Unsupervised learning project (88780)

Zohar Yakobi – 322691585 and Sharon Komissarov – 322880964.

March 29, 2020

Contents

1 Abstract

1.1 The data

The data we chose is "Credit card Fraud data": 284,807 X 31 where each line represents a credit card transaction, the columns are a little more complicated: There are 3 categorical columns which are: "Class", "Amount", "Time" and in addition There are another 28 columns that are the product of dimensionality reduction of PCA on the original data (which we probably did not receive due to privacy reasons). In this project we will use various models and methods in order to see how accurate they are in detecting whether a transaction is a normal payment or a fraud.

1.2 Our goals

- Understand the distribution of the data that was provided to us.
  - Visualize the data and understand if it's separable.
  - Determine the clustering algorithms we are going to use and decide which one gave the best performance.
  - Decide whether a transaction can be represented as anomaly.
  - Evaluate the results with tools that are suitable to imbalanced data as we have.

2 Description of the tasks

2.1 Statistics

We performed some basic statistics: we first calculated the correlation matrix between the columns of the data, but because the data we received went through a PCA process, there are no high correlations between the columns and therefore the correlation between the columns did not help us at all.

As I mentioned there is a column called "Class" that represents whether the transaction is fraud or not: 0 represents a clean transaction (not fraud), 1 represents fraud. According to an analysis we made, 0.172 percent of the data are frauds and 99.928 percent of the data are legal transactions:

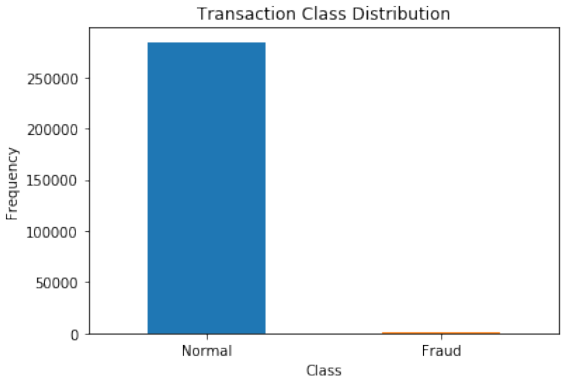


Figure 1

2.2 Visualization

We have made a number of basic visualizations: we compared between the average amount of the fraud transactions and the average of the legal transactions and we found that the frauds column is significantly larger:

Figure 2

You can pay attention to another interesting visualization that shows that the frauds and legal deals are running roughly the same over time (meaning that time does not so much affect a transaction whether it is fraud or not):

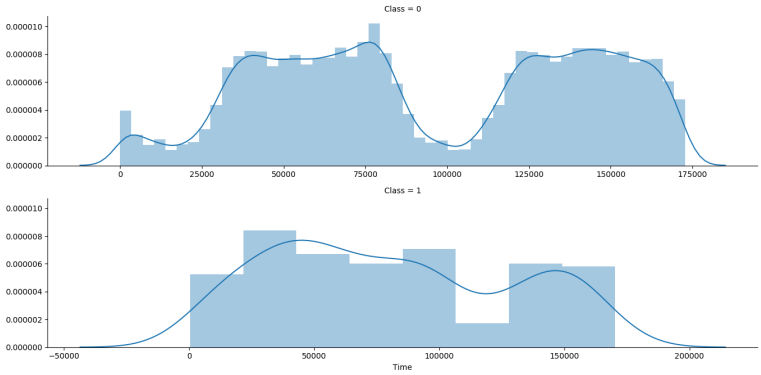


Figure 3

In addition, we plotted the distribution of each column and it seems standard:

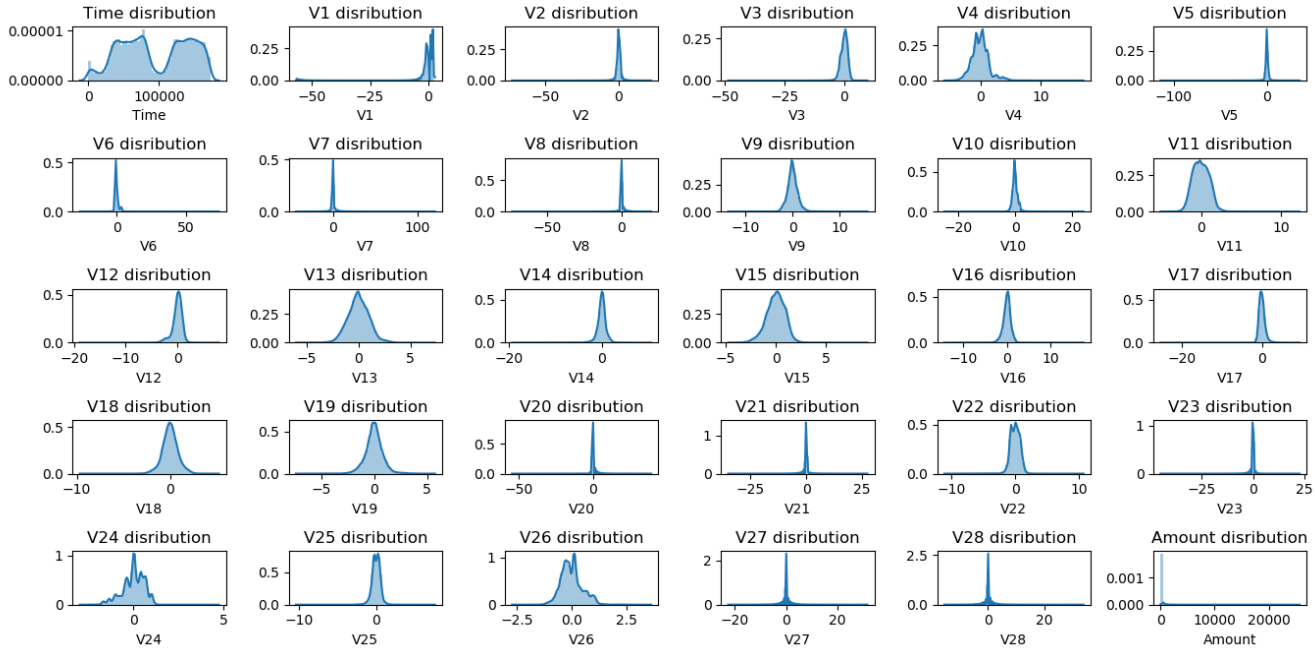


Figure 4

2.3 The significant actions in the project

After seeing quite a few visualizations and statistics, we decided to reduce dimensions in many kinds of tools we learned in the lecture to make it easier to cluster and plot the data.

Our next step is the clustering itself, we wanted to cluster the data (for two clusters that are fraud and not fraud) using cluster algorithms learned in class.

In addition to reducing dimensions and clustering, we have also turned to another aspect which is anomaly detection to try to cluster the data and compare results.

