

ANALYTICS FOR FINANCIAL SERVICES

Project Report and Summary

2018

**Scenario A: Technical : Build
a model for predictions in
financial analytics**

Final Project

**BIG DATA
ANALYTICS**
FINANCIAL SERVICES

BigData
analytic
al S

Name: AHSAN AFTAB
Master of Science in Business Analytics and Big Data
Course: ANALYTICS FOR FINANCIAL SERVICES
Submitted to: **PROFESSOR ANTONIO PITA LOZANO**
Date: **10-06-2018**



ahsan.aftab@student.ie.edu



IE Business School, Spain

ANALYTICS FOR FINANCIAL SERVICES

06-06-2018

Inside This Report

1. A Brief Introduction
2. Tools Used
3. Summary of Results
4. Conclusions
5. Appendix

Data Summary

Training dataset = 522939 instances with class named as 'target'

Test dataset = 174313 instances with class not available and need to be predicted.

Variables are of type: nominal, numerical, boolean

THE MOST RELEVANT VARIABLES SHOW A CUMULATIVE PERCENTAGE OF MORE THAN 90% IN THE MODELLING OF PREDICTIONS OF TARGET VARIABLE

A Brief Introduction

The problem provided for this project is that of a binary classification problem.

The problem can also be treated as Logistic Regression problem provided the variable treatment is carried out as such.

We have to predict target variable that is dichotomous in nature.

In finance, such logistic or decision problem are common and require analysis of various variables pertaining to business, customer and time.

We expect the logistic regression and decision trees to perform better over such a problem. Although random forest and tree classifiers can also provide very similar results,

Tools Used for design and implementation

The following tools have been used to analyze the given dataset:

- 1- **R and Rstudio**
- 2- **Dataiku, Weka and IBM SPSS** for Analytics and validation
- 3- **Java Spring with Weka java libraries** for machine learning algorithms.

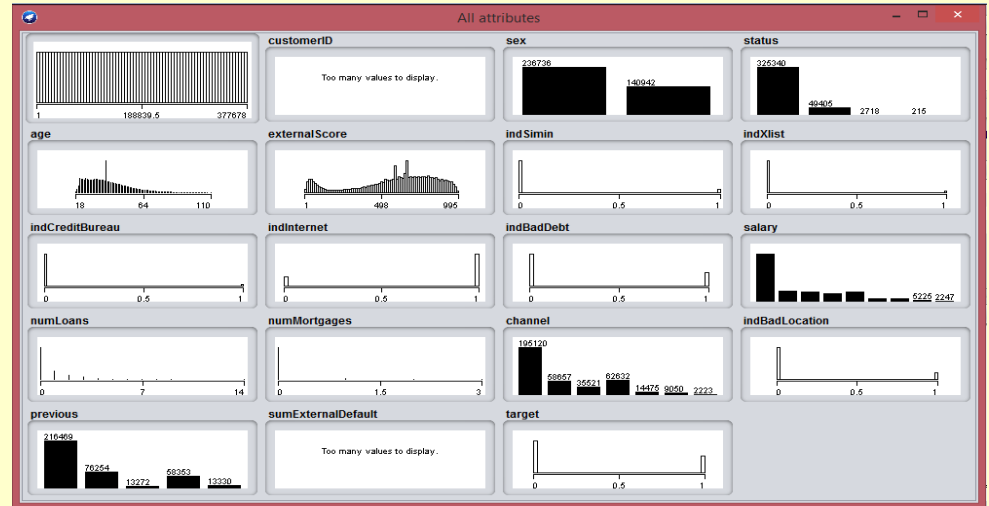
The results have been shared from various tools however the code provided is the final and working model implemented in R. Accuracy achieved through this model is approx. 70%, though future work might improve further the performance of the model.

The missing values have been treated in different way and are explained in the R code provided and in the text below.

Summary of results

THE DISTRIBUTION OF VARIOUS VARIABLES

The distribution of various variables can be seen in the figure below:



Most of the distributions are skewed to the right.

