CREDIT CARD FRAUD DETECTION USING DATA MINING TECHNIQUES

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Abstract

Many businesses, particularly the financial industry, have been able to expand their services to customers all over the world, thanks to the evolution of the internet. Users now find convenience in making payment for services online, using their credit cards. Due to this technological advancement, fraudsters are continuously improvising ways to steal money from consumers online, thereby making credit card fraud exponentially worse. The domain for this study is focused on Financial Data Security/Credit Card Security. Which is aimed at helping financial institutions to detect and predict suspicious activities. The key challenge is how to improve the accuracy of fraud detection with an increasing number of user-per-second transactions. The rise in the number of users and online transactions has caused these systems to have heavy workloads. In this study we are going to identify credit card fraudulent transactions using various types of supervised machine learning algorithms. To be able to determine which algorithm gives the best prediction, i'll be comparing three data mining techniques which are Logistic regression, Xgboost and Random forest.

1 Introduction

Many businesses, particularly the financial industry, have been able to expand their services to customers all over the world, thanks to the evolution of the internet. Users now find convenience in making payment for services online, using their credit cards.

Due to this technological advancement, fraudsters are continuously improvising ways to steal money from consumers online, thereby making credit card fraud exponentially worse.

Financial institutions have now been saddled with the responsibility of ensuring that customers/consumers of their services can perform safe transactions using their credit card for electronic payments of products and services delivered on the internet.

In detecting and combating these credit card frauds, data mining techniques have been introduced due to it's powerful techniques and algorithms that can be applied through information discovery to detect or predict fraud from unusual patterns extracted from data collected.

However, there are several other approaches in detecting fraudulent transactions which includes Decision Trees, Classification With Logistics Regression and so on.

In this study, we shall discuss the use of R programming language to analyse and compare three data mining techniques which are: Logistics Regression, Random Forest and Xgboost, in detecting fraudulent transactions.

2 Domain Description

The domain for this study is focused on Financial Data Security/Credit Card Security. Which is aimed at helping financial institutions to detect and predict suspicious activities.

Usually when transactions happen, there is a payer and a receiver, and a gateway (financial institutions, issuing/acquiring banks, credit card processors, or the switch) through which money is paid. These actors are potential targets for attackers or fraudsters.

Before a fraud can happen, fraudsters usually perform some information gathering (called reconnaissance), and then attempt to use this information to make fraudulent transactions on-behalf of the credit card owner.

There is an evolving need to protect or safeguard the money and credit information of users from attackers using datasets and patterns of suspicious activities.

3 Problem Definition

Detection of fraud in financial transactions is one of the most critical concerns facing financial firms.

A credit card is a plastic card that allows you access to credit that can be used on making transactions, reducing debt, and receiving benefits.

Credit card fraud happens when someone uses your credit card or credit account to make a payment that you did not approve.

The key challenge is how to improve the accuracy of fraud detection with an increasing number of user-per-second transactions. The rise in the number of users and online transactions has caused these systems to have heavy workloads.

In this study we are going to identify credit card fraudulent transactions using various types of supervised machine learning algorithms. To be able to determine which algorithm gives the best prediction, i'll be comparing three data mining techniques which are Logistic regression, Xgboost and Random forest.

3.1 Data Mining Techniques

Predicting fraud detection in this paper would use the 'Supervised Machine Learning Algorithm'.

3.1.1 Supervised Machine Learning Algorithm

'A supervised strategy works by exploiting the system's previous fraudulent and non-fraudulent transactions, using them to define a model capable of classifying new transactions into a specific class (i.e., legitimate or fraudulent)'

Supervised learning problems can be further classified into problems of regression and classification.

Popular examples of supervised machine learning algorithms are

- Logistics regression for regression problems
- Random forest for classification and regression problems
- Xgboost

3.1.2 Logistics Regression Algorithm

Logistic Regression is a machine learning algorithm, a predictive analysis algorithm focused on the idea of probability, which is used for classification problems.

An example of classification problems are Online transactions fraud or not fraud. The logistic regression is also called the linear regression it predicts the probability of occurrence by fitting a data to a logistics function;

O = $e^{(}I0 + I1 * x)/(1 + e^{(}I0 + I1 * x))Where,$

O is the predicted output

I0 is the bias or intercept term

I1 is the coefficient for the single input value (x).

