Credit Score Algorithm

Report for Indian Institute of Technology, Bombay - DS203: Programming for Data Science (2022)

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***Abstract*—To ensure that the banks are lending money only to those who can absolutely pay back their loan on time, banks should have as much information as possible on the borrower, including his credit history, income, and net worth distributed throughout various asset classes. Our work is to analyze the data and come up with a means of quantifying the credit worthiness of a customer. This quantifying of the customer's credit worthiness is done by predicting the credit score, which ranges from 300 to 900. Before predicting the credit score, we have to deal with the missing values in the dataset. We have used the following imputation techniques: Imputation using mean and kNN Imputation, to fill in the missing values and described why is one better than the other. Now onto the credit score, we built four ML models to train our dataset, and compared the accuracy of each of the models and selected the best. As a result, we are developing a system that identifies the candidates deserving of receiving a loan of a specific amount using a quantifiable metric calculated using the borrower's data. This system can then be automated into a system that accepts these massive amounts of data and provides us with just one piece of information over all others: should the bank lend to this particular borrower, this particular sum, or not. The data is sourced from the Resource drive [1] of a Risk Modelling tutorial by Skillcate.**

I. Introduction

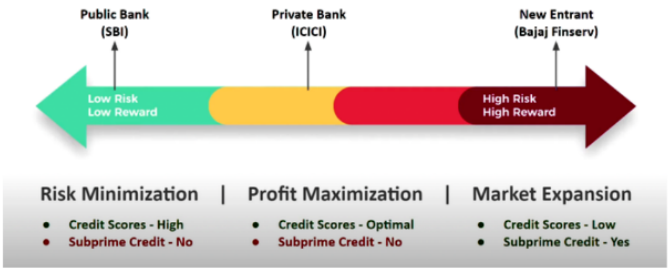
One pillar of paramount importance of Capitalism is the fractional reserve system which allows banks and other certified institutions to lend to individuals who in turn become private entrepreneurs or consumers of goods and services. As long as the borrower is returning the debt on time, the system is in harmony and the world is a good place. The problems begin when the borrower defaults on their loan and perhaps in the worst of cases declare bankruptcy. If the lending institution faces many of such cases, it can run out of cash and even get forced to go under. If it is a giant bank, it may even cause a dent to the entire national or global economy just like Lehmann Brothers collapse of 2008 sent shockwaves across the planet. There are also secondary players such as insurance companies selling policies to such banks, like AIG in 2008, who may not be aware about the quality of loans the bank lends out, leading them to charging lower premiums or adverse selection.

From all this we can see it is very important for a bank to only lend to borrowers who can most certainly return their debt + interest on time. That requires the bank to know as much as possible about the borrower, his credit history, his income and his net worth spread across different asset types. But there is a problem, the borrower always knows more about themselves than a bank can know about them. This phenomenon, in a nutshell, is known as information asymmetry.

In order to bridge this gap we need a system that tells us who are the candidates worthy of getting a loan of a particular sum - note that someone may be worthy of a particular sum but not of a higher amount - in a quantifiable metric calculated based on the borrower's data, that can then be automated into a system that takes in these huge piles of data and gives us just one information over all other, should the bank lend to this particular borrower, this particular sum, or not. Enter credit score

A credit score is a number from 300 to 850 that depicts a consumer's creditworthiness. The potential lenders. A credit score is based on credit history: number of open accounts, total levels of debt, repayment higher the score, the better a borrower looks to history, and other factors. Lenders use credit scores to evaluate the probability that an individual will repay loans in a timely manner. Your credit score, a statistical analysis of your creditworthiness, directly affects how much or how little you might pay for any lines of credit that you take out. A person's credit score also may determine the size of an initial deposit required to obtain a smartphone, cable service, or utilities, or to rent an apartment. And lenders frequently review borrowers' scores, especially when deciding whether to change an interest rate or credit limit on a credit card.

The second challenge depending upon your objectives as a bank, whether your objective is to maximise profit by ensuring minimum number of borrowers default on their borrowings or, to expand your business by lending out maximum number of loans which in turn implies lending to borrowers with relatively subprime credit ratings and hence suffer greater risks. For example, if you are SBI Bank, your approach will be to lend only to individuals or businesses with a positive track record i.e. a good credit rating, but if you are bajaj fin-services your approach should be to take higher risk and lending to small scale entrepreneurs looking to create startups with tech. or otherwise for the opportunity to get maximum returns on a few bets even if it involves losing on maximum number of their lendings.



Now how to solve this issue ? Perhaps the best approach would be to have an algorithm that assigns the score to all the investments upon analysing the data input and then depending upon the risk appetite the firm can have a minimum threshold beyond which no matter what the firm will not lend to the borrower. The second major issue is the lack of data about the borrower which makes it hard for the firm to make accurate predictions about the borrower's ability to repay. Now to solve this issue we can either use simple imputation i.e. filling the missing value with the mean median or mode, KNN imputation i.e. filling the missing value with related cases or just use removal of data which is often unfeasible as the maximum number of NA data values is 188 which can lead to huge data loss.

II. Data

Coming to the data sets, data plays an important role in the development, monitoring, and maintenance of credit scoring models.

The data used for credit scoring comes from diverse and multidimensional sources. For credit scoring, traditionally, credit data are used, including amount of loan, type of loan, maturity of loan, guarantees and collateral value, historical payment, performance such as default information and payments in arrears, amounts owed, length of credit history, new credit, and types of credit. These data are factored into a credit score as indicators of willingness and ability to pay. Most of data that credit companies deal with, including our data implemented in the model consists of the Derogatories Count.

Derogatory marks are negative, long-lasting indications on your credit reports that generally mean you didn't pay back a loan as agreed. For example, a late payment or bankruptcy appears on your reports as a derogatory mark. These derogatory marks generally stay on your credit reports for up to 7 or 10 years (sometimes even longer) and damage your scores.

