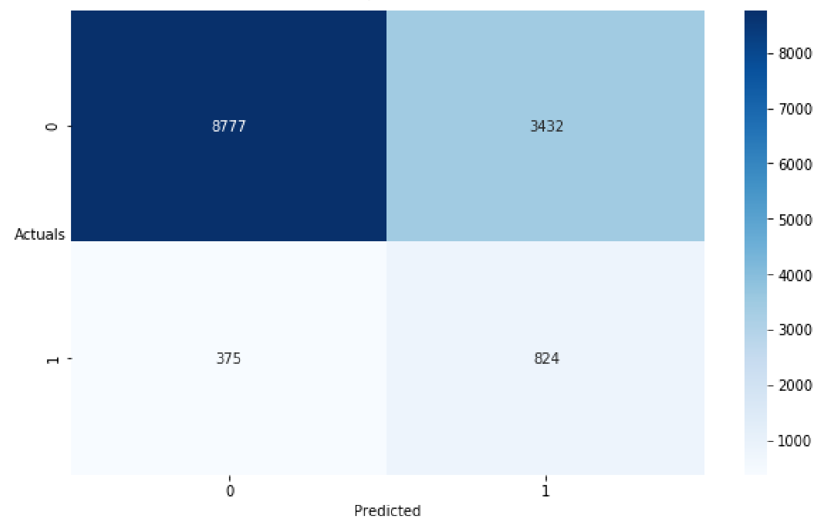
Logistic Regression - Train Data - Model with Default Cut-OFF point



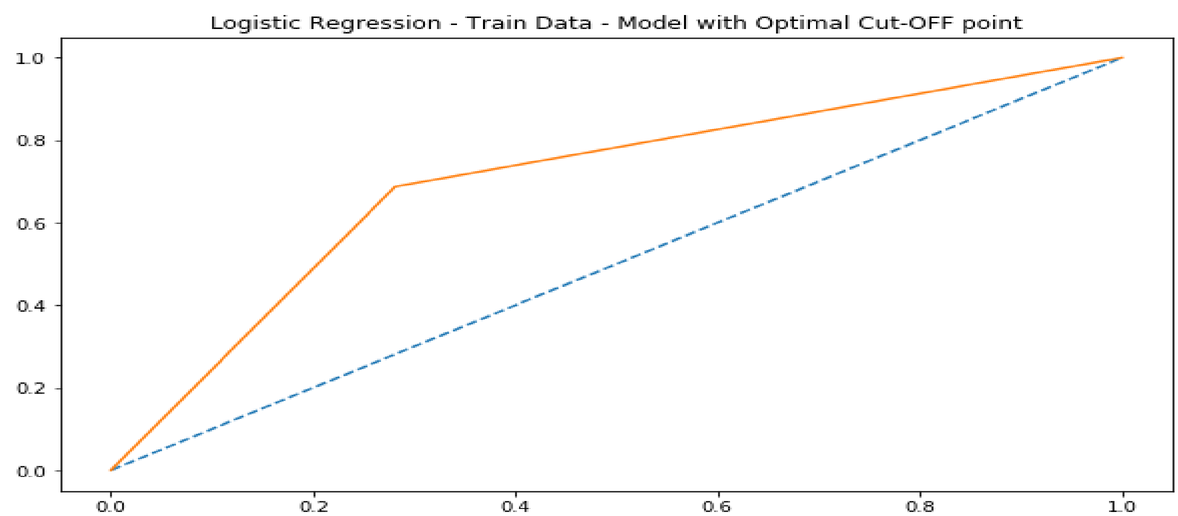
Inference : Recall at 4.8 percent and precision at 46.4 percent which only 4.8% defaults predicted correctly with a default cutoff 0.5. But Specificity 99 percent indicates that the most loan accounts are showing as non default.
AUC – 52

