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Identifying the factors responsible for loan defaults and classification of customers using SAS® Enterprise Miner

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ABSTRACT

Lending business is crucial to the profitability of a bank or financial institution. Loan defaults, delay in repayment by customers lead to problems in cash flow position. The last economic crisis in US was triggered by loan defaults.

This study aims to identify the factors contributing towards loan defaults, delay in repayments as well as the characteristics of a borrower who will honor all the obligations of a loan. The results enable us to determine the relationship between loan and customer characteristics and the probability to default. The results may also be used to appraise and monitor credit risk at the time of loan approval and during the currency of the loan.

The data set consists of all loans issued through December, 2015 along with the loan status. It contains 111 variables such as the details of customer's loan account, amount, application type – individual or joint, principal outstanding, amount paid, interest rate, length of employment, annual income, loan status, verification status, purpose of loan and so on. Loan status has several levels – current, default, in grace or late due. There were 421,095 records in the dataset.

The factors contributing towards loan default were identified and predicted using models such as logistic regression, decision tree and artificial neural networks. The identified factors will then be implemented using random forest method to classify the customers whether they are good loans or bad loans. The classification will enable the lending institutions and investors to optimize their policies and strategies to reduce the loan defaults and also to make informed decisions about the current customers at the risk of default.

INTRODUCTION

The loan data for December 2015 was extracted from the website of Lending Club, an online credit market place. Lending Club facilitates the borrowing and lending of loans. All its operations are online and has no branch infrastructure, unlike banks. Personal loans, business loans and medical finance form the portfolio of Lending Club. To date, Lending Club has facilitated over 20 billion dollars in loans with an annual net return rate of 7.55%. In light of these high returns and the increasing popularity, it is imperative to understand the characteristics which make a loan good or lead to default.

DATA COLLECTION AND PREPARATION

The data was downloaded from the Lending Club website, an online market place. The final dataset contained the following variables.

Role	Level	Count
ID	Nominal	1
Input	Interval	79
Input	Nominal	15
Target	Nominal	1

Figure 1. Variable Summary

The dataset has two variables with the role 'ID'. The variable 'Member_ID 'was retained and the variable 'ID' was removed. For the Joint application type, there were three variables. 100% of the values for these variables were missing. The three variables are 'annual_inc_joint', 'dti_joint', 'verification_status_joint'. Further, the records for the joint application type were removed and only accounts of type individual were considered for modeling.

The variables like 'recoveries', 'total_rec_late_fee', 'pymnt_plan', 'policy_code' amongst others were removed as most of the records had the same value. For example, pymnt_plan had the value 'n' for all observations except one. The variable 'desc' was removed as it had information supplementary to the variable 'purpose'. Similarly, we removed the variable 'sub_grade' and retained the variable 'grade'.

The final data set consisted of 91,233 observations and 96 variables. The table enumerates some of the variables:

Variable	**Level**	**Description**
last_pymnt_amnt	Interval	Last total payment amount received
last_pymnt_d	Nominal	Last month payment was received
total_rec_prncp	Interval	Principal received to date
out_prncp	Interval	Remaining outstanding principal for total amount funded
Purpose	Nominal	A category provided by the borrower for the loan request.
int_rate	Nominal	Interest Rate on the loan
Recoveries	Interval	Post charge off gross recovery
funded_amnt_inv	Interval	The total amount committed by investors for that loan at that point in time.
total_rec_int	Interval	Interest received to date

Figure 2. Data Dictionary for the Final Dataset

DATA EXPLORATION

Exploratory analysis indicated that most of the records have loan_status 'Current' and the percentage of loans in 'Charged Off' and 'late (31-120) days' are similar.

