Credit Card Fraud Detection

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17/03/2020

Abstract

According to Nilson Report (https://nilsonreport.com) the credit card frauds cost business and card issuers around 28 billion dollars in 2018. As we are moving into a cashless society this number is going to grow steadily. When talking about fraudulent transactions, most people think about the values defrauded. However, the total cost of the frauds has to be understood in its whole extension:

1) There is the loss due to the fraud itself (what most people see)
2) There is the cost associated with managing the losses – cancelling orders and refunding charges (exceeds

   the cost of the frauds 300%)
3) There is the cost of mistakenly rejecting orders
4) There is the cost of developing and applying mechanisms to avoid fraud.

Therefore, the problem is not only what you lose due the frauds themselves, but the cost to mitigate the negative impact and manage the process (update security measures, block and reissue cards, reimburse customers etc), the cost of building and maintaining mechanisms to prevent the frauds and of course the cost of losing money when you unduly block a sales assuming wrongly it is a fraud.

Therefore, many financial organizations are facing the challenge of building a successful fraud detection model which is easy to maintain and highly effective in spotting frauds and at the same time doesn´t have a too high falsepositive rate. Certain ML algorithms seem to be well suited to address all these issues. They can help automatize the process of adjusting for identifying new types of fraud (the big problem with the current processes) and it can archive an effective identification rate without too many falsenegative.

Problem statement /Business problem

Our objective is to spot possible frauds in credit card operations. This identification will be based on the client´s profile, the seller´s profile and the data of the transaction itself. The objective is to flag transactions with the high possibility of fraud.

Today frauds spin around 4% of all sales made with credit cards in Brazil. Our client already has mechanisms in place that detects potential fraudulent transactions, however, these mechanisms have two problems:

1) They deploy semistatic rules that generate a scenario where people in the background have to keep looking for new types of fraud to keep adjusting the current model.

2) The process suffers a paradoxical problem: if it is too stringent it creates problems for the clients blocking legit sales if it is too lose it allows a too high level of fraud. A middle term is difficult to

archive – even more so when you have to keep adjusting the rules.

To address these two issues, the idea would be to create a model that would not only identify (or at least flag) the suspect transactions but also would identify changes in the patterns and adapt automatically to new fraud patterns.

In order to do that we managed to get a database merging the three data sources (client, seller and transaction) and the idea is to develop a machine learning model which not only assertive (Assertive meaning identify a high percentage of the actual frauds without blocking too many legit ones) but adaptable.
We were verbally informed that the current mechanism spots around 50% (2% of the total) of potential frauds and flags around 2% of legit ones (false positive). If that is true (We have no way to verify this information), it means that the current process gets it right at around 2% of all transactions and wrong at 2%. In summary, it can stop 50% of all fraudulent transactions and has a false positive rate of 2%.

It is interesting to notice that although frauds correspond to just 4% of all transactions, they answer for 8% of the total value of the transactions. It means each 1% of fraud elimination corresponds to approximately R$ 16.000.000,00 /month (CAD 5.330.000,00).

Datasets/Getting the data

We used a real anonymized and sanitized dataset representing a subset of the transactions that occurred during one day of September of 2019 in Brazil, totalling 290.398 transactions.

Data dictionary

The database contains three sources: • Clients data • Sellers data • And transactional data. Information regarding the clients:

. • Age
. • Sex
. • Income
. • Average expenditure in recurrent payments per transaction
. • Average expenditure buying goods (Using the card directly) per transaction
. • Average expenditure buying services (using the card directly) per transaction
. • Average expenditure buying goods online per transaction
. • Average expenditure buying services online per transaction Information about the seller:
. • Score of the seller (Number 0 to 100) indicating the ranking of the seller regards frequency of frauds. Information about the transactions:
. • Type: which one of the five categories it belongs (0recurrent, 1goods, 2services, 3online goods or 4online services).
. • Value of the transaction
. • If the addresses of the seller and the buyer are in the same city
. • If the addresses of the seller and the buyer are in the same country
. • If the transaction was fraudulent or not (Y or N)

	City	Country
Buyer and seller same city and country	1	1
Buyer and seller different cities same country	1	0
Buyer and seller in different cities and countries	0	0

Data exploration

The data used contained 14 variables with 290398 observations. The variables included sex, age, income,

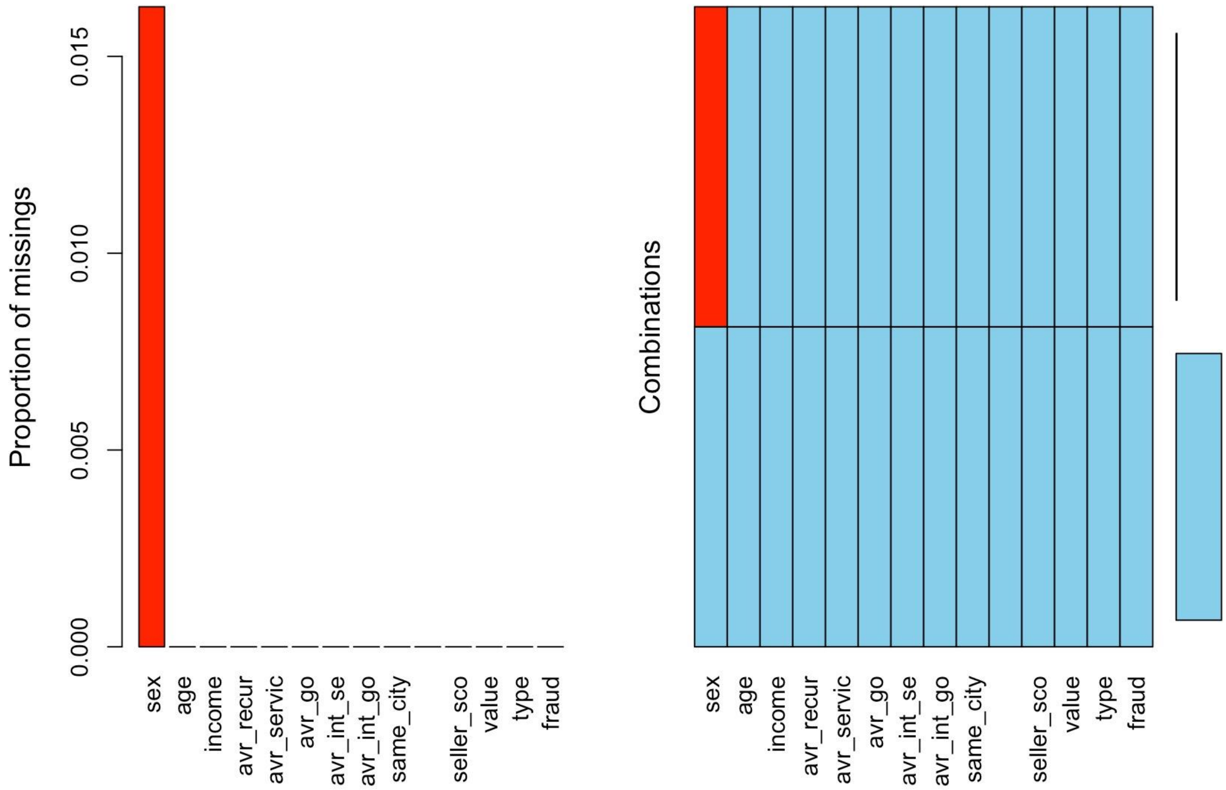
avr_recur, avr_servic, avr_go, avr_int_se, avr_int_go, same_city, same_count, seller_sco, value, type, fraud. The details can be seen below.
Checking the data structure and frist 10 rows.

```
## sex age income avr_recur avr_servic avr_go avr_int_se avr_int_go same_city
## 1    M  39   D    65.19  107.12  45.32   37.89  149.93  1
## 2    F  27   E    84.93   38.80  30.70  164.52  106.43  1
## 3    M  56   E    36.28  154.23  66.16   57.50   66.24  0
## 4    F  64   E   113.85   32.49  19.78  123.18   97.33  1
## 5    M  30   E   117.19   77.08  65.95  118.37   87.77  0
## 6    M  29   E    50.40   99.48  32.39  138.93   17.53  0
## 7    M  61   E    98.17  141.08  49.83  113.71  150.62  1
## 8    F  64   E    37.40   84.32  79.83   88.40   96.83  1
## 9    M  47   E    41.89   74.00  29.24  143.81   33.89  1
## 10   F  57   E    51.95   86.26  89.76   88.24   33.36  1
##    same_count seller_sco    value type fraud
## 1           1         46    28.21    3     N
## 2           1          2    22.47    3     N
## 3           1         57 1253.14    4     N
## 4           1         40 1494.10    4     Y
## 5           0         76 1219.75    4     N
## 6           1         51 1040.58    4     N
## 7           1         36    48.17    0     N
## 8           1         24    29.55    1     N
## 9           1         43    21.55    1     N
## 10          1         22    49.73    0     N
```

```
## 'data.frame':        290398 obs. of   14 variables:
##   $ sex        :  Factor w/ 3 levels " ","F","M": 3 2 3 2 3 3        3 2 3 2 ...
##   $ age        :  int   39 27 56 64 30 29 61 64 47 57    ...
```

```
## $ income : Factor w/ 5 levels "A","B","C","D",..: 4 5 5 5 5 5 5 5 5 5 ...
## $ avr_recur : num 65.2 84.9 36.3 113.8 117.2 ...
## $ avr_servic: num 107.1 38.8 154.2 32.5 77.1 ...
## $ avr_go : num 45.3 30.7 66.2 19.8 66 ...
## $ avr_int_se: num 37.9 164.5 57.5 123.2 118.4 ...
## $ avr_int_go: num 149.9 106.4 66.2 97.3 87.8 ...
## $ same_city:int 1 1 0 1 0 0 1 1 1 1...
## $ same_count: int 1 1 1 1 0 1 1 1 1 1...
## $ seller_sco: int 46 2 57 40 76 51 36 24 43 22 ...
## $ value : num 28.2 22.5 1253.1 1494.1 1219.8 ...
## $ type :int 3 3 4 4 4 4 0 1 1 0...
## $ fraud :Factor w/ 2 levels "N","Y": 1 1 1 2 1 1 1 1 1 1...
```

Checking for missing values




```
sum(is.na(df))
```

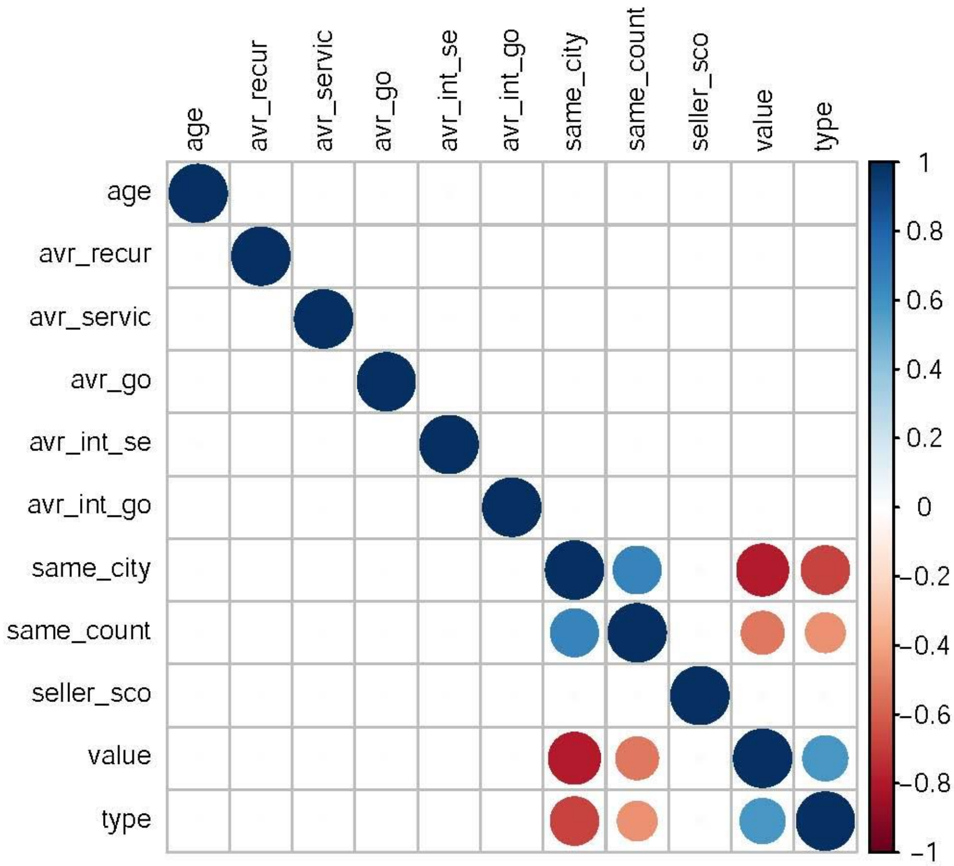
```
## [1] 0
```

We discovered that there are 4722 missing values in sex column since we can’t use mean or mode methods for categorical variable sex we decided to remove all missing values in sex column.

```
df <na.omit(df)
```

Checking correlations between features in our dataset

```
correlations <cor(df[, sapply(df, is.numeric)], method="pearson")
corrplot(correlations, number.cex = .9, method = "circle", type = "full",
tl.cex=0.8,tl.col = "black")
```



We can observe that most of the features in our dataset are not correlated. There is a strong negative correlation between same_city and value and between same_city and type. We will check the variable importance after we create some models.