If you have a lower score coupled with a derogatory mark, you may have a hard time getting approved for credit or may get less-than-ideal credit terms. But the good news is that the impact to your credit of all derogatory marks decreases over time. A derogatory mark can land on your credit reports in two ways:

- A creditor or lender may report negative information to the credit bureaus, which is then translated into a derogatory mark.
- Or the credit bureaus can add public records to your credit reports. These may include bankruptcies, civil judgments and tax liens.

However, thanks to stronger public-record data standards that the credit bureaus have recently agreed to, consumers nationwide will see fewer tax liens and civil judgments on their credit reports.

III. Exploratory Data Analysis

Every single credit scoring company deals with tons of data that they analyse using models powered by K Neighbour Classifiers, Random Forest, Logistic Regression, etc. Now we will present to you a model comprising of data from 3000 customers, their individual IDs and 28 Variables for each customer based on their credit history and transactional behaviour categorising them as defaulter or punctual, providing hallmark for their credibility. Following is the list of variables we have in our data set : 'ID', 'DerogCnt', 'CollectCnt', 'BanruptcyInd', 'InqCnt06', 'InqTimeLast', 'InqFinanceCnt24', 'TLTimeFirst', 'TLTimeLast', 'TLCnt03', 'TLCnt12', 'TLCnt24', 'TLCnt', 'TLSum', 'TLMaxSum', 'TLSatCnt', 'TLDel60Cnt', 'TLBadCnt24', 'TL75UtilCnt', 'TL50UtilCnt', 'TLBalHCPct', 'TLSatPct', 'TLDel3060Cnt24', 'TLDel90Cnt24', 'TLDel60CntAll', 'TLOpenPct', 'TLBadDerogCnt', 'TLDel60Cnt24', 'TLOpen24Pct'.

- As IDs are inert variables which do not impact our analysis, we will drop that column.
- We have taken the data of total 3000 customers, out of which 2500 are found to be normal, whereas 500 are fraudulent indicating a fraud rate of 20%.

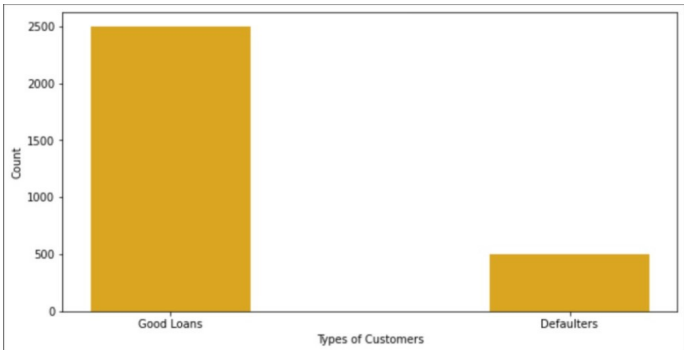
A. Identify and treatment of nulls in Datas

Upon observing the data set, we find that it contains a lot of null entries which maybe a result of domain specific problems, unavailability of significant credit history or corrupt measurements.

- InqTimeLast has 188 values missing
- TLCnt has 3 values missing
- TLSum has 40 values missing
- TLMaxSum has 40 values missing
- TLSatCnt has 4 values missing
- TL75UtilCnt has 99 values missing
- TL50UtilCnt has 99 values missing
- TLBalHCPct has 41 values missing
- TLSatPct has 4 values missing
- TLOpenPct has 3 values missing
- TLOpen24Pct has 3 values missing

Now as we saw that the maximum number of NA values is 188 and their direct removal is going to cause significant data loss and hence this method is infeasible, henceforth we will use, imputation, the process of replacing missing data using substituted values. The objective of these procedures is to create a collection of data objects that will practically support the next step of identifying useful features by making sure that

Variable Name	Label	Role
Target	Target = 1 (Defaulters), Target = 0 (Good Loans)	Target
BanruptcyInd	Bankruptcy Indicator	Input
TLBadDerogCnt	Bad Dept plus Public Derogatories	Input
CollectCnt	Collections	Input
InqFinanceCnt24	Finance Inquires 24 Months	Input
InqCnt06	Inquiries 6 Months	Input
DerogCnt	Number Public Derogatories	Input
TLDel3060Cnt24	Number Trade Lines 30 or 60 Days 24 Months	Input
TL50Utilent	Number Trade Lines 50 pct Utilized	Input
TDel60Cnt24	Number Trade Lines 60 Days or Worse 24 Months	Input
TDe160CntAll	Number Trade Lines 60 Days or Worse Ever	Input
T75UtIlCnt	Number Trade Unes 75 pct Utilized	Input
Tel90Cnt24	Number Trade Unes 90+ 24 Months	Input
TLBadCnt24	Number Trade Unes Bad Debt 24 Months	Input
TLDel60Cnt	Number Trade Unes Currently 60 Days or Worse	Input
TLSatCnt	Number Trade Lines Currently Satisfactory	Input
TLCnt12	Number Trade Lines Opened 12 Months	Input
TLCnt24	Number Trade Unes Opened 24 Months	Input
TLCnt03	Number Trade Unes Opened 3 Months	Input
TSatPct	Percent Satisfactory to Total Trade Lines	Input
TLBalHCPct	Percent Trade Line Balance to High Credit	Input
TLOpenPct	Percent Trade Lines Open	Input
TLOpen24Pct	Percent Trade Unes Open 24 Months	Input
TLTimeFirst	Time Since First Trade Une	Input
InqTimeLast	Time Since Last Inquiry	Input
TLTimeLast	Time Since Last Trade Line	Input
TLSum	Total Balance All Trade Lines	Input
TLMaxSum	Total High Credit All Trade Lines	Input
TL_Cnt	Total Open Trade Unes	Input
ID	Customer ID	ID




```
 #   Column           Non-Null Count
---  ------           --------------
 0   TARGET           3000 non-null
 1   DerogCnt         3000 non-null
 2   CollectCnt       3000 non-null
 3   BanruptcyInd     3000 non-null
 4   InqCnt06         3000 non-null
 5   InqTimeLast      2812 non-null
 6   InqFinanceCnt24  3000 non-null
 7   TLTimeFirst      3000 non-null
 8   TLTimeLast       3000 non-null
 9   TLCnt03          3000 non-null
 10  TLCnt12          3000 non-null
 11  TLCnt24          3000 non-null
 12  TLCnt            2997 non-null
 13  TLSum            2960 non-null
 14  TLMaxSum         2960 non-null
 15  TLSatCnt         2996 non-null
 16  TLDel60Cnt       3000 non-null
 17  TLBadCnt24       3000 non-null
 18  TL75UtilCnt      2901 non-null
 19  TL50UtilCnt      2901 non-null
 20  TLBalHCPct       2959 non-null
 21  TLSatPct         2996 non-null
 22  TLDel3060Cnt24   3000 non-null
 23  TLDel90Cnt24     3000 non-null
 24  TLDel60CntAll    3000 non-null
 25  TLOpenPct        2997 non-null
 26  TLBadDerogCnt    3000 non-null
 27  TLDel60Cnt24     3000 non-null
 28  TLOpen24Pct      2997 non-null
```

