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Fraud Detection in Mobile Money Transactions Using Machine Learning

Haimeng Kang

Fraud Detection in Mobile Money Transactions
Using Machine Learning

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Haimeng Kang

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Abstract – This study explores an effective data mining system for fraud detection in mobile financial transactions. Attempting two broad-used supervised machine learning models, random forest and gradient boosting, the study aims to test and compare their applicability in the detection of fraudulent records. Both classification models were developed using a synthetic dataset of mobile money transactions, which was generated based on a sample of real transactions extracted from an international mobile money service company.

Keywords: fraud detection; classification; random forest; gradient boosting; confusion matrix; F1-score

I. Introduction

With the continuous development of technologies, as well as the emergence of new communication channels, mobile money service has been increasingly popular. The service acts as a convenient tool for trades between customers and merchants, by converting cash into "electronic money". Electronic money can be used to pay goods or services to merchants, transited to bank accounts, or transferred between users, etc. [1] All these functions can be achieved with only a few operations on cellular phones.

Despite of the convenience, electronic payment service has been a target for financial deception for several years. Between 2015 and 2016, a single criminal gang already spent more than $1.5 million on fraudulent purchases via Apple Pay [2]; in 2015, fraudsters attacked hundreds of PayPal accounts and caused a $1 million fraud scheme [3]. It was estimated that losses due to online payment fraud will increase double yearly rates by 2020 [4]. Therefore, a detection system for such crimes are crucial for banks, mobile application companies and mobile service users.

While studies in this field are needed, such research are often hindered by the scarcity of public fraudulent transaction data. This is mainly caused by the intrinsically private nature of financial records. To solve this problem, Phua, C. et al. [5] mentioned synthetic data that matches closely to authentic data could be an alternative; Barse, et al. [6] believed synthetic dataset is able to train and adapt a system, which can be utilized on actual data; Rieke, R. et al. [7] used simulated logs based on real transactions to capture abnormal mobile payments. Consequently, the synthetic data approach is also used in this paper.

The objective of the study is to construct and validate an accurate detecting model for fraudulent mobile money payments. To build a proper probing system, the study adopted supervised learning, where known normal and fraud cases were used to train the models to learn their characteristics. The basic idea is to partition the raw data frame into two subsets, training set and validation set. The former trains random forest and gradient boosting with labeled data, making the systems exploit the patterns of legal and illegal transactions, thus systems are able to predict which class a new observation belongs to. Models will then be applied to the validation set, to verify both methods and their accuracies will be evaluated and compared.

The research is constructed as follows: Section II gives a review of related works in the region of mobile transaction detection. Section III introduces the resource and structure of dataset, the characteristics of classification models, as well as the measurement of accuracy. Section IV involves exploratory data analysis, training and validation, as well as the classification results. Section V gives explanations for the results and final conclusions.

II. Literature Review

A general review of the fraud detection could be found in the research from Bolton, R. J. et al. [8] and Phua, C. et al. [5]. In the past 20 years, to meet the needs of the market, numbers of detecting tools have been developed and published. Previous efforts have addressed supervised algorithms, including neural networks, Decision Tree, Support Vector Machines (SVM), logistic regression and so on. For example, decision tree or random forest was adopted in Xuan, S. et.al. [9], Liu, C. et al. [10], and Sahin, Y. G., & Duman, E. [11].

The following are some detailed introductions. Xuan, S. et.al. [9] employed two kinds of random forest: Random-tree-based random forest and CART-based random forest, and applied them on a real-life credit card transaction dataset in China. They chose precision rate, recall rate and F-score to measure the two algorithms' predictive veracity.

Liu, C. et al. [10] took financial ratios as the independent variables to judge if a payment is legit or not. They not only adopted random forest, but also used four statistic models, including both parametric and non-parametric models. Random forest was concluded to have the highest accuracy.

Sahin, Y. G., & Duman, E. [11] was the very first study that compared the predicting accuracy of decision tree and SVM. It employed ID3, C5.0 and C&RT from decision tree algorithms, and found out that in general, decision tree methods have the better predicting capability. The performances of both methodologies were assessed with suspicion scores, which is the probability of the credit card payment to be fraudulent.

III. Research Methodology

3.1. Data

The dataset selected in the experiment is from Kaggle.com. It is composed of 6,362,620 transaction records, which were all generated by a financial mobile money simulator called *PaySim*. *PaySim* is able to imitate real-life financial records, and created this synthetic dataset based on a sample of real transactions from a one-month financial log of a mobile money service company. The name of the company was not revealed, yet it was stated to be an international organization providing services to cellular phone users, in order to let them use electronic wallets on phones to transfer money with each other.

The data provider has shrunk this synthetic dataset to ¼ of the size of the original dataset. There are 11 attributes in total, including 7 independent variables representing the features of a transaction, 1 dependent variable standing for the status of a transaction, and 3 variables that are not considered as relevant influencers, which will be dropped in section V.

A list of all variables is demonstrated as Table 1. For clarification purposes, some of the variables are explained with more details in the following paragraphs.