We convert sex, income, type columns into the categorical data type and continue with data exploration.

```
df$sex <as.factor(df$sex)
df$income <-
as.factor(df$income)
df$type <as.factor(df$type)
```

Below we can see statistical descriptions for each feature in our dataset

After removing NA values from sex columns the data set contains 285,676 transactions. The mean value of all transactions is $180.88 while the largest transaction recorded in this data set amounts to $1499.98. The distribution of the monetary value of all transactions is rightskewed.

Let’s see the number of fraudulent transactions

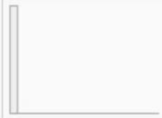
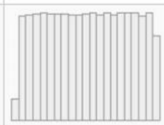
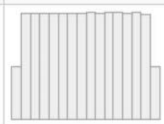
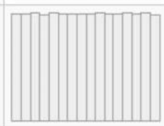
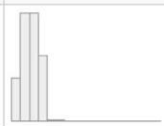
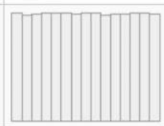
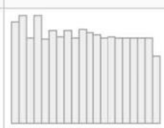
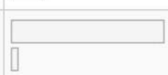
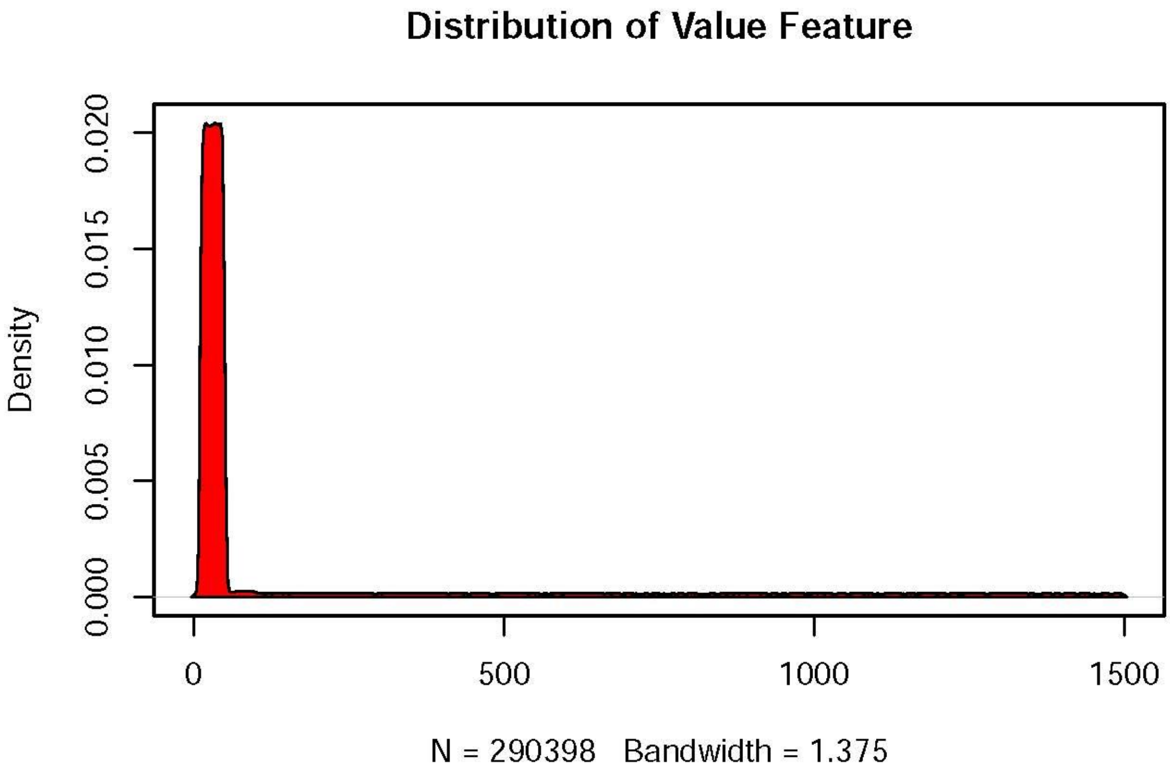
No	Variable	Stats / Values	Freqs (% of Valid)	Graph	Valid	Missing
1	sex [factor]	1. · 2. F 3. M	4722 (1.6%) 149101 (51.3%) 136575 (47.0%)		290398 (100%)	0 (0%)
2	age [integer]	Mean (sd) : 49.8 (17.3) min < med < max: 18 < 49 < 2019 IQR (CV) : 29 (0.3)	67 distinct values		290398 (100%)	0 (0%)
3	income [factor]	1. A 2. B 3. C 4. D 5. E	4540 (1.6%) 220 (0.1%) 3260 (1.1%) 19188 (6.6%) 263190 (90.6%)		290398 (100%)	0 (0%)
4	avr_recur [numeric]	Mean (sd) : 79 (28.8) min < med < max: 29 < 79.1 < 129 IQR (CV) : 50 (0.4)	10001 distinct values		290398 (100%)	0 (0%)
5	avr_servic [numeric]	Mean (sd) : 80 (43.2) min < med < max: 5 < 80.1 < 155 IQR (CV) : 74.8 (0.5)	15001 distinct values		290398 (100%)	0 (0%)
6	avr_go [numeric]	Mean (sd) : 50 (23.1) min < med < max: 10 < 50 < 90 IQR (CV) : 40 (0.5)	8001 distinct values		290398 (100%)	0 (0%)
7	avr_int_se [numeric]	Mean (sd) : 111.2 (66.9) min < med < max: 30 < 106.6 < 830 IQR (CV) : 76.2 (0.6)	20170 distinct values		290398 (100%)	0 (0%)
8	avr_int_go [numeric]	Mean (sd) : 85 (43.3) min < med < max: 10 < 85 < 160 IQR (CV) : 75 (0.5)	15001 distinct values		290398 (100%)	0 (0%)
9	same_city [integer]	Min : 0 Mean : 0.8 Max : 1	0 : 60162 (20.7%) 1 : 230236 (79.3%)		290398 (100%)	0 (0%)
10	same_count [integer]	Min : 0 Mean : 0.9 Max : 1	0 : 30006 (10.3%) 1 : 260392 (89.7%)		290398 (100%)	0 (0%)
11	seller_sco [integer]	Mean (sd) : 48.6 (28.8) min < med < max: 0 < 48 < 99 IQR (CV) : 50 (0.6)	100 distinct values		290398 (100%)	0 (0%)
12	value [numeric]	Mean (sd) : 180.9 (352.9) min < med < max: 0 < 35.2 < 1500 IQR (CV) : 25.3 (2)	53795 distinct values		290398 (100%)	0 (0%)
13	type [factor]	1. 0 2. 1 3. 2 4. 3 5. 4	56215 (19.4%) 56980 (19.6%) 58028 (20.0%) 59057 (20.3%) 60118 (20.7%)		290398 (100%)	0 (0%)
14	fraud [factor]	1. N 2. Y	278645 (96.0%) 11753 (4.0%)		290398 (100%)	0 (0%)