LOGISTIC REGRESSION – TRAIN DATA - WITH OPTIMUM CUTOFF 0.09

Figure 1.2



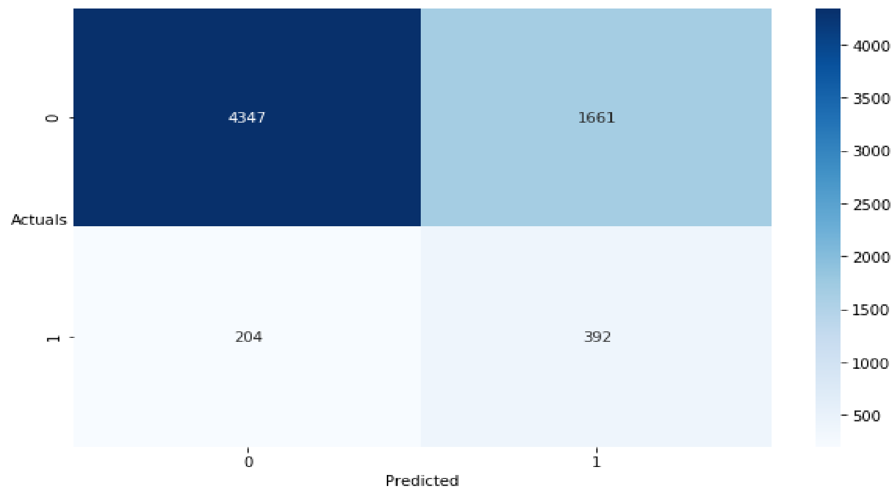
	precision	recall	f1-score	support
0	0.959	0.719	0.822	12209
1	0.194	0.687	0.302	1199
accuracy			0.716	13408
macro avg	0.576	0.703	0.562	13408
weighted avg	0.891	0.716	0.775	13408



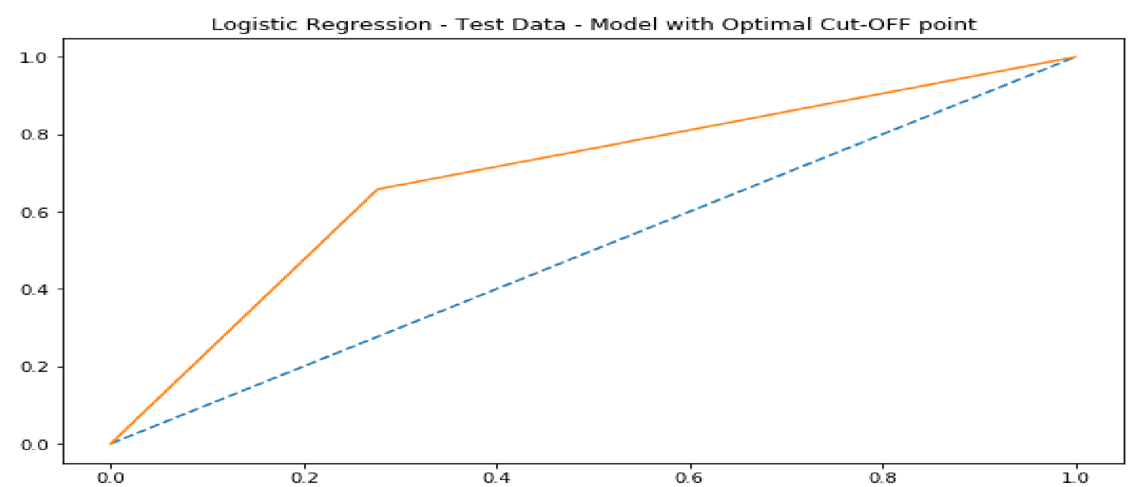
Inference : Recall at 68 percent and precision at 19.4 percent is lowest, with 68% defaults is predicted correctly with a optimum cutoff 0.09. Specificity 71.9 percent. AUC – 70

LOGISTIC REGRESSION – TEST DATA - WITH OPTIMUM CUTOFF 0.09

Figure 1.3



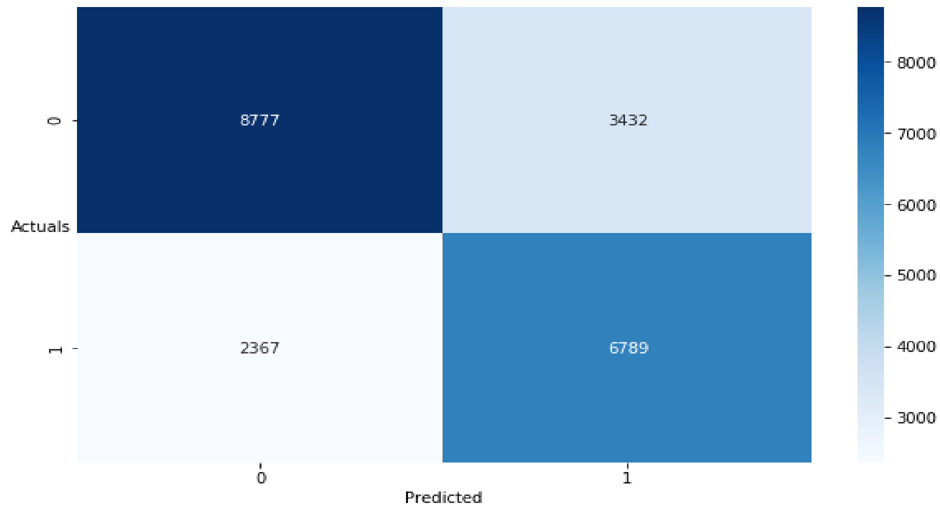
	precision	recall	f1-score	support
0	0.955	0.724	0.823	6008
1	0.191	0.658	0.296	596
accuracy			0.718	6604
macro avg	0.573	0.691	0.560	6604
weighted avg	0.886	0.718	0.776	6604