Table 1. Summary of Variables

	Variable Name	Format Example	Description
1	step	5	Each step is an hour of time in real world. The largest number for step is 744 (the 30th day)

2	type	PAYMENT (Categorical variable)	Transaction types (CASH-IN, CASH-OUT, DEBIT, PAYMENT and TRANSFER)
3	amount	8424.74	Transaction amount in local currency
4	nameOrig	C1000001725	Customer who started the transaction
5	oldbalanceOrig	351422.72	The initial balance of sender before the transaction
6	newbalanceOrig	257557.59	The new balance of sender after the transaction
7	nameDest	M1974356374	Customer/Merchant who received the transaction
8	oldbalanceDest	526950.37	The initial balance of receiver before the transaction
9	newbalanceDest	771436.84	The new balance of receiver after the transaction
10	isFraud	1 (Categorical variable)	The status of a transaction (0 as legitimate and 1 as fraudulent)
11	isFlaggedFraud	0 (Categorical variable)	The status that **the system identified** for a transaction — here an attempt to transfer more than 200,000 (in local currency) in a single transaction will be flagged as an illegal attempt (0 as normal and 1 as illegal attempt)

Step refers to each hour of one month: for example, each record with *step = 1* means it happened in the first hour on the first day of the experimental month, and each record with *step = 744* occurred in the last hour of the month.

Type is a categorical variable involving 5 different transaction types, including CASH-IN, CASH-OUT, DEBIT, PAYMENT and TRANSFER. CASH-IN means the customer's account balance increased with cash inflow; CASH-OUT is opposite to CASH-IN, with cash outflow to decrease the account balance; DEBIT signifies sending money from the mobile service (electronic wallet) to a bank account; PAYMENT denotes customers paying goods or services to merchants, which will reduce customer's account balances and increase merchants' account balances; TRANSFER is the process of transferring money between users.

isFlaggedFraud is an additional attribute that the mobile service system used for controlling massive transfers. According to the definition, when there was an attempt to transfer more than 200,000 units (in local currency) in a single transaction, *isFlaggedFraud* would be set to 1; otherwise it would be 0. It doesn't have a definite relation with *isFraud*.

3.2. Methods

Determining the transaction status can be regarded as a classification problem in supervised learning. The basic idea is to:

1. Partition the data into two subsets: training set and validation set. Training set is used to train the model, by letting it learn the pattern between independent variables and dependent variable; in other words, teach it how to use independent variables to predict the outcome variable (in this case, the binary class).
2. After the model has predicting capability, it will be applied to the inputs in validation sample and predict the outputs. We will then compare the predicted outcomes with the actual outcomes to evaluate its performance.

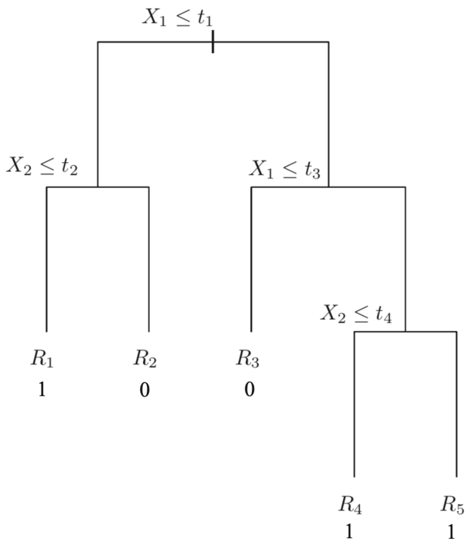
As stated earlier, the supervised learning algorithms employed in this study are random forest and gradient boosting.

3.2.1. Decision tree

Since random forest and boosted trees are both extensions of decision tree, we will explain this concept firstly. Decision tree, or more specifically, classification tree, is a data-driven method to classify records into mutually exclusive subgroups.

Fig. 1 is an illustration of decision tree. Assuming root node — the first independent variable — as X_1, and the cutoff value as t_1, starting from the root node, each node is split into two successor nodes. The left node contains data that are less than or equal to t_1, while the right node includes data that are larger than t_1. Then, these two nodes will be split again according to a new predictor X_i (or it could still be X_1) and a new splitting value t_i. Following that, data are recursively partitioned, until we get to a node without successors (e.g. there is no split to make statistical difference on the distribution of data).

Fig. 1. Decision Tree



(Source: J, G. et al. (2017). *An introduction to statistical learning: with applications in R*. p. 308 [15].)

To decide the class of a record, it will be dropped all the way down to a terminal node (R_i). For example, the leftmost route implies: IF ($X_1 \leq t_1$) AND ($X_2 \leq t_2$), THEN *Class* = R_1= 1; what is to say, a record that satisfies these conditions will be categorized into *Class* = 1. Following that, the entire tree can be transformed into a set of rules for classification.