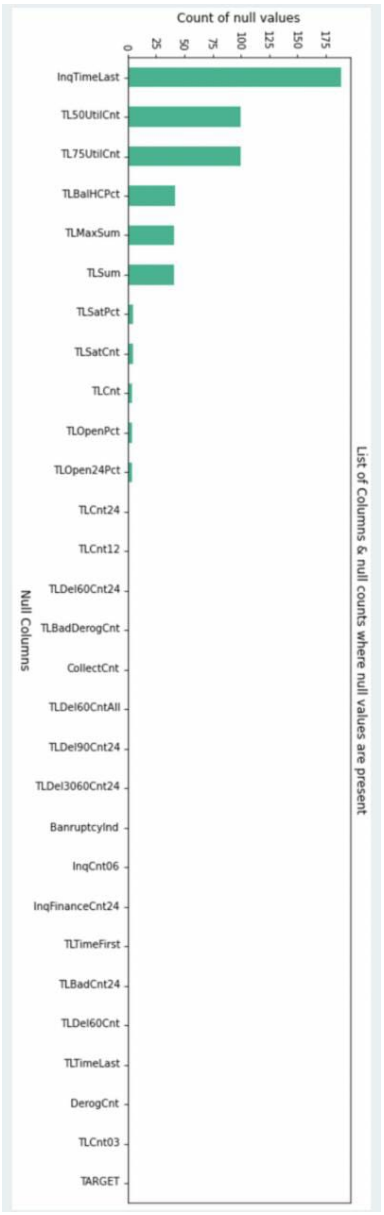
all quantitative data meet quality requirements for automated processing.

We will create a model to predict the missing values, created for each feature that has missing values.

For missing value imputation, we can use simple imputation, kNN imputation or simply remove the data by removing rows with NA values. But as we saw, the maximum possible number of rows with NA values is 188. Therefore, removing 188 rows is not a feasible solution since it will lead to a huge data loss.

B. Simple Imputation

It is basically the process of completing our dataset by filling the missing information using the row average method for that feature variable assuming no correlation with other features in our dataset The behaviour of particular customer's missing credit info is assumed similiar to average of other customer. The model is also affected by outliers and lead to loss of a potential good customers due to highly non uniform behaviour of defaulters. For example : As shown in the table the deviation between the mean and the maximum value of the data sets is humungous which are the outliers with non uniform behaviour skewing the mean. This can have adverse implications such as good customers losing out on loans as their score is demeaned



using this skewed mean instead of the average of majority population.

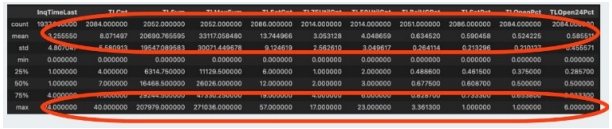


Fig. 1. Simple Imputation

C. kNN imputation

It is basically a model created for each feature that has missing values, taking as input values of perhaps all other input features. Using K-nearest neighbour model, a new sample is imputed by finding the samples in the training set "closest" to it and averaging the nearby points to fill in the value. We will show that kNN impute appears to provide a more robust and sensitive method for missing value estimation and kNN impute surpass the commonly used row average method (as well as filling missing values with zeros). Configuration of KNN imputation often involves selecting the distance measure (e.g. Euclidean) and the number of contributing neighbours for each prediction, the k hyperparameter of the KNN algorithm.

```
TARGET            3000 non-null
DerogCnt          3000 non-null
CollectCnt        3000 non-null
BanruptcyInd      3000 non-null
InqCnt06          3000 non-null
InqTimeLast       3000 non-null
InqFinanceCnt24   3000 non-null
TLTimeFirst       3000 non-null
TLTimeLast        3000 non-null
TLCnt03           3000 non-null
TLCnt12           3000 non-null
TLCnt24           3000 non-null
TLCnt             3000 non-null
TLSum             3000 non-null
TLMaxSum          3000 non-null
TLSatCnt          3000 non-null
TLDel60Cnt        3000 non-null
TLBadCnt24        3000 non-null
TL75UtilCnt       3000 non-null
TL50UtilCnt       3000 non-null
TLBalHCPct        3000 non-null
TLSatPct          3000 non-null
TLDel3060Cnt24    3000 non-null
TLDel90Cnt24      3000 non-null
TLDel60CntAll     3000 non-null
TLOpenPct         3000 non-null
TLBadDerogCnt     3000 non-null
TLDel60Cnt24      3000 non-null
TLOpen24Pct       3000 non-null
```

Fig. 2. kNN Imputation

The primary advantage of KNN imputation over simple imputation is its feature of not getting skewed due to certain outlier data sets. This was the primary reason good borrowers were losing out on debt due to a skewed mean, but since KNN only considers nearby neighbours, the problem is solved.