Each column in the input data has an associated I coefficient (a constant real value) that must be learned from the training data. Logistic function is used in the logistic regression in which the cost function quantifies the error, as its model's response is compared with the true value.

3.1.3 Xgboost Algorithm

Xgboost stands for eXtreme Gradient Boosting. Xgboost is a supervised learning approach that is based on the approximation of functions by optimising unique loss functions, It is an implementation of the fast and efficient gradient boosted decision trees.

The implementation of the algorithm was designed for the utilisation of compute time and memory resources. A design goal was to make the best use of available resources to train the model.

Typically, the XGBoost is fast. When compared to other gradient boosting implementations, it is very fast.

'The boosting function consists of three simple steps:

- An initial model F0 is defined to predict the target variable y. This model will be associated with a residual (y – F0)
- A new model h1 is fit to the residuals from the previous step
- Now, F0 and h1 are combined to give F1, the boosted version of F0. The mean squared error from F1 will be lower than that from F0:

To improve the performance of F1, we could model after the residuals of F1 and create a new model F2:

$$F_1(x) <- F_0(x) + h_1(x)$$

$$F_2(x) <- F_1(x) + h_2(x)$$

This can be done for 'm' iterations, until residuals have been minimized as much as possible':

$$F_m(x) <- F_{m-1}(x) + h_m(x)$$

3.1.4 Random Forest Classifier

'Random forest is a supervised learning algorithm which constructs and fuses several decision-making trees to make predictions more accurate and steady.' Random forest can be used for both classification and regression problems. Below you can see how a random forest would look like with two trees:

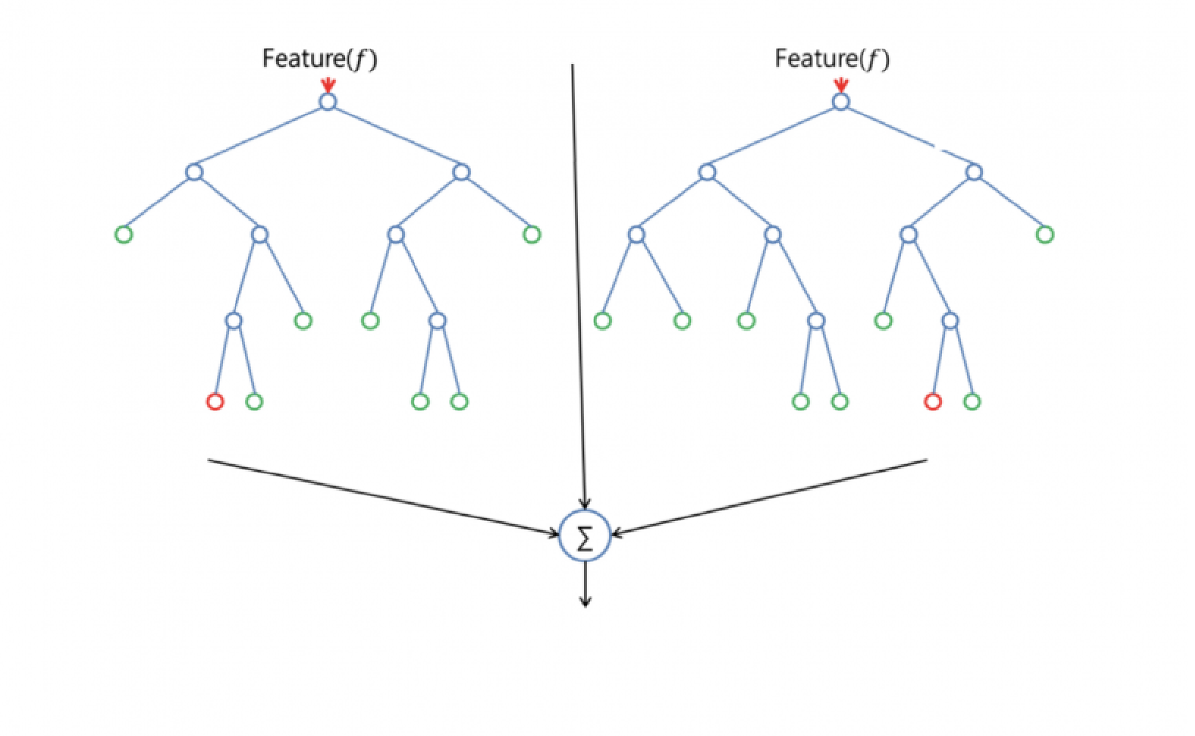

Fig. 1. Random Forest

3.2 AUC AND ROC CURVE

AUC stands for Area Under the Curve Plot it is a calculation of the relationship between false positive and true positive. The greater the AUC, the better the model usually is. The "steepness" of the curve, nevertheless, is also important to inspect, as this reflects the maximisation of the true positive rate while decreasing the false positive rate.