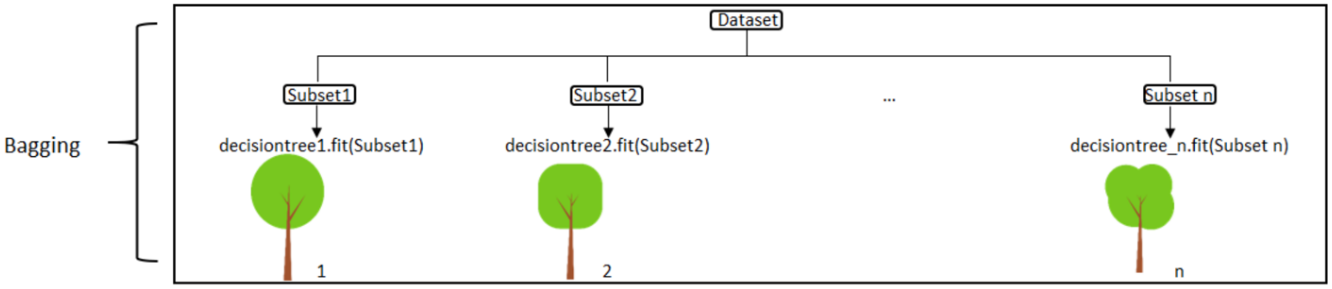
3.2.2. Random Forest

Random forest has an improved performance compared with decision tree, because it combines predictions from a multitude of trees. We can understand it as “wisdom of the crowd”. It usually involves three steps:

1. Randomly draw multiple samples (with replacement) from the dataset;
2. For each sample/subset, apply a random set of predictors and create a tree;

3. Collect classification decisions from all the trees and select the class with the highest number of votes.

Fig. 2. Random Forest

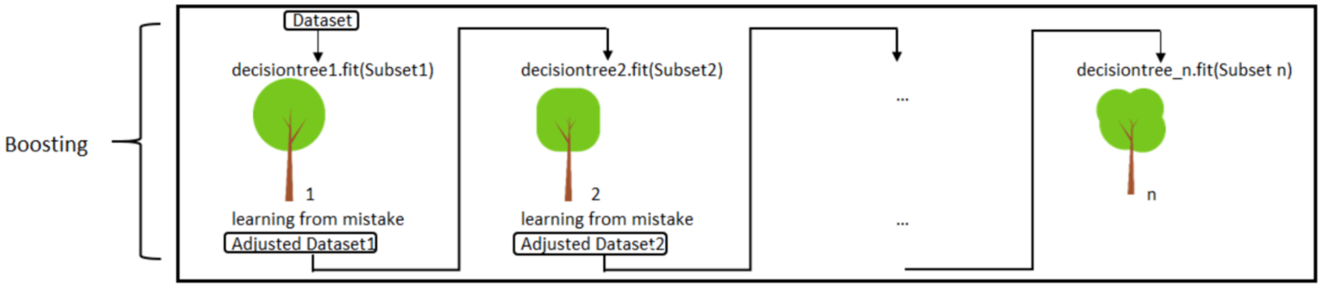

Bagging
Dataset
Subset1
Subset2
...
Subset n
decisiontree1.fit(Subset1)
decisiontree2.fit(Subset2)
decisiontree_n.fit(Subset n)
1
2
n

(Source: Chen, L. (2019). Medium.com, Towards Data Science. [13].)

3.2.3. Gradient Boosting

The second approach that uses multiple trees to improve is boosting. Boosting is an iterative process in which each tree focuses on the misclassifications of the previous tree, so as to avoid repeating mistakes. In this way, every tree is enhanced comparing with the previous one (Fig. 3). The classification result of gradient boosting is also a combination of predictions from each decision tree.

Fig. 3. Boosted Trees



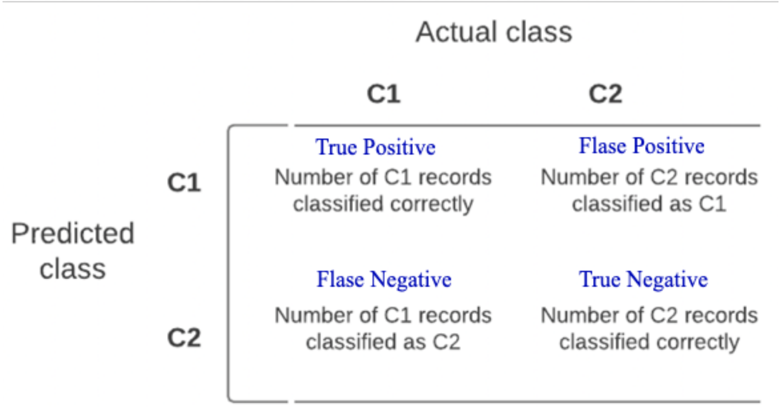
(Source: Chen, L. (2019). Medium.com, Towards Data Science. [13].)

3.2.4. Confusion Matrix

Confusion matrix is an easy way to assess a classifier's performance, by estimating both correct and incorrect classification rates. The upper left cell and lower right cell represent the total number of correct classifications, while the other two calculate the records that were misclassified.

In confusion matrix, accuracy is defined as $accuracy = \frac{\text{True Positive + True Negative}}{\text{Total Records}}$.

Fig. 4. Confusion Matrix



		Actual class	
		C1	C2
Predicted class	C1	True Positive Number of C1 records classified correctly	Flase Positive Number of C2 records classified as C1
	C2	Flase Negative Number of C1 records classified as C2	True Negative Number of C2 records classified correctly

3.2.5. Precision, Recall, and F-1 Score

However, accuracy itself is not enough for the performance evaluation. In this study, a false negative is far more costly than a false positive: a false positive means putting a legal record into the fraud class C1, which can be at most consider as oversensitive and requires some extra examination; a false negative, on the other hand, is putting a fraudulent record into the legit class C2, which is serious and can cause loss for the company and its users.