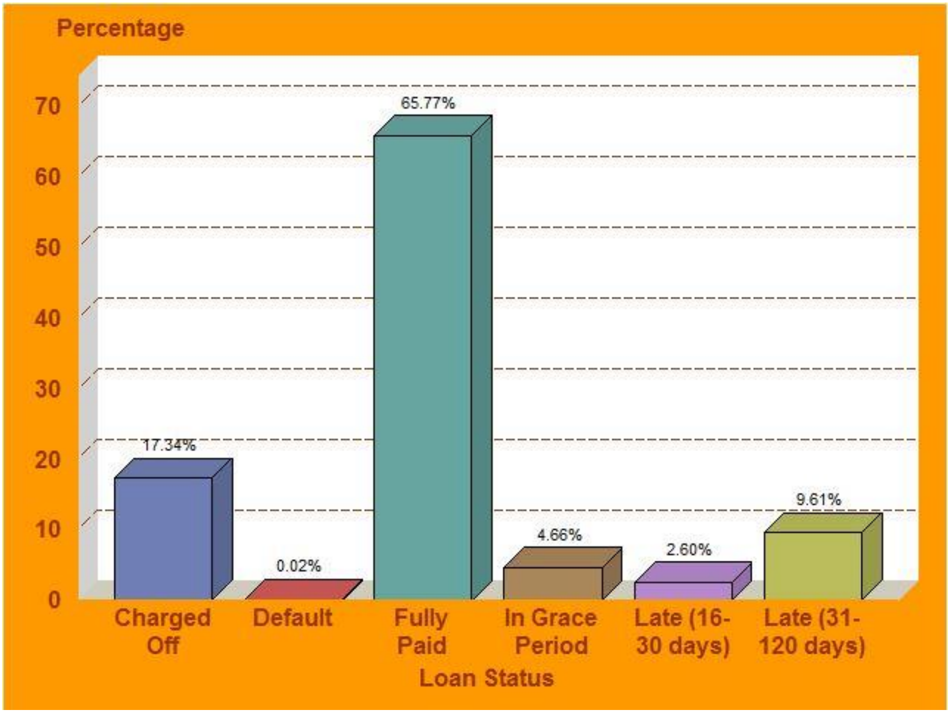


Figure 3. Distribution of Target Variable Loan_Status

From the dataset, observations with loan status ‘Current’ were not considered for modeling as these are considered loans which are still making payments within timelines. The observations in the final dataset belonged to one of the six types of loan_status. The variable was converted into a binary variable with the levels ‘1’ and ‘0’. Level ‘1’ included ‘Charged Off’, ‘Default’ and ‘Late (31 – 120days)’. Level ‘0’ included ‘Fully Paid’, ‘In Grace period’ and ‘late (16 – 30 days)’. This conversion done by Replacement node. Imputation of variables with missing values done using Tree method for class variables and using Median for the interval variables. ‘Max Normal’ method was used to transform variables.

DATA PARTITION

Data was partitioned into Training data (70%) and Validation data (30%) based on the optimal method of partition ratio, which was required for modeling.

VARIABLE CLUSTERING AND SELECTION

The high number of variables in the dataset causes problems of collinearity and redundancy. Variable clustering node helped in choosing the optimum number of variables. Criterion for variable clustering was correlation. We have elected the representative variable for the cluster using the value for 1-R-square.The variable clustering node created 20 clusters.

Variable Selection node selects the important input variables based on the statistic R-square to predict the target variables. This node rejected variables with low R-square. For this paper, variables with R-square above 0.005 taken as the selection criterion.

Cluster 3	PWR_REP_last_pymnt_amnt	0.8038	0.1851	0.2407	Transformed: Replacement: last_pymnt_amnt
	PWR_REP_total_pymnt	0.9642	0.4176	0.0614	Transformed: Replacement: total_pymnt
	PWR_REP_total_pymnt_inv	0.9642	0.4176	0.0614	Transformed: Replacement: total_pymnt_inv
	PWR_REP_total_rec_prncp	0.9646	0.2425	0.0467	Transformed: Replacement: total_rec_prncp

Cluster 7	SQRT_REP_out_prncp	1.0000	0.1015	0.0000	Transformed: Replacement: out_prncp
	SQRT_REP_out_prncp_inv	1.0000	0.1015	0.0000	Transformed: Replacement: out_prncp_inv

Cluster 10	SQRT_REP_collection_recovery_fee	0.9978	0.0594	0.0023	Transformed: Replacement: collection_recovery_fee
	SQRT_REP_recoveries	0.9978	0.0596	0.0023	Transformed: Replacement: recoveries

Figure 4. Variables selected through variable clustering

MODELING

1. Decision Tree

Decision tree was the initial model, as our target was a binary target and the tree will enable us to build a strategy to identify loan defaults by making classifications and setting up rules and also to understand the interrelation between the variables by studying each node of classification of the decision tree.