ROC stands for Receiver Operating Characteristic which is a measure of the predictive quality of a classifier that compares and visualises the trade-off between the sensitivity and specificity of the model. A ROC curve reveals the real positive rate on the Y-axis and the false positive rate on the X-axis, both on a global average and per-class basis, when plotted. Therefore, the optimal point is the top-left corner of the diagram where false positives are zero and true positives are one.

In this paper AUC and ROC's Curves are plotted for each Machine learning algorithm.

4 Data Set Description

'The dataset includes credit card purchases made by European cardholders in September 2013.

This dataset presents two-day transactions, in which we have 492 frauds out of 284,807 transactions. The dataset is very unbalanced, and 0.172 percent of all transactions are of the positive class (fraud).

It only includes numerical input variables resulting from the processing of a PCA. The key PCA components are features V1.V2. ...V28. 'Time' and 'Amount' are the only features that are not converted with PCA. The 'Time' feature includes the seconds between any transaction and the first dataset transaction.

The 'Amount' feature is the transaction amount, which can be used for example-depending on cost-sensitive learning. The "class" function is the response variable, which, in the event of fraud, takes value 1, or value 0.'

This data set was gotten from kaggle

5 Data Set Pre-processing

Our aim is to use 31 variables from the dataset and the description to predict a class variable.

5.1 Pre-Processing Steps

Below are the steps taken to process the data

- Step 1: Download the dataset
- Step 2: Read the dataset
- Step 3: Run an exploratory and statistical analysis of the dataset
- Step 4: Run the number of rows, fraudulent and non fraudulent count of the dataset
- Step 5: Split the dataset into 2 (training and verification dataset each)

listings

5.2 Install Packages and load libraries

```
library(dplyr) # for data manipulation
library(caTools) # for train/test split
library(ggplot2) # for data visualization
library(Rborist)# for random forest model
library(xgboost) # for xgboost model
```

```
# Input data files are available in the "../input/" directory.
```

Reading the dataset

```
dataset<- read.csv("../input/creditcard.csv")
```

This is the exploratory analysis of the data set

```
Str (df)
'data.frame': 284807 obs. of  31 variables:
 $ Time   : num  0 0 1 1 2 2 4 7 7 9 ...
 $ V1     : num  -1.36 1.192 -1.358 -0.966 -1.158 ...
 $ V2     : num  -0.0728 0.2662 -1.3402 -0.1852 0.8777 ...
 $ V3     : num  2.536 0.166 1.773 1.793 1.549 ...
 $ V4     : num  1.378 0.448 0.38 -0.863 0.403 ...
 $ V5     : num  -0.3383 0.06 -0.5032 -0.0103 -0.4072 ...
 $ V6     : num  0.4624 -0.0824 1.8005 1.2472 0.0959 ...
 $ V7     : num  0.2396 -0.0788 0.7915 0.2376 0.5929 ...
 $ V8     : num  0.0987 0.0851 0.2477 0.3774 -0.2705 ...
 $ V9     : num  0.364 -0.255 -1.515 -1.387 0.818 ...
 $ V10    : num  0.0908 -0.167 0.2076 -0.055 0.7531 ...
```

```
$ V11   : num  -0.552 1.613 0.625 -0.226 -0.823 ...
$ V12   : num  -0.6178 1.0652 0.0661 0.1782 0.5382 ...
$ V13   : num  -0.991 0.489 0.717 0.508 1.346 ...
$ V14   : num  -0.311 -0.144 -0.166 -0.288 -1.12 ...
$ V15   : num  1.468 0.636 2.346 -0.631 0.175 ...
$ V16   : num  -0.47 0.464 -2.89 -1.06 -0.451 ...
$ V17   : num  0.208 -0.115 1.11 -0.684 -0.237 ...
$ V18   : num  0.0258 -0.1834 -0.1214 1.9658 -0.0382 ...
$ V19   : num  0.404 -0.146 -2.262 -1.233 0.803 ...
$ V20   : num  0.2514 -0.0691 0.525 -0.208 0.4085 ...
$ V21   : num  -0.01831 -0.22578 0.248 -0.1083 -0.00943 ...
$ V22   : num  0.27784 -0.63867 0.77168 0.00527 0.79828 ...
$ V23   : num  -0.11 0.101 0.909 -0.19 -0.137 ...
$ V24   : num  0.0669 -0.3398 -0.6893 -1.1756 0.1413 ...
$ V25   : num  0.129 0.167 -0.328 0.647 -0.206 ...
$ V26   : num  -0.189 0.126 -0.139 -0.222 0.502 ...
$ V27   : num  0.13356 -0.00898 -0.05535 0.06272 0.21942 ...
$ V28   : num  -0.0211 0.0147 -0.0598 0.0615 0.2152 ...
$ Amount: num  149.62 2.69 378.66 123.5 69.99 ...
$ Class : int  0 0 0 0 0 0 0 0 0 0 ...
```