Consequently, we need three new metrics for the assessment.

Precision: It counts out of all the records that are predicted as positive, how many of them are actually positive. The formula is $Precision = \frac{\text{True Positive}}{\text{True Positive+False Positive}}$.

Recall (also termed as *Sensitivity*): It counts out of all the actual positive records, how many of them are correctly classified as positive. The formula is $Recall = \frac{\text{True Positive}}{\text{True Positive+False Negative}}$.

F1-Score: It is a measure that seeks a balance between *Precision* and *Recall*. But unlike *accuracy*, it doesn't concentrate much on true negative (the total number of legal records that were classified correctly). The formula is *F1-score* $= 2 \text{ x } \frac{\text{Precision x Recall}}{\text{Precision+ Recall}}$.

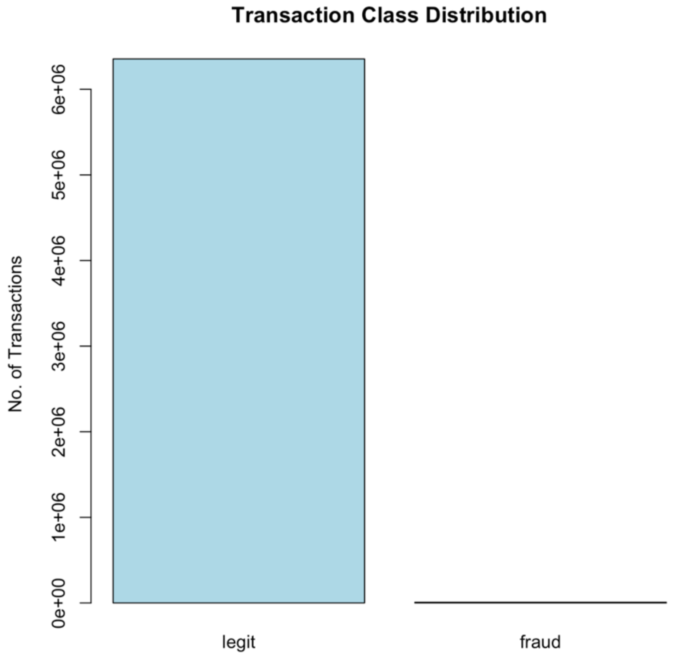
IV. Experiment and Analysis

4.1. Exploratory Data Analysis

4.1.1. isFraud

There is no mismatched or missing value in the dataset. However, as shown in Fig. 4, the records are highly imbalanced in the two classes, with only 8213 fraudulent cases (0.13%) and 6,354,407 (99.87%) legitimate cases. To mitigate the effect caused by skewness, stratified sampling can be adopted to create subsamples (section *4.2*), in which fraudulent and non-fraudulent transactions will be equally distributed.

Fig. 4. Distribution of Two Classes

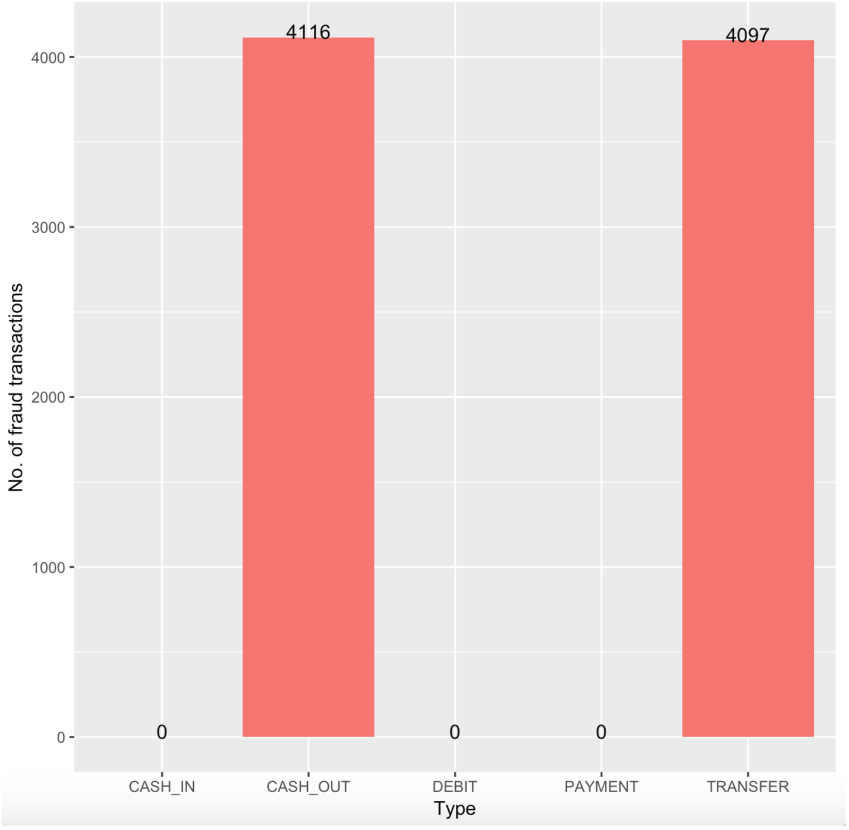


(6e+06 represents the number of legit transactions is 6 x 10^6)

4.1.2 type

type is a categorical variable with 5 possible values: CASH-IN, CASH-OUT, DEBIT, PAYMENT and TRANSFER. To explore each *type* value is crucial or not for the research, the distribution of fraud cases in all the types is shown in Fig. 5.