3 The method and parmeters we used

3.1 Work process

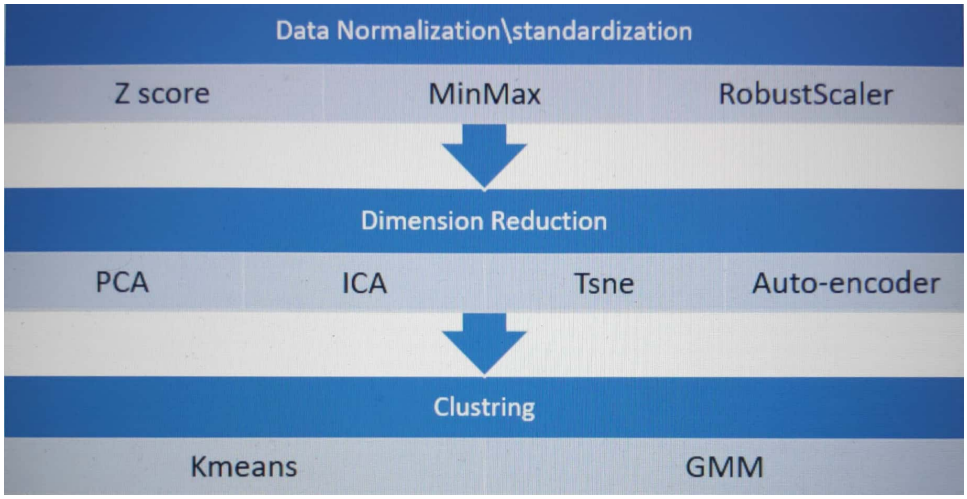


Figure 5

3.2 Data Normalization/standardization

The methods chosen are widely used for data analysis purposes.
Each one has its advantages upon the other methods when dealing with different aspects of the data (outliers, dispersion , etc).
therefore, we decided to examine a variety of techniques and to get the best performance possible.

3.3 Dimension Reduction

3.3.1 Tsne

After the basic preprocessing and normalization, we run Tsne on a small amount of the data equally distributed between fraud and legal transactions.
Tsne can give us an indication if further clustering models will perform well in separating fraud cases from non-fraud cases.

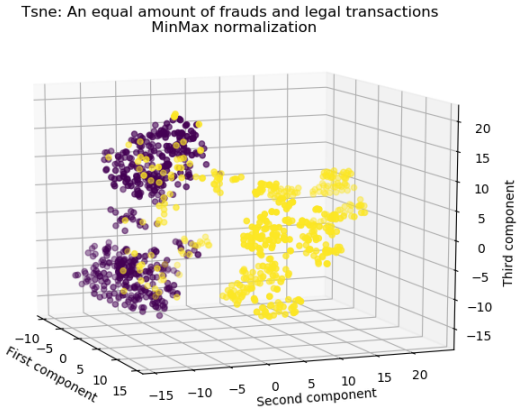


Figure 6

3.3.2 Linear methods

To avoid the curse of high dimensionality, for further clustering and to obtain visualization of the whole data, PCA had a major advantage due to the proportionally large two to three eigenvalues of the covariance matrix upon the other ones. The three largest eigenvalues described more than 80 percent of the variance.

We also implemented ICA because of the possibility that the data isn't normally distributed.

3.3.3 Un-linear methods

Since the previously introduced methods cannot describe more than linear connections of the data.
We tried an un-linear technique which is the Auto-encoder.
In the implementation process of the Auto-encoder, we used a Neural network with two hidden layers, the architecture looked as follows.

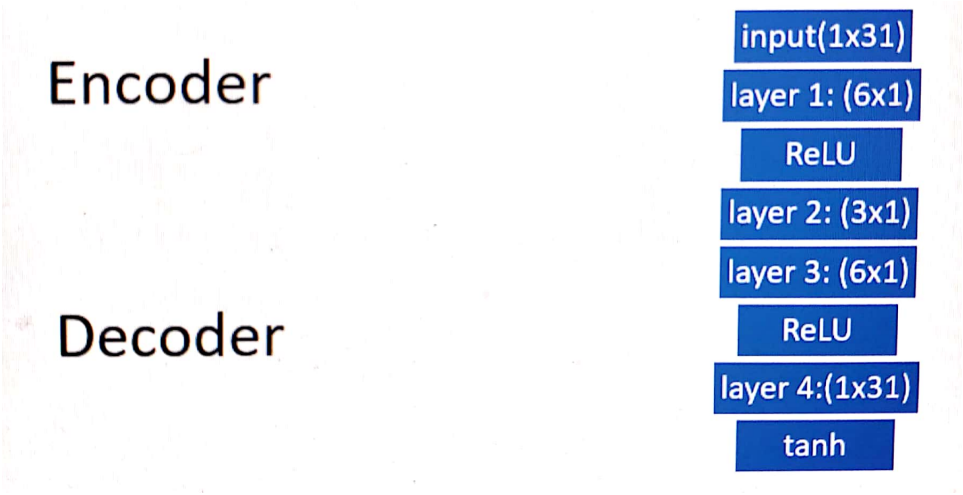


Figure 7

Also here we reduced the data into three dimensions for visualization purposes.

3.4 Clustering

We executed every possible combination (Brute force) of the normalization and dimension reduction methods mentioned above together with different clustering algorithms in order to determine the best one. The clustering algorithms that we used are K-means and GMM.