The dataframe has 284807 observations with 31 variables. The variable ‘Class’ indicates whether a transaction is fraudulent(1) or not (0).

Summary (dataframe) a statistical exploration of the data set

```
  Time              V1                  V2                  V3
           V4
 Min.   :     0   Min.   :-56.40751   Min.   :-72.71573   Min.
   :-48.3256   Min.   :-5.68317
 1st Qu.: 54202   1st Qu.: -0.92037   1st Qu.: -0.59855   1st Qu.:
   -0.8904   1st Qu.:-0.84864
 Median : 84692   Median :  0.01811   Median :  0.06549   Median :
   0.1799   Median :-0.01985
 Mean   : 94814   Mean   :  0.00000   Mean   :  0.00000   Mean   :
   0.0000   Mean   : 0.00000
 3rd Qu.:139320   3rd Qu.:  1.31564   3rd Qu.:  0.80372   3rd Qu.:
   1.0272   3rd Qu.: 0.74334
 Max.   :172792   Max.   :  2.45493   Max.   : 22.05773   Max.   :
   9.3826   Max.   :16.87534
       V5                   V6                  V7                  V8
               V9
 Min.   :-113.74331   Min.   :-26.1605   Min.   :-43.5572   Min.
   :-73.21672   Min.   :-13.43407
 1st Qu.:  -0.69160   1st Qu.: -0.7683   1st Qu.: -0.5541   1st Qu.:
   -0.20863   1st Qu.: -0.64310
 Median :  -0.05434   Median : -0.2742   Median :  0.0401   Median :
   0.02236   Median : -0.05143
```

```
Mean   :  0.00000   Mean   :  0.0000   Mean   :  0.0000   Mean   :  0.00000   Mean   :  0.00000
3rd Qu.:  0.61193   3rd Qu.:  0.3986   3rd Qu.:  0.5704   3rd Qu.:  0.32735   3rd Qu.:  0.59714
Max.   : 34.80167   Max.   : 73.3016   Max.   :120.5895   Max.   : 20.00721   Max.   : 15.59500
     V10                 V11                 V12                 V13                 V14
Min.   :-24.58826   Min.   :-4.79747   Min.   :-18.6837   Min.   :-5.79188   Min.   :-19.2143
1st Qu.: -0.53543   1st Qu.:-0.76249   1st Qu.: -0.4056   1st Qu.:-0.64854   1st Qu.: -0.4256
Median : -0.09292   Median :-0.03276   Median :  0.1400   Median :-0.01357   Median :  0.0506
Mean   :  0.00000   Mean   : 0.00000   Mean   :  0.0000   Mean   : 0.00000   Mean   :  0.0000
3rd Qu.:  0.45392   3rd Qu.: 0.73959   3rd Qu.:  0.6182   3rd Qu.: 0.66251   3rd Qu.:  0.4931
Max.   : 23.74514   Max.   :12.01891   Max.   :  7.8484   Max.   : 7.12688   Max.   : 10.5268
     V15                V16                 V17                 V18                 V19
Min.   :-4.49894   Min.   :-14.12985   Min.   :-25.16280   Min.   :-9.498746   Min.   :-7.213527
1st Qu.:-0.58288   1st Qu.: -0.46804   1st Qu.: -0.48375   1st Qu.:-0.498850   1st Qu.:-0.456299
Median : 0.04807   Median :  0.06641   Median : -0.06568   Median :-0.003636   Median : 0.003735
Mean   : 0.00000   Mean   :  0.00000   Mean   :  0.00000   Mean   : 0.000000   Mean   : 0.000000
3rd Qu.: 0.64882   3rd Qu.:  0.52330   3rd Qu.:  0.39968   3rd Qu.: 0.500807   3rd Qu.: 0.458949
Max.   : 8.87774   Max.   : 17.31511   Max.   :  9.25353   Max.   : 5.041069   Max.   : 5.591971
     V20                 V21                 V22                  V23                 V24
Min.   :-54.49772   Min.   :-34.83038   Min.   :-10.933144   Min.   :-44.80774   Min.   :-2.83663
1st Qu.: -0.21172   1st Qu.: -0.22839   1st Qu.: -0.542350   1st Qu.: -0.16185   1st Qu.:-0.35459
Median : -0.06248   Median : -0.02945   Median :  0.006782   Median : -0.01119   Median : 0.04098
Mean   :  0.00000   Mean   :  0.00000   Mean   :  0.000000   Mean   :  0.00000   Mean   : 0.00000
3rd Qu.:  0.13304   3rd Qu.:  0.18638   3rd Qu.:  0.528554   3rd Qu.:  0.14764   3rd Qu.: 0.43953
```

```
Max.   : 39.42090   Max.   : 27.20284   Max.   : 10.503090   Max.   :
  22.52841   Max.   : 4.58455
     V25                  V26                  V27                  V28
                Amount
Min.   :-10.29540   Min.   :-2.60455   Min.   :-22.565679   Min.
  :-15.43008   Min.   :    0.00
1st Qu.: -0.31715   1st Qu.:-0.32698   1st Qu.: -0.070840   1st Qu.:
  -0.05296   1st Qu.:    5.60
Median :  0.01659   Median :-0.05214   Median :  0.001342   Median :
  0.01124   Median :   22.00
Mean   :  0.00000   Mean   : 0.00000   Mean   :  0.000000   Mean   :
  0.00000   Mean   :   88.35
3rd Qu.:  0.35072   3rd Qu.: 0.24095   3rd Qu.:  0.091045   3rd Qu.:
  0.07828   3rd Qu.:   77.17
Max.   :  7.51959   Max.   : 3.51735   Max.   : 31.612198   Max.   :
  33.84781   Max.   :25691.16
    Class
Min.   :0.000000
1st Qu.:0.000000
Median :0.000000
Mean   :0.001728
3rd Qu.:0.000000
Max.   :1.000000
>
```