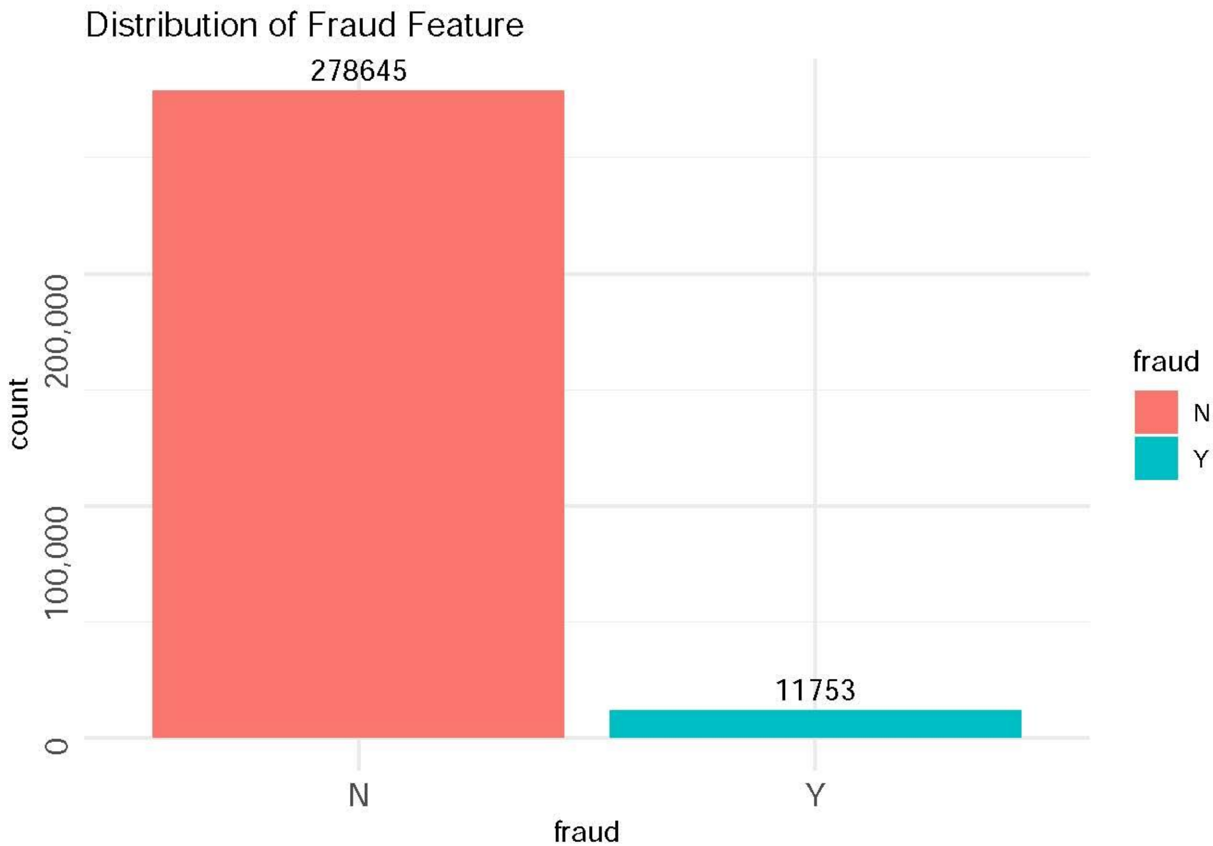
Figure 1: Table 1



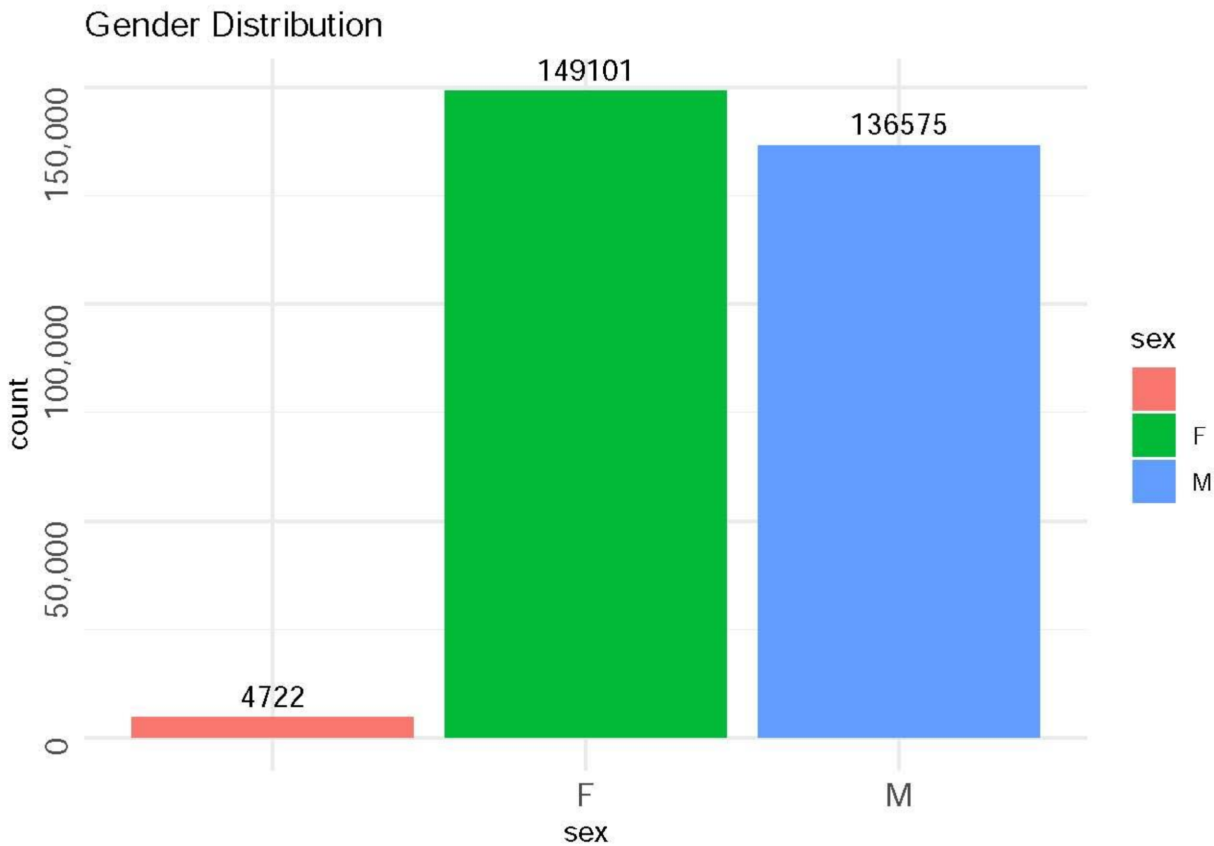
N Y ## 278645 11753

N Y ## 95.952796 4.047204

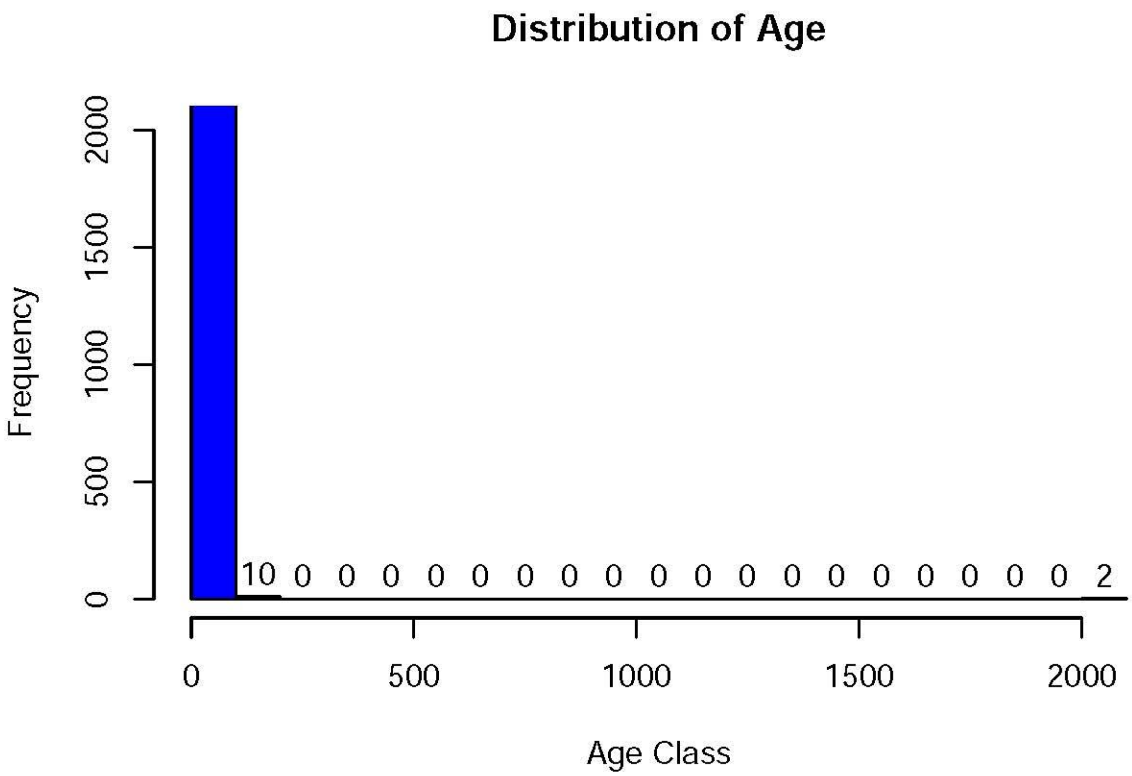
As expected, most transactions are nonfraudulent and our data is quite imbalanced. In fact, 95.95% of the transactions in this data set were not fraudulent while only 4.05% were fraudulent. The graph below highlights this significant contrast.



Let’s examine the sex column. We can see that gender distribution is almost balanced, there are 52% of female and 48% male customers.

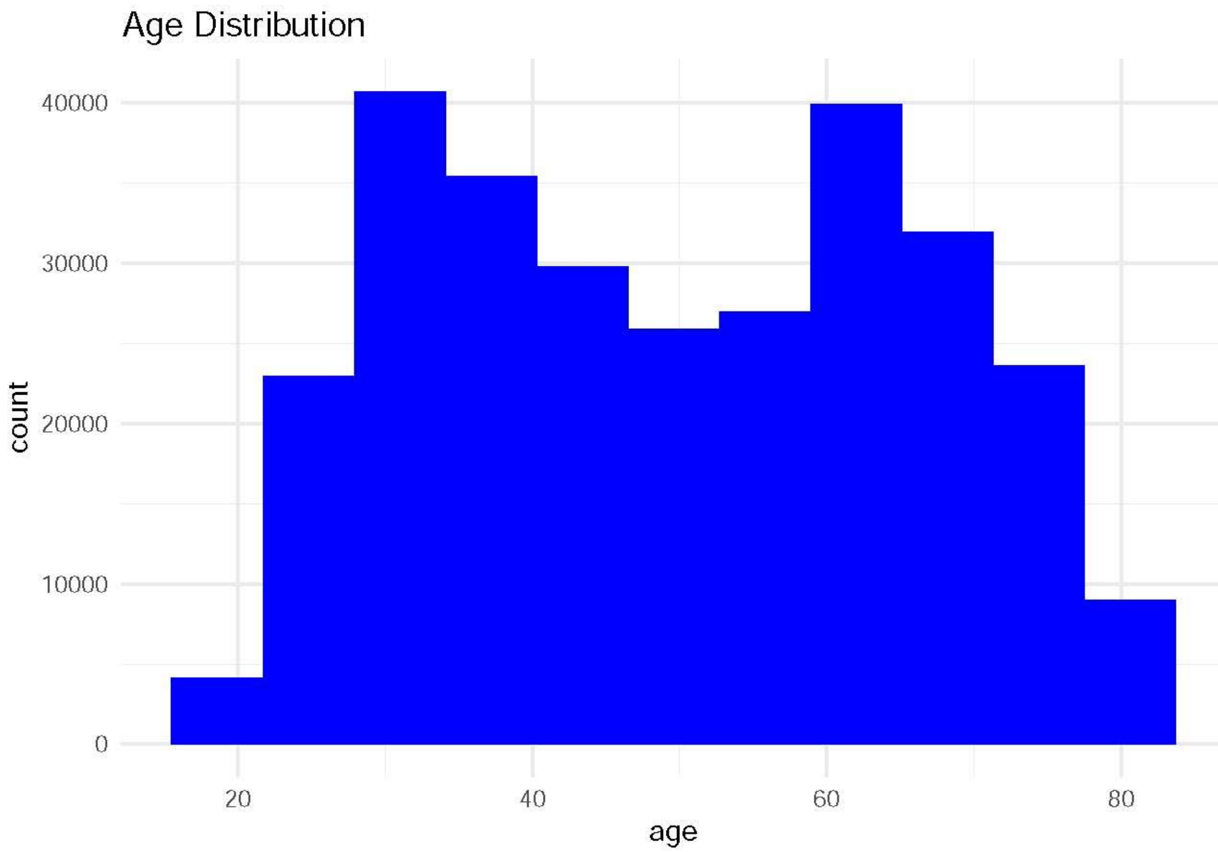


Let’s examine the age column.



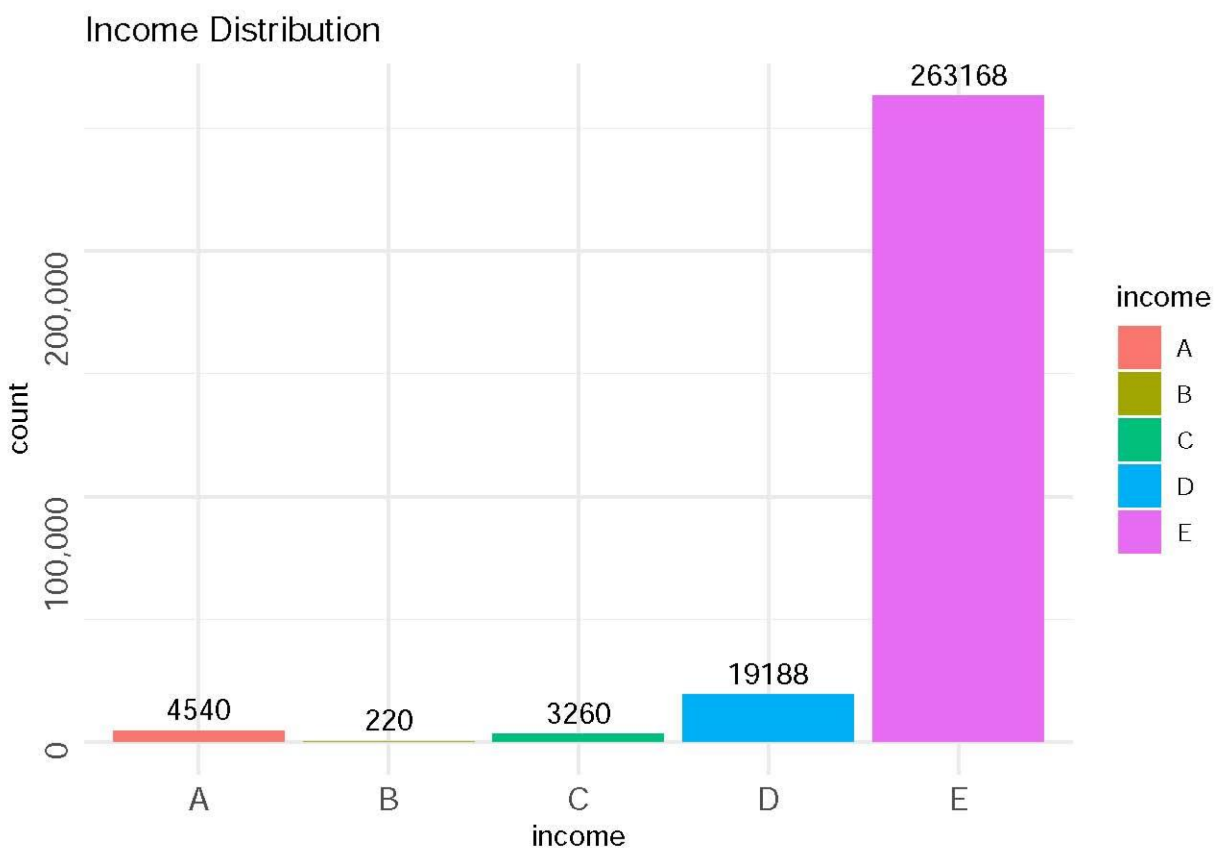
There are a few outliers in the age column probably related to typos. We will remove them.

```
df <df %>% filter(age < 95)
```