The evaluation of clustering stability will be performed by silhouette analysis and the quality will be evaluated with confusion matrix.

3.5 Anomaly Detection

We used this technique on our dataset because we have solid evidences that the fraud transactions are behaving as anomalies.
As can be seen in figure 2 the average amount of a fraud transaction is significantly higher than the average of the legal ones.
This pattern can also be seen in the MSE loss function when using the autoencoder.
therefore we used two methods to find these anomalies.

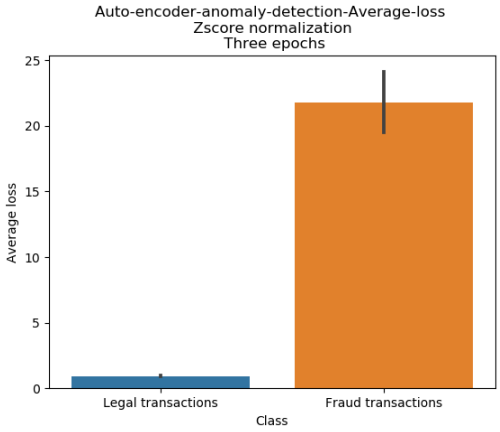


Figure 8

3.5.1 Autoencoder

The architecture here is the same as in the Autoencoder for dimension reduction.
We trained the model using the whole data for 3 epochs, due to the easy task given to the model (returning the input) adding more epochs didn't show any improvement.
The N transactions with the largest MSE on the model will be identified as anomalies (where N is a hyper parameter).

3.5.2 Isolation forest

The algorithm is based on the fact that anomalies are data points that are few and different. As a result of these properties, anomalies are susceptible to a mechanism called isolation.

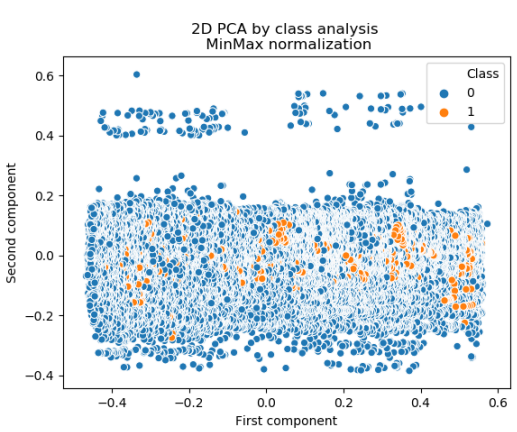
4 Results

4.1 Dimension reduction

Unfortunately, as can be seen the dimension reduction (linear and nonlinear) didn't separate the data well.

4.1.1 Linear methods

PCA:



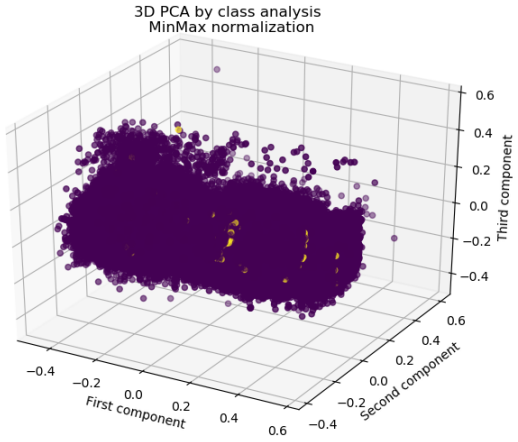
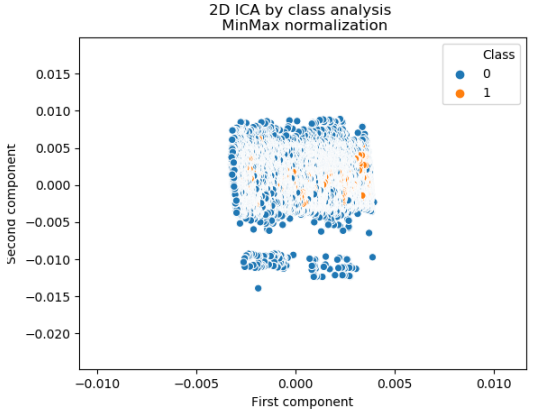