Missing Values Treatment:

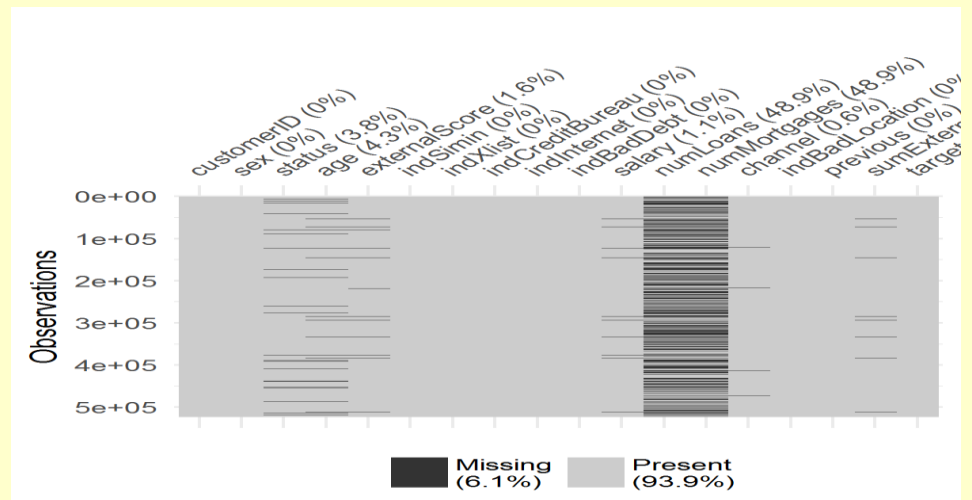
The columns numLoans and numMortgages have more than 50% data missing. We can replace the missing values with 0s.

The age variable can be replaced by median since distribution is skewed to the right.

The other missing values can be replaced by 75th quartile majority value in order to improve accuracy of the model.

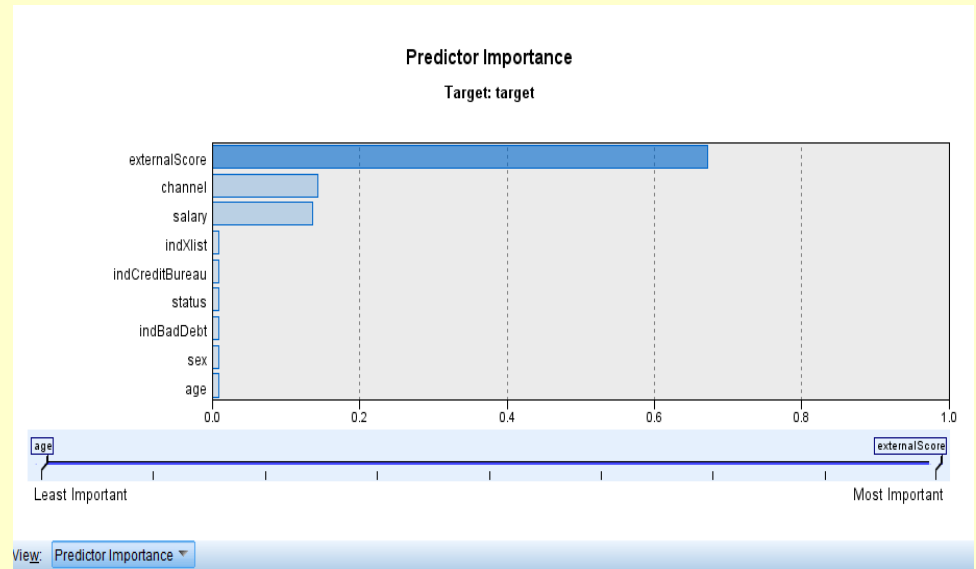
The final dataset over which predictions are to be made, also has missing values and will be treated in similar way to training dataset.

THE MISSING VALUES IN THE DATA



THE MOST RELEVANT VARIABLES AS PREDICTORS

The most relevant variables in making predictions are: externalScore, channel, and salary.