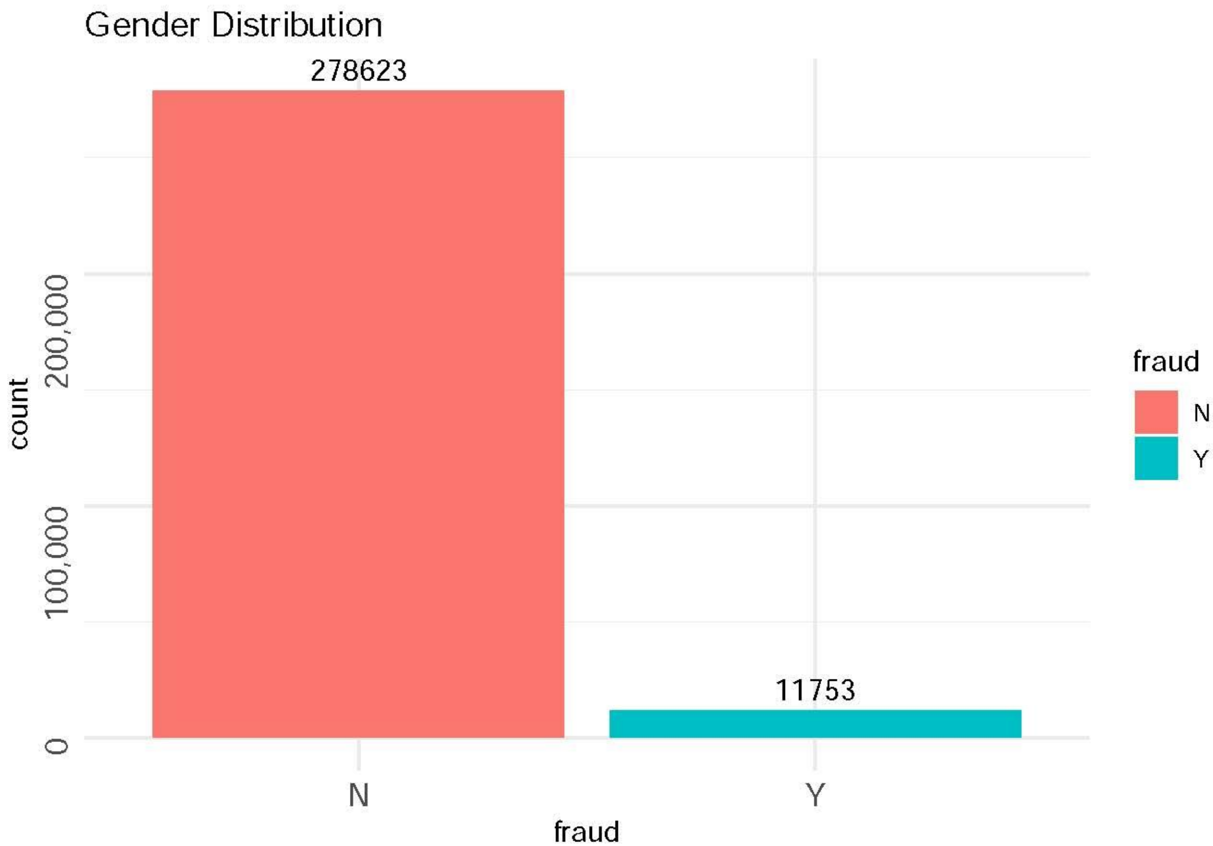
Now age distribution looks more realistic, and data distribution looks binomial, with two spikes in 30 and 65 year age groups.

Let’s look at the income feature.

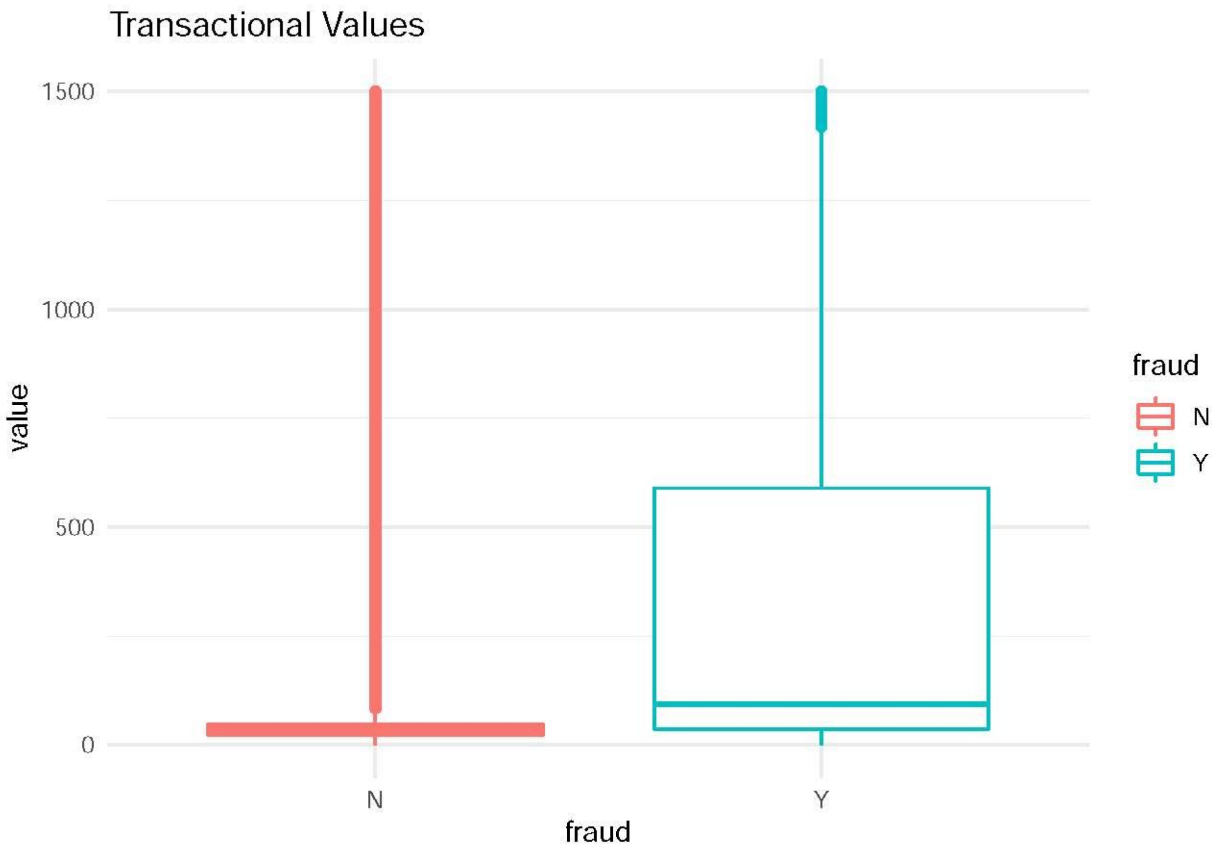


##
A B C D E
1.56349010 0.07576384 1.12268232 6.60798413 90.63007962

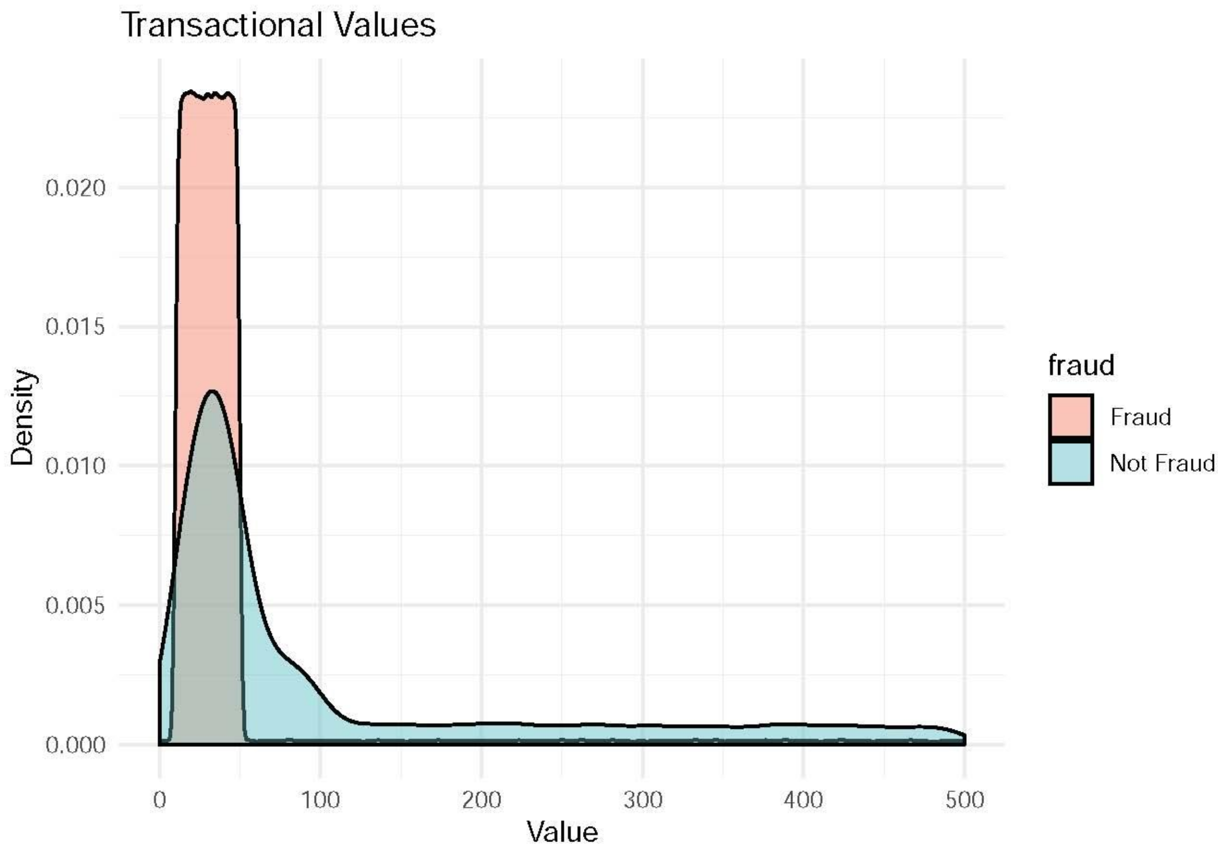
The dataset is dominated by one income group category (E 90.64%). E income category is the category with the lowest income level. There are a few customers in the highest income class (A 1.57% and B 0.08%)