Figure 9, Figure 10

ICA:



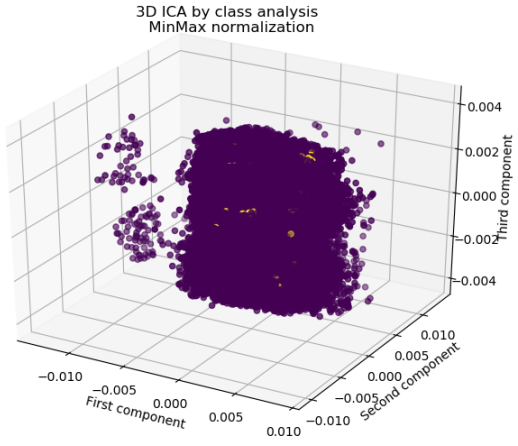


Figure 11, Figure 12

4.1.2 Nonlinear methods

Autoencoder:

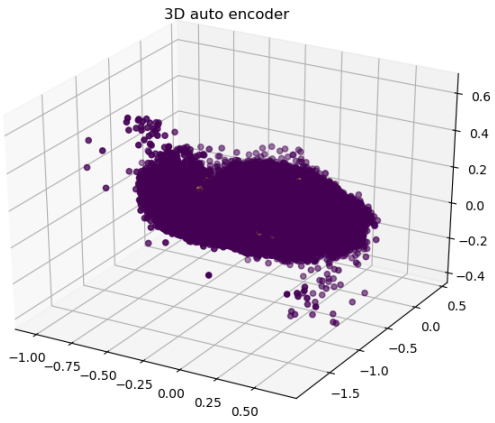


Figure 13

4.2 Clustering

Due to the incapability of the dimension reduction methods to show the separation of the data to clusters, the results of the clustering aren't satisfying.

K-means:

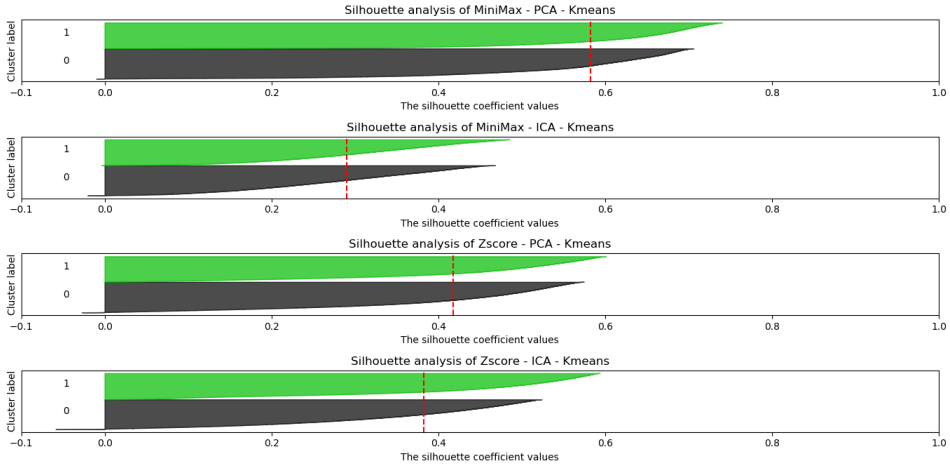


Figure 14

GMM:

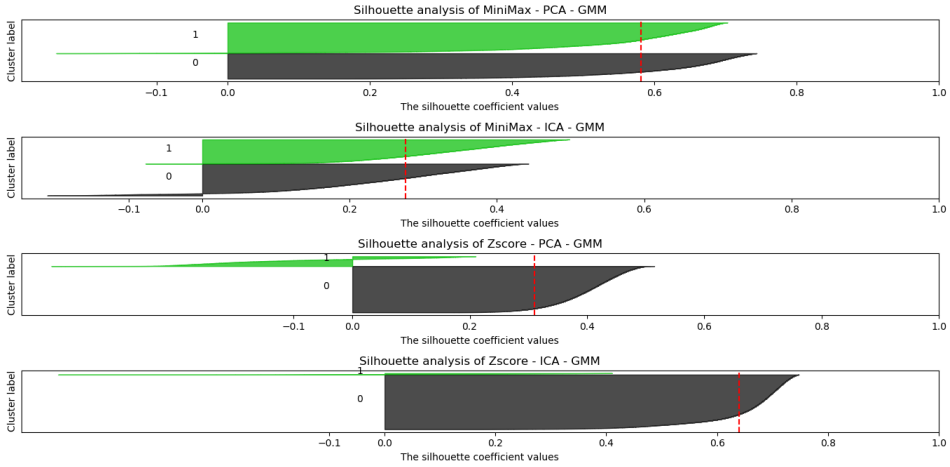


Figure 15

The only possible combinations size wise are Zscore - PCA - GMM and Zscore – ICA – GMM.

Although the average silhouette score of the other combinations is high their cluster size doesn't match the ratio between the legal transactions and the frauds.

Therefore, we have made a confusion matrix to both combinations:
Zscore - PCA - GMM:

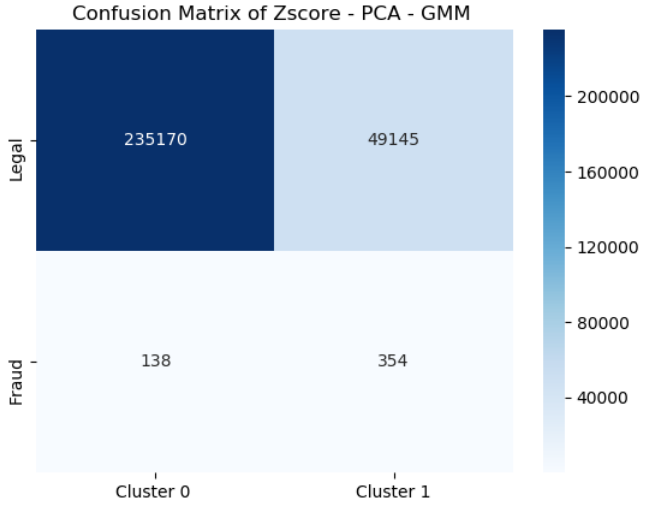


Figure 16

Zscore - ICA - GMM:

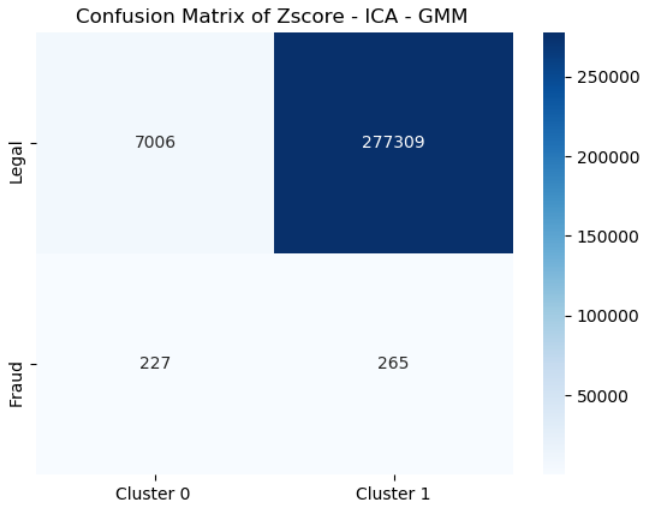


Figure 17

The results are inconclusive, and it can't be said that the frauds are divided into one cluster.
Both clusters don't have a significant difference in the number of frauds transactions in them.
The number of legal transactions in both clusters is enormous relatively to the frauds.

4.3 Anomaly detection

4.3.1 Autoencoder

By testing the autoencoder with all the different normalizations, we found it **extra sensitive** to the normalization performed in the preprocessing stage.

The method that gave the best results was the Zscore.

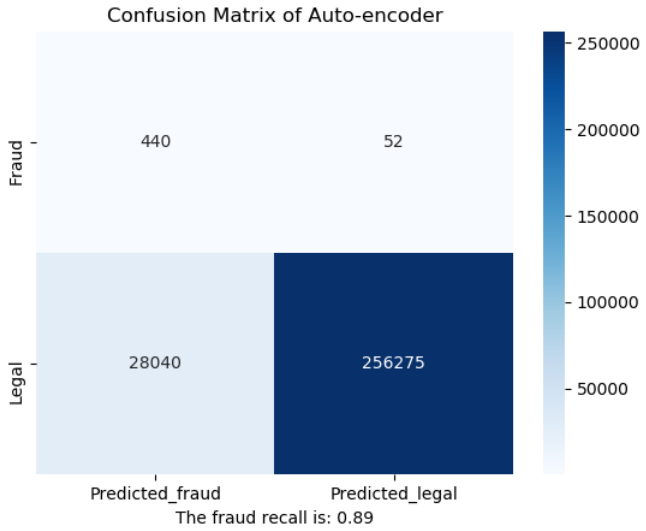


Figure 18

As it can be seen, the fraud recall is almost 90 percent which means that the majority of the frauds is recognized by the model as fraud transactions.

These results are satisfying the need of identifying frauds.

Although the fraud precision is quite low, its acceptable because of the significant Imbalance in the data.

4.3.2 Isolation forest

By testing the isolation forest with all the different normalizations, we found that **it's not sensitive** to the normalization performed in the preprocessing stage.

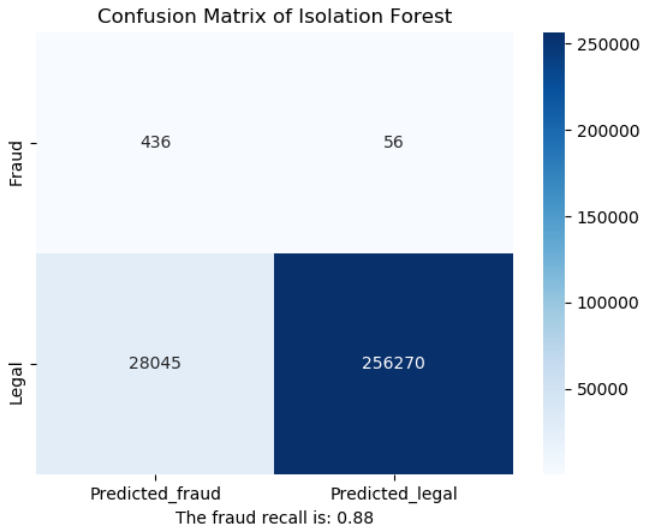


Figure 19

The results are almost similar to the autoencoder as well as the conclusions.

5 Conclusion

In this project we tried to reflect everything we learned during the course.

We were fascinated to explore which algorithms will performe well and which won't.

The fact that the data wasn't easily separable made us try different methods and aspects that we didn't see directly in the lectures.

Each normalization gave different results for each method, the MinMax showed the best results when reducing dimensions, while Z score and robustScaler gave the best results in anomaly detection.

The tsne visualization was very beneficial and gave us motivation to continue the analysis.

Although the variance explained by the principal components was relatively high, all the dimensionality reduction algorithms couldn't visibly separate the data.

In addition, we couldn't implement KPCA and tsne on the whole data because of running time reasons.

Because of the inability mentioned above the clustering algorithm that we used could not cluster the fraud and the legal transactions.

A valuable lesson is that dimension reduction methods don't always preserve the division in the data .

Therefore, we decided to review other directions such as anomaly detection.

A wrong approach could have been using the accuracy evaluation. But we chose the precision – recall and confusion matrix evaluation, which in them our models performed well.

From a supervised point of view, it could have been possible to use the given labels in order to subsample the data to a group that has an equal number of frauds and legal transactions. This will dramatically reduce the imbalance of the data and may make the supervised and unsupervised models better.

Finally, we came to a main conclusion that fraud and legal transactions distribute similarly which made the tusk of fraud detection very difficult.