Algorithms Used for Modeling

- Binary Tree Classification
- Logistic Regression
- Neural Network
- Random Forest
- Bayesian Network Model
- Decision Tree Model

COMPARISON OF MODELS HAVE BEEN MADE FOR:

The comparison of results for the following algorithms follows:

- Binary Tree Classification
- Logistic Regression
- Neural Network
- Random Forest
- Bayesian Network Model
- Decision Tree Model

The results showed that the Logistic Regression performed better in terms of resource requirements and results achieved. Accuracy achieved = 69.40%

Comparison of Results from different models

NEURAL NETWORK

Results for output field target				
Comparing \$N-target with target				
'Partition'	1_Training		2_Testing	
Correct	271,582	69.25%	90,749	69.39%
Wrong	120,568	30.75%	40,040	30.61%
Total	392,150		130,789	

DECISION TREE

Results for output field target				
Comparing \$R-target with target				
'Partition'	1_Training		2_Testing	
Correct	271,989	69.36%	90,674	69.33%
Wrong	120,161	30.64%	40,115	30.67%
Total	392,150		130,789	

RANDOM FOREST

Results for output field target				
Comparing \$R-target with target				
'Partition'	1_Training		2_Testing	
Correct	256,450	65.4%	85,073	65.05%
Wrong	135,700	34.6%	45,716	34.95%
Total	392,150		130,789	

LOGISTIC REGRESSION

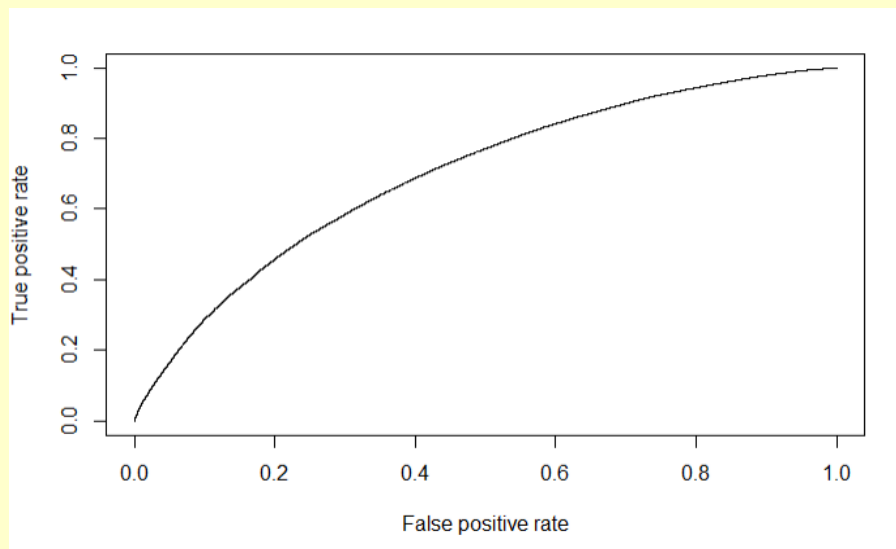
Results for output field target				
Comparing \$L-target with target				
'Partition'	1_Training		2_Testing	
Correct	271,998	69.36%	90,792	69.42%
Wrong	120,152	30.64%	39,997	30.58%
Total	392,150		130,789	

BAYESIAN NETWORK

Results for output field target				
Comparing \$B-target with target				
'Partition'	1_Training		2_Testing	
Correct	271,232	69.17%	90,745	69.38%
Wrong	120,918	30.83%	40,044	30.62%
Total	392,150		130,789	

Conclusions

- The final code for the project has been implemented in R notebook and has been provided along with the code with description.
- The split used between test and train dataset during validation phase: 75%-25%
- The final accuracy achieved at the end of the project for the given dataset during validation phase : 69.9%
- The ROC curve obtained after validation phase:
- The final output file: output.csv gives the predicted values with customer Ids. To be evaluated by the teacher with actual predictions.