Fig. 5. Number of fraudulent transactions in each type

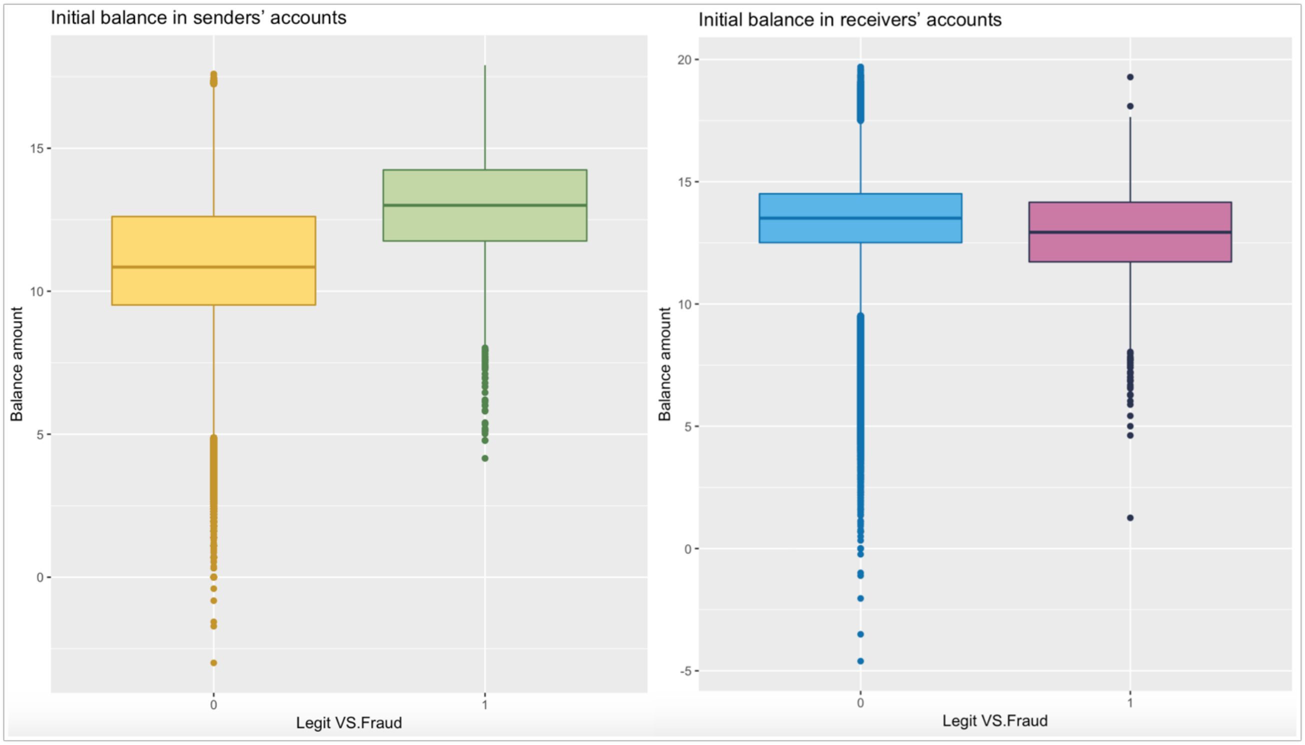


It turns out all the fraudulent records were either CASH_OUT or TRANSFER. To simply later analysis, we decided to only keep these two types and the other three were left out. A dummy data frame was created to extract *type.CASH_OUT* and *type.TRANSFER*, which were combined with all the other variables.

4.1.3 oldbalanceOrig & oldbalanceDest

Fig. 6 is the distribution of legit and fraudulent records in *oldbalanceOrig* and *oldbalanceDest*. The left box plot indicates fraudulent transactions were more likely to appear in accounts with higher *oldbalanceOrig*, which means accounts with higher initial balance are more tend to be attacked. As for the right box plot, it implies that accounts with lower initial balance are more likely to be the receivers involved in a fraud.

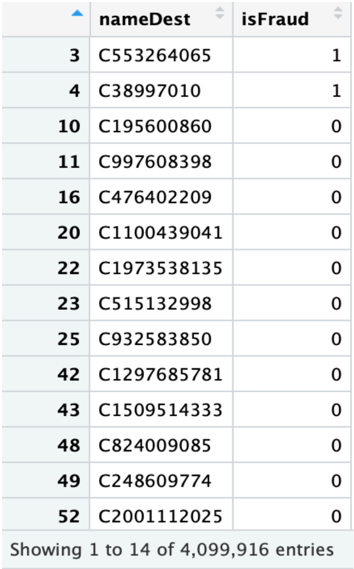
Fig. 6. Distribution of Fraudulent and Non-fraudulent Records



4.1.4 nameOrig & nameDest

nameOrig and *nameDest* are ID numbers for customers or merchants. Theoretically, if they have any relation with *isFraud*, it could be the frequency of the occurrence of ID numbers — IDs that show up frequently may have higher possibility of participating in frauds. To figure out whether the hypothesis is correct or not, all the IDs which appeared more than once were picked out and listed with their corresponding account status. Fig. 7 shows the first 14 rows in one of the two-column tables, which contains *nameDest* with frequency ≥ 2 and *isFraud*.