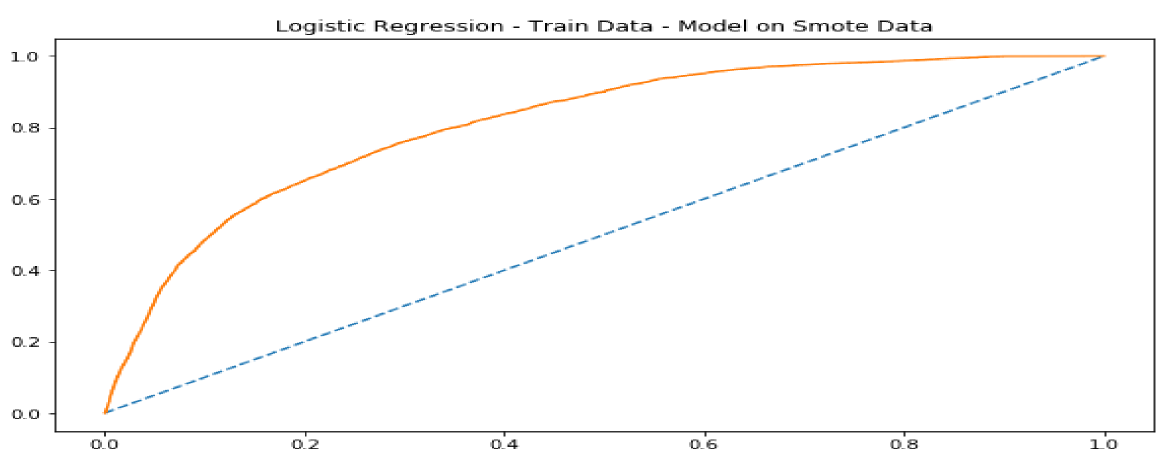
Inference : Test set Recall reduced to 65.8 percent and precision at 19.1 percent is lowest, with 65.8% defaults is predicted correctly with a optimum cutoff 0.09. Specificity 72.4 percent. AUC – 69

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

Figure 1.4



	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.

LDA - LINEAR DISCRMINANT ANALYSIS

LDA - LINEAR DISCRMINANT ANALYSIS

With default values for both train and test datasets.

Table 1.2

	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 1.3

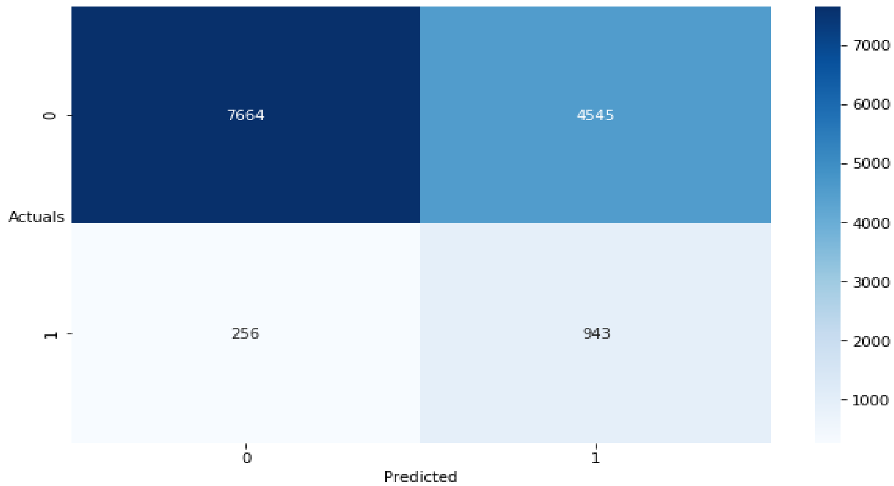
	precision	recall	f1-score	support
0	0.92	0.98	0.95	6008
1	0.37	0.10	0.16	596
accuracy			0.90	6604
macro avg	0.64	0.54	0.55	6604
weighted avg	0.87	0.90	0.88	6604

Inference :

