Fraud Detection

Santi

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```
loadLibraries() #This is just a function that loads essential stats libraries.
```

```
## [1] "The following libraries were loaded: ISLR2,ggplot2, dplyr, \n\n    glmnet, leaps, boot, gam, tr
```

```
fraud <- read.csv('fraud_detection.csv', header = TRUE)
head(fraud)
```

```
##   step     type   amount    nameOrig oldbalanceOrg newbalanceOrig
## 1    1  PAYMENT  9839.64 C1231006815        170136      160296.36
## 2    1  PAYMENT  1864.28 C1666544295         21249       19384.72
## 3    1 TRANSFER   181.00 C1305486145           181           0.00
## 4    1 CASH_OUT   181.00  C840083671           181           0.00
## 5    1  PAYMENT 11668.14 C2048537720         41554       29885.86
## 6    1  PAYMENT  7817.71   C90045638         53860       46042.29
##      nameDest oldbalanceDest newbalanceDest isFraud isFlaggedFraud
## 1 M1979787155              0              0       0              0
## 2 M2044282225              0              0       0              0
## 3  C553264065              0              0       1              0
## 4   C38997010          21182              0       1              0
## 5 M1230701703              0              0       0              0
## 6  M573487274              0              0       0              0
```

```
# Look at data dims.
dim(fraud)
```

```
## [1] 6362620      11
```

```
# See if there are any NA's  and duplicate entries.
sum(is.na(fraud))
```

```
## [1] 0
```

```
sum(duplicated(fraud))
```

```
## [1] 0
```

Data Summary and Graphs

Let's make a summary for the data and convert the *isFraud* and *isFlaggedFraud* to factors, so we can run the classification models.

```
summary(fraud)
```

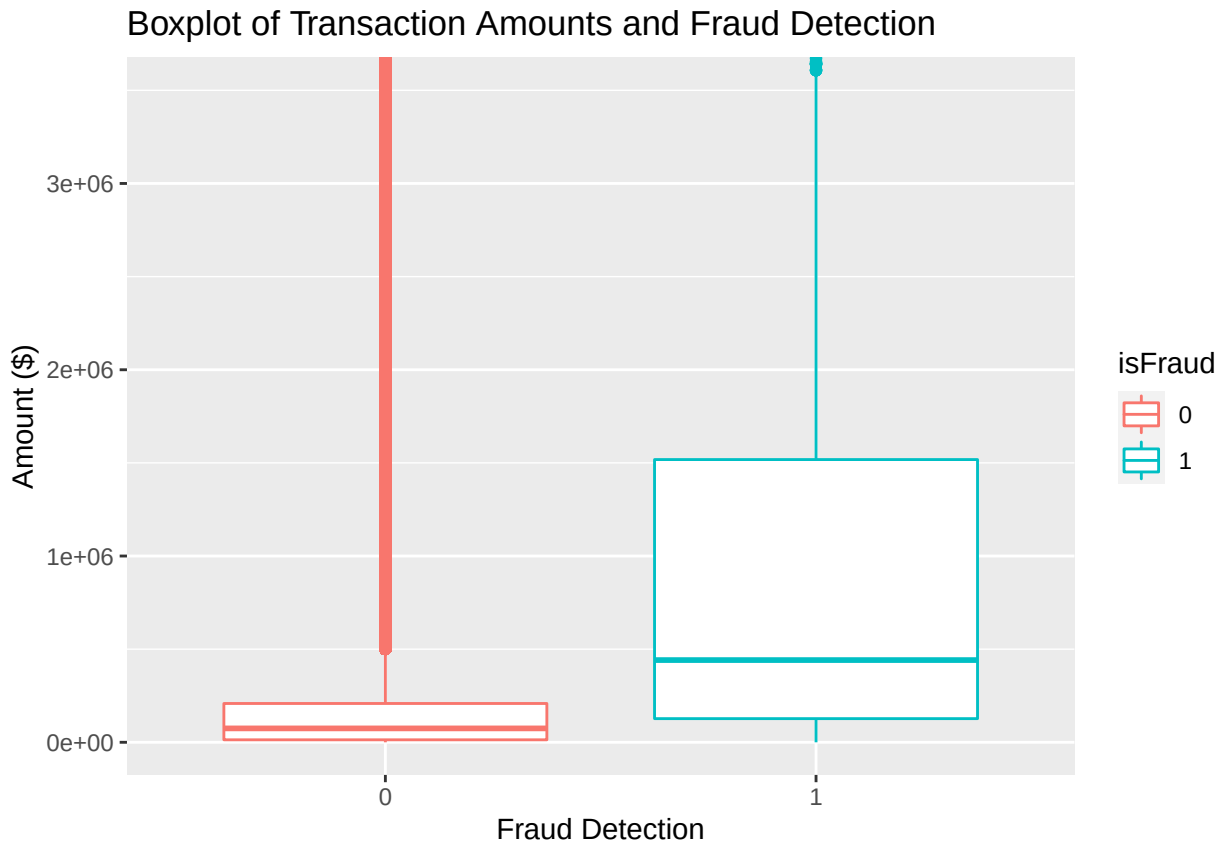
```
##       step           type               amount           nameOrig
##  Min.   :  1.0   Length:6362620     Min.   :       0   Length:6362620
##  1st Qu.:156.0   Class :character   1st Qu.:   13390   Class :character
```