The important variables from Decision Tree are in Output 1. Decision tree considered variables like term, last_pymnt_d for decision-making.

Variable Importance

Variable Name	Label	Number of Splitting Rules	Importance	Validation Importance	Ratio of Validation to Training Importance
PWR_REP_total_rec_prncp	Transformed: Replacement: total_rec_prncp	9	1.0000	1.0000	1.0000
TG_IMP_last_pymnt_d	Transformed: Imputed last_pymnt_d	2	0.4312	0.4304	0.9982
SQRT_REP_out_prncp_inv	Transformed: Replacement: out_prncp_inv	3	0.2844	0.2859	1.0052
SQRT_REP_collection_recovery_fee	Transformed: Replacement: collection_recovery_fee	2	0.2424	0.2385	0.9841
TG_IMP_last_credit_pull_d	Transformed: Imputed last_credit_pull_d	1	0.1879	0.1982	1.0545
term		3	0.1183	0.1098	0.9283

Output 1. Important variables from Decision Tree

Event Classification Table

Data Role=TRAIN Target=REP_loan_status Target Label=Replacement: loan_status

False Negative	True Negative	False Positive	True Positive
1287	44127	2510	15939

Data Role=VALIDATE Target=REP_loan_status Target Label=Replacement: loan_status

False Negative	True Negative	False Positive	True Positive
546	18901	1087	6836

Output 2. Sensitivity Analysis

There were a total 21 leaf nodes in the tree diagram.

<u>The English rules for a loan to turn out as a bad loan is</u>

WHERE Transformed: Replacement: total_rec_prncp < 0.581 AND

Transformed: Imputed last_pymnt_d _OTHER_ Or Missing AND

Transformed: Replacement: total_rec_prncp < 0.4889 Or Missing AND

Transformed: Replacement: total_rec_prncp < 0.4108

<u>In case for a loan to turn out as a good loan,</u>

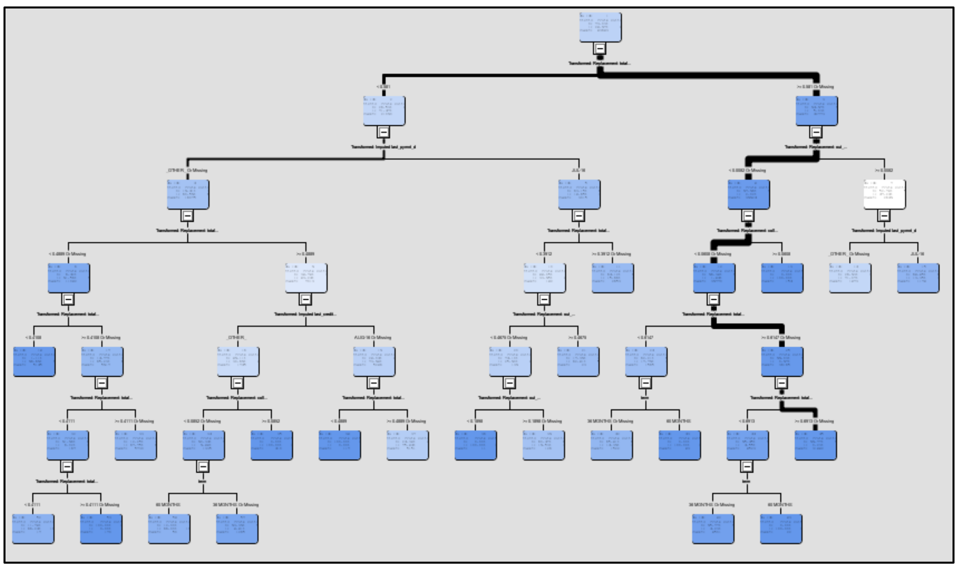
WHERE Transformed: Replacement: total_rec_prncp >= 0.581 Or Missing AND

Transformed: Replacement: out_prncp_inv < 0.0082 Or Missing AND

Transformed: Replacement: collection_recovery_fee < 0.0608 Or Missing AND

Transformed: Replacement: total_rec_prncp >= 0.6147 Or Missing AND

Transformed: Replacement: total_rec_prncp >= 0.6913 Or Missing



Output 3. Decision Tree

2. Logistic Regression

Logistic regression model provides prediction for the binary target variable 'loan_status' by estimating probabilities, that help in predicting the results for the new cases, with a comparatively higher degree of accuracy.