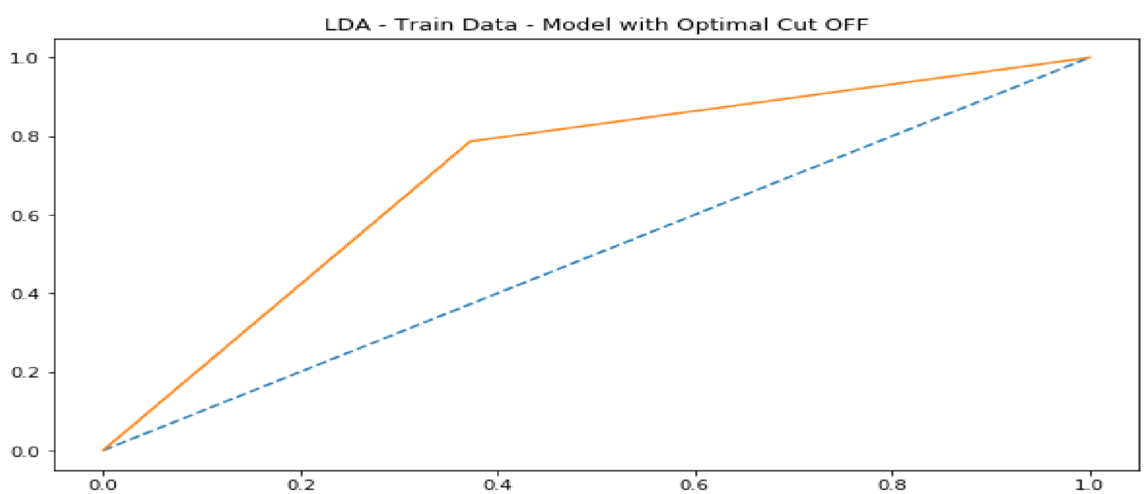
Recall for both train and test data for LDA model with default values show poor recall scores of 12 & 10 percent and having precision being lowest. Prediction of loan defaults correctly at 10 percent levels is very poor metrics.

LDA – TRAIN DATASET – CUTOFF – 0.06

Figure 1.5



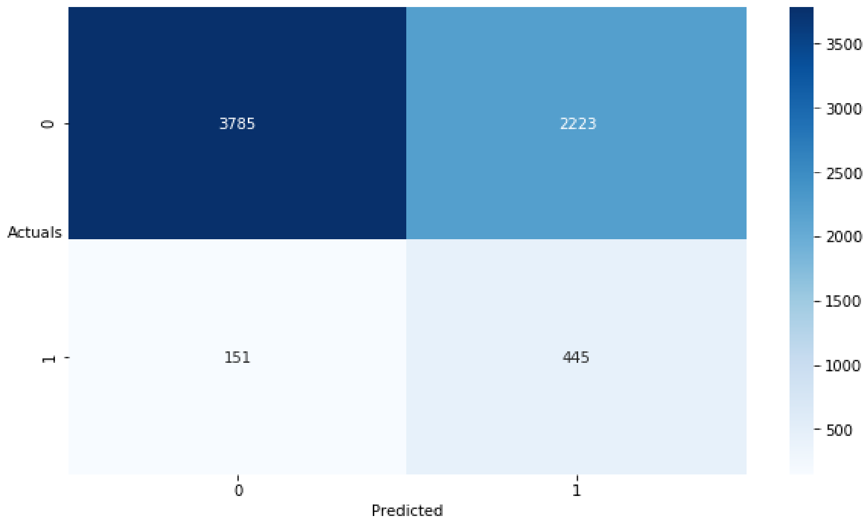
	precision	recall	f1-score	support
0	0.968	0.628	0.761	12209
1	0.172	0.786	0.282	1199
accuracy			0.642	13408
macro avg	0.570	0.707	0.522	13408
weighted avg	0.897	0.642	0.719	13408



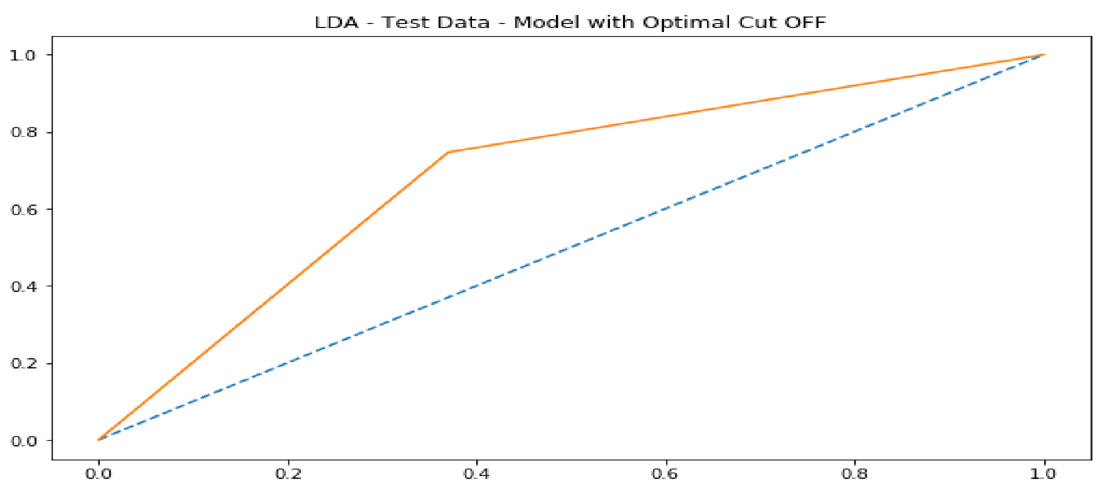
Inference : Recall at 78 percent and precision at 17 percent which 78% of defaults predicted correctly with a optimum cutoff 0.06 is a very good but precision being low. AUC- 70.