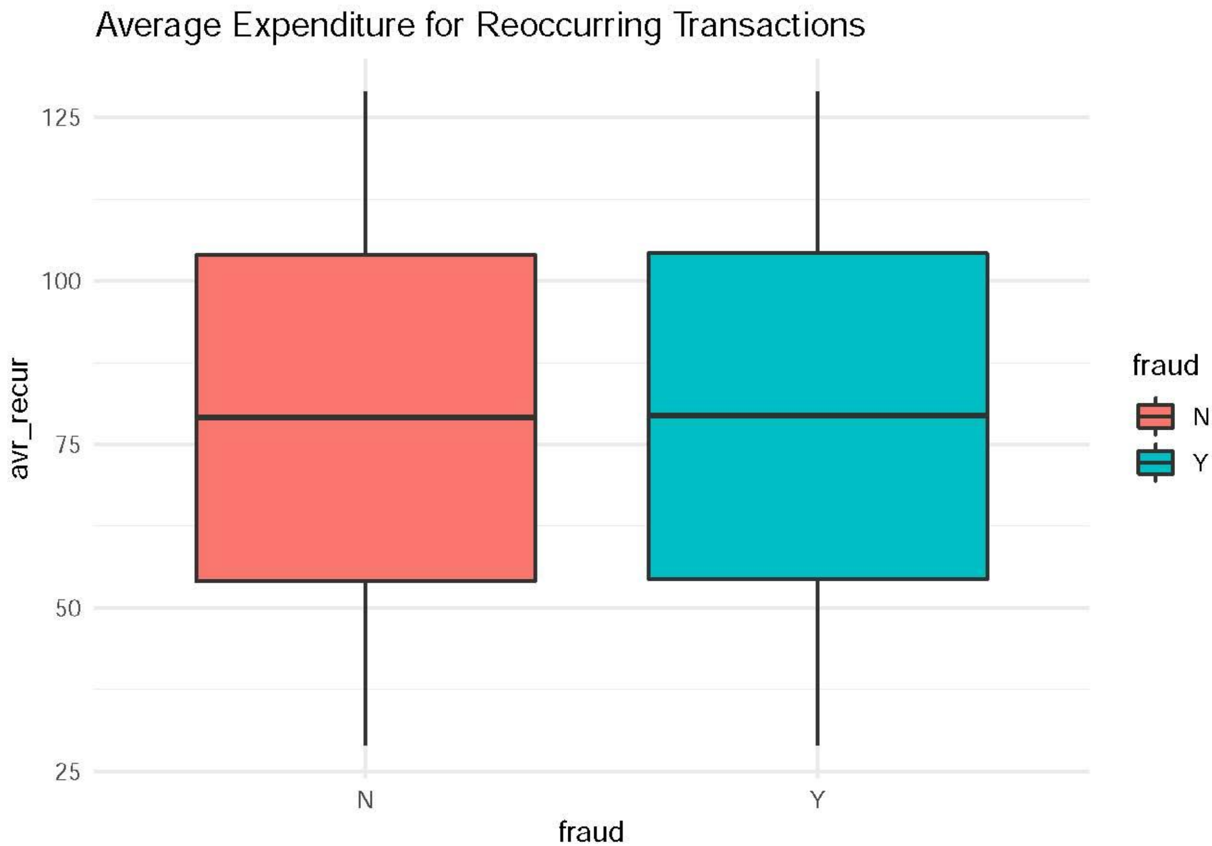
It’s clear from the box plot and density graph below that most of fraud transactions occurred in lower rage, between $5 and $55 of the transaction value. However, we also see that other values of fraud transactions are evenly distributed.



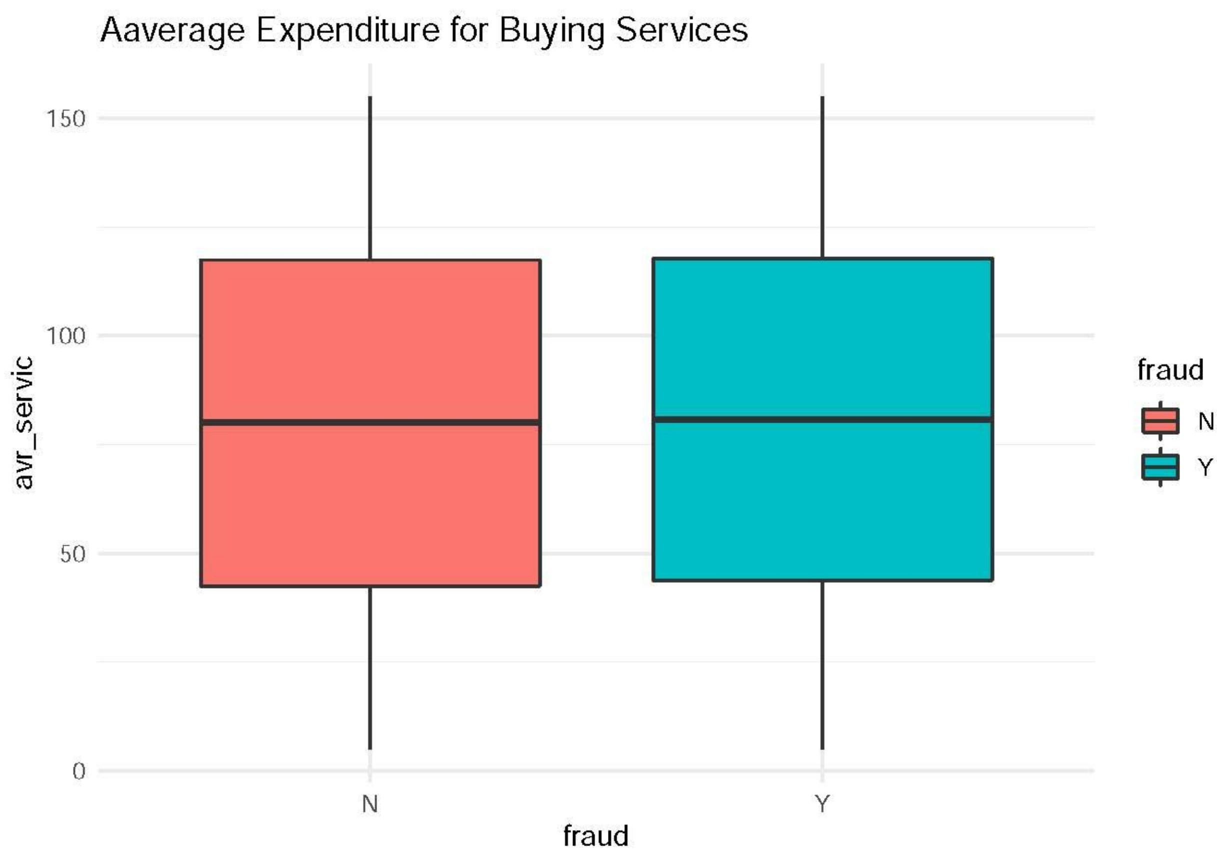
Warning: Removed 40345 rows containing nonfinite values (stat_density).



Let’s boxplot avr_recur (average expenditure for reoccurring transactions) against fraud



Interestingly to see that there are no clear differences between fraud and not fraud for this feature. Next, we check avr_servic (average expenditure for buying services) against fraud



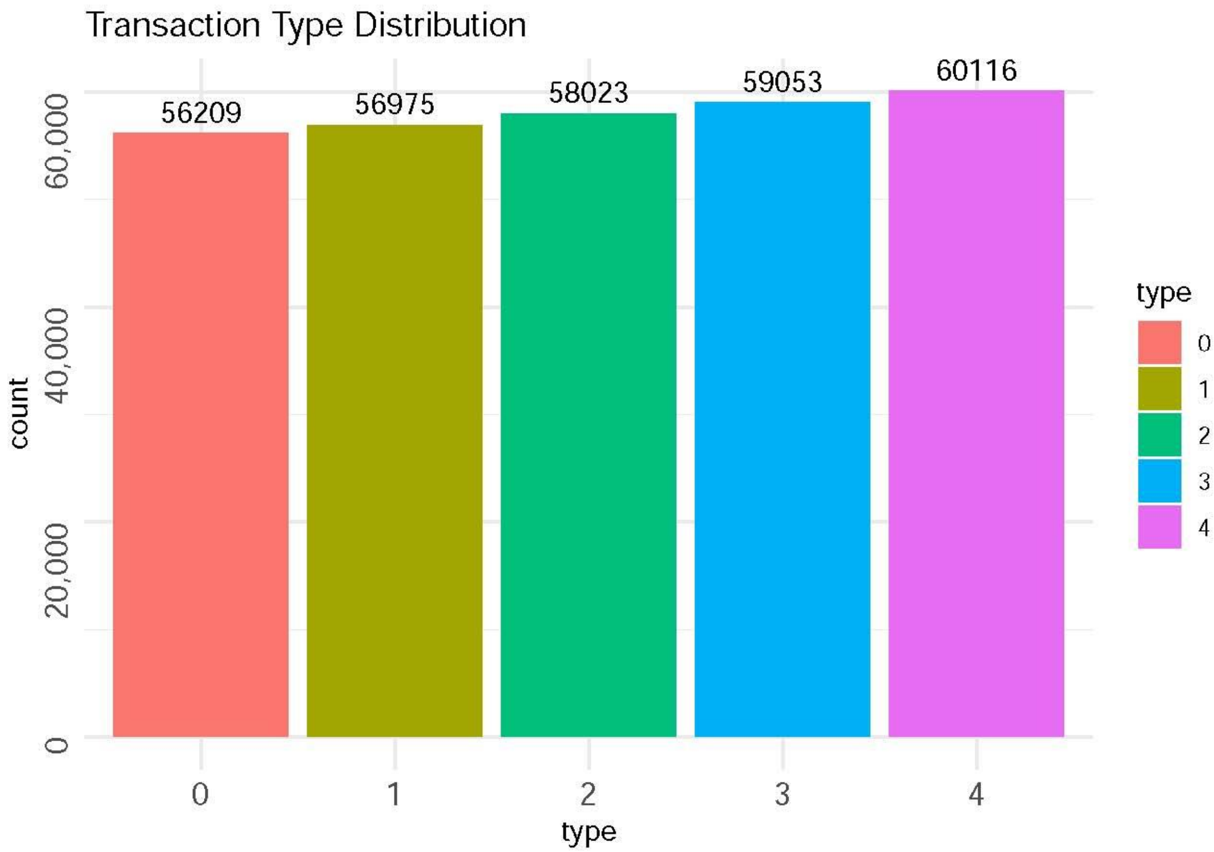
Similar picture as we’ve seen before, the range of transactions is between 0 and 160 for both fraud and not fraud transactions.

Let’s take a look at avr_go (average expenditure for buying goods) against fraud There is no clear difference between two (fraud, not fraud) classes. We will continue checking avr_int_se (average expenditure for buying services online) and avr_int_go (average expenditure for buying goods online)

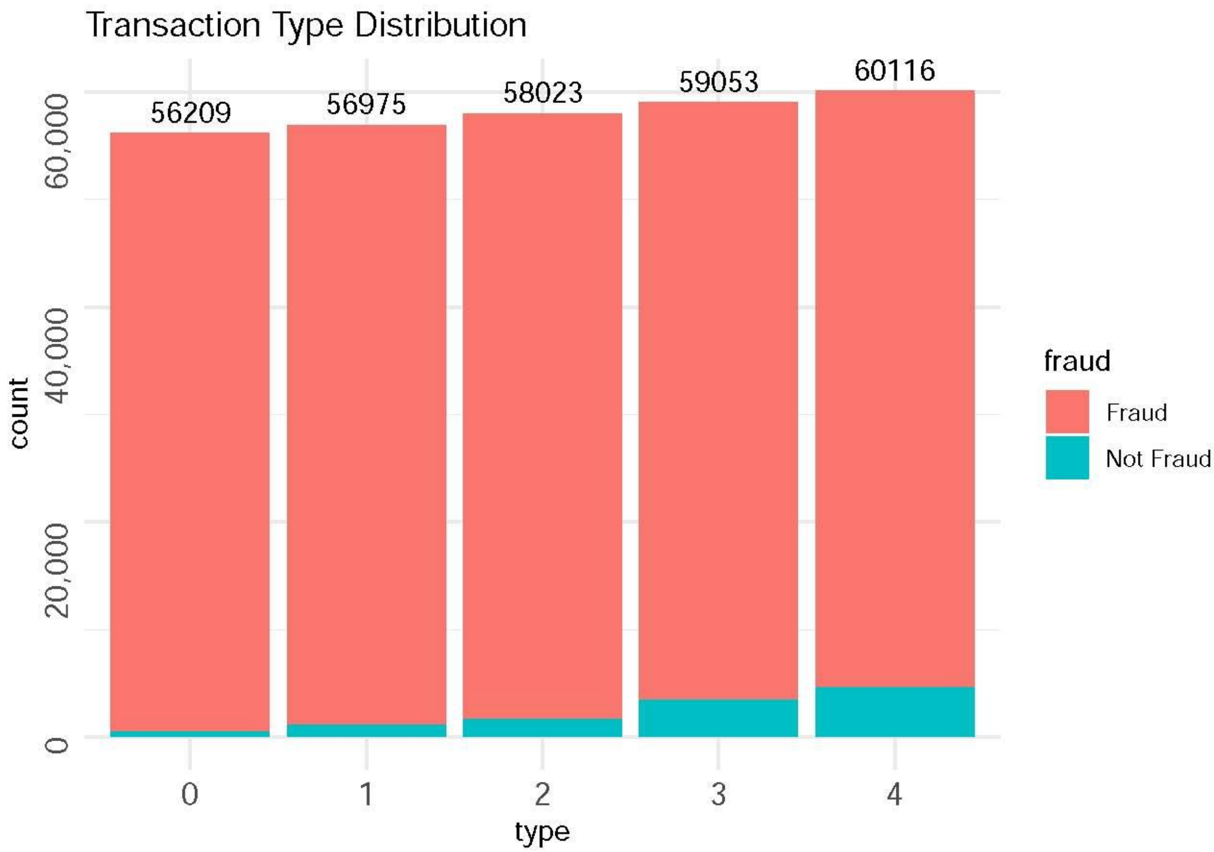

Average Expenditure for Buying Goods
avr_go
75
50
25
N
Y
fraud
fraud
N
Y

We see high variability in data for both fraudulent and not fraudulent transactions for avr_int_se feature. It looks like most of the fraudulent transactions occurred for the online services category.