Stepwise regression was the chosen variable selection method. This method chose ten variables, some of them being transformed variables. Variables chosen are – PWR_REP_total_rec_prncp, SQRT_REP_collection_recovery_fee, SQRT_REP_out_prncp_inv, and TG_IMP_last_pymnt_d.

Analysis of Maximum Likelihood Estimates						
Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	6.9077	0.0920	5632.54	<.0001
PWR_REP_total_rec_prncp		1	-17.1923	0.1717	10025.37	<.0001
SQRT_REP_collection_recovery_fee		1	66.7564	128.6	0.27	0.6037
SQRT_REP_out_prncp_inv		1	2.8337	0.0497	3254.57	<.0001
TG_IMP_last_pymnt_d	JUL-16	1	-1.8584	0.0289	4136.01	<.0001

Output 4. Output from Logistic Regression Model

Event Classification Table

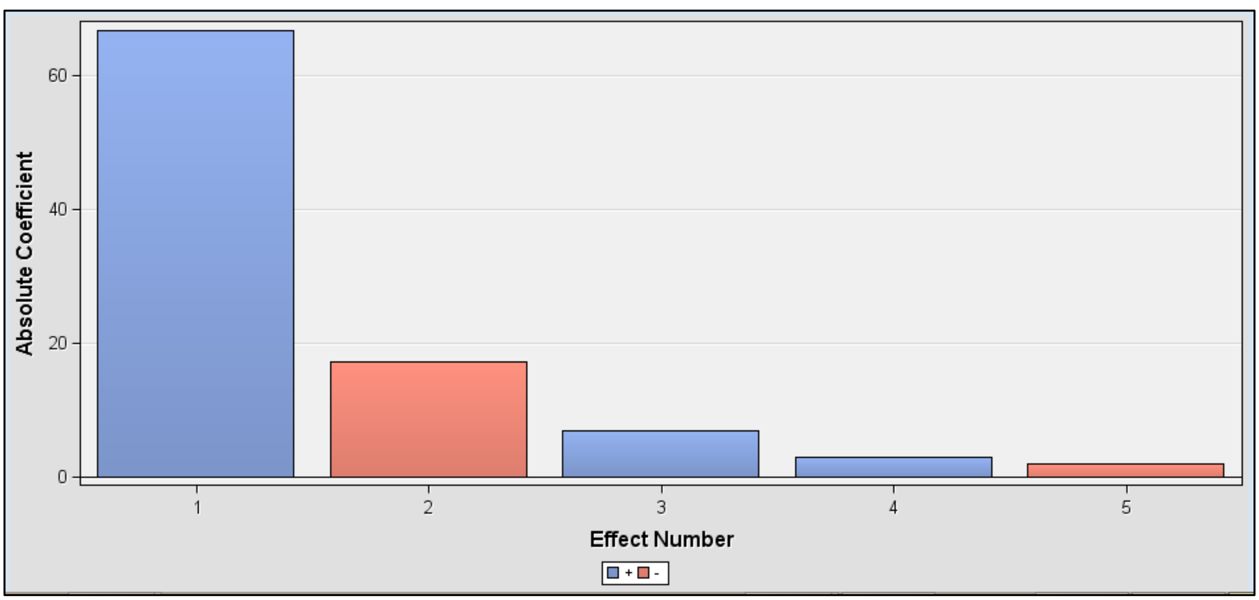
Data Role=TRAIN Target=REP_loan_status Target Label=Replacement: loan_status

False Negative	True Negative	False Positive	True Positive
2910	44474	2163	14316

Data Role=VALIDATE Target=REP_loan_status Target Label=Replacement: loan_status

False Negative	True Negative	False Positive	True Positive
1239	19033	955	6143

Output 5. Sensitivity Analysis



Output 6. Effects Plot

The Effects Plot provides whether predictors have a positive effect or a negative effect on the response variable new_tar. From the Effects Plot,

- SQRT_REP_collection_recovery_fee has a positive effect with an absolute coefficient of 66.75638
- PWR_REP_total_rec_prncp has a negative effect with an absolute coefficient of 17.19229
- Intercept has a positive effect with an absolute coefficient of 6.907717
- SQRT_REP_out_prncp_inv has a positive effect with an absolute coefficient of 2.833697
- TG_IMP_last_pymnt_dJUL_16 has a negative effect with an absolute coefficient of 1.858424

Similar to the decision tree, total principal received, last payment date, collection recovery fee and outstanding principal play a role in deciding whether a loan will be good or bad.