LDA – TEST DATASET – CUTOFF – 0.06

Figure 1.6



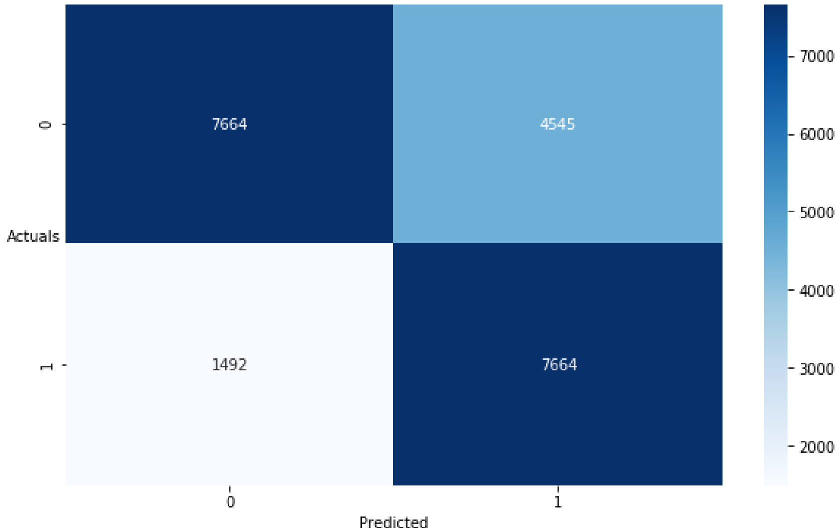
	precision	recall	f1-score	support
0	0.962	0.630	0.761	6008
1	0.167	0.747	0.273	596
accuracy			0.641	6604
macro avg	0.564	0.688	0.517	6604
weighted avg	0.890	0.641	0.717	6604



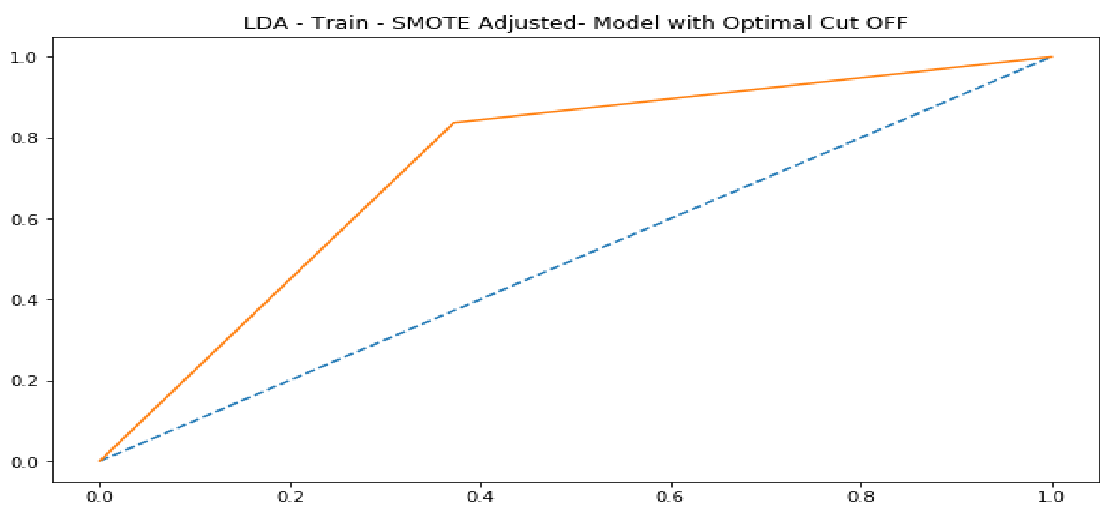
Inference : Recall reduced to 74 percent on test data and precision at 16 percent which 74% of defaults predicted correctly with a optimum cutoff 0.06 is a very good but precision being low. AUC- 68.

LDA – SMOTE DATASET – CUTOFF – 0.06

Figure 1.7



	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.

II. Model Tuning

- For the purpose of model tuning, ensemble modelling Random forest was used.

RANDOM FOREST MODEL

- From sklearn , imported grid search & random forest classifier ,used grid search to get the ideal features.
- Fit it on to the Train dataset.
- Got the best parameters.
- Predicted on both train, test and train with smote dataset.
- Computed confusion matrix, Summary and ROC curve AUC values.