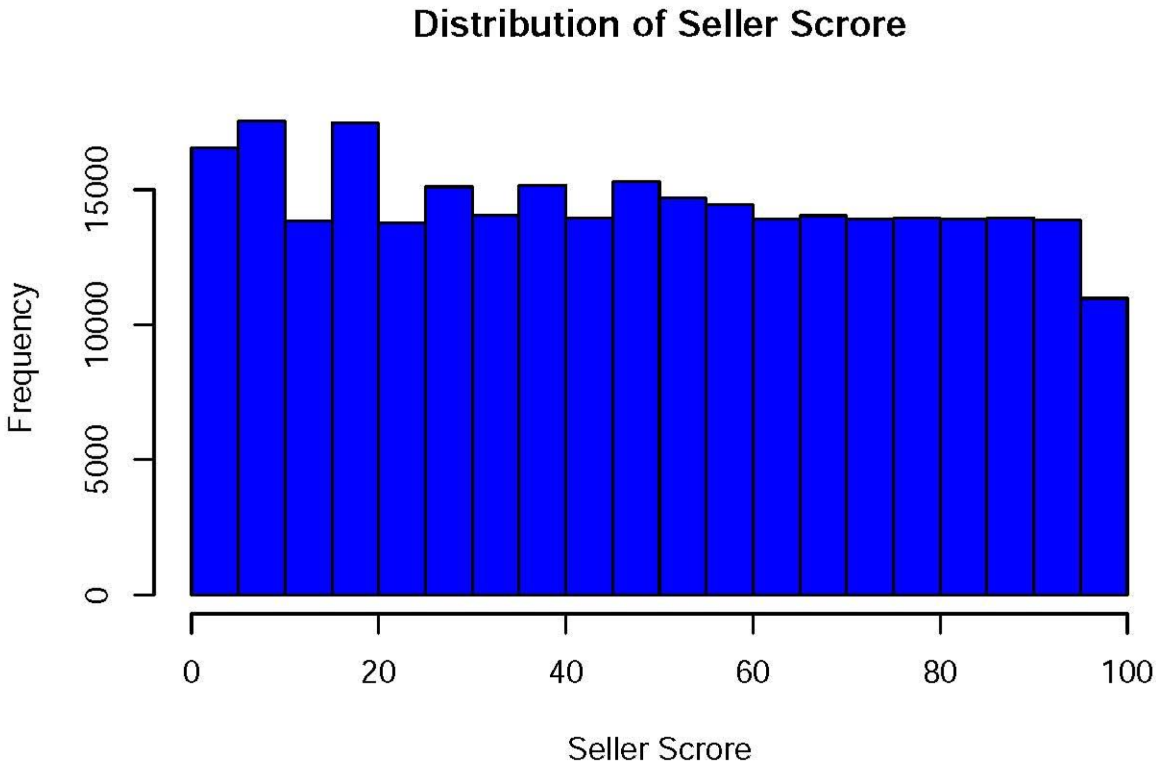
Next, we explore the type of transaction feature. This feature describes five categories each transaction belongs to (0recurrent, 1goods, 2services, 3online goods or 4online services)



The type feature has a uniform distribution.



It seems the online services category has the highest percentage of fraudulent transactions. Cheking seller score feature.



Interestingly to see that seller score feature has a uniform distribution.

Very interesting, only seven seller scores have fraudulent transactions and only two of the seven have a very high percentage of fraud.

The conclusion of our analysis showed that the factors affecting the chance of fraud have much more to do with the type of the transaction, how far from the average the value of the transaction is and the income of the buyer (wealth people tend to have fewer frauds – better financial education?). And only after that, we have the score of the seller.

Note that the only personal parameter which seems to affect the level of fraud is the income (Age and sex doesn´t seem to have any significant impact). Now with or database adjusted we tested three possible strategies:

Selecting the training data and the test data

The idea is to use 95% of the measurements as our training data and 5% as our test data. We had a database with 290.398 clients and we separated it into training data 275.878 and test data 14.520.

Approach /Analytical problem

Initially, we realized that the variable value only has a meaning as long it is compared with the average expenditure with this particular type of transaction. Given this fact, we realized that it would be necessary to create a synthetic variable called "Dispersion". Dispersion is created comparing the value of the transaction and its type with the average expenditure with this particular type. Example: If the value is equal R$ 20,00 and type equal 0. That means this is a recurrent transaction. The average expenditure with recurrent transactions is R$ 25,00. In that case "Dispersion" will be: absolute (2520)/25 > 0.20. This variable gives us a view of how far from the average the value of the transaction.

In sequence, we evaluated if we could deploy the method decisiontree directly to identify the frauds. The results were a bit disappointing, although the accuracy seems to be good it happens just because the data is imbalanced, and the frauds are 4% of the total.

The objective is to actually say if the transaction is a fraud or not (not just calculate the chance it to be). Note it identified correctly only 26% of the frauds (157 out of 588), although with a very low false positive (0,2%).

```
Confusion Matrix and Statistics

          Reference
Prediction     N     Y
         N 13898   431
         Y    34   157

               Accuracy : 0.968
                 95% CI : (0.965, 0.9708)
    No Information Rate : 0.9595
    P-Value [Acc > NIR] : 4.669e-08

                  Kappa : 0.391

 Mcnemar's Test P-Value : < 2.2e-16

            Sensitivity : 0.9976
            Specificity : 0.2670
         Pos Pred Value : 0.9699
         Neg Pred Value : 0.8220
             Prevalence : 0.9595
         Detection Rate : 0.9572
   Detection Prevalence : 0.9868
      Balanced Accuracy : 0.6323
```

However, the method indicated how many clusters would be ideal (74) and also gave us an idea about how to proceed. The tree also discovered an interesting pattern: The personal data has almost nothing to do with the results. The relevant factors identified were:

. • Score of the seller – Indicates the seller is often target for frauds (probably due type of service or lack of internal controls). • The type of transaction – Internet services have a way more frauds than everybody else

. • City – Transactions where the buyer and the seller are in different cities have much more frauds (they tend to overlap with internet services sales). • Dispersion (How far from the average spent with this kind of item the value of the operation is)

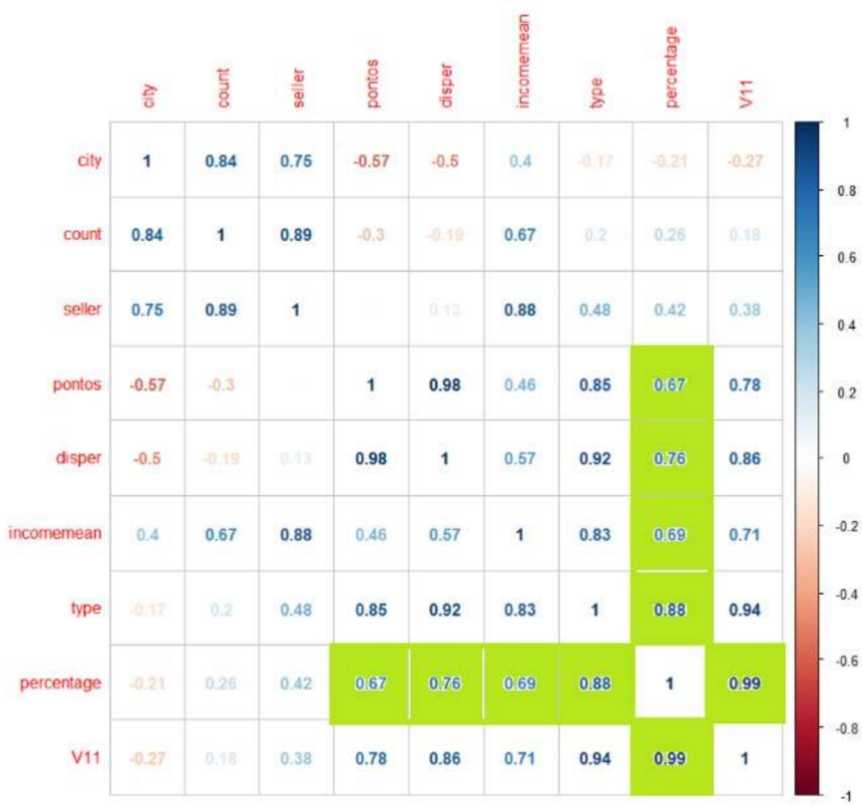
Then, we decided to create a second synthetic variable (V11). To get to the V11 we grouped the transactions using kmeans and checked the % of the frauds in each cluster. In sequence, we verified to which cluster the transaction belongs and loaded this % into V11.

In the sequence when we grouped the transactions by clusters we noticed that there were direct and inverse correlations between some of the variables and the frequency of occurrence of frauds. Analyzing it further we realized that we could measure this correlation in a variable. Therefore we created a third synthetic variable which we called "Points"

The correlations identified were as follows: That understanding allowed us to create an algorithm that gives the transaction a score between 1 and 8 (the closer you get to 8 the bigger the chances to have a fraud). That variable becomes another of our indicators. Therefore we created three synthetic variables "Dispersion", "V11" and "Points".

	fraud	total	percentage	pontos	incomemean	city	count	seller	disper	type	V11	V12
1	0	0	0.00000000	0	0.0000000	0.00000000	0.0000000	0.0000000	0.00000000	0.0000000	0.00000000	0.0000000
2	11129	257284	0.04325570	1	0.2224684	0.78694773	0.8936676	0.4836477	0.03171155	0.5155814	0.04148007	0.9585199
3	10665	176858	0.06030262	2	0.2193214	0.69504541	0.8478000	0.3839804	0.04185849	0.6262858	0.05724616	0.9427538
4	9028	84225	0.10718908	3	0.2374615	0.38884540	0.6939401	0.3978975	0.07532368	0.8855479	0.09684283	0.9031572
5	8539	68613	0.12445163	4	0.2299642	0.28858617	0.6347340	0.3975054	0.08782032	0.9205853	0.11061024	0.8893898
6	7797	55553	0.14035246	5	0.2170008	0.26569850	0.6040410	0.3427865	0.09242719	0.9258642	0.12386626	0.8761337
7	4907	31702	0.15478519	6	0.2181868	0.04520746	0.5522413	0.3000573	0.11571376	0.9813297	0.13721372	0.8627863
8	2056	22233	0.09247515	7	0.2097575	0.00000000	0.3972168	0.2496612	0.12394320	0.9885648	0.09891327	0.9010867
9	787	8812	0.08931003	8	0.2p00000	0.00000000	0.0000000	0.2306427	0.13803058	0.9929159	0.09794667	0.9020533

Correlation	Chance of fraud (Correlation)
Mean income goes up frequency of frauds goes down	Inverse
Mean same city goes up frequency of frauds goes down	Inverse
Mean same country goes up frequency of frauds goes down	Inverse
Mean seller score goes up frequency of fruads goes down	Inverse
Mean dispersion goes up frequency of frauds goes up	Direct
Mean type goes up frequency of frauds goes up	Direct
cluster % positive Mean goes up frequency of frauds goes up	Direct
Cluster % negative Mean goes up frequency of frauds goes down	Inverse



As we can see, the percentage of frauds has strong correlation with five variables:

V11 => Synthetic variable V11 (come from the clustering process % of frauds associated with the profile) is also very effective predictor. (0.99)

Type => type of the transaction (Recurrent, in person or online). (0.88)

Disper=> Synthetic variable which indicates how far from the average expenditures of this specific client

with that specific kind of item the transaction is. (0.76)

Income => Income of the buyer (0.69)

Pontos => synthetic variable merging eight parameters (0.67)

Once we finished creating the synthetic variables we evaluated that we need to treat the data regards three

aspects:

• Encoding • Crossvalidation (to test each model)

The kfold crossvalidation procedure provides a good general estimate of model performance that is not too optimistically biased, at least compared to a single traintest split.