```
##  Median :239.0   Mode  :character   Median :   74872   Mode  :character
##  Mean   :243.4                      Mean   :  179862
##  3rd Qu.:335.0                      3rd Qu.:  208721
##  Max.   :743.0                      Max.   :92445517
##  oldbalanceOrg      newbalanceOrig       nameDest
##  Min.   :       0   Min.   :       0   Length:6362620
##  1st Qu.:       0   1st Qu.:       0   Class :character
##  Median :   14208   Median :       0   Mode  :character
##  Mean   :  833883   Mean   :  855114
##  3rd Qu.:  107315   3rd Qu.:  144258
##  Max.   :59585040   Max.   :49585040
##  oldbalanceDest      newbalanceDest         isFraud
##  Min.   :        0   Min.   :        0   Min.   :0.000000
##  1st Qu.:        0   1st Qu.:        0   1st Qu.:0.000000
##  Median :   132706   Median :   214661   Median :0.000000
##  Mean   :  1100702   Mean   :  1224996   Mean   :0.001291
##  3rd Qu.:   943037   3rd Qu.:  1111909   3rd Qu.:0.000000
##  Max.   :356015889   Max.   :356179279   Max.   :1.000000
##  isFlaggedFraud
##  Min.   :0.0e+00
##  1st Qu.:0.0e+00
##  Median :0.0e+00
##  Mean   :2.5e-06
##  3rd Qu.:0.0e+00
##  Max.   :1.0e+00
```

```
fraud$isFraud <- as.factor(fraud$isFraud)
```

Now we can start our exploratory analysis. The transaction amount has a large number of ouliers, so we will restrice the amount value to $3,500,000.

```
ggplot(data = fraud, aes(x = isFraud, y = amount, color = isFraud)) +
  coord_cartesian( ylim =  c(0, 3500000)) +
  geom_boxplot() +
  ylab('Amount ($)') +
  xlab('Fraud Detection') +
  ggtitle('Boxplot of Transaction Amounts and Fraud Detection')
```




```
flagged_table <- table(fraud$isFraud, fraud$isFlaggedFraud)
flagged_table
```

```
##
##           0       1
##   0 6354407       0
##   1    8197      16
```

```
correct_flag <- table(fraud$isFraud, fraud$isFlaggedFraud)[2,2] /
                sum(table(fraud$isFraud, fraud$isFlaggedFraud)[2,])
cat(correct_flag * 100, "% of the fradulent transactions were flagged as such.")
```

```
## 0.1948131 % of the fradulent transactions were flagged as such.
```

Note the system we currently have does poorly when at detecting fraudulent transactions (0.19%). The names of the person making and receiving the transactions are also recorded but they offer no significance so we remove those from the data set.