IV. Outliers and Correlation in Data

A. Correlation

Till now we have imputed for missing values and made our data useable by the computer. Now let us understand about the interdependence of variables (correlation) and how certain variables heavily impact our computation (outliers).

Data Correlation: Is a way to understand the relationship between multiple variables and attributes in our dataset using statistics

Using Correlation, you can get some insights such as:

- One or multiple attributes depend on another attribute or are a cause for another attribute. It helps us in imputation, assuming similiar behaviours among customers with similiar credit records.
- One or multiple attributes are associated with other attributes which may cause multicollinearity, hence, issues in prediction

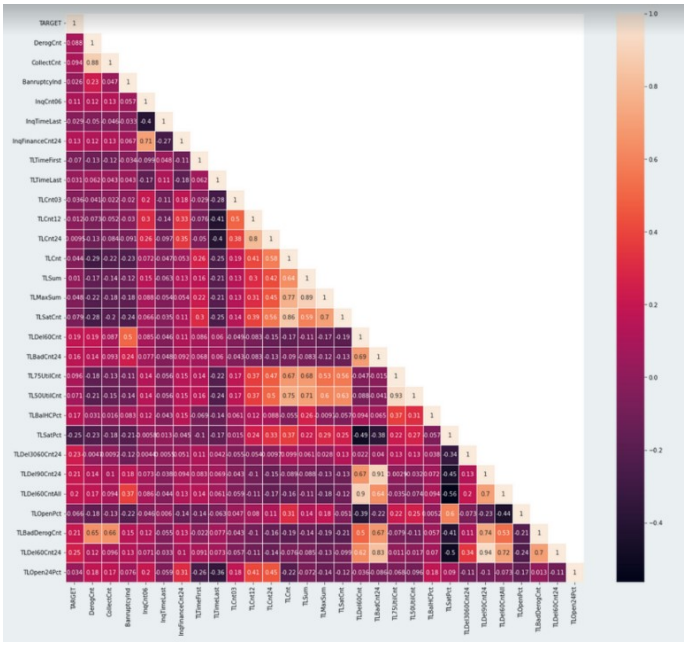


Fig. 3. Colour Coded Correlation matrix

Above is a correlation heat-map for our data. The variables which are having maximum negative impact on the probability of a customer defaulting are (with their correlation coefficient):

- TLDel60Cnt24 (0.252026)
- TLDel3060Cnt24 (0.233709)
- TLDel90Cnt24 (0.211577)

Why is it so ? Lets' go back to what TLDelCnt denotes TelDel_n_Cnt24 denotes the number of trades lines currently held by the customer with a period of 24 months due past n days. It represents the number of times the subject has been 30, 60, or 90 days delinquent, respectively. With n as 60 days or worse, a 24 Month long trade-line is worsened and should highly reduce the credibility of the customer.

Similar behaviour is observed for trade lines with a period of 24 months due past 30 or 60 days The variables that will have maximum negative correlation - positive impact on credibility of a customer are:

- TLCnt03 (-0.036116)
- TLCnt12 (-0.012391)
- TLCnt24 (-0.009525)

A tradeline helps you improve your credit score until you close it within the given period, so it will reap all the benefits a good credit score enables you to achieve.

Even seasoned trade-lines are considered to be the best trade- lines as they can significantly affect your credit score because of its credit history.

A report by Finance Monthly states that purchasing 2-3 seasoned tradelines can help increase your credit score by 720-850 in just one month.

The same is visible in our data also. TLCnt_n denotes the number of trade lines opened in the last n months. Note that these trades may now be open or closed, paid as agreed, delinquent, or derogatory, and so on.

TARGET	1.000000
TLDel60Cnt24	0.252026
TLDel3060Cnt24	0.233709
TLDel90Cnt24	0.211577
TLBadDerogCnt	0.208152
TLDel60CntAll	0.195863
TLDel60Cnt	0.185942
TLBalHCPct	0.167845
TLBadCnt24	0.163796
InqFinanceCnt24	0.132562
InqCnt06	0.106663
TL75UtilCnt	0.095996
CollectCnt	0.093748
DerogCnt	0.088100
TL50UtilCnt	0.070804
TLOpen24Pct	0.033585
TLTimeLast	0.030648
BanruptcyInd	0.025651
TLSum	0.009988
TLCnt24	-0.009525
TLCnt12	-0.012391
InqTimeLast	-0.028542
TLCnt03	-0.036116
TLCnt	-0.044204
TLMaxSum	-0.047951
TLOpenPct	-0.065911
TLTimeFirst	-0.069597
TLSatCnt	-0.079046
TLSatPct	-0.253949

As more number of trade-lines are opened in a shorter duration, it has a higher impact on improvement of borrower's credibility.

Also, TLSatPct having a correlation coefficient of -0.253949, is having the maximum impact on improving one's credit score, since it denotes "Percent Satisfactory to Total Trade Lines" i.e. the percentage number of trade lines closed on time by the borrower. The same is visible in our data also.

B. Outliers

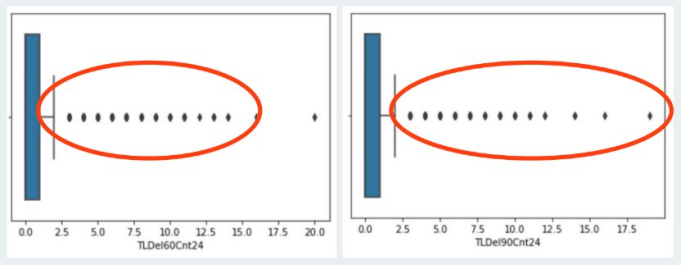
Now we are clear about the correlation of data variables among themselves, it can be felt that if a certain dataset is significantly larger or smaller than the remaining pack, it can have skewing impact on our measure of central tendancies, in our model, the mean. An outlier maybe caused due to variability in data, or due to experimental or human errors, but it can also be due to a case of fraudulent transaction.

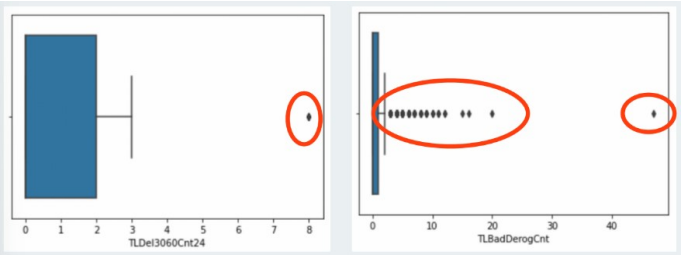
Thus detection of these frauds is in many ways similar to detection of the outliers. The frauds are data sets with high payments, high rate of purchase, data items that the customer never purchased, etc which reflect as outliers in our data more often than not. As we saw above, outliers are already affecting our data and the credit record of our customers

	InqTimeLast	TLCnt	TLSum	TLMaxSum	TLSatCnt	TL75UtilCnt	TL50UtilCnt	TLBalHCPct	TLSatPct	TLOpenPct	TLOpen24Pct
count	1937.000000	2084.000000	2052.000000	2052.000000	2086.000000	2014.000000	2014.000000	2051.000000	2086.000000	2084.000000	2084.000000
mean	3.255650	8.071497	20690.765595	33117.058480	13.744966	3.053128	4.048859	0.634520	0.590458	0.524225	0.585511
std	4.807047	5.580913	19547.086583	30071.449678	9.124819	2.562810	3.049817	0.264114	0.213296	0.219127	0.465571
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	1.000000	4.000000	6314.750000	11129.500000	6.000000	1.000000	2.000000	0.488600	0.461500	0.376000	0.286700
50%	1.000000	7.000000	16468.500000	26026.000000	12.000000	2.000000	3.000000	0.677500	0.608700	0.500000	0.500000
75%	4.000000	11.000000	29244.500000	47330.250000	19.000000	4.000000	6.000000	0.828700	0.733300	0.653800	0.833300
max	24.000000	40.000000	207979.000000	271036.000000	57.000000	17.000000	23.000000	3.361300	1.000000	1.000000	6.000000

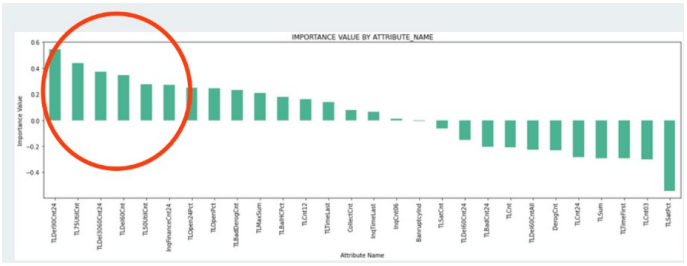
For most of our feature variables, 75% of our data is far less than the maximum values present in our data set.

These outliers can play an important role in the model's forecasting behaviour. Although they represent events that occur with a small probability and a high impact, it is often the case that outliers are a result of system error. For example, a numerical variable that is assigned to the value 999, can represent a code for a missing value, instead of a true numerical variable. That aside, outliers can be easily detected by the use of boxplots. Box plots are used to show distributions of numeric data values, especially when you want to compare them between multiple groups. They are built to provide high-level information at a glance, offering general information about a group of data's symmetry, skew, variance, and outliers. Some plots of highly correlated feature variables, i.e. those having greater weightage for precision are shown below:





Now coming to the treatment, not losing much on our data, we removed outliers for the feature variables which were highly positively or negatively correlated with our Target variable, hence having higher weights in our Model. This improved our various model's accuracy by a substantial magnitude. On these reduced attribute sets, our techniques will detect frauds with less memory and computation requirements. Let us analyse each of our model's performance to notice how this helped us avoid bad loans and ensure more of good ones.



This brings us to the end of our exploratory data analysis. We have completed a thorough understanding of correlation, outliers, their treatment and how it impacts our data sets. Now let us understand the verious credit scoring methedologies and the machine learning models that can help us in producing a valid credit score used to predict the nature of the loans. Refer to the code attached with the report to see the detailed python implementation of the same.

V. Credit Scoring Methodologies

The methods used for credit scoring are evolving from traditional statistical techniques to innovative methods such as artificial intelligence, including machine learning such as random forests, gradient boosting, and deep neural networks. With the central objective of making models that provide maximum utility to industry and avoiding unnecessary jargon, we researched upon various models and predictor variable combinations. We then realised the 4 models of LogisticsRegression, Random Forest Classification, Decision Trees and K-Nearest Neighbours will provide a holistic viewpoint and necessary accuracy in our predication while at the same time ensuring our models can be explained to people with no prior professional technical experience in the arena of machine learning.

- We have analysed 2 datasets, one with outliers removed from the weighted feature variables based on correlations existing among them and one without losing any data with outliers intact.
- We also implemented a methodology for the selection of the key variables in order to establish a credit scoring model.