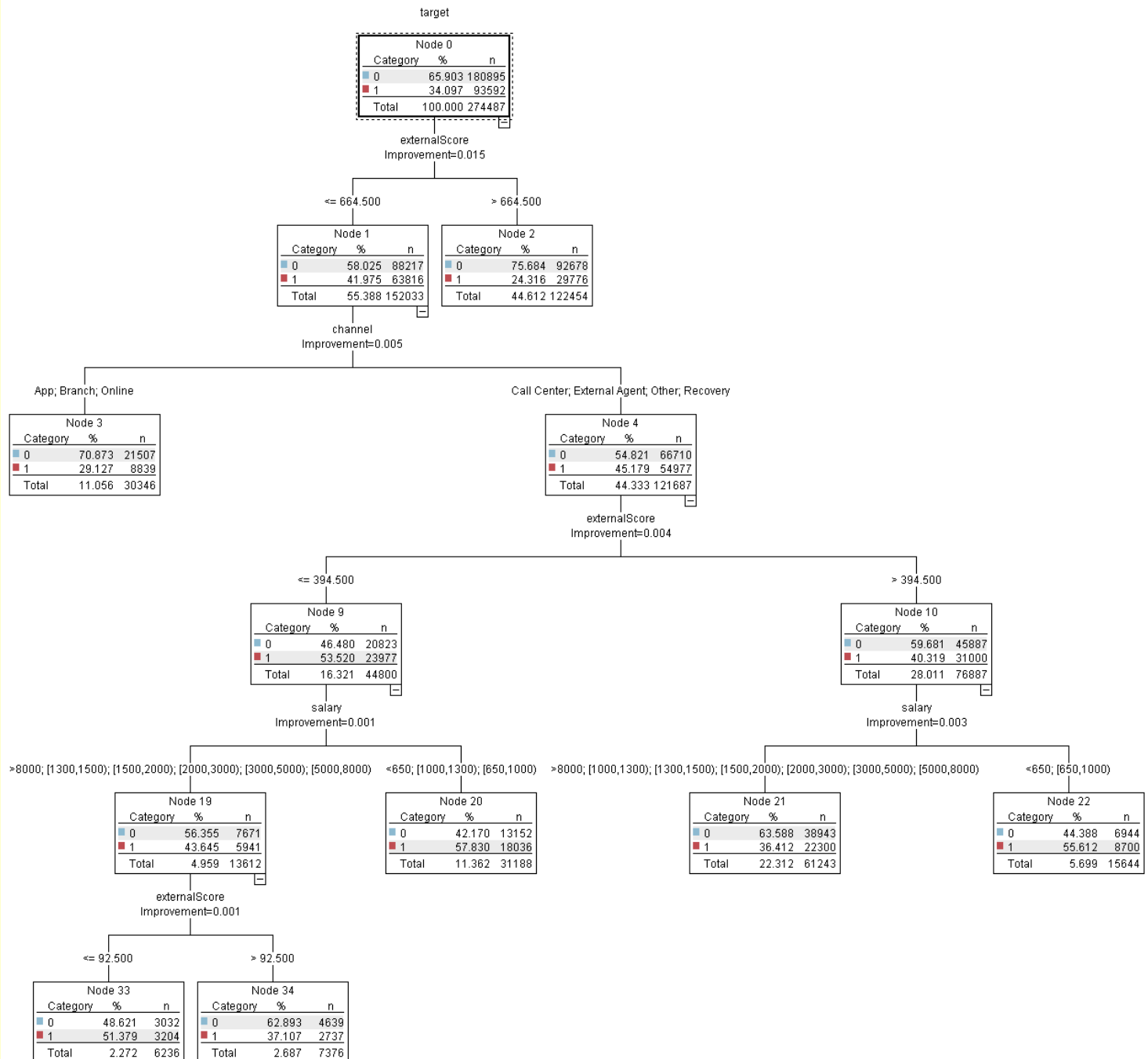


Advice from financial and business perspective

- The prediction are to be made on dataset with no missing values and customer care can take action on relevant predictions.
- Even though system trained on missing data, the model when applied to cases with no missing value will yield better results.
- The externalscore, channel and salary are the major players to decide the prediction values to be 1 or 0 and rightly so from the banking perspective.
- The designed model can be applied to real-time system after further optimization.
- The model's accuracy can be improved by integrating it with time series data.

Appendix

The decision tree diagram for the model:



The ROC Curve Ideal Behavior:

