**An Analysis of Classification Algorithms for Credit Card Fraud Detection**

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# **Introduction**

Advances in computing and networking have led to a rise in the occurrence of credit card fraud (Quah and Sriganesh, 2008). The author notes that the increase in online banking and online shopping has also led to this increase in credit card fraud. According to the Banking & Payments Federation of Ireland (BPFI) the total number of online and mobile banking payments in 2014 was approximately 64 million (Banking & Payments Federation of Ireland, 2015).

There are numerous ways fraud can be implemented. One instance where fraud can occur is through the use of social engineering (Atkins and Huang, 2013). Social engineering is the process of manipulating individuals into performing certain actions through deceit. Social engineering can take form in a number of different approaches such as fake emails ,which on first sight appear to have legitimate credentials and therefore the victim trusts this and enters the required information. The exploitation can also occur through phone calls where the fraudster claims to be someone else generally from a large reputable organisation and ascertains the victims information that way.

(Atkins and Huang, 2013) outline another form of social engineering called dumpster diving whereby the fraudster ciphers through the individual or organisations rubbish to extract information from mail for example. The also describe the situation where the fraudster gains entry to a premises and utilises the data from information boards. These are some of the simplest approaches to gaining information for deceitful purposes.

Another way credit card fraud can occur is through counterfeit cards (Ghosh and Reilly, 1994). The authors notes that due to the difficulty in counterfeiting credit cards, this approach is more systematic. Another systematic approach documented by the authors is fraudulent applications for credit cards where the fraudster gains access to the victim personal details and requests a credit card using his/her details.

Therefore, the purpose of this document is to analyse the effectiveness of three machine learning algorithms for credit card fraud classification. The proposed algorithms to be implemented are K Nearest Neighbour (KNN), Logistic Regression (LR) and Random Forest (RF).

# **Literature Review**

Many financial institutions now use data mining and machine learning to assist there existing measures for fraud the detection. (Ghosh and Reilly, 1994) state that financial institutions have, in the past, detected fraud simply by noting discrepancies in the fraudsters handwriting. In cases where the fraudster has access to a credit card these institutions rely on spotting transaction irregularities. Due to the increasing usage of online banking and payments as outlined previously, these financial institutions rely heavily on machine learning algorithms to alert them to any unusual transaction patterns.

(Ghosh and Reilly, 1994) designed a system which uses a P-RCE Artificial Neural Network (ANN) to classify fraudulent accounts for Mellon Bank. This ANN is a three layer feed forward neural network that makes two passes of the training data and then produces a fraud score.

Their system combined 50 variables to produce 20 features that were then passed to the ANN for account classification. As there were fewer fraudulent transactions than valid transactions, the authors ensure that all fraudulent transactions were included in the sample for training the ANN. When tested using two million transactions, the system vastly improved the fraud detection measures currently in place in Mellon Bank by only requiring a review of 50 accounts per day as opposed to reviewing 750.

Although fraudulent accounts and transactions can largely be classified by data mining and machine learning techniques, there is still a requirement for human verification (Quah and Sriganesh, 2008). Instead of reviewing hundreds or thousands of accounts of transactions, banking personnel only need to verify the accounts or transactions that are flagged as fraudulent by their data mining or machine learning model making the whole process more efficient.

(Quah and Sriganesh, 2008) outline a system for real time fraud detection that uses a neural network to cluster accounts as genuine or fraudulent. In essence the authors have implemented a clustering algorithm such as KNN using a form of ANN that allows for more dynamic relationships in the data.

(Ao and International Association of Engineers, 2011) provide an analysis of three machine learning algorithms for fraud detection. The algorithms analysed are Naïve Bayes, KNN and LR. The study was carried out on a dataset with approximately 280,000 transactions that was highly unbalanced. It is worth noting that the KNN algorithm was only .3% less accurate than Naïve Bayes. As the authors used several other methods to evaluate the effectiveness of each algorithm, KNN was actually the optimal algorithm. Noticeably LR provided quite a poor classification accuracy of approximately 54%.

Similarly (Shen et. al, 2007) provide an analysis of three machine learning algorithms for credit card fraud detection. In contrast to the study done by (Ao and International Association of Engineers, 2011), the authors analyse decision trees, neural networks and LR also. In this study neural networks provided the best performance followed by LR and decision trees. Again, the dataset in this study suffers from a highly unbalanced set of classifications as only 0.07% of the training data was labelled as fraudulent.

(Duman et. al, 2013) developed a fraud detection system for a Turkish bank which detects 97% of fraudulent transactions. In addition to the previously mentioned studies, this too suffered from highly unbalanced data where the authors had 978 fraudulent transactions and 22 million valid transactions. Therefore, the authors had to use a stratified sample of the data that included all the fraudulent transactions and only a fraction of the valid transactions. The authors tested multiple existing data mining algorithms as well as some ensembles of these algorithms to determine the best solution for fraud detection. From this analysis, the authors determined that the Migrating Birds Optimisation algorithm was the best option.

(Mahmud et. al, 2016) provide a comprehensive overview of different types of machine learning algorithm to deduce the best approach to correctly detecting fraudulent transactions. The authors found that meta algorithms such as RotationForest, Bagging and RandomCommittee provided the highest accuracies for fraud detection. The accuracies for these algorithms ranged from 98.13% to 98.25%.

(Bhattacharyya et al., 2011) present an analysis of three machine learning algorithms for credit card fraud classification. The algorithms analysed by the authors are LR, Support Vector Machines and Random Forest (RF). Like previous studies, this also suffers from the effects of a highly unbalanced dataset. The authors tested each algorithm on samples with different rates of fraudulent transactions. All three algorithms reported impressive accuracies with RF providing the highest accuracies overall.

# **Research Methodology**

## Dataset

The dataset for this analysis was sourced from Kaggle (Machine Learning Group - ULB, n.d.).

The dataset contains 284,807 transactions, 492 of which are fraudulent. The dataset consists of thirty-one features in total. Twenty-eight of these features are the result of a principal component analysis transformation and are labelled from V1 to V28. The other variables consist of time in seconds from the first transaction, the amount of the transaction and the class of the transaction, where 0 represents a valid transaction and 1 represents a fraudulent transaction.

## Exploratory Data Analysis

Exploratory Data Analysis (EDA) is one of the first steps to undertake when working with large quantities of data. More specifically the author aims to visualise the data to determine an relationships or outliers within the data itself. To perform EDA the author intends to use the R programming language (R: The R Project for Statistical Computing, n.d.). R was primarily designed for statistical analysis and provides a wide range of packages which make visualising and modelling the data an efficient process. Therefore each of the algorithms will be implemented and analysed in R. It is worth noting that the analysis could also have been undertaken in Python which is equally as efficient at performing statistical analysis.

Once the dataset was loaded into the R environment, the author plotted Time on the x axis, the transaction amount on the y axis and then coloured each observation based on its class, as shown in figure 1. As you can see from the plot of all observations where transaction amount is on the y axis and time in seconds from the first transaction is on the x axis, it is evident that the data set is highly unbalanced as it is difficult to locate any green data points which indicate a fraudulent transactions. In producing this plot, the alpha level which refers to the transparency of the data point was dynamically set based on the class of the observation which enabled the author to roughly locate fraudulent transactions beneath all the valid transaction data points.

When making the plot in figure 1, the author was alerted that one row of data was not considered for the plot as it contained a null value.



**Figure 1.** Transaction Amount vs. Time

Following this the author retrieved summary statistics for the fraudulent transactions by sub setting the raw data so it only included the fraudulent transactions. The fraudulent transaction amounts had a mean of €122.21 and a maximum of €2125.87. Noticeably the minimum fraudulent transaction was for a value of €0.00. This could be an error in the dataset or the result of a fraudulent transaction that was less than 1 cent. Based on this the fraudulent data was then filtered to see how many of the transactions were less than fifty cent. This resulted in thirty four transactions being classified as fraudulent where the transaction amount was fifty cent or less. This seemed quite high number of transactions for quite an insignificant amount of money. This prompted the author to look at how many fraudulent transactions had a value of ten cent or less which resulted in thirty two transactions.

Considering the maximum value of the fraudulent transactions and the number of transactions that were less than fifty cent, the values of the fraudulent transactions were plotted against the time of the transaction. Figure 2 shows the dispersion of the fraudulent transactions.



**Figure 2.** Dispersion of fraudulent transactions

As you can see in Figure 2, there is no distinct relationship between the fraudulent transactions and the time. It is also noticeable that the majority of the fraudulent transactions are below €250 and more specifically they are closer to zero. To see exactly where these points lie, two plots are created which essentially zoom in on the y axis. The first plot looks at the all the transactions that have a value of less than €10. Again there appears to be no obvious relationship in this plot but it is noticeable that many of the data points have transaction amounts between €0 and €2.50. The second plot looks at all the transactions above €10. Similarly, there appears to be no obvious relationship in the data.

The second plot also shows that the data points become even more dispersed once the transaction amount becomes greater than €500. To confirm that the relationship between all fraudulent transactions and time is not linear the *cor()* function was used to get the correlation between both. This resulted in a value of 0.04873 which confirms the lack of a relationship between the data.



**Figure 3.** Dispersion of transactions with limits on the y axis.

As the majority of the variables are the result of a principle component analysis transformation, the EDA is quite limited as there is no description of what variables V1 to V28 represent making them much harder to work with. This is in direct contrast to the studies outlined previously as the authors had a more thorough description of the datasets they were working with.

# **Algorithms Description**

## K Nearest Neighbour

## Logistic Regression

## Random Forest

# **References**