As one of the biggest challenge of building credit scoring models is also to decide which are the most relevant features to be selected for the task. In practice, the data used for the models may be collected from various sources, and sometimes the size of the data is small, in relation to the number of features considered. In addition, there might be some features in the data, which may not be significant to credit risk, or some of them may be correlated with each other. Thus, these data issues might result in a misleading interpretation of the credit scoring model and a very poor performance of it.

The feature selection process is a solution to these issues. Since, it is an arbitrary, and unsystematic task since there is no

specific theory, and works differently on different data. therefore, for this report we have implemented feature selection, forward stepwise selection, on one of model which is by far giving most accurate results - The RandomForest Classifier.

Now we will study about all these 4 models in brief and understand the various observations that we spot. Each of them have a different processing algorithm and perform differently on verious metrics. Let us delve into the comparitive study of these models to see which one emerges out on top.

VI. Model Building

A. Logistic Regression

Logistic regression is one of the most popular Machine Learning algorithms, which comes under the Supervised Learning technique. It is used for predicting the categorical dependent variable using a given set of independent variables. Logistic regression predicts the output of a categorical dependent variable. Therefore the outcome must be a categorical or discrete value. It can be either Yes or No, 0 or 1, true or False, etc. but instead of giving the exact value as 0 and 1, it gives the probabilistic values which lie between 0 and 1.

Y("TARGET") = 1 if a borrower defaults or 0 otherwise.

Since it provides the probability that the response variable is 1, a threshold must exist that classifies data into two or more categories; the default threshold is 0.5, and if a sample whose probability of defaulting is equal to or greater than 0.5, it is classified as 1 and 0 otherwise. Firstly we trained the

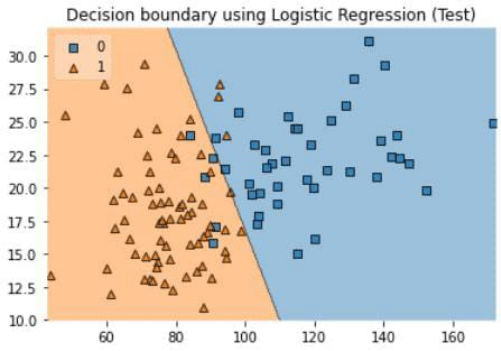


Fig. 4. Logistic Regression Visualization

model over our dataset and weights are assigned to various features depending upon their impact on TARGET variables differentiating the borrowers as defaulter or punctual and redictions are compared with the actual behaviour of borrowers in our test dataset.

The variables with maximum weights, were cleaned against any kind of deviation due to outliers and on finally implementing the model it yielded an accuracy score of 91.38

B. k Nearest Neighbour

kNN is one of the simplest supervised machine learning algorithm mostly used to make classifications or predictions about the grouping of an individual data point. It measures/stores all available cases and classify new cases based on a similarity measure. It serves as an example of a non- parametric statistical approach and is based on an assumption that similar inputs have similar outputs. Given a positive integer K and a test observation x0, this classifier first identifies K points that are closest to x0 in the training data set represented by N0 and then kNN classifies the test observation x0 to the class that has the highest probability. This simple yet efficient approach made the KNN very popular and widely used in data mining and statistics.

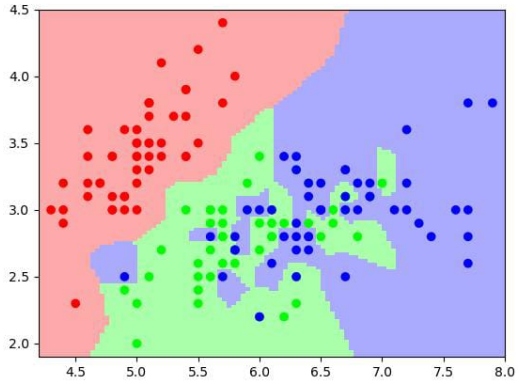


Fig. 5. KNN Visualization

We choose a metric on the space of applicants and take the k- nearest neighbour (k-NN) of the input pattern that is nearest in some metric sense. A new applicant will be classified in the class to which the majority of the neighbours belong.

Also, since it seems to depend on degree of correlation with feature variables, its performance increase as we remove the outliers from highly correlated feature variables.

KNN gives an accuracy of 88.75% with outliers removed.

It is a fairly intuitive procedure and as such it could be easily explained to business managers who would need to approve its implementation. It can also be used dynamically by adding applicants when their class becomes known and deleting old applicants to overcome problems with changes in the population over time. Despite this, nearest neighbour models have not been widely adopted in the credit scoring industry. One reason for this is the perceived computational demand not only must the design set be stored, but also the nearest few cases among maybe 100, 000 design set elements must be found to classify each applicant.

C. Decision Trees

Decision Trees (DTs) are a non-parametric supervised learning method used for classification and regression. The goal is to create a model that predicts the value of a target variable by learning simple decision rules inferred from the data features. A tree can be seen as a piecewise constant approximation.

It is used in credit scoring practice only as a supporting tool to accompany parametric estimation methods. It serves, for example, in the process to select characteristics with the highest explanatory power.

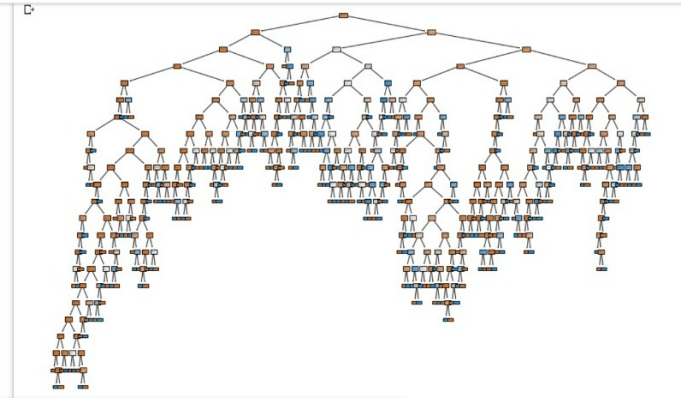


Fig. 6. Decision Tree Visualization

Decision Trees are not sensitive to noisy data or outliers since, extreme values or outliers, never cause much reduction in Residual Sum of Squares(RSS), because they are never involved in the split.