3. Neural Networks

Neural network models provide an algorithm to determine the effects of interactions of various variables on the target variable. This model is useful to solve business problems with a lot of data and several variables.

From the iteration plot for misclassification rate, an optimized solution was obtained aftrer 11 iterations.

The NEURAL Procedure

Optimization Results
Parameter Estimates

N	Parameter	Estimate	Gradient Objective Function
1	PWR_REP_total_rec_prncp_H11	-1.509876	-0.000007924
2	_DUP	4.160357	-0.000013967
3	SQRT_REP_out_prncp_inv_H11	-2.245724	-0.000014020
4	PWR_REP_total_rec_prncp_H12	1.187741	0.000014813
5	_DUP1	-0.396422	0.000000726
6	SQRT_REP_out_prncp_inv_H12	-0.290675	-0.000009708
7	PWR_REP_total_rec_prncp_H13	-0.726752	-0.000036392
8	_DUP2	1.524539	-0.000054878
9	SQRT_REP_out_prncp_inv_H13	0.303963	-0.000086827
10	TG_IMP_last_pymnt_dJUL16_H11	0.131814	-0.000036285
11	TG_IMP_last_pymnt_dJUL16_H12	-3.430820	-0.000003819
12	TG_IMP_last_pymnt_dJUL16_H13	0.015160	-0.000101
13	BIAS_H11	-2.787395	0.000054813
14	BIAS_H12	3.263534	-0.000005555
15	BIAS_H13	0.675003	0.000223
16	H11_REP_loan_status1	3.939497	-0.000045884
17	H12_REP_loan_status1	1.680573	0.000037170
18	H13_REP_loan_status1	6.715310	0.000039194
19	BIAS_REP_loan_status1	-2.237941	0.000006575

Value of Objective Function = 0.1868455999

Output 7. Parameter Estimates from Neural Networks Model

Event Classification Table

Data Role=TRAIN Target=REP_loan_status Target Label=Replacement: loan_status

False Negative	True Negative	False Positive	True Positive
2321	44075	2562	14905

Data Role=VALIDATE Target=REP_loan_status Target Label=Replacement: loan_status

False Negative	True Negative	False Positive	True Positive
996	18884	1104	6386

Output 8. Sensitivity Analysis

4. Random Forest

Random forest is an ensemble model and can be effectively used for classification. This model constructs several decision trees on the training data. The model then combines trees having low correlation. This model deals well with imbalanced data.

Event Classification Table

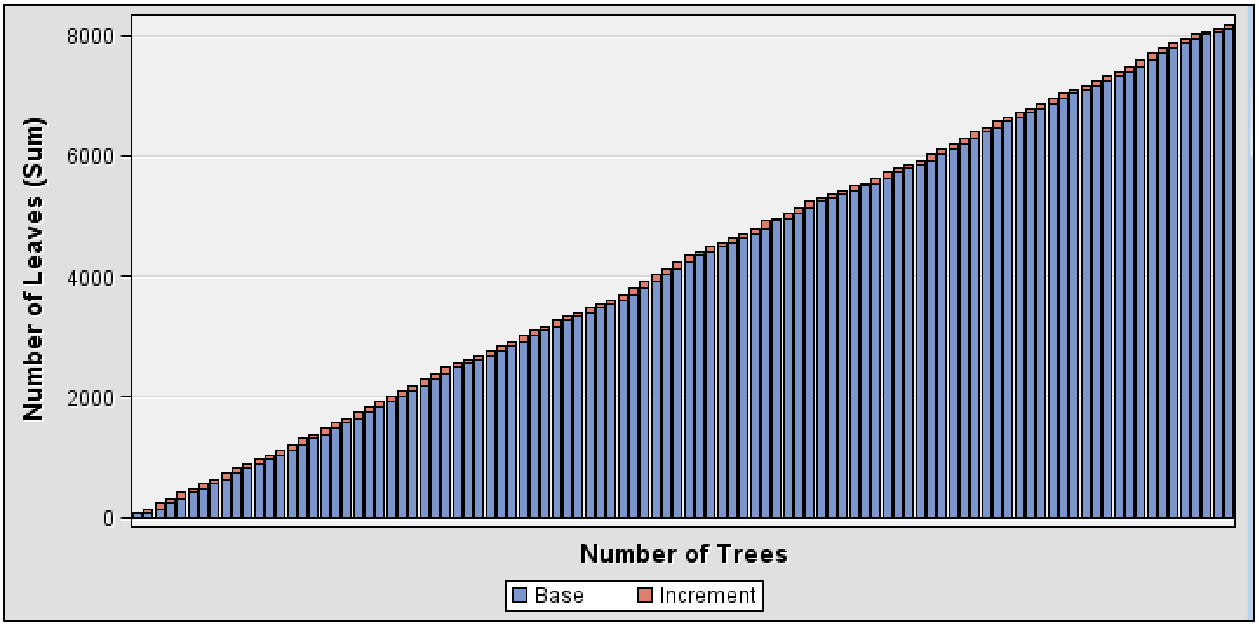
Data Role=TRAIN Target=REP_loan_status Target Label=Replacement: loan_status