```
fraudNew <- subset(fraud, select = - c(nameOrig, nameDest))
attach(fraudNew)
```

```
## The following objects are masked from fraudNew (pos = 3):
##
##     amount, isFlaggedFraud, isFraud, newbalanceDest, newbalanceOrig,
##     oldbalanceDest, oldbalanceOrg, step, type

## The following objects are masked from fraudNew (pos = 4):
##
##     amount, isFlaggedFraud, isFraud, newbalanceDest, newbalanceOrig,
```

```
##     oldbalanceDest, oldbalanceOrg, step, type
```

```
dim(fraudNew)
```

```
## [1] 6362620       9
```

Now lets run some data analysis. First let's make a train and test set. Let's randomly select 100,000 observations as our training data and the rest as test data. Why? Well if I do a larger amount my computer really slows down.

```
set.seed(3)

train <- sample(1:nrow(fraudNew), 100000)
test <- (-train)

fraud_train <- fraudNew[train, ]
fraud_test <- fraudNew[test, ]

isFraud_test <- fraudNew[test, 'isFraud']
```

#Logistic Regression

First let's do logistic regression to detect fraudulent transactions. Since this data has a high null rate, we know we will run into issues.

```
null_tab <-table(isFraud)

null_rate <- table(isFraud_test)[1]/length(isFraud_test)
null_rate
```

```
##         0
## 0.9987101
```

```
set.seed(3)

fraud_glm = glm(isFraud ~ ., data = fraud_train,
                family = binomial)
```

```
## Warning: glm.fit: algorithm did not converge
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
summary(fraud_glm)
```

```
##
## Call:
## glm(formula = isFraud ~ ., family = binomial, data = fraud_train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
##  -8.49     0.00     0.00     0.00     8.49
##
## Coefficients: (1 not defined because of singularities)
##                  Estimate Std. Error    z value Pr(>|z|)
## (Intercept)    -2.117e+15  7.425e+05 -2.851e+09   <2e-16 ***
## step            1.892e+11  1.501e+03  1.261e+08   <2e-16 ***
## typeCASH_OUT    1.810e+15  7.458e+05  2.427e+09   <2e-16 ***
## typeDEBIT      -2.185e+15  2.726e+06 -8.017e+08   <2e-16 ***
## typePAYMENT     1.778e+15  7.412e+05  2.399e+09   <2e-16 ***
```

```
## typeTRANSFER   -1.888e+15  1.020e+06 -1.852e+09   <2e-16 ***
## amount          1.399e+07  6.951e-01  2.013e+07   <2e-16 ***
## oldbalanceOrg   8.560e+08  1.583e+00  5.409e+08   <2e-16 ***
## newbalanceOrig -9.814e+08  1.587e+00 -6.184e+08   <2e-16 ***
## oldbalanceDest  8.134e+07  4.332e-01  1.878e+08   <2e-16 ***
## newbalanceDest -8.770e+07  4.287e-01 -2.046e+08   <2e-16 ***
## isFlaggedFraud         NA         NA         NA       NA
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance:  2053.9  on 99999  degrees of freedom
## Residual deviance: 11678.1  on 99989  degrees of freedom
## AIC: 11700
##
## Number of Fisher Scoring iterations: 25
```

```
# Predict the responders that are diagnosed with heart disease.
glm_pred = predict(fraud_glm, data = fraudNew[test, ], type = 'response')
vec = rep(0, length(isFraud))
vec[glm_pred >= 0.2] = 1