Fig. 7. The first 14 rows in *nameDest - isFraud* table



	nameDest	isFraud
3	C553264065	1
4	C38997010	1
10	C195600860	0
11	C997608398	0
16	C476402209	0
20	C1100439041	0
22	C1973538135	0
23	C515132998	0
25	C932583850	0
42	C1297685781	0
43	C1509514333	0
48	C824009085	0
49	C248609774	0
52	C2001112025	0

Showing 1 to 14 of 4,099,916 entries

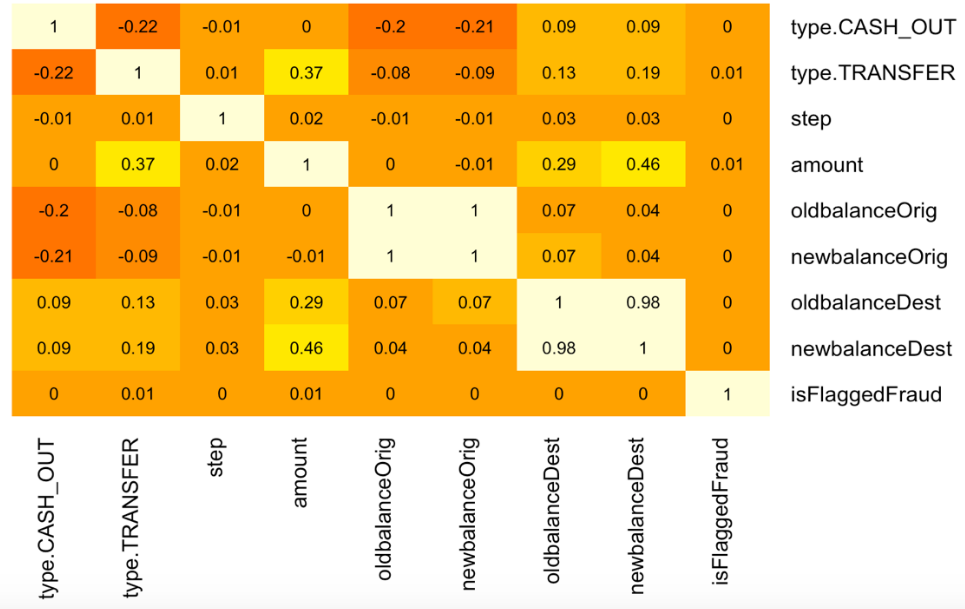
Observing the two tables we just created, the frequency of *nameOrig* or *nameDest* doesn't appear to have a significant relationship with account status. For example, all the receiver IDs appeared over 100 times had never joined in a single fraud, yet some ID numbers that only showed up for a few times were proved to participated in frauds. The occurrences of ID numbers were random and have neither a positive nor a negative relation with *isFraud*, thus *nameOrig* or *nameDest* are omitted from later analysis.

4.1.5 isFlaggedFraud

The definition of *isFlaggedFraud* seems to be inconsistent with the data. As stated in the description of dataset, in order to control large transfers from one account to another, the system will mark the single transactions with more than 200,000 transferred as *isFlaggedFraud =1*. Nonetheless, *isFlaggedFraud* can remain 0 despite the condition was met, and there were only 16 "*isFlaggedFraud* = 1" out of over 6 million entries.

Fig. 8 is a correlation matrix with color-coding, which demonstrates the correlation coefficients among variables. It is easy tell that there is no significant correlation between *isFlaggedFraud* and any predictor variable, thus this column will be dropped from the dataset.