False Negative	True Negative	False Positive	True Positive
1532	44621	2016	15694

Data Role=VALIDATE Target=REP_loan_status Target Label=Replacement: loan_status

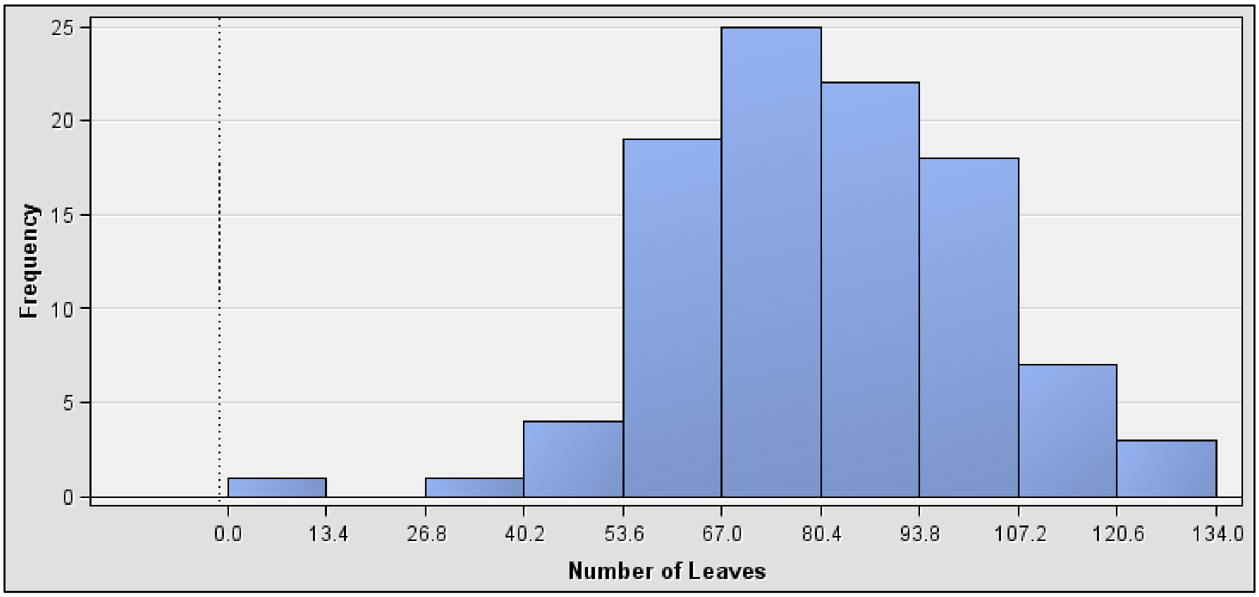
False Negative	True Negative	False Positive	True Positive
655	19098	890	6727