Number of fraud/Non-fraud data of whole data

```
 #nrow(transactions);
[1] 284807

#Non fraud count
> length(which(transactions$Class == 0))
[1] 284315

#Fraud count
> length(which(transactions$Class == 1))
[1] 492
```

In comparison to 284315, there are only 492 fraud cases in total of 284807, which amounts to 99,82 percent of the fraud cases without a blueprint.

Splitting the dataset

```
 # Split data to training and verification sets 80:20
Where 80 is training set and 20 is verification set
library(caTools)
split <- sample.split(transactions, SplitRatio = 0.8)
training <- subset(transactions, split = TRUE)
verification <- subset(transactions, split = FALSE)
```

5.3 Experiments and Analysis Using Data Mining Techniques

5.4 Classification using logistics regression

```
  # Classification using logistics regression
classifier <- glm(formula = training$Class ~.,
                  family = binomial, data = training[, -30])
pred <- predict(classifier, type = 'response', newdata = verification[,
    -30])

# AUC of ROC function

  # Run the ROCR functions for AUC calculation
roc_perf <- performance(prediction(pred, verification[, 30]), 'tpr', '
    fpr')
roc_sens <- performance(prediction(pred, verification[, 30]), 'sens', '
    spec')

roc_auc <- performance(prediction(pred, verification[, 30]), 'auc')
roc_err <- performance(prediction(pred, labels=verification[, 30]), '
    err')

# AUC value
auc <- roc_auc@y.values[[1]]

#AUC of Precision and recall

prc_frame <- data.frame(pred, training$Class)
prc <- pr.curve(prc_frame[prc_frame$training.Class == 'YES',]$pred,
  prc_frame[prc_frame$training.Class == 'NO',]$pred,
                curve = TRUE)
plot(roc_perf)
plot(prc)
```