table(vec, isFraud)
```

```
##    isFraud
## vec       0       1
##   0 6345563    8203
##   1    8844      10
```

#Bagging

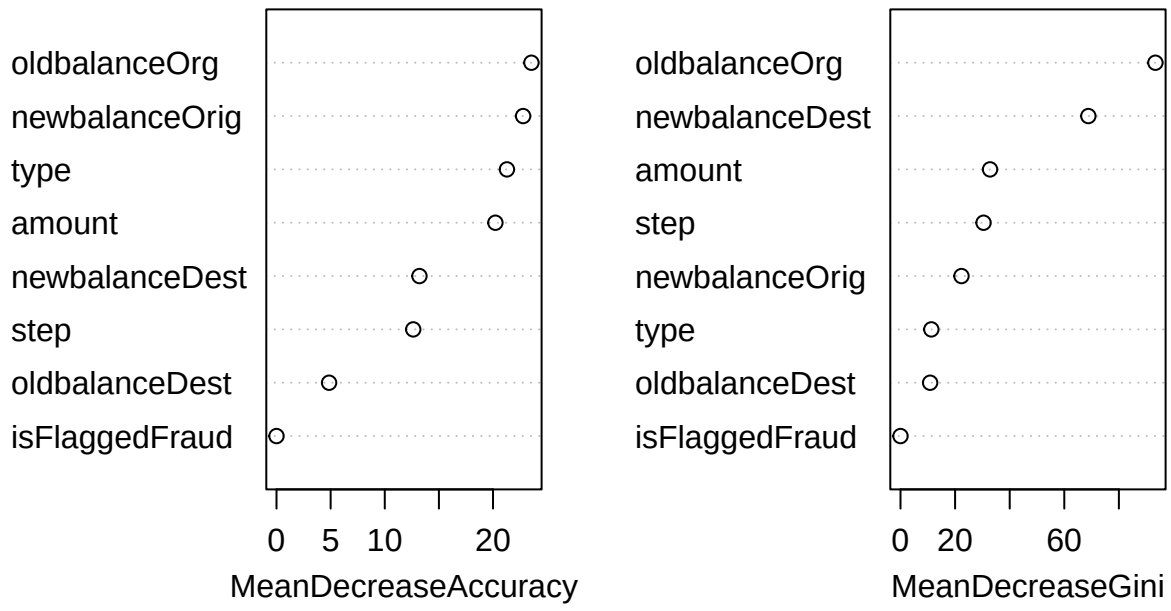
Let's first do bagging with 100 trees.

```
set.seed(3)
bag_fraud <- randomForest(isFraud ~ ., data = fraudNew, subset = train,
                          mtry = 8, ntree = 100, importance = TRUE)
```

Once that is done, predict the remaining fraud cases. We use `type = 'class'` since we are doing classification. This will allow us to make a table to determine accuracy (see below).

```
set.seed(3)

yhat_bag <- predict(bag_fraud, newdata = fraud_test, type = 'class')
varImpPlot(bag_fraud, main = 'Predictor Importance Using Bagging')
```



In this case note that Mean Decrease Accuracy is low for the first 4 predictors: old balance of the account initiating the transaction (*oldbalanceOrg*) , the new balance of the destination account holder, (*newbalanceDest*), the type of transaction *type* and the transaction amount (*amount*) and then follow a large jump.

```
# Table
bag_table <- table('Prediction' = yhat_bag, 'True Value' = isFraud_test)
bag_table
```

```
##           True Value
## Prediction       0       1
##          0 6254275    2203
##          1     267    5875
```