Hence, when we remove the non-uniform data, it does not improve the performance but due to less of data now available to train the model, the change in prediction values turn out to be ambiguous as shown:

The advantages of the this method in credit scoring are that it is very intuitive, easy to explain to management and it is able to deal with missing observations.

The major disadvantage is the computational burden in case of large datasets since at each node every characteristic has to be examined. Very often the resulting tree is quite large so that the process of model-learning becomes too time consuming. Some emperical studies also note that often the trees are not stable since small changes in a training set may considerably alter the structure of the whole tree.

D. Random Forest Classifier

We also experimented with the Random Forest Classifier. The Random forest or Random Decision Forest is a supervised Machine learning algorithm used for classification, regression, and other tasks using decision trees.

A random forest is a classification algorithm used commonly in both regression and classification problems given the easy interpretation and good reflection on human decision-making.

Random Forest is capable of identifying important features. As with many machine learning algorithms, the Random Forest model can be seen as a black box: it is not possible to define the process completely from input to output. However, there are ways to look inside the algorithm. An extremely powerful example is the ability to compute a feature's importance. There are two different categories of feature selection methods, i.e. filter approach and wrapper approach. The wrapper approach uses a machine-learning algorithm to measure the goodness of the set of selected features. The measurement relies on the performance of the learning algorithm such as its accuracy and precision values. The wrapper model uses a learning accuracy for evaluation. In the methods using the wrapper model, all samples should be divided into two sets, i.e. training set and testing set. The algorithm runs on the training set, and then applies the learning result on the testing set to measure the prediction accuracy.

As we implemented forward stepwise selection, sizes of selected subsets of varies from 20 to 28 features and target values are predicted.

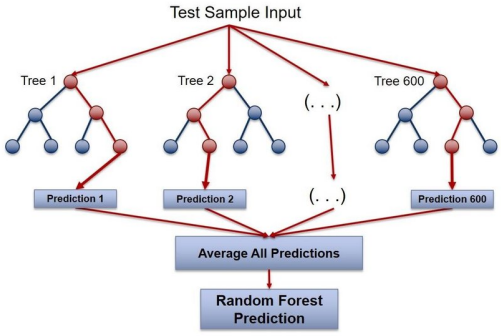


Fig. 7. Random Forest Classifier Visualization

Another feature is added to the subset, and values are redicted using RF Model. If the accuracy of the predicted values improve, the process is continued.

And we get an optimum set of feature variables which provide us with best results for the predicted Target variables for the borrowers in our test dataset.

After implementation of forward stepwise selection upon Random Forest Classifier, best subset comes out to be consisiting of all28 feature variables. This shows data set contains only specific features .

Hence, Random Forest Model gives a final accuracy of 91.14after outliers are removed and best subset of feature variables is chosen.

VII. Effect of Outlier Removal

1) For Logistic Regression:

- Percentage good lends made rose from 97.1 % to 99.7 %
- Percentage bad lends avoided rose from 85.3 % to 92.1 %

With Outliers	Predicted Bad	Predicted Good
Observed Bad	87	15
Observed Good	14	484
Without Outliers	**Predicted Bad**	**Predicted Good**
Observed Bad	35	3
Observed Good	1	379

2) For k Nearest Neighbour:

- Percentage good lends made rose from 94.1% to 97.1 %
- Percentage bad lends avoided rose from 89.3 % to 94.7 %

With Outliers	Predicted Bad	Predicted Good
Observed Bad	91	11
Observed Good	29	469
Without Outliers	**Predicted Bad**	**Predicted Good**
Observed Bad	36	2
Observed Good	11	369

3) For Random Forest Classifier:

- Percentage good lends made rose from 98.0 % to 99.7%
- Percentage bad lends avoided rose from 85.3 % to 94.7 %

With Outliers	Predicted Bad	Predicted Good
Observed Bad	87	15
Observed Good	10	488
Without Outliers	**Predicted Bad**	**Predicted Good**
Observed Bad	36	2
Observed Good	1	379

4) For Decision Trees: Since Decision trees are not impacted by weights, the change in this case is ambiguous.

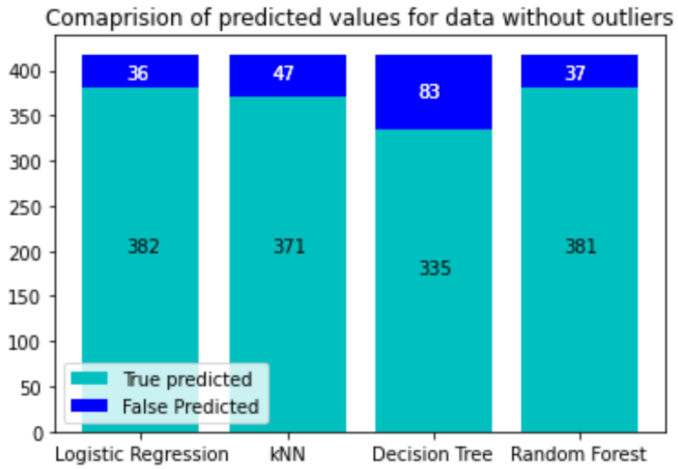
- Percentage good lends made fell from 92.8 % to 87.1 %
- Percentage bad lends avoided rose from 68.6% to 89.5 %

