ANOMALY DETECTION IN ECUADOR PAYMENTS SYSTEM

Curso sobre tecnologías Financieras y Banca Central

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CHALLENGES OF PAYMENT SYSTEMS

EFFICIENT + SECURITY = ROBUST PAYMENT SYSTEMS

Growth in the use of electronic channels

Working to strengthen security

RESEARCH GOALS

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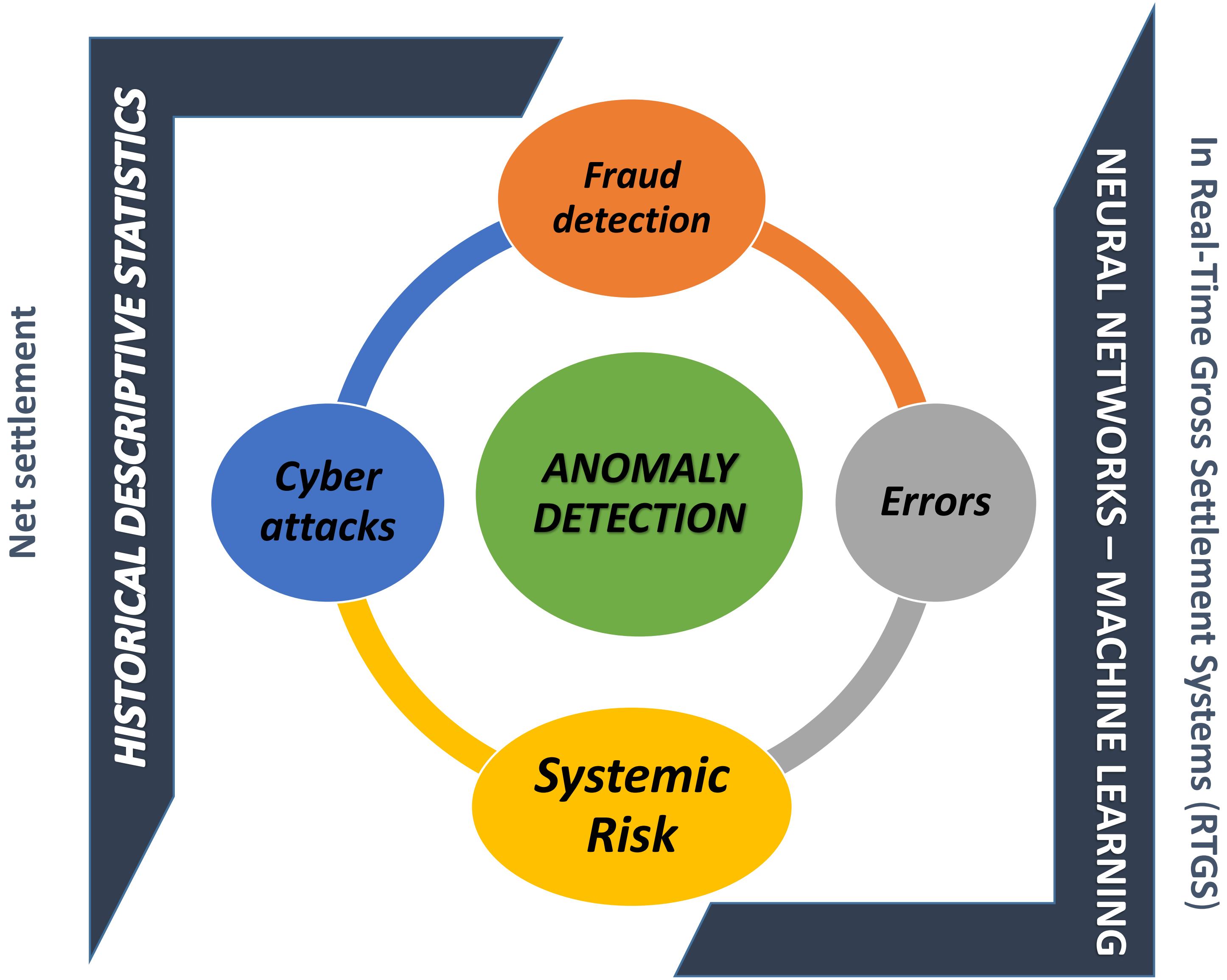
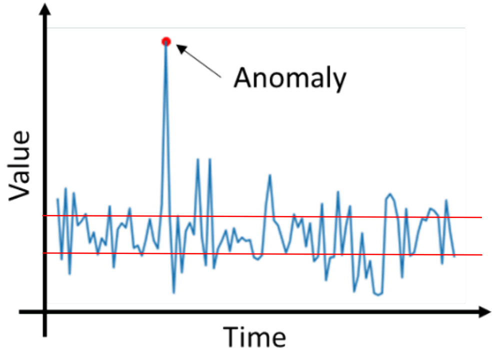


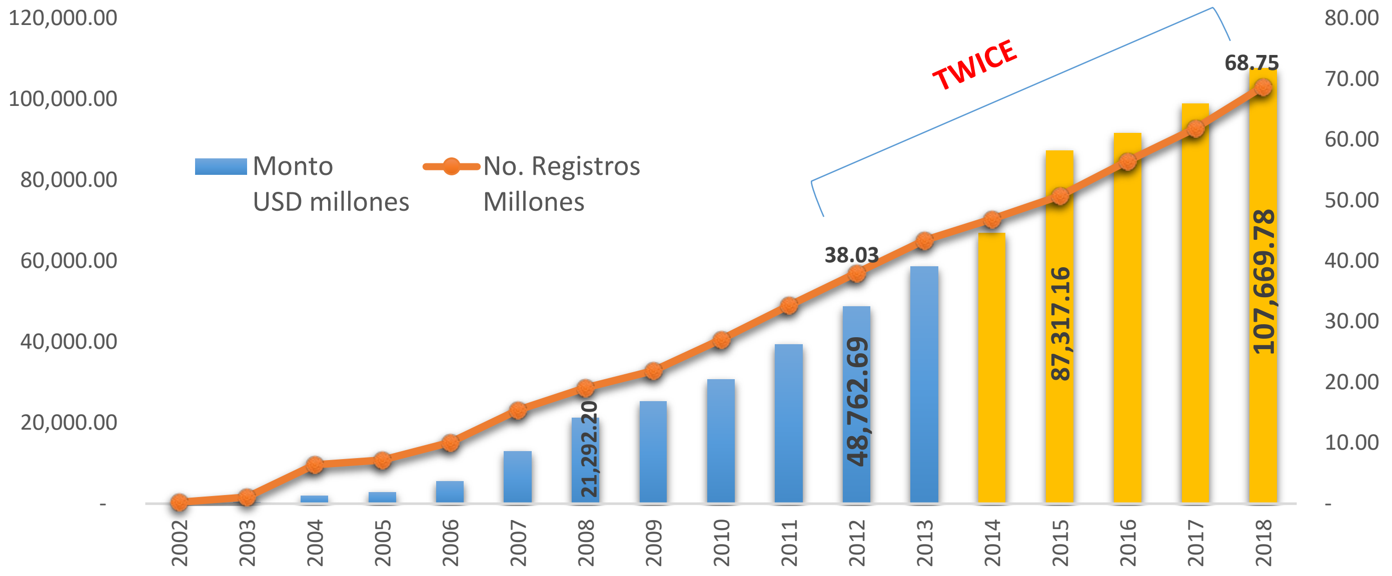


¨A pattern that does not conform to expected behavior¨

ANALYZED PAYMENT SYSTEM

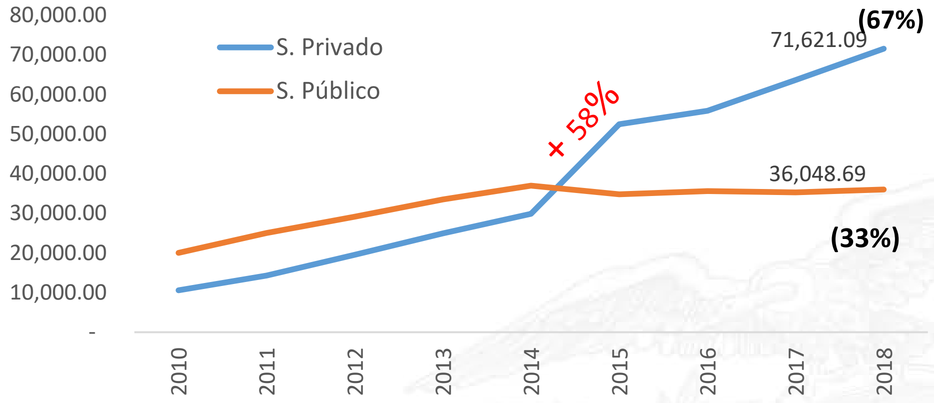
BANCO CENTRAL DEL ECUADOR

Amount and Number of Operations in SPI (USD millions)



- ***SPI has Deferred settlement: 3 per day – not in the Real Time***
- **The annual amount represents 98% of Ecuador's GDP**

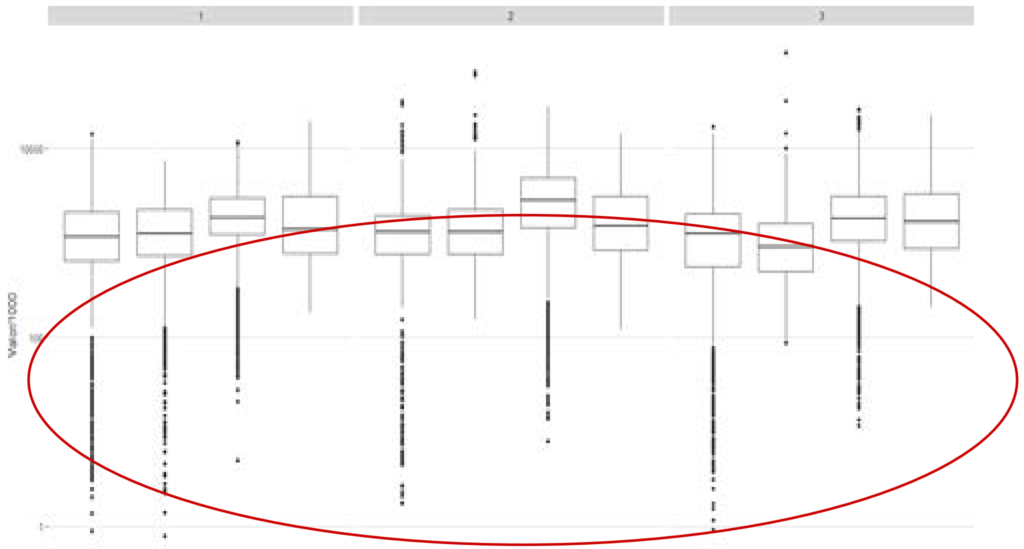
Amount per sector (USD millions)

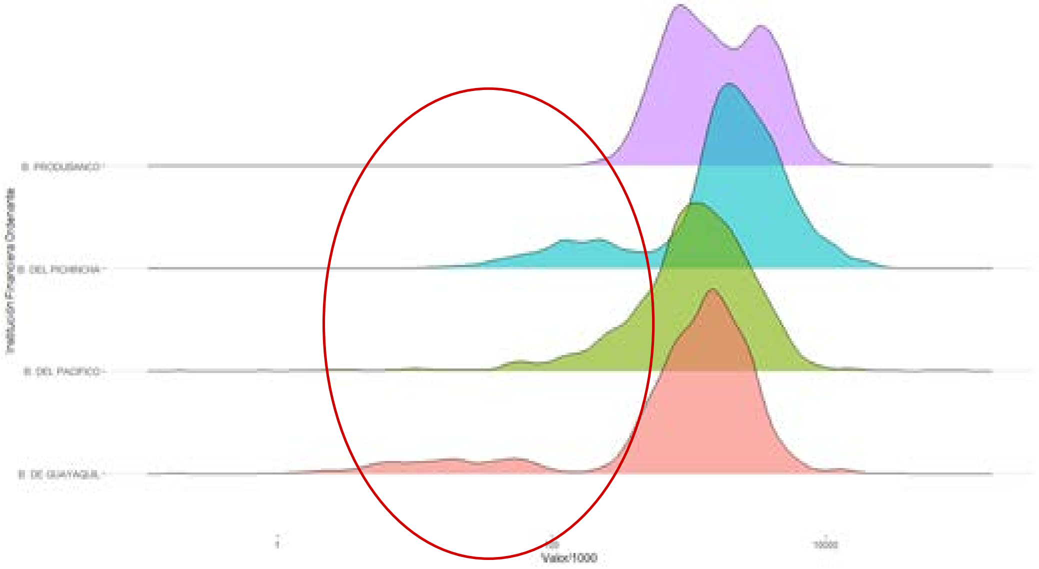


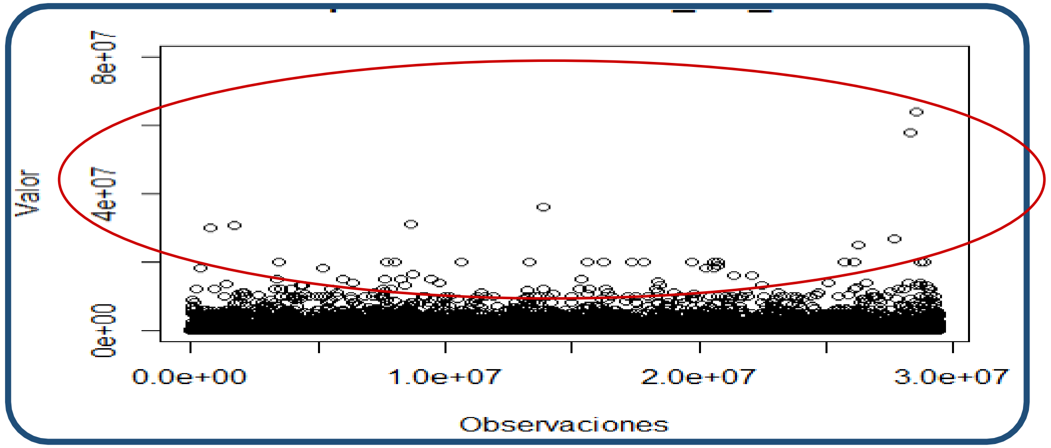
- ***344 participants and The Central Bank of Ecuador (BCE)***
- ***8 Private Banks and BCE (32%) channeled 86% in 2018.***
- ***Amounts grow by 8% annually***

THERE ARE ANOMALOUS PAYMENS?

BANCO CENTRAL DEL ECUADOR







It looks like!

HISTORICAL DESCRIPTIVE STATISTICS - CURRENT SUPERVISION

BANCO CENTRAL DEL ECUADOR

1. ***Monitoring for each new transaction:*** *Amount*
2. ***Monitoring for each cut:*** *Amount and Frequency (3 cuts deferred)*

VS.

HISTORICAL PROFILE PER BANK- *Descriptive Statistics Analysis (weekly, monthly, annual)*

ALERT IF:

- It is greater than the historical maximum
- Very close to the historical maximum and infrequent (Percentiles 99%, P99.9%)
- Very far from its historical average amount
- Duplications
- New participants
- Transaction Over USD 10,000
- Position and distance in the interval (Uniform Distribution) *
- To alert we also use our own business parameters

This monitoring is currently implemented in Ecuador. It is based on the historical behavior of the entity in this payment system.

In a controlled and testing environment, this monitoring has been *detected operational errors in a specific bank*

* $$F(x) = \frac{x - Per}{Max - Per}$$

Donde $F(x) \in [0,1]$, esto nos indica la posición del Monto entre el percentil y el máximo.

NEURAL NETWORKS – MACHINE LEARNING

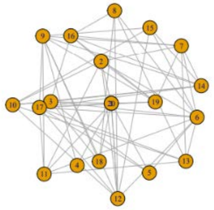
Objective: *Apply Machine Learning techniques to Automatically detect atypical payments*

- We use for reference Triepels, 2017. They make a model to detect anomalies in Real-Time Gross Settlement Systems

- Anomaly detection allows to automatically identify **unusual payment behavior** and may help to initiate timely interventions

- It´s a different approach to measure systemic risk. Payment data provide an accurate and system-wide overview of how banks manage their liquidity over time.

- An autoencoder is a feed-forward neural network that learns features from data by compressing it to a lower dimensional space, and accordingly, reconstructing it back in the original space. We try this to the anomalies detections.



AUTOENCODER

An autoencoder is an artificial feedforward neural network that is trained to reconstruct the input layer at the output layer. It does this by processing the input through a bottleneck layer in which a set of neurons form a representation of the input in a lower dimensional space.

We employ a three(3) -layered autoencoder to compress and reconstruct liquidity vectors. The autoencoder can be defined by two functions:

Encoder function ϕ: $\phi\left(a^{(k)}\right) = f^{(l)}\left(W_1 a^{(k)} + b_1\right)$

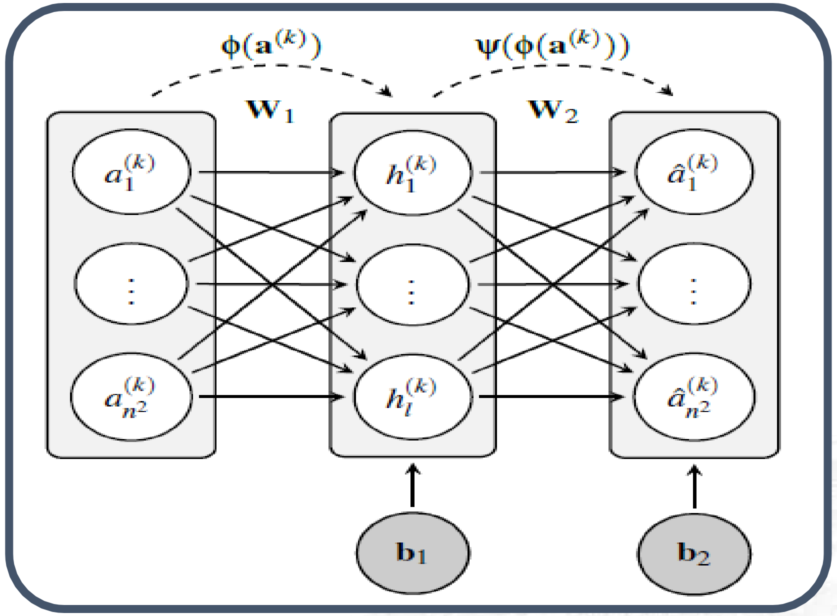
Decoder function ψ: $\psi\left(a^{(k)}\right) = g^{(n^2)}\left(W_2 \phi\left(a^{(k)}\right) + b_2\right)$

Parameters $\theta = \{W_1, W_2, b_1, b_2\}$ of the autoencoder are estimated from historic liquidity flows. **We do this by minimizing the MRE:**

$$\theta = \underset{W_1, W_2, b_1, b_2}{arg\,min}\; MRE(D)$$

We apply stochastic gradient descent in conjunction with back-propagation to solve this optimization problem.

- Unsupervised learning, Detection of outliers (not predicting),



Sequential network architecture: 3 layers (input, hidden, and output) - (Triepels, 2017)

DEFINITIONS

$B = \{b_1, \dots b_n\}$ is a set of n banks participating in a interbank payment system (SPI)

$T = \{t_1, \dots, t_m\}$ is an ordered set of **m** time intervals

We extract $D = \{A_1, \dots A_m\}$ a set of **m** liquidity matrices from a **SPI** system where each $A^{(k)} \in D$ is the $n * n$: matrix:

$$A^{(k)} = \begin{bmatrix} a_{11}^{(k)} & \cdots & a_{1n}^{(k)} \\ \vdots & \ddots & \vdots \\ a_{n1}^{(k)} & \cdots & a_{nn}^{(k)} \end{bmatrix} \qquad (1)$$

Each element $a_{ij}^{(k)} \in [0, +\infty)$ is the liquidity flow between b_i and b_j at t_k. $A^{(k)}$ is a liquidity matrix

For analysis purposes, Liquidity Vector:

$$a^{(k)} = \left[a_{11}^{(k)}, \dots, a_{n1}^{(k)}, \dots, a_{1n}^{(k)}, \dots, a_{nn}^{(k)}\right]^T \qquad (2)$$

ANOMALY DETECTION

If the reconstruction error of a liquidity vector is low, it is a frequently recurring pattern that the compression model has learned to compress well. If it´s Is large, then the model does not recognize the liquidity flows and fails to reconstruct their values. ***IT IS AN ANOMALY.***

Let M be a lossy compression model. We measure the reconstruction error (RE) of $a^{(k)}$ after its compressed and reconstructed by M by:

$$RE\left(a^{(k)}\right) = \frac{1}{2}\left\|\psi\left(\phi\left(a^{(k)}\right)\right) - a^{(k)}\right\|^2$$

$RE\left(a^{(k)}\right)$ is the non-negative reconstruction error aggregated over all liquidity flows between the banks at time interval tk. $a^{(k)}$ **is considered anomalous** if the reconstruction error is high:

$RE\left(a^{(k)}\right) \geq \varepsilon$. Here, $\varepsilon > 0$ is a threshold.

Finally, by taking the mean of the reconstruction error of all liquidity vectors in D we obtain the overall **Mean Reconstruction Error (MRE):**

$$MRE(D) = \frac{1}{m}\sum_{k=1}^{m} RE\left(a^{(k)}\right)$$

APPLICATION IN ECUADOR CASE

Data:

- *10.268 client payments from the interbank payment system (SPI)*
- *Jan 2018 – Dec 2018*
- *Aggregated over 741 cuts in the year- (3 cuts per day * 247 working days)*
- *4 largest banks*
- *The liquidity flows were transformed by a log transformation (highly skewed distribution less skewed)*
- *Min-max normalization was in turn performed to normalize their values to the [0,1] interval.*

Data partitioning:

- ***Training set:** 318 liquidity vectors corresponding to six months (April until September). The parameters of the autoencoders were learned from a training set*
- ***Holdout set:** 183 liquidity vectors corresponding to the first three months (January until March). To optimize the number of neurons of the autoencoders we use a Holdout set .*
- ***Test set:** 240 liquidity vectors corresponding to six months to 4 months months (October until December). Finally, we evaluated the autoencoders on a test set*

We implemented Two autoencoders: *Compare two common activation functions: relu, tanh*

1) ***Tanh activations** in the hidden layer and Rectified linear unit (ReLU) activations in the output layer*

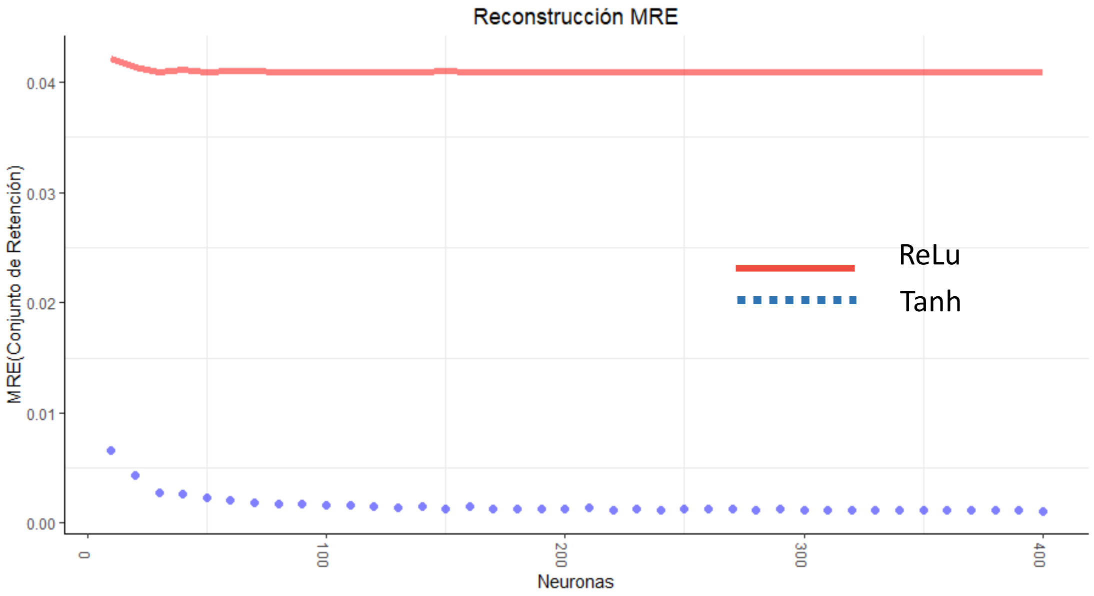
2) ***Rectified linear unit (ReLU)** in the hidden layer and Rectified linear unit (ReLU) activations in the output layer*

CHOOSING OPTIMAL NETWORK ARCHITECTURE (first results)

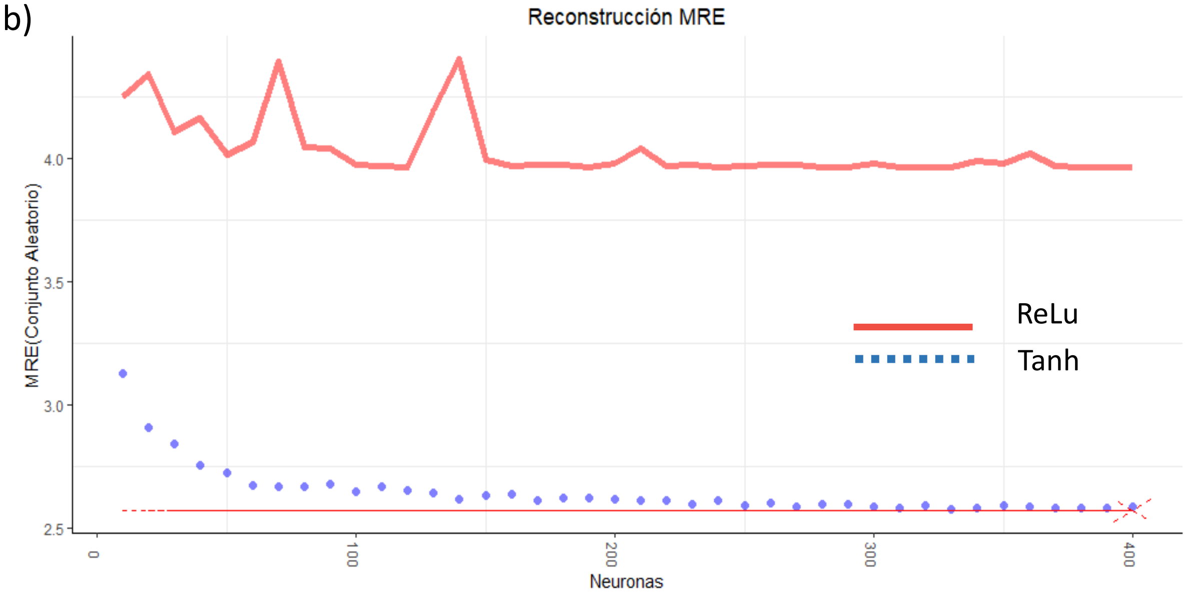
The number of neurons was optimized by a grid search.

Figure: **(a)** The MRE of the **holdout set** estimated by the linear and sigmoid autoencoder having a different number of neurons in the hidden layer. **(b)** The same graph as (a) but instead estimated **on a set of random liquidity vectors**. The dotted line represents the lower bound of the MRE. Compare two common activation functions: relu, tanh

a)



b)



- *Stochastic gradient descent in conjunction with back-propagation was in turn applied to learn the parameters from the training set.*
- *During the grid search, a set of autoencoders having a different number of neurons $l \in \{10,20,\ldots,400\}$ in the hidden layer.*
- *We investigated the point were adding more neurons did not yielded a better error.*
- ***In the first instance, we chose to use 310 neurons in the hidden layer of the autoencoders with an MRE around 0.0011 in a tanh autoencoder. The Tanh autoencoder reconstructed the random set better than the ReLu autoencoder. (holdout set and ramdom set)***
- *To determined whether the autoencoders approximated the **identity mapping** by evaluating their MRE on a set of uniformly sampled liquidity vectors. In the optimal case, the MRE of the autoencoders on these random liquidity vectors equals a **lower bound*.***

Mean Reconstruction Error (MRE)

HOW WELL THE AUTOENCODERS WERE ABLE TO RECONSTRUCT THE ORIGINAL TEST SET

We determined how well the autoencoders were able to reconstruct the original test set.

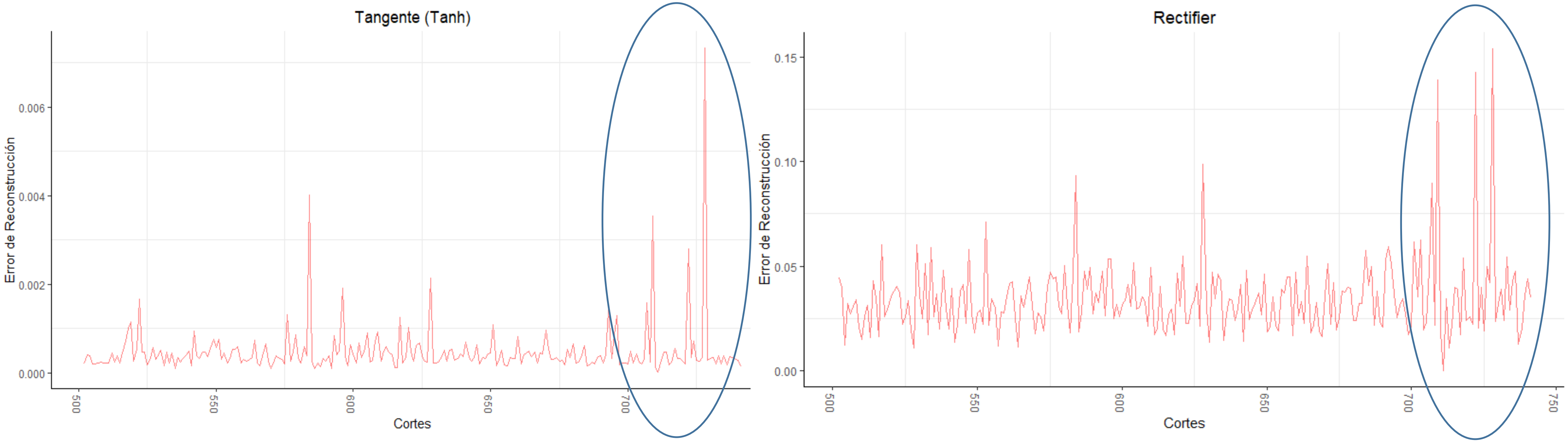
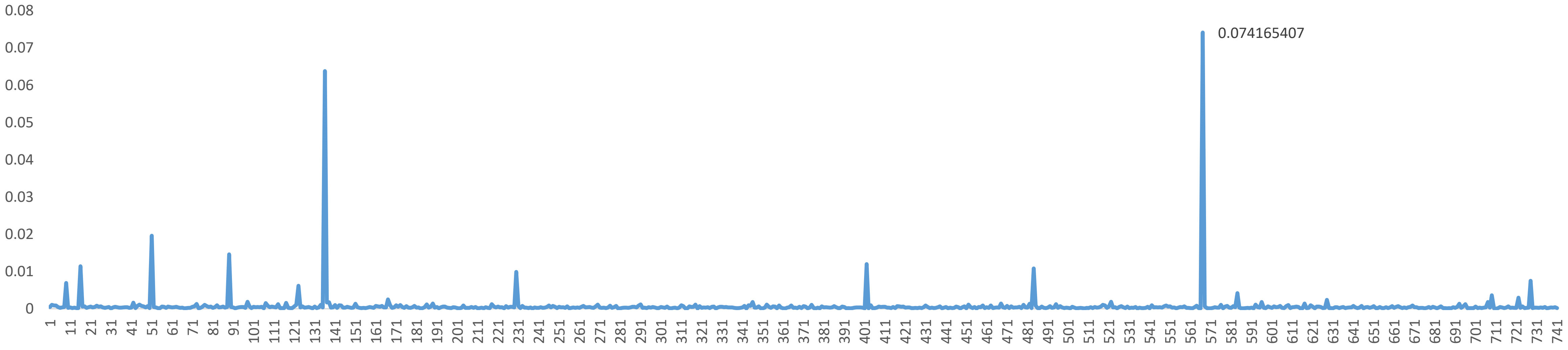


Figure 3: The reconstruction error of the original test set estimated by the ReLu and Tanh autoencoder for each time interval.

- *The error curves of the autoencoders are quite similar and exhibit fluctuations.*
- *Some autoencoders had difficulties reconstructing the liquidity vectors (Large errors). (caused by a few very large liquidity flows) -* ***ANOMALIES***

MODEL APPLICATION FOR THE ENTIRE DATABASE



- *The model has detected 51 cuts as atypical in 2018. They are atypical because their estimated MRE is greater than 0.0011 (the estimated threshold in the model)*

- To make a preliminary comparison we made an estimate using (Z-score) in which 38 cuts of the 51 detected by the auto-encoder coincide.

NEXT

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DEL ECUADOR

- Calculate the lower limit to test the built-in autocoders such as Triepels (2017)

- Compare results and efficacy of autoencoder to traditional methods

- Try with alternate network architectures and activation functions and evaluate the model with extra tests, Compare findings/approaches

- Make Commercial Bank Run Simulation: *the reconstruction error increased rapidly as the payment network started to change unexpectedly. This allows us to prove how good the autoencoder is to detect anomalies*

- *We have first promising results but additional testing and fine tuning is necessary*

Z Score or Standard Score

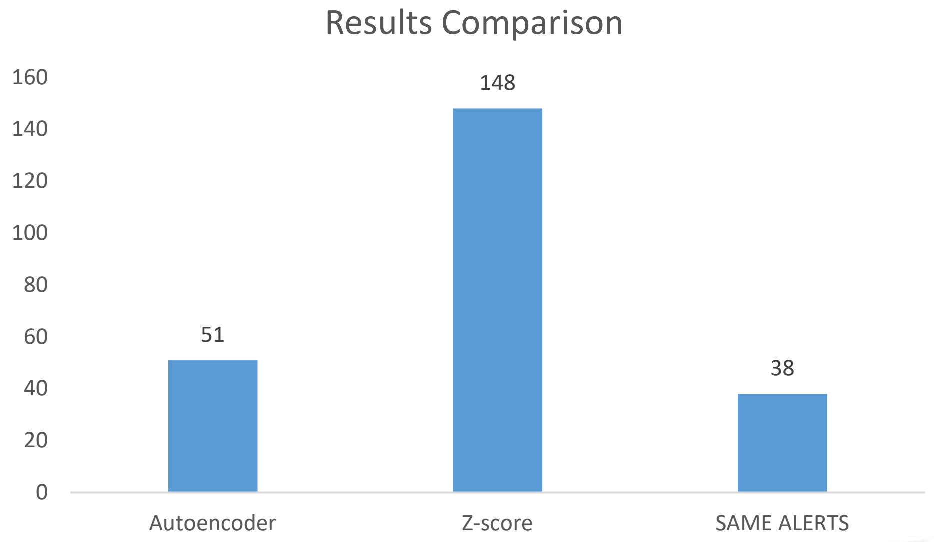
Describe a data point in terms of its relationship with the mean and standard deviation of a group of points.

- Eliminate the effects of location and data scale
- Standardization of the data (mean 0 and Standard Deviation 1)

$$x_i' = \frac{x_i - \mu}{\sigma}$$

If $|x_i'| > 3$ then x_i is an atypical

Where:
μ:Medium.
σ: Standard deviation.



Training alternatives

New dataset

- Data consist on 3 months of payments (61 operations days): January, June and December.
- 24 participants were considered for the study, being the most active
- MinMax normalization were performed on all the data
- The training set consists on the 80% of the total of the data, while validation and testing set consisted on 10% of the data each one

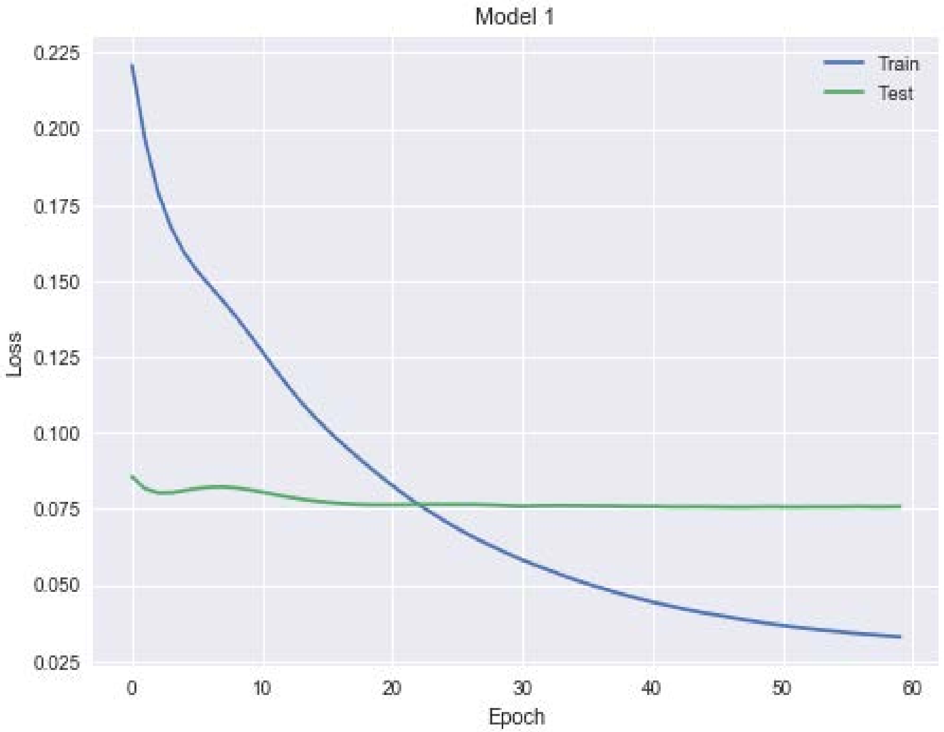
Models trained

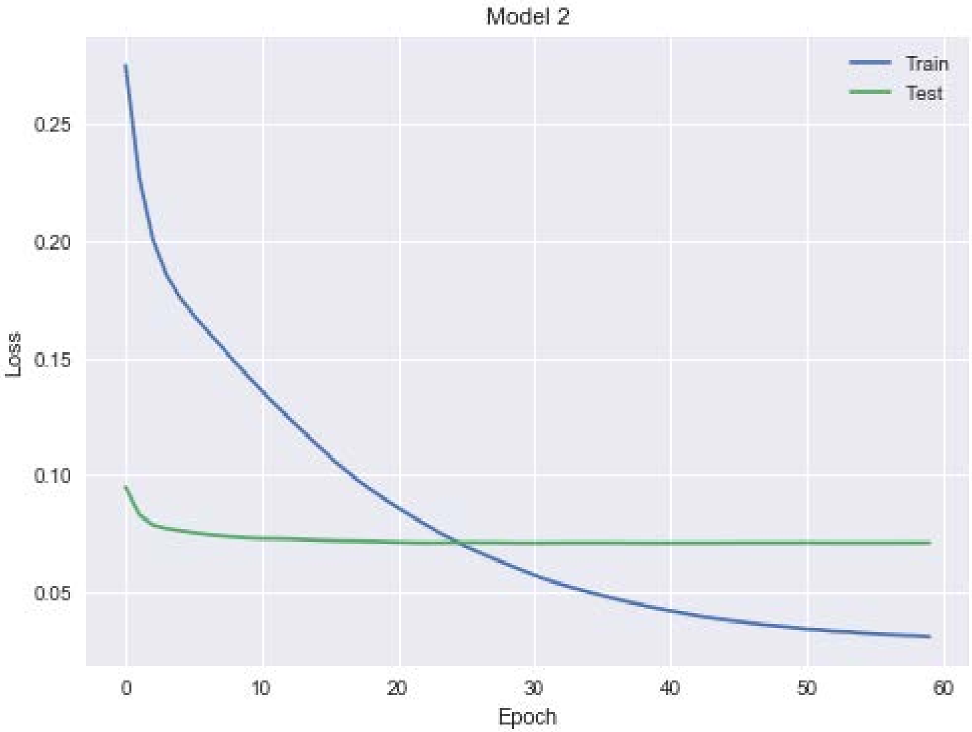
- For this new experiment two autoencoder models were trained:

  - The first model architecture consists of one hidden layer with 250 neurons, having as first activation function tanh and a relu activation function for the output layer.

  - The second architecture consists of three hidden layers, having 275 neurons, 150 neurons and 275 neurons, respectively. The activation function used in each layer were tanh.

Model assessment





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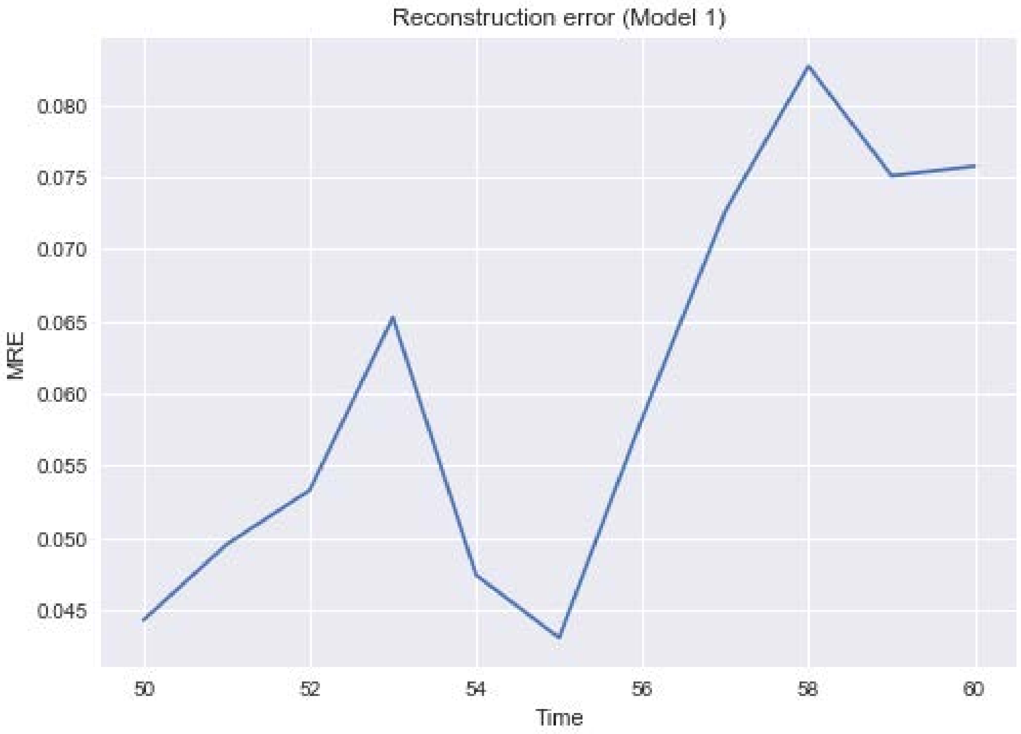