```
sum(diag(bag_table))/ sum(bag_table)
```

```
## [1] 0.9996056
```

```
bag_table[2,2]/ sum(bag_table[2, ])
```

```
## [1] 0.9565288
```

#Random Forests

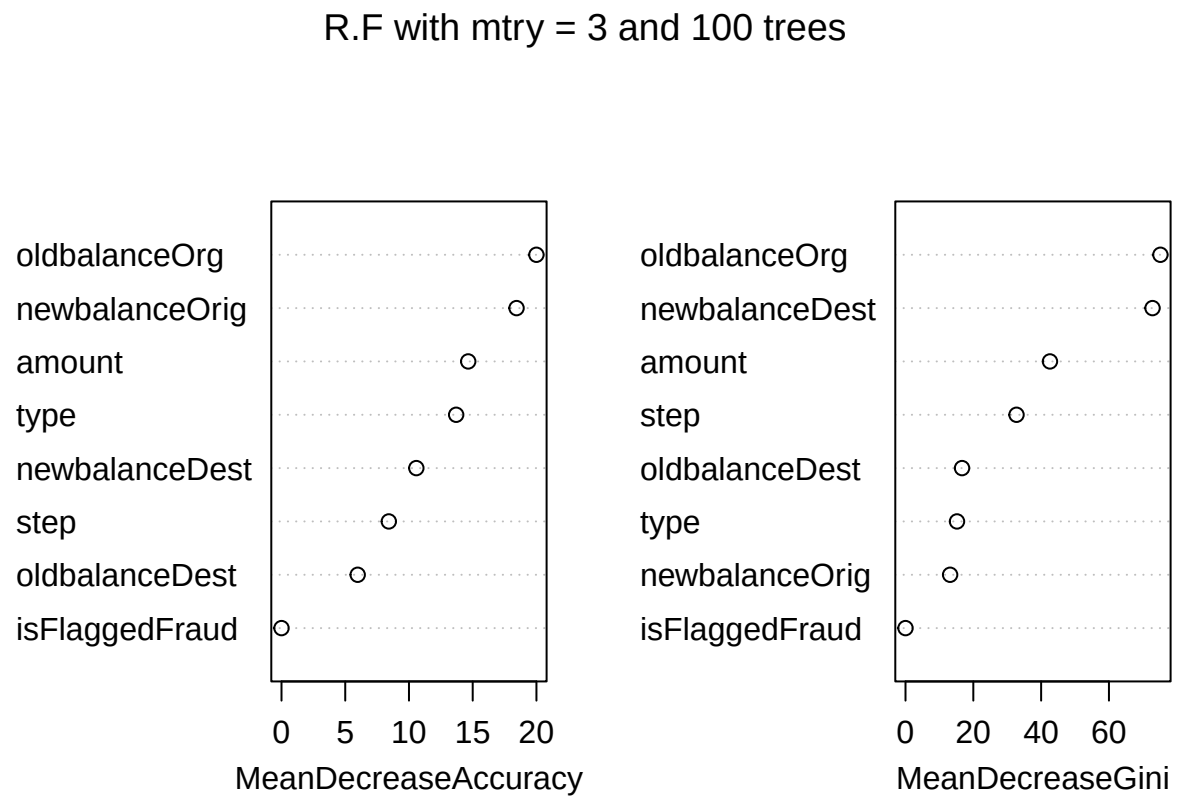
Let's try random forests on the training data set. We allow the model to pick $\sqrt{8} \approx 3$ features at each node. With 1,00 trees.6

```
set.seed(3)
rf_fraud <- randomForest(isFraud ~ ., data = fraudNew, subset = train,
                         mtry = 3, ntree = 100, importance = TRUE)
```

```
set.seed(3)

yhat_rf <- predict(rf_fraud, newdata = fraud_test, type = 'class')

varImpPlot(rf_fraud, main ='R.F with mtry = 3 and 100 trees')
```



Here the most important predictors are The old balance of the account initiating the transaction, (*oldbalanceOrg*) , the new balance of the destination account holder, (*newbalanceDest*), and the transaction amount (*amount*)

```
# Table
rf_table <- table('Prediction' = yhat_rf, 'True Value' = isFraud_test)
rf_table
```

```
##            True Value
## Prediction       0       1
##          0 6254444    2277
##          1      98    5801
```

```
sum(diag(rf_table))/ sum(rf_table)
```

```
## [1] 0.9996208
```

```
rf_table[2,2]/ sum(rf_table[2, ])
```

```
## [1] 0.983387
```

Now as mentioned before this data set has a large null rate. So our overall error would be small if we simply made our predictions all be zero. Instead we focus our results on the fraud detection rate. That is to

Flagged	Bagging	Boosting
0.19%	95.65%	98.34%

Table 1: Fraud Detection Rate

say, we measure how well our model is at detection fraud itself. Below are such rates for the flagged rate $isFlaggedFraud$, bagging, and boosting.