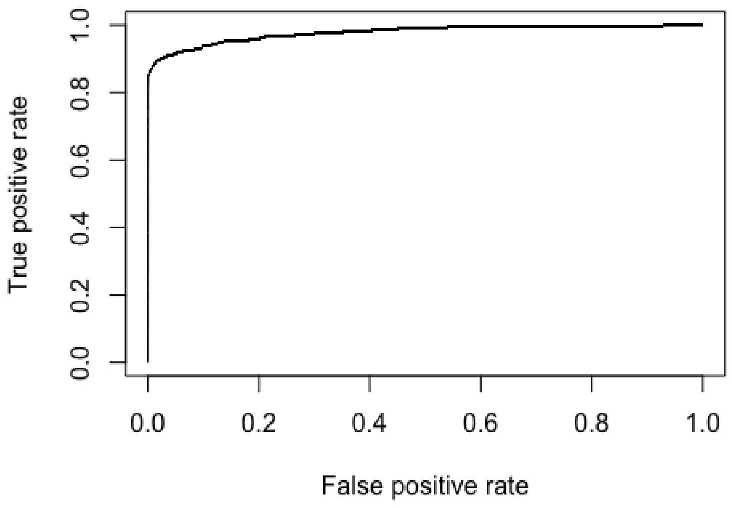

Fig. 2. ROC curve for Logistics Regression

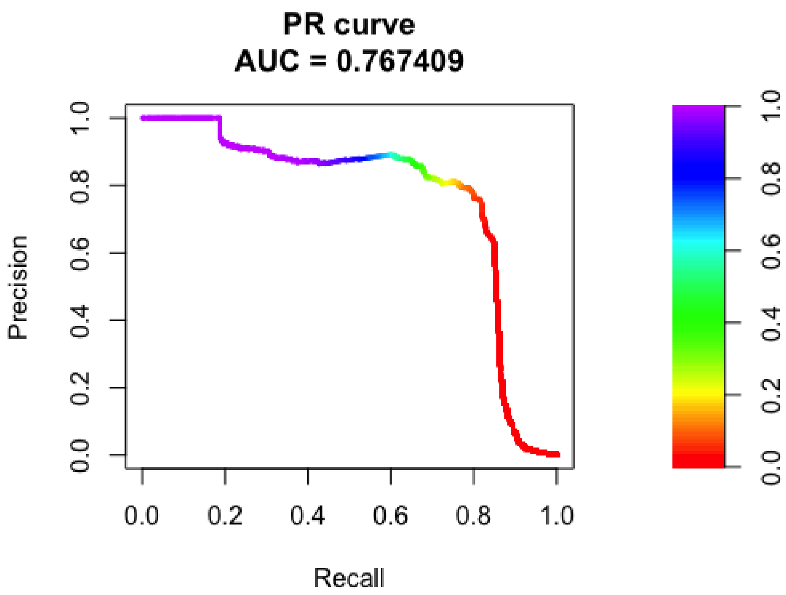

Fig. 3. PRAUC Curve for Logistics Regression

5.5 Classification using Xgboost

```
 classifier_xg = xgboost(data = as.matrix(training[,-30]),label =
   training$Class,nrounds = 10)
pred_xg = predict(classifier_xg,type = 'response', newdata = as.matrix(
   verification[,-30]))

[1] train-rmse:0.352859
[2] train-rmse:0.247056
```

```
[3]  train-rmse:0.173442
[4]  train-rmse:0.122216
[5]  train-rmse:0.086481
[6]  train-rmse:0.061590
[7]  train-rmse:0.044805
[8]  train-rmse:0.033556
[9]  train-rmse:0.026252
[10]  train-rmse:0.021914

# AUC of ROC function

  # Run the ROCR functions for AUC calculation

roc_perf <- performance(prediction(pred_xg, verification[, 30]), 'tpr',
    'fpr')
roc_sens <- performance(prediction(pred_xg, verification[, 30]), 'sens'
   , 'spec')

roc_auc <- performance(prediction(pred_xg, verification[, 30]), 'auc')
roc_err <- performance(prediction(pred_xg, labels=verification[, 30]),
   'err')

# AUC value

auc <- roc_auc@y.values[[1]]

#AUC of Precision and recall

prc_frame <- data.frame(pred_xg, training$Class)
prc <- pr.curve(prc_frame[prc_frame$training.Class == 'YES',]$pred_xg,
                prc_frame[prc_frame$training.Class == 'NO',]$pred_xg,
                curve = TRUE)
plot(roc_perf)
plot(prc)
```