Fig. 8. Correlation Matrix I

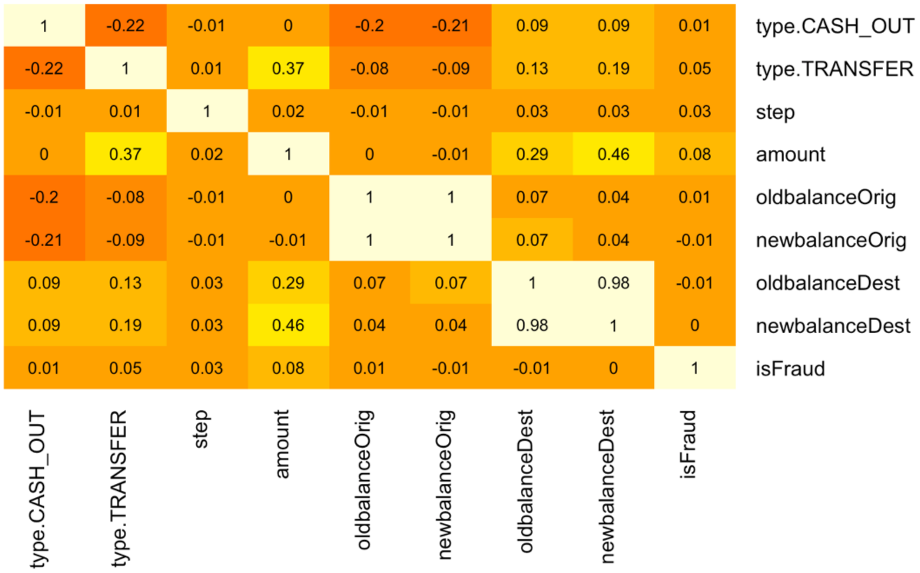


	type.CASH_OUT	type.TRANSFER	step	amount	oldbalanceOrig	newbalanceOrig	oldbalanceDest	newbalanceDest	isFlaggedFraud
type.CASH_OUT	1	-0.22	-0.01	0	-0.2	-0.21	0.09	0.09	0
type.TRANSFER	-0.22	1	0.01	0.37	-0.08	-0.09	0.13	0.19	0.01
step	-0.01	0.01	1	0.02	-0.01	-0.01	0.03	0.03	0
amount	0	0.37	0.02	1	0	-0.01	0.29	0.46	0.01
oldbalanceOrig	-0.2	-0.08	-0.01	0	1	1	0.07	0.04	0
newbalanceOrig	-0.21	-0.09	-0.01	-0.01	1	1	0.07	0.04	0
oldbalanceDest	0.09	0.13	0.03	0.29	0.07	0.07	1	0.98	0
newbalanceDest	0.09	0.19	0.03	0.46	0.04	0.04	0.98	1	0
isFlaggedFraud	0	0.01	0	0.01	0	0	0	0	1

4.1.6. Significance of independent variables

The dataset now has 9 variables: *type.CASH_OUT*, *type.TRANSFER*, *step*, *amount*, *oldbalanceOrig*, *newbalanceOrig*, *oldbalanceDest*, *newbalanceDest*, and *isFraud*. To figure out the relationships between *isFraud* and the 9 variables, we chose to draw another color matrix containing all the correlation coefficients (Fig. 9). It appears *type.TRANSFER*, *step*, and *amount* have relative high correlations with *isFraud*.

Fig. 9. Correlation Matrix II



	type.CASH_OUT	type.TRANSFER	step	amount	oldbalanceOrig	newbalanceOrig	oldbalanceDest	newbalanceDest	isFraud
type.CASH_OUT	1	-0.22	-0.01	0	-0.2	-0.21	0.09	0.09	0.01
type.TRANSFER	-0.22	1	0.01	0.37	-0.08	-0.09	0.13	0.19	0.05
step	-0.01	0.01	1	0.02	-0.01	-0.01	0.03	0.03	0.03
amount	0	0.37	0.02	1	0	-0.01	0.29	0.46	0.08
oldbalanceOrig	-0.2	-0.08	-0.01	0	1	1	0.07	0.04	0.01
newbalanceOrig	-0.21	-0.09	-0.01	-0.01	1	1	0.07	0.04	-0.01
oldbalanceDest	0.09	0.13	0.03	0.29	0.07	0.07	1	0.98	-0.01
newbalanceDest	0.09	0.19	0.03	0.46	0.04	0.04	0.98	1	0
isFraud	0.01	0.05	0.03	0.08	0.01	-0.01	-0.01	0	1

4.2. Training and Validation

After the exploratory data analysis in section *4.1*, there are still 6,362,620 entries in total, with 8213 of them being illegal.

The legit class is significantly high in this imbalanced dataset; if we use such a set to train models, they will tend to automatically classify new observations into the legit class, because they would then be correct over 99% of the time. To deal with this issue, we could use undersampling, the method of downweighting the majority class relative to the rare class, to create an equally distributed set for training. As for the validation set, records in it could remain imbalanced distributed, since that is the pattern of real-life mobile transactions.

The steps in undersampling include:

1. Separate the two classes of records into two distinct sets, legit set and fraud set;

2. Randomly select 4106 records (50%) from the legit set and 4106 records (0.65%) from the fraud set, and combine them to form the training set;
3. Put the rest of fraudulent transactions (4107 records) into validation set;
4. To remain the original ratio of fraud vs. non-fraud cases (8213 : 6354407), randomly select 3,176,817 records from the remaining legal records, and put them into the validation set.

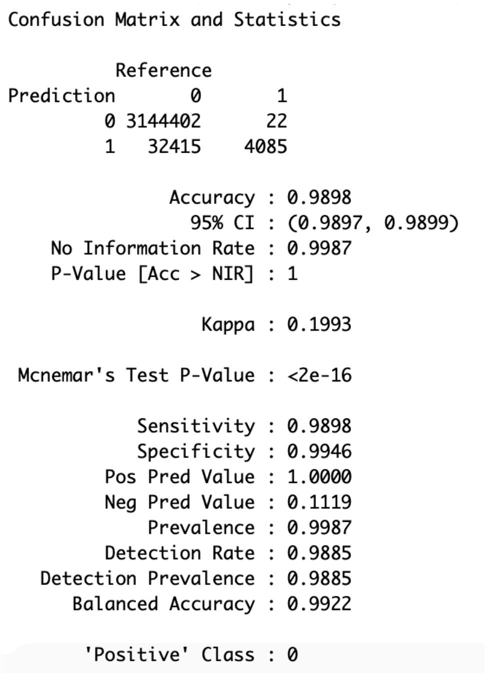
4.3. Test

4.3.1. Random Forest

After attempting various numbers of trees to grow, as well as different numbers of variables to be randomly sampled as candidates at splits, 50 trees and 5 variables were believed to be ideal options. Applying the model on the validation set, we got a confusion matrix as Fig. 10.