Output 9. Classification Table from Random Forest Model

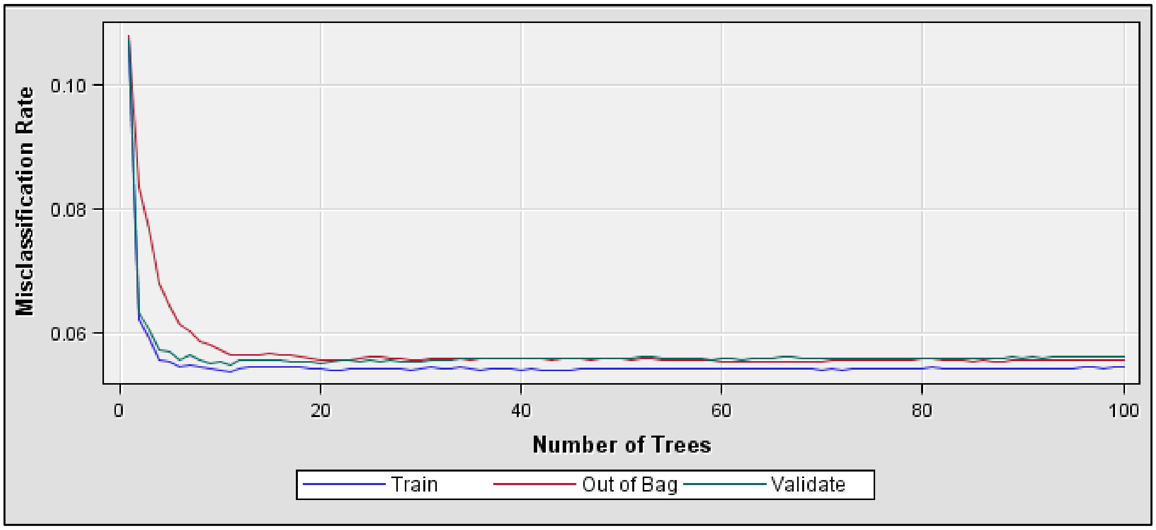


Output 10. Output from Random Forest Model

From the Leaf Statistics plot, we observed that there was a decline after 80.4 trees even though additional training was given.