• Balancing using SMOTE (The database is very imbalanced – frauds are just 4% of the samples)

At 4%, this is clear we have a skewed and imbalanced dataset. Imbalanced data pose classification problem for predictive modelling as most of the machine learning algorithms are used for classification were designed around the assumption of an equal number of examples for each class.

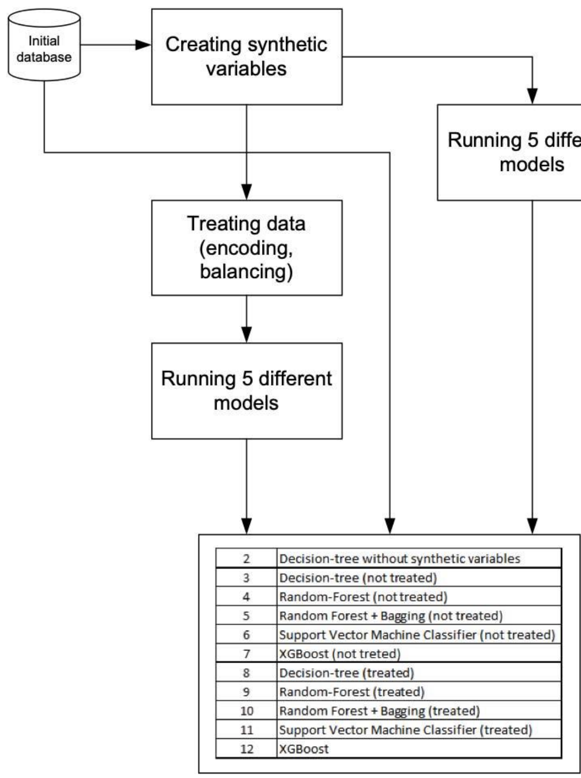
As a result, models train on imbalanced data have poor predictive performance specifically on minority class. Specifically, for fraud detection where predicting the minority class in the most important aspect of the model.

Synthetic Minority Oversampling Technique makes data balanced by synthesizing new data from the existing dataset using KNN. The approach is effective because new synthetic examples from the minority class are created that are plausible and relatively close in feature space to existing examples from the minority class.

Once we got the data encoded and balanced we tested five methods to spot frauds. We also tested these five methods without treating the data just to check if balancing the data was, in fact, improving the quality of the identification process. In a way, it was a research process.

• Decisiontree (Baseline Model) • RandomForest • Random Forest + Bagging • Support Vector Machine Classifier • XGBoost

In logical terms we created the following analysis scenarios: This strategy of testing several possible techniques was important because we needed to explore alternatives and try through these techniques to improve the success rate of the identification process.



Summary of findings /Evaluating the results

We tested several models training to identify which ones yield the best results. It was a systematic process, where we run the algorithm and evaluate the confusion Matrix. The objective was to identify the % of frauds identified correctly and the percentage of false positive.

Using DecisionTree model (not treated)

The composition of these variables applied in a Decision treemethod generated the following result: In a test set composed by 5% of the total database (5% of 290.398 > 14.520)

• The model identified as fraud and they were in fact frauds 231 (1,57%) • The model identified as fraud but they were not 444 (3,05%) • The model identified as not being frauds but they were 357 (2,45%) • The model identified as not being frauds and they in fact were not 13.488 (93,78%)

It spotted 60,71% of the frauds with a false positive rate (444 >3,05%)

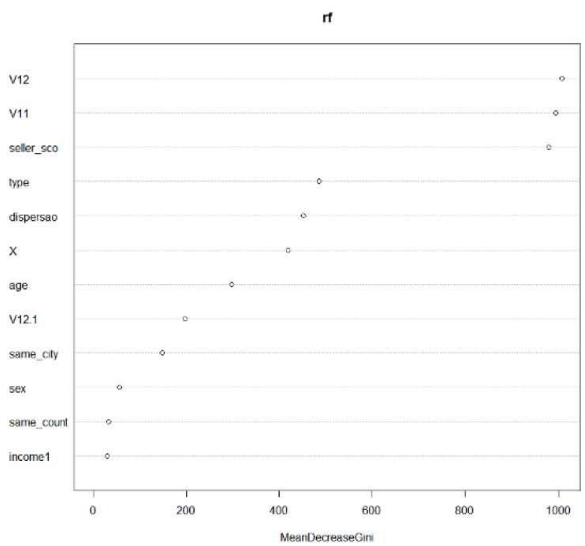
```
Confusion Matrix and Statistics

          Reference
Prediction     0     1
         0 13488   231
         1   444   357

               Accuracy : 0.9535
                 95% CI : (0.95, 0.9569)
    No Information Rate : 0.9595
    P-Value [Acc > NIR] : 0.9998

                  Kappa : 0.4902

 Mcnemar's Test P-Value : 3.353e-16

            Sensitivity : 0.9681
            Specificity : 0.6071
         Pos Pred Value : 0.9832
         Neg Pred Value : 0.4457
             Prevalence : 0.9595
         Detection Rate : 0.9289
   Detection Prevalence : 0.9448
      Balanced Accuracy : 0.7876

       'Positive' Class : 0
```

Using Random Forest model (not treated) If instead using decision tree we use random forest the results would be like: In a test set composed by 5% of the total database (5% of 290.398 > 14.520)

• The model identified as fraud and they were in fact frauds 364 (2,5%) • The model identified as fraud but they were not 315 (2,1%) • The model identified as not being frauds but they were 224 (1,5%) • The model identified as not being frauds and they in fact were not 13.617 (93,9%)

It spotted 62% of the frauds with false positive rate (False positive >2,1%) Therefore using random forest would be more effective in identifying frauds but would triple the percentage of false positive.

```
Confusion Matrix and Statistics

          Reference
Prediction     0     1
         0 13617   224
         1   315   364

               Accuracy : 0.9629
                 95% CI : (0.9597, 0.9659)
    No Information Rate : 0.9595
    P-Value [Acc > NIR] : 0.0195472

                  Kappa : 0.5553

 Mcnemar's Test P-Value : 0.0001059

            Sensitivity : 0.9774
            Specificity : 0.6190
         Pos Pred Value : 0.9838
         Neg Pred Value : 0.5361
             Prevalence : 0.9595
         Detection Rate : 0.9378
   Detection Prevalence : 0.9532
      Balanced Accuracy : 0.7982

       'Positive' Class : 0
```



Note the relative importance of the synthetic variables.

1. 1. Pontos – V12 – Synthetic variable
2. 2. V11 Kmeans % Synthetic variable
3. 3. Seller_scor – Original variable (seller info)
4. 4. Type of transaction Original variable

5. Dispersion – synthetic variable Note that this ranking doesn´t match exactly the ranking identified when using correlation.

Using the Random Forest + Bagging model (not treated)

In a test set composed by 5% of the total database (5% of 290.398 > 14.284)

• The model identified as fraud and they were in fact frauds 457 (3,14%) • The model identified as fraud but they were not 677 (4,6%) • The model identified as not being frauds but they were 131 (0,9%) • The model identified as not being frauds and they in fact were not 13.255 (91,28%)

It spotted 77% of the frauds with false positive rate (False positive >4,6%)

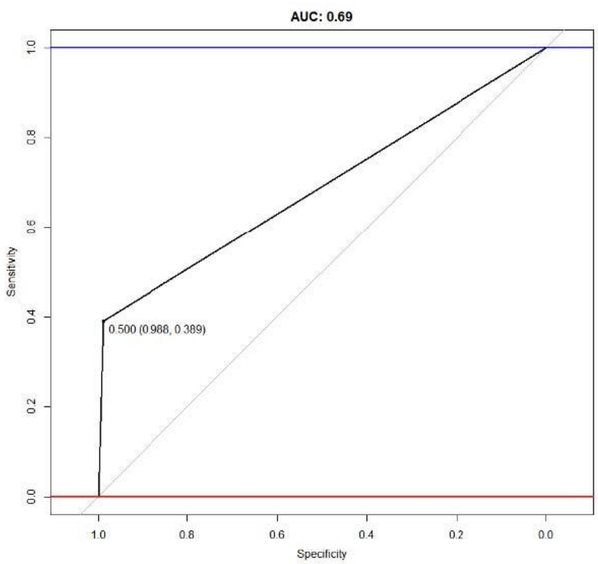
```
Confusion Matrix and Statistics

          Reference
Prediction     0     1
         0 13255   131
         1   677   457

               Accuracy : 0.9444
                 95% CI : (0.9405, 0.948)
    No Information Rate : 0.9595
    P-Value [Acc > NIR] : 1

                  Kappa : 0.5043

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

            Sensitivity : 0.9514
            Specificity : 0.7772
         Pos Pred Value : 0.9902
         Neg Pred Value : 0.4030
             Prevalence : 0.9595
         Detection Rate : 0.9129
   Detection Prevalence : 0.9219
      Balanced Accuracy : 0.8643

       'Positive' Class : 0
```

Using the Support Vector Machine Classifier model (not treated) In a test set composed by 5% of the total database (5% of 290.398 > 14.520)

• The model identified as fraud and they were in fact frauds 229 (1,5%) • The model identified as fraud but they were not 162 (1,1%) • The model identified as not being frauds but they were 359 (2,4%) • The model identified as not being frauds and they in fact were not 13.770 (94,83%)

It spotted 38,94% of the frauds with false positive rate (False positive >1,1%)

```
Confusion Matrix and Statistics

          Reference
Prediction     0     1
         0 13770   359
         1   162   229

               Accuracy : 0.9641
                 95% CI : (0.961, 0.9671)
    No Information Rate : 0.9595
    P-Value [Acc > NIR] : 0.002212

                  Kappa : 0.45

 Mcnemar's Test P-Value : < 2.2e-16

            Sensitivity : 0.9884
            Specificity : 0.3895
         Pos Pred Value : 0.9746
         Neg Pred Value : 0.5857
             Prevalence : 0.9595
         Detection Rate : 0.9483
   Detection Prevalence : 0.9731
      Balanced Accuracy : 0.6889

       'Positive' Class : 0
```



Using the XGBoost model(Not treated)

In a test set composed by 5% of the total database (5% of 290.398 > 14.520)

• The model identified as fraud and they were in fact frauds 537 (3,6%) • The model identified as fraud but they were not 780 (5,3%) • The model identified as not being frauds but they were 51 (0,3%) • The model identified as not being frauds and they in fact were not 13.152 (90,57%)

It spotted 91,33% of the frauds with false positive rate (False positive >5,30%)

```
Confusion Matrix and Statistics

          Reference
Prediction     0     1
         0 13152    51
         1   780   537

               Accuracy : 0.9428
                 95% CI : (0.9389, 0.9465)
    No Information Rate : 0.9595
    P-Value [Acc > NIR] : 1

                  Kappa : 0.5379

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

            Sensitivity : 0.9440
            Specificity : 0.9133
         Pos Pred Value : 0.9961
         Neg Pred Value : 0.4077
             Prevalence : 0.9595
         Detection Rate : 0.9058
   Detection Prevalence : 0.9093
      Balanced Accuracy : 0.9286

       'Positive' Class : 0
```

Using DecisionTree model (treated with SMOTE)

The composition of these variables applied in a Decision treemethod generated the following result: In a test set composed by 5% of the total database (5% of 290.398 > 14.520)

• The model identified as fraud and they were in fact frauds 314 (2,1%) • The model identified as fraud but they were not 1.036 (7,13%) • The model identified as not being frauds but they were 274 (1,88%) •

The model identified as not being frauds and they in fact were not 12.896 (88,81%) It spotted 53,40% of the frauds with a false positive rate (False positive > 7,13%)

```
Confusion Matrix and Statistics

          Reference
Prediction     0     1
         0 12896   274
         1  1036   314

               Accuracy : 0.9098
                 95% CI : (0.905, 0.9144)
    No Information Rate : 0.9595
    P-Value [Acc > NIR] : 1

                  Kappa : 0.2836

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

            Sensitivity : 0.9256
            Specificity : 0.5340
         Pos Pred Value : 0.9792
         Neg Pred Value : 0.2326
             Prevalence : 0.9595
         Detection Rate : 0.8882
   Detection Prevalence : 0.9070
      Balanced Accuracy : 0.7298

       'Positive' Class : 0
```