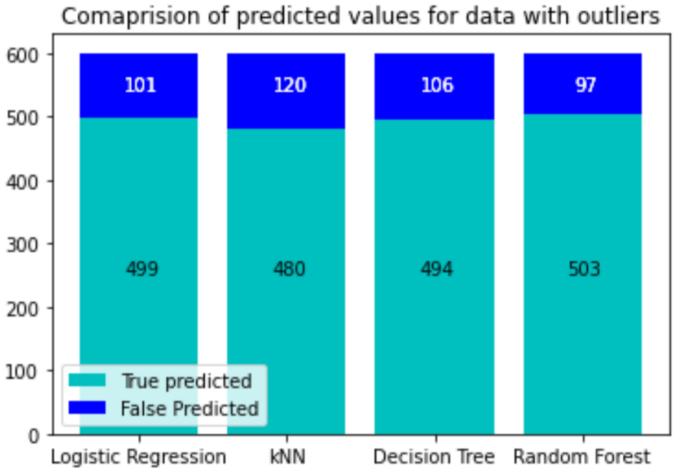
With Outliers	Predicted Bad	Predicted Good
Observed Bad	70	32
Observed Good	36	462
Without Outliers	**Predicted Bad**	**Predicted Good**
Observed Bad	34	4
Observed Good	49	331

VIII. Interpretation of Results

Accuracy Scores	With Outliers	Without Outliers
Logistic Regression	83.17 %	91.38 %
K Nearest Neighbour	80 %	88.75 %
Decision Tress	82.33 %	80.14 %
Random Forest Classifier	83.83 %	91.14 %

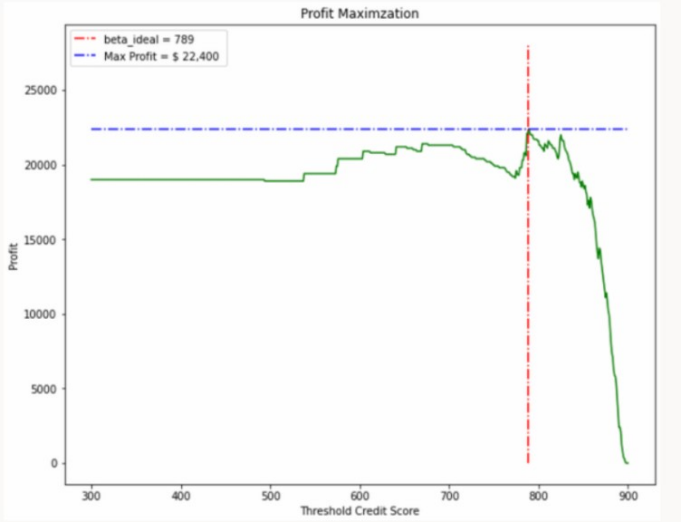
In general there is no overall ”best” method. What is the best will depend on the details of the problem, the data structure, the characteristics used, the extent to which it is possible to separate the classes by using those characteristics





and the objective of the classification (overall misclassification rate, cost-weighted misclassification rate, bad risk rate among those accepted, some measure of profitability, etc.) The various methods are often very comparable in results. As explained and shown in the table the Random Forrest Classifier performs best with outliers 83.83 % accuracy and the logistic regression model performs best when our data set is without outliers 91.38% accuracy.

Now to get the credit score corresponding to being a punctual borrower we have scaled the probability of a good borrower obtained from the data of our logistic regression model on the scale of 300 to 900 which is the commonly used scale by major credit score companies like CIBIL, TransUnion, Equifax, Experian, etc. From the 418 borrower’s data sets out of which 380 yield a positive result and 38 of them end up as defaulters, this gives to us a scale which the bank can use to set a threshold above which it would be in the best interests of the bank to lend so as to minimize the defaulters, occurring due to information asymmetry and other factors. If we assume a scene where a bank can make $100 profit from lending to a good customer and suffers a $500 loss from lending to a bad customer, we will observe that a threshold credit score of 789 gives the bank the sweet spot of maximum profit ($22,400).



IX. Conclusion

The process of determining the credit score is a complicated endeavour, the hardships are further amplified due to lack of credit history of borrowers and cluttered data sets. The stakes during the practical application of our models are astronomical as even a tiny computational, syntax or logical error can lead to a deserving firm miss out on loan preventing their business to expand, a household missing out on necesarry revenue in times of crisis even if they have the necessary assets or collateral or a bank can get into severe trouble if it ends up lending to sub prime borrowers or on the other hand, miss out on great relationships with night net worth powerful clients by denying them loans when they are more than capable of repayment.

On the voyage to solve this problem we developed a thorough understanding of information asymmetry, trade lines, derogatory marks and analysed a large data implemented in our model. We had the onus of exploiting the complete power of the strongest tool of humanity, artificial intelligence and computer science and put our best foot forward by implementing 4 complete models and providing the background about each in east to understand literature. We urge everyone reading this report to go through our model file and understand each step which will help paint the complete picture. We hope you enjoyed reading our work just as much as we loved making it. Thanks a lot for reading till the end.

X. Future Works

The accuracy of our model for predicting credit scores can be improved by using deep neural networks whose number of layers and nodes in each layer can be decided as per the requirements. To avoid overfitting, we can include regularisation, such as dropout and L2 regularisation. We can even optimise our algorithm using RMSprop or learning rate decay. Lastly, we can find ways to make the algorithm computationally efficient.

References

[1] Credit Scoring and its approaches by University of Pretoria
[2] Credit scoring and Risk Modelling tutorial by Skillcate
[3] Simple Imputation using Scikit-learn
[4] kNN Imputation using Scikit-learn
[5] GeeksforGeeks guide on Random Forest Classifier using Scikit-learn
[6] Python tutorial on k-Nearest-Neighbour algorithm