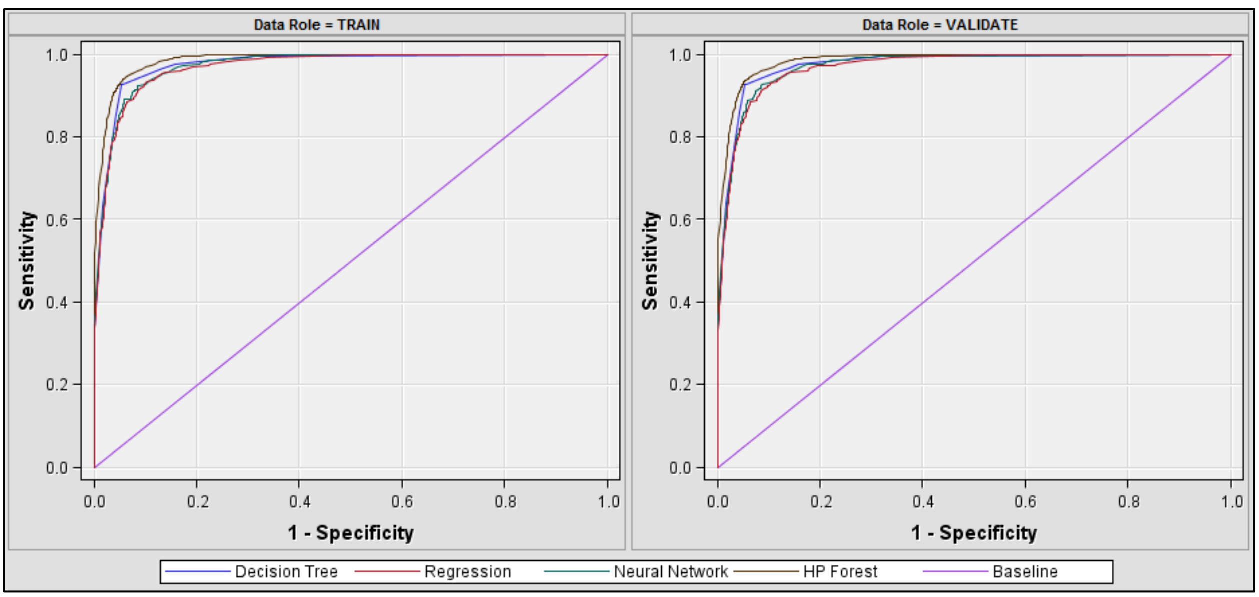
Output 11. Output from Model



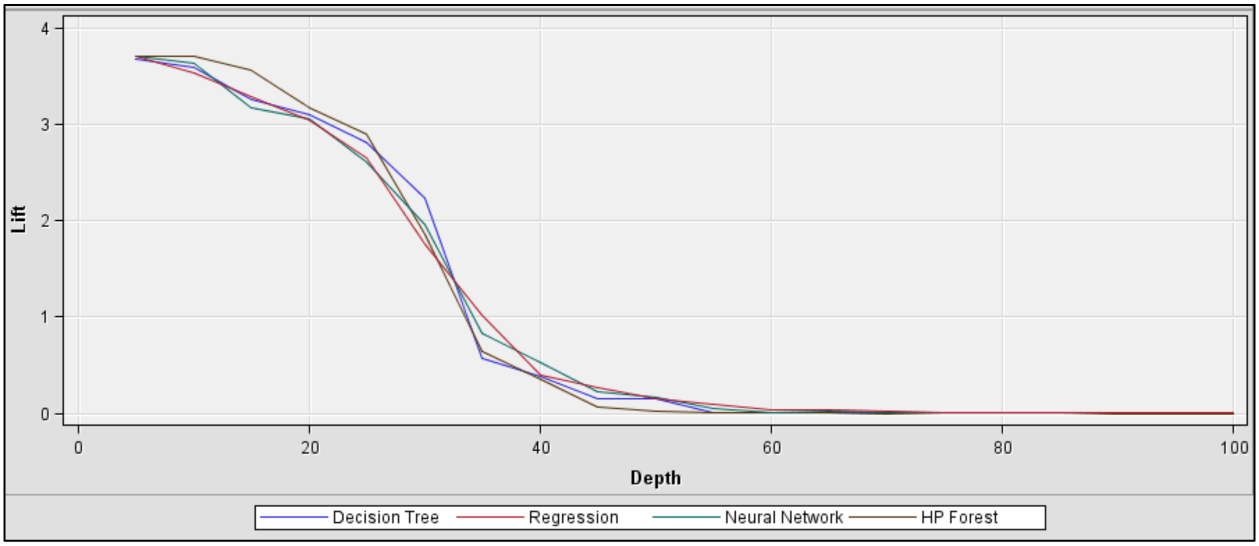
Output 12. Output from Model

MODEL COMPARISION

Comparing the validation Misclassification Rate for the models, HP Forest had the lowest misclassification rate and hence was chosen to be the best model as the target was binary.



Output 13. Output from Model



Output 14. Output from Model

Model	Misclassification Rate
HP Forest	**0.05619**
Decision Tree	**0.05966**
Neural Network	**0.07672**
Logistic Regression	**0.08016**

Output 15. Output from Model

CONCLUSION

To identify the characteristics of a loan default, the loan status, which go into defining a good loan and a bad loan was converted into a binary target variable. Further, data preparation was done by exploring the variables for the type of values, the missing percentage and redundancy.

Models employed were decision tree, logistic regression, neural networks and random forest. These models were chosen to make classification of characteristics underlying a good loan and bad loan, and to make predictions thereon. These models also are good for large and imbalanced data sets. HP Forest was the best model as it had the lowest misclassification rate.

Intuitively, loan default cases are attributable to total principal received, outstanding principal, and last payment date. A higher principal would imply higher risk of default. The logistic regression model considered all these variables. Credit appraisal at the time of loan sanction takes into account the risk along with the capacity of the borrower to repay. Principal amount determines the periodic repayment amount. These characteristics will help in determining the loan defaults in future. Further, this also determines the loan term.

While these details govern loan quality, the intention of the borrower to repay is another important consideration. This is where verification status comes in. Regular and timely repayments characterize a good loan.

An ongoing review of these variables would help monitor loan status and risk of default by an investor.

Briefly, quantum of repayment amount, the regularity of payments, and loan grade contribute toward making a loan a good loan or a bad loan.

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