Train

- Recall – 39
- Precision - 85
- Accuracy – 94
- AUC – 69

Test

- Recall – 31
- Precision - 77
- Accuracy – 93
- AUC - 65

Train_Smote

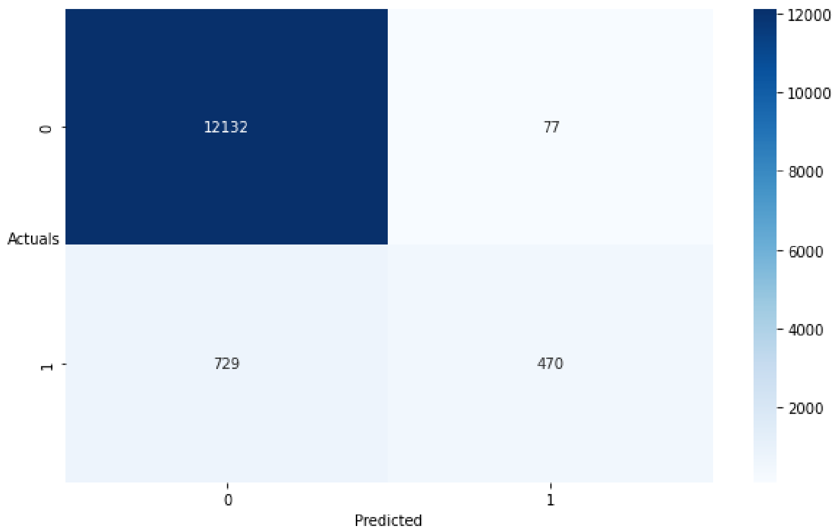
- Recall – 91
- Precision – 93
- Accuracy – 93
- AUC – 93

Inference :

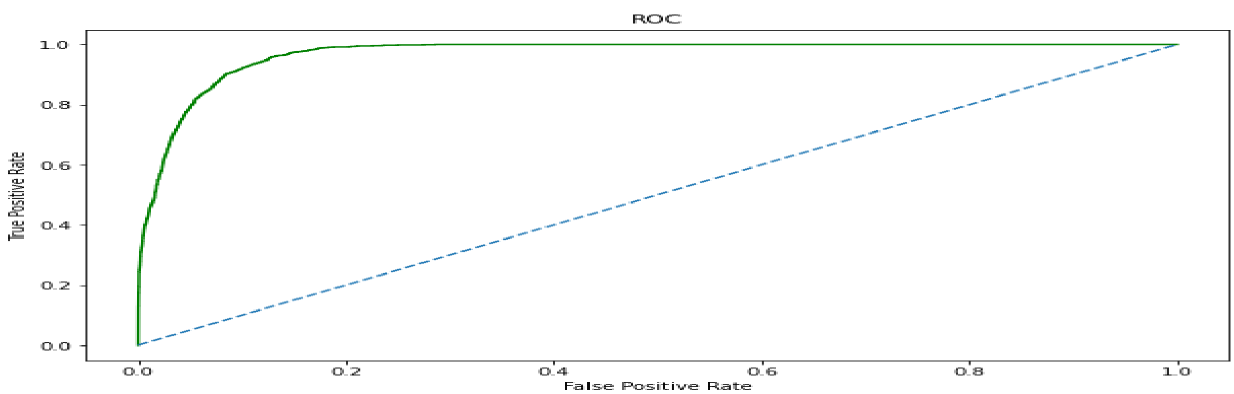
- Both Train and test results showed low recall scores.
- By applying Smote, The Recall, Precision, and AUC has improved to a greater extend shows that the model with regularizing the data is more robust.
- Recall at 91 percent and precision at 93 percent which 91% the loan defaults are predicted correctly with a optimum grid features is a very good model when smote is applied. Recall is at maximum compared to Train and Test datasets. Both Recall and precision are high with a regularized data.
- SMOTE was used for tuning the model. Random forest achieved the maximum accuracy compared to all the models.