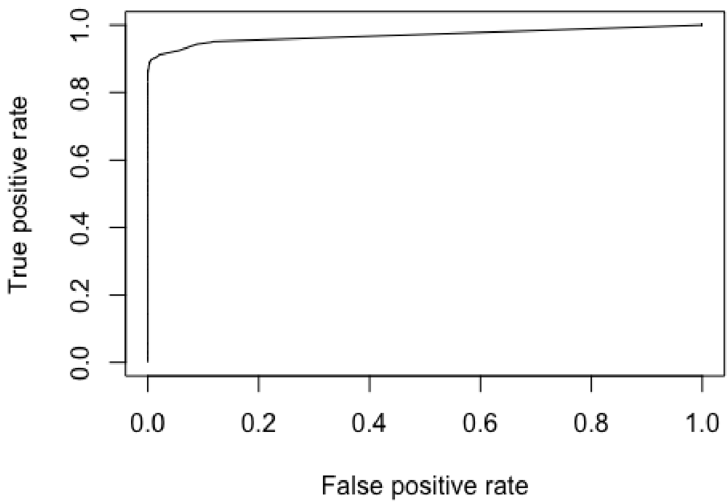

Fig. 4. ROC Curve For Xgboost

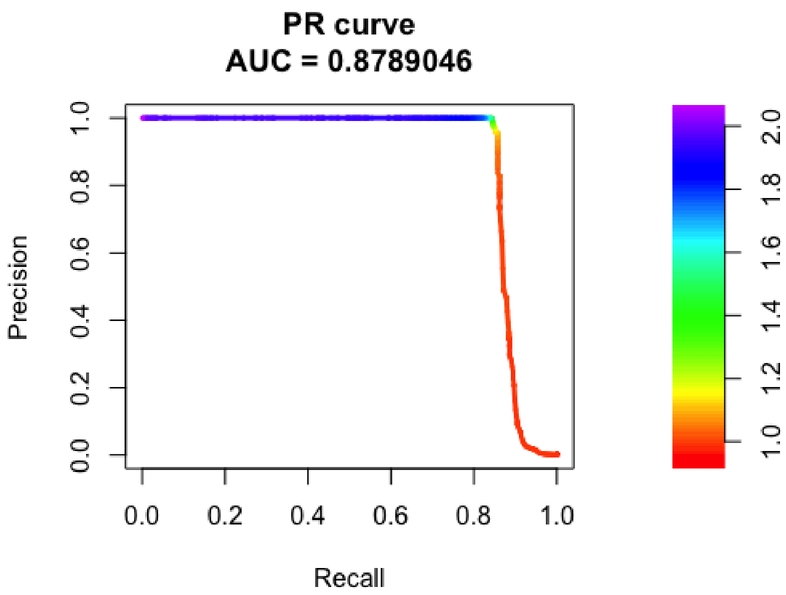

Fig. 5. PRAUC Curve for Xgboost

5.6 Classification using Random Forest

```
  x = training[, -30]
y = training[,30]
rf_fit = Rborist(x, y, ntree = 1000, minNode = 20, maxLeaf = 13)

rf_pred <- predict(rf_fit, verification[,-30], ctgCensus = "prob")
prob <- rf_pred$prob