Using Random Forest (treated with SMOTE)

The composition of these variables applied in a Decision treemethod generated the following result: In a test set composed by 5% of the total database (5% of 290.398 > 14.520)

• The model identified as fraud and they were in fact frauds 463 (0,8%) • The model identified as fraud but they were not 1.163 (8,0%) • The model identified as not being frauds but they were 125 (3,1%) • The model identified as not being frauds and they in fact were not 12.769 (87,94%)

It spotted 78,40% of the frauds with a false positive rate (False positive >8,0%)

```
Confusion Matrix and Statistics

          Reference
Prediction     0     1
         0 12769   125
         1  1163   463

               Accuracy : 0.9113
                 95% CI : (0.9066, 0.9159)
    No Information Rate : 0.9595
    P-Value [Acc > NIR] : 1

                  Kappa : 0.3815

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

            Sensitivity : 0.9165
            Specificity : 0.7874
         Pos Pred Value : 0.9903
         Neg Pred Value : 0.2847
             Prevalence : 0.9595
         Detection Rate : 0.8794
   Detection Prevalence : 0.8880
      Balanced Accuracy : 0.8520

       'Positive' Class : 0
```

Using the Random Forest + Bagging (treated with SMOTE)

In a test set composed by 5% of the total database (5% of 290.398 > 14.520)

• The model identified as fraud and they were in fact frauds 487 (3,3%) • The model identified as fraud but they were not 905 (6,23%) • The model identified as not being frauds but they were 101 (0,6%) • The model identified as not being frauds and they in fact were not 13.027 (89,71%)

It spotted 82,82% of the frauds with false positive rate (False positive >9,9%)

```
Confusion Matrix and Statistics

          Reference
Prediction     0     1
         0 13027   101
         1   905   487

               Accuracy : 0.9307
                 95% CI : (0.9265, 0.9348)
    No Information Rate : 0.9595
    P-Value [Acc > NIR] : 1

                  Kappa : 0.4612

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

            Sensitivity : 0.9350
            Specificity : 0.8282
         Pos Pred Value : 0.9923
         Neg Pred Value : 0.3499
             Prevalence : 0.9595
         Detection Rate : 0.8972
   Detection Prevalence : 0.9041
      Balanced Accuracy : 0.8816

       'Positive' Class : 0
```

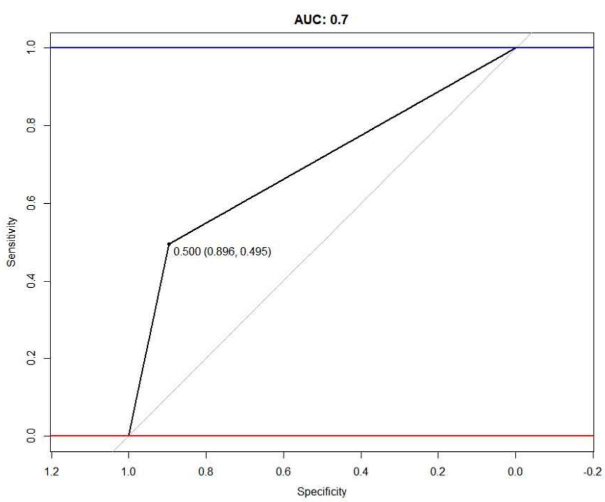
Using the Support Vector Machine Classifier model (treated with SMOTE)

In a test set composed by 5% of the total database (5% of 290.398 > 14.520)

• The model identified as fraud and they were in fact frauds 291 (2,0%) • The model identified as fraud but they were not 1450 (9,9%) • The model identified as not being frauds but they were 297 (2,0%) • The model identified as not being frauds and they in fact were not 12.482 (85,96%)

It spotted 49,49% of the frauds with false positive rate (False positive >9,9%)

```
Confusion Matrix and Statistics

          Reference
Prediction     0     1
         0 12482   297
         1  1450   291

               Accuracy : 0.8797
                 95% CI : (0.8743, 0.8849)
    No Information Rate : 0.9595
    P-Value [Acc > NIR] : 1

                  Kappa : 0.2016

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

            Sensitivity : 0.8959
            Specificity : 0.4949
         Pos Pred Value : 0.9768
         Neg Pred Value : 0.1671
             Prevalence : 0.9595
         Detection Rate : 0.8596
   Detection Prevalence : 0.8801
      Balanced Accuracy : 0.6954

       'Positive' Class : 0
```



Using the XGBoost model(treated with SMOTE)

In a test set composed by 5% of the total database (5% of 290.398 > 14.520)

• The model identified as fraud and they were in fact frauds 558 (3,8%) • The model identified as fraud but they were not 927 (6,3%) • The model identified as not being frauds but they were 30 (0,2%) • The model identified as not being frauds and they in fact were not 13.005 (89,56%)

It spotted 94,90% of the frauds with false positive rate (False positive >5,30%)

```
Confusion Matrix and Statistics

          Reference
Prediction     0     1
         0 13005    30
         1   927   558

               Accuracy : 0.9341
                 95% CI : (0.9299, 0.9381)
    No Information Rate : 0.9595
    P-Value [Acc > NIR] : 1

                  Kappa : 0.5099

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

            Sensitivity : 0.9335
            Specificity : 0.9490
         Pos Pred Value : 0.9977
         Neg Pred Value : 0.3758
             Prevalence : 0.9595
         Detection Rate : 0.8957
   Detection Prevalence : 0.8977
      Balanced Accuracy : 0.9412

       'Positive' Class : 0
```

Summarizing the methods and conclusion:

Scenario	Method	% frauds spotted	% false positives
1	**Current process**	**50,00%**	**2,00%**
2	Decision-tree without synthetic variables	26,00%	0,20%
3	Decision-tree (not treated)	60,71%	1,59%
4	Random-Forest (not treated)	62,00%	2,16%
5	Random Forest + Bagging (not treated)	77,00%	4,60%
6	Support Vector Machine Classifier (not treated)	38,94%	1,10%
7	XGBoost (not treted)	91,32%	5,30%
8	Decision-tree (treated)	53,40%	7,13%
9	Random-Forest (treated)	78,74%	8,00%
10	Random Forest + Bagging (treated)	82,82%	6,23%
11	Support Vector Machine Classifier (treated)	49,48%	9,90%
12	XGBoost (treated)	94,89%	6,38%

The table above represents a potential improvement of 44,89 % over the current model. That means in practical terms that every day you would be able to spot something around 5.936 additional frauds, totalizing a value around CAD 8.444.000 a month in terms of avoided frauds. Of course, there is also the issue of the false positive that can lead to alienating clients, which due to our lack of understanding of the business is hard for us to define what would be acceptable.

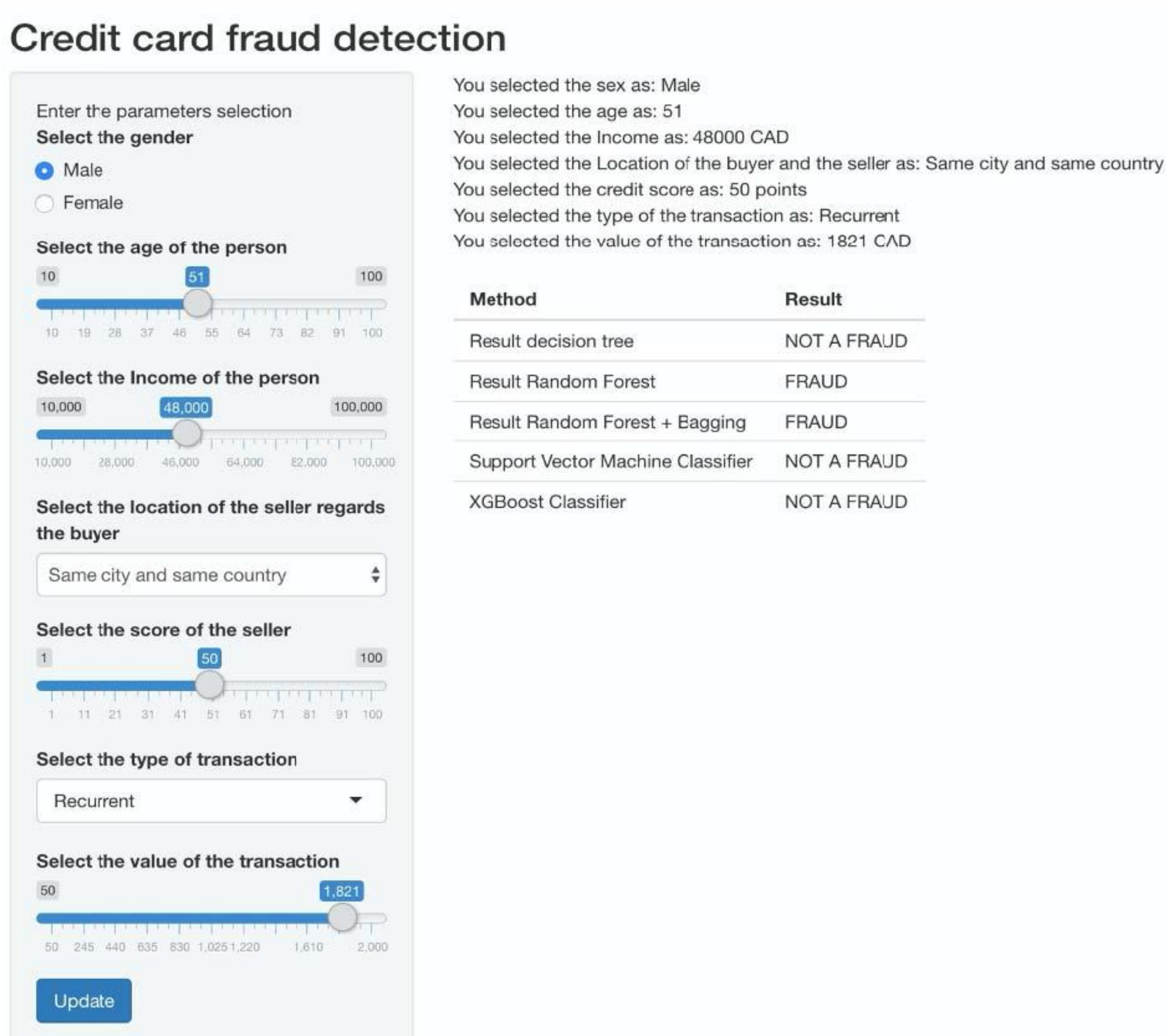
However, the client can improve the most accurate model by accepting higher losses, especially from highnet-worth cardholders, in order to prevent alienating those clients and losing business due to the increase in false-positive detection.

Another important additional advantage would be having the dynamic process as it "learns" new patterns as they appear and therefore will demand less effort to maintain.

We understand that the actual implementation of the model needs to be analyzed with care and skepticism, tests need to be made and eventual performance issues evaluated. (We need to remember that the whole verification has to occur in few seconds just after the user made the transaction – although in the online services we may have the option of letting an order "pending approval").

In summary, although we recognize that there are several issues that need to be evaluated it seems clear that deploying the machine learning model to this process would add a lot of value and surely should be considered.

Shiny App



We created and deployed a simple shiny app (can be seen here https://stant.shinyapps.io/fraud/) that evaluates five models we built previously. The app loads Decision Tree, Random Forest, Tree Bagging, SVM and XGBoost model previously saved using file RDA format. All these models were trained on balanced data using SMOTE. The app uses new features that we engineered previously (Dispersion, V10, V11, pontos). The enduser can select the following variables to predict fraudulent transactions: age, sex, income, the score of the seller, transaction type, value of the transaction. The output of the app shows a table with the prediction for each model. We believe that the current app can be further improved for example it can take a majority voting and shows only one output based on all models. It can provide more accurate results since certain models are good at predicting fraud and others are good at limiting falsepositive results.

Limitations

We faced a few significant hardware issues that limited our app to perform the comparison of all 10 models (5 models with SMOTE and 5 models without SMOTE). The same issue we faced when we tried to add a majority voting for the shiny app. When deployed the app online using shinyapps.io however we experienced out of memory issues even with a limited amount of models. Despite all limitations, we still believe that the app and models can have business applications for the client and can be used in tandem with the current model/processes to detect fraudulent transactions.