RANDOM FOREST – TRAIN DATASET

Figure 1.8



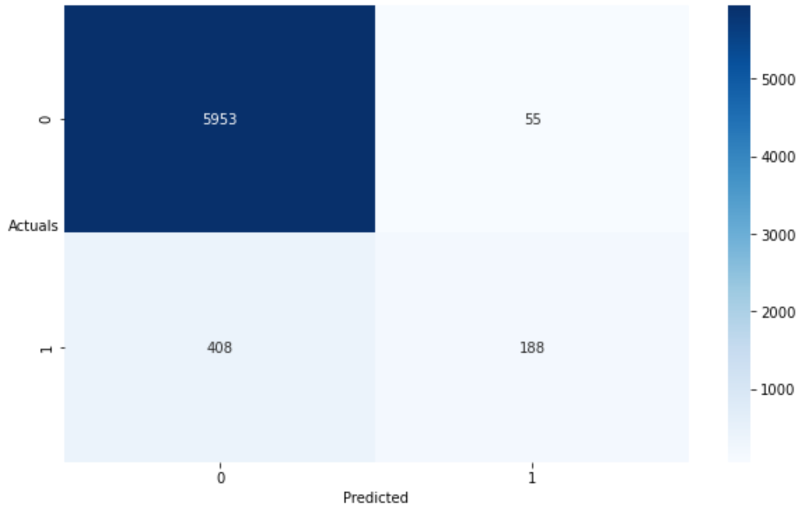
	precision	recall	f1-score	support
0	0.943	0.994	0.968	12209
1	0.859	0.392	0.538	1199
accuracy			0.940	13408
macro avg	0.901	0.693	0.753	13408
weighted avg	0.936	0.940	0.929	13408



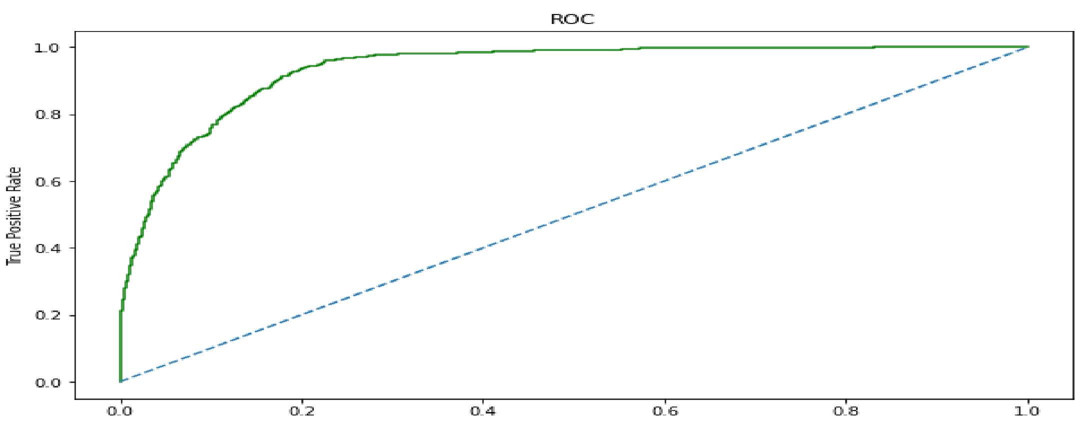
Inference : Recall at 39 percent and precision at 85 percent which 39% of loan defaults predicted correctly which is very low.
AUC- 69.

RANDOM FOREST – TEST DATASET

Figure 1.9



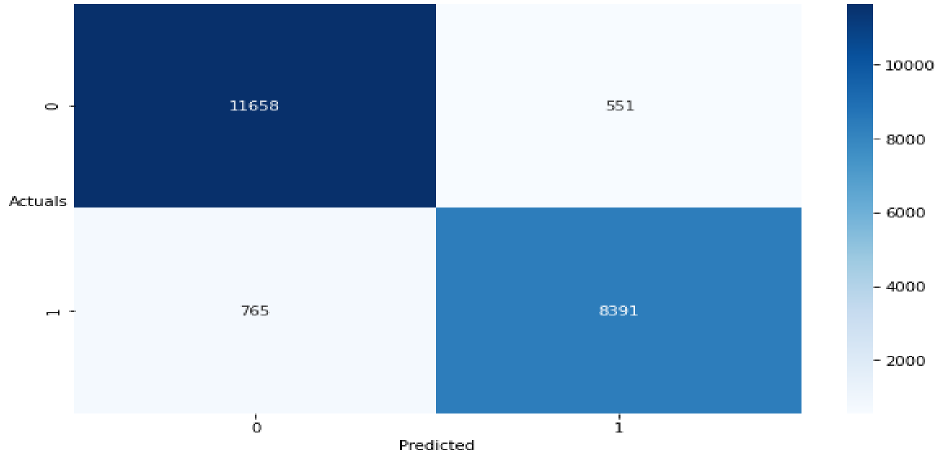
	precision	recall	f1-score	support
0	0.936	0.991	0.963	6008
1	0.774	0.315	0.448	596
accuracy			0.930	6604
macro avg	0.855	0.653	0.705	6604
weighted avg	0.921	0.930	0.916	6604



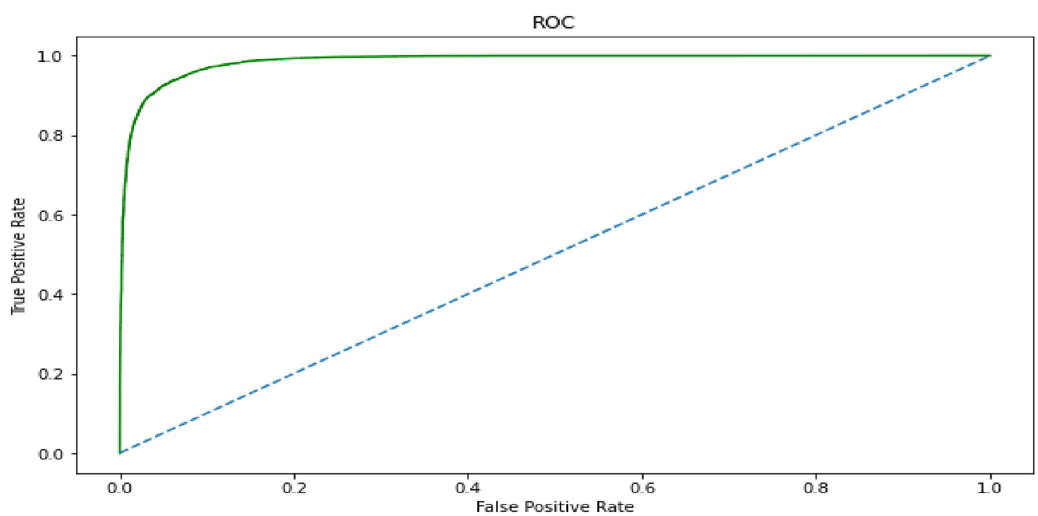
Inference : Recall reduced to 31 percent and precision at 77 percent which 31% of loan defaults predicted correctly which is very low.
AUC- 65.

RANDOM FOREST – SMOTE DATASET

Figure 2.0



	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.

III. Comparison - Optimum Model

Models	Dataset	Precision	Recall	F1-Score	Accuracy	AUC
Logistic Regression with Default Cut-Off	Train	0.464	0.048	0.088	0.91	0.521
Logistic Regression with Optimal Cut-Off	Train	0.194	0.687	0.302	0.716	0.703
Logistic Regression with Optimal Cut-Off	Test	0.191	0.658	0.296	0.718	0.691
Logistic Regression on SMOTE	SMOTE Train	0.664	0.741	0.701	0.724	0.812
Linear Discriminant Analysis - LDA	Train	0.39	0.12	0.18	0.9	0.785
Linear Discriminant Analysis - LDA	Test	0.37	0.1	0.16	0.9	0.772
Linear Discriminant Analysis with Optimal Cut-OFF	Train	0.172	0.786	0.282	0.642	0.707
Linear Discriminant Analysis with Optimal Cut-OFF	Test	0.167	0.747	0.273	0.641	0.688
Linear Discriminant Analysis - LDA on SMOTE	SMOTE Train	0.628	0.837	0.717	0.717	0.735
Random Forest Model	Train	0.843	0.38	0.524	0.938	0.686
Random Forest Model	Test	0.773	0.309	0.441	0.929	0.649
Random Forest Model on SMOTE	SMOTE Train	0.939	0.92	0.929	0.94	0.937

- **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.**
- **Random forest is an optimum model but it's a black box model were no insights on the variables are achieved. Only magnitude of the variables is achieved.**

IV. Business Implications

- **Random forest is an optimum model but it's a black box model were no insights on the variables are achieved. Only magnitude of the variables is achieved.**

```
In [237]: pd.DataFrame({'Variable':X_res.columns,
                         'Importance':best_grid1.feature_importances_}).sort_values('Importance', ascending=False)
```

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

- **For Business implications – Logistic Model is preferred, as it give enormous information on the variables.**

VARIABLES	COEFFICENT	Exp(Coeff)
NUM_EMI_CHANGES_RANGE_CAT	0.130300000000	1.139170083
NET_RECEIVABLE	0.003000000000	1.003004505
NET_LTV	0.002300000000	1.002302647
EXCESS_AVAILABLE	0.000060840000	1.000060842
PRE_EMI_DUEAMT	0.000011210000	1.00001121
PAID_INTEREST	0.000001540000	1.00000154
LOAN_AMT	-0.000000025480	0.999999975
OUTSTANDING_PRINCIPAL	-0.000000116700	0.999999883
PAID_PRINCIPAL	-0.000002954000	0.999997046
BALANCE_TENURE	-0.003900000000	0.996107595
CITY_NEW	-0.017700000000	0.982455725
Intercept	-0.285200000000	0.751863867
FOIR	-0.868400000000	0.419622408
PRODUCT	-0.982800000000	0.374261698

- **For every unit change in EMI – we observe 113% chance of customer defaulting the loan than not defaulting. Likewise the other variables also NET_LTV, FOIR, Etc tend to predict well the default status of the customer.**