```

```
# roc.curve(training$Class, prob[,2], plotit = TRUE)

roc_perf <- performance(prediction(prob[,2], verification[, 30]), 'tpr'
    , 'fpr')
roc_sens <- performance(prediction(prob[,2], verification[, 30]), 'sens
    ', 'spec')

roc_auc <- performance(prediction(prob[,2], verification[, 30]), 'auc')
roc_err <- performance(prediction(prob[,2], labels=verification[, 30]),
     'err')

auc <- roc_auc@y.values[[1]]

prc_frame <- data.frame(prob[,2], training$Class)
prc <- pr.curve(prc_frame[prc_frame$training.Class == 'YES',]$prob
    ...2.,
                prc_frame[prc_frame$training.Class == 'NO',]$prob...2.,
                curve = TRUE)
plot(roc_perf)
plot(prc)
```

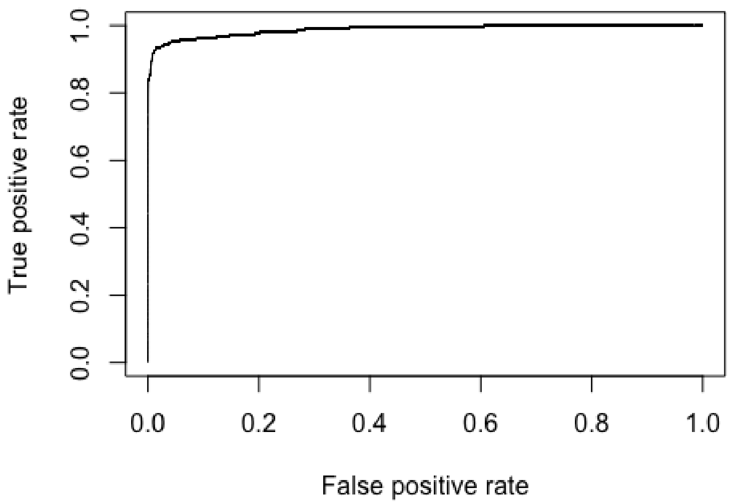

Fig. 6. ROC Curve for Random Forest

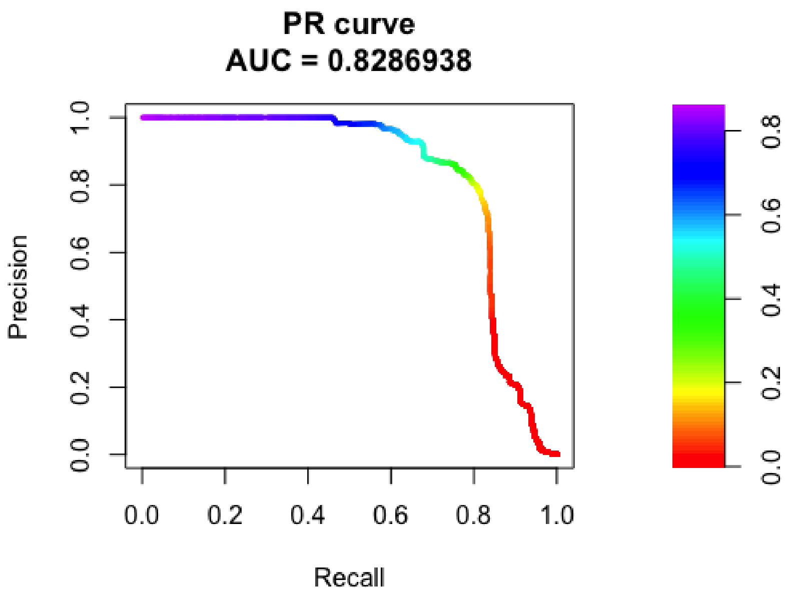

Fig. 7. PRAUC Curve for Random Forest

6 Results

The generated result shows that in a case of a high imbalanced ratio, AUC will not produce an accurate output, while PRAUC provides an accurate ratio of false positive to true positive

The XGBOOST model performed the best with an auc score of 0.878, while both the random forest and logistic regression models showed fair results.

7 Conclusion

In the era of digital transformation where electronic payment has been adopted in making delivery of services easy and much quicker, credit card fraud detection systems can play an essential role in minimizing the numbers of fraudulent transactions.

Furthermore, this study compares data mining techniques used to demonstrate unbalanced dataset of credit card fraud where fraudulent cases are few compared to regular transaction cases.

This paper used supervised machine learning algorithms.

The accuracy is 0.767, 0.878 and 0.828 for logistic regression, Xgboost and Random forest classifier, respectively. By contrasting all three techniques, the Xgboost model was found to perform better than the Random Forest and Logistic Regression models.

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