According to the confusion matrix, the overall accuracy is 0.9898, *Recall* (Sensitivity) is 0.9898, and *Precision* (Pos Pred Value) is 1.00000. *F1-score* is 2 x $\frac{1 \text{ x } 0.9898}{1+ 0.9898}$ = 0.99487.

Fig. 10. Confusion Matrix for Random Forest



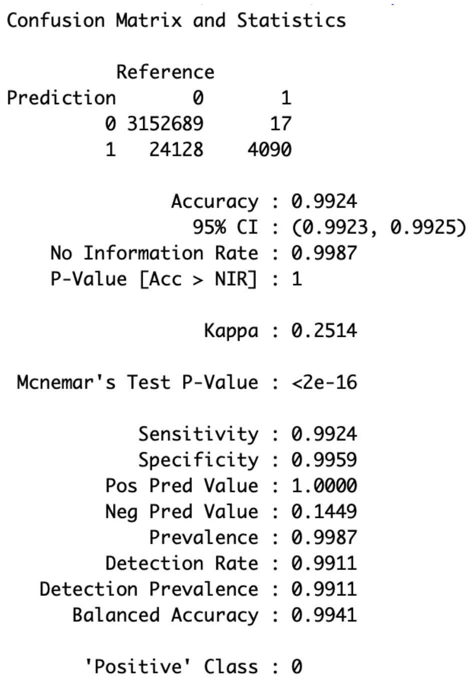
```
Confusion Matrix and Statistics

          Reference
Prediction       0       1
         0 3144402      22
         1   32415    4085

               Accuracy : 0.9898
                 95% CI : (0.9897, 0.9899)
    No Information Rate : 0.9987
    P-Value [Acc > NIR] : 1

                  Kappa : 0.1993

 Mcnemar's Test P-Value : <2e-16

            Sensitivity : 0.9898
            Specificity : 0.9946
         Pos Pred Value : 1.0000
         Neg Pred Value : 0.1119
             Prevalence : 0.9987
         Detection Rate : 0.9885
   Detection Prevalence : 0.9885
      Balanced Accuracy : 0.9922

       'Positive' Class : 0
```

4.3.2. Gradient Boosting

Similar to random forest, we used 50 trees for training the boosting model and achieved the confusion matrix in Fig. 11.

According to the confusion matrix, the overall accuracy is 0.9924, *Recall* (Sensitivity) is 0.9924, and *Precision* (Pos Pred Value) is 1.0000. *F1-score* is 2 x $\frac{1 \text{ x } 0.9924}{1+ 0.9924}$ = 0.99619.

Fig. 11. Confusion Matrix for Boosted Trees



```
Confusion Matrix and Statistics

          Reference
Prediction       0       1
         0 3152689      17
         1   24128    4090

               Accuracy : 0.9924
                 95% CI : (0.9923, 0.9925)
    No Information Rate : 0.9987
    P-Value [Acc > NIR] : 1

                  Kappa : 0.2514

 Mcnemar's Test P-Value : <2e-16

            Sensitivity : 0.9924
            Specificity : 0.9959
         Pos Pred Value : 1.0000
         Neg Pred Value : 0.1449
             Prevalence : 0.9987
         Detection Rate : 0.9911
   Detection Prevalence : 0.9911
      Balanced Accuracy : 0.9941

       'Positive' Class : 0
```

V. Discussion and Future Work

According to the F-scores we got in section *4.3*, both models achieved high accuracy, and boosted tree has a relative better performance. The accuracies are higher than expected, and we consider part of the reason could be the synthetic nature of the dataset. In future work, we can try to find more real-life transaction records to test the tree models, and adopt other methodologies, like logistic regression or k-means clustering.

In section *4.1.2*, we found out all the fraudulent records belonged to either CASH_OUT or TRANSFER. CASH-OUT represents outflow of a customer's account balance, and when there are abnormal outflows, they usually happen when customers lose complete access and control to their accounts [12]. Such situation can be caused by SIM phishing swap, fake support calls to obtain pin code, phone lost, etc. [12]. As for TRANSFER, it refers to the transfer of money between user's accounts. Fraudsters take advantage of it by financial deception, like frauds which make customers believe they need to firstly pay deposits to receive a large amount of money prizes. However, in real life, there should also be some illegal records in the other three transaction types, which can be left for future research.

There are actually two fraud detecting methodologies: misuse detection and anomaly detection. Misuse detection refers to deciding a new observation belongs to which class of the two; anomaly detection is using historical data to build profile for normal transactions behaviors, thus models can identify a record when it deviates from the normal patterns [10]. In this study we chose to only focus on the misuse detection, because anomaly detection requires amounts of successive sample data. In the future, with more collected data, we may attempt the anomaly detection as well and make a comparison between the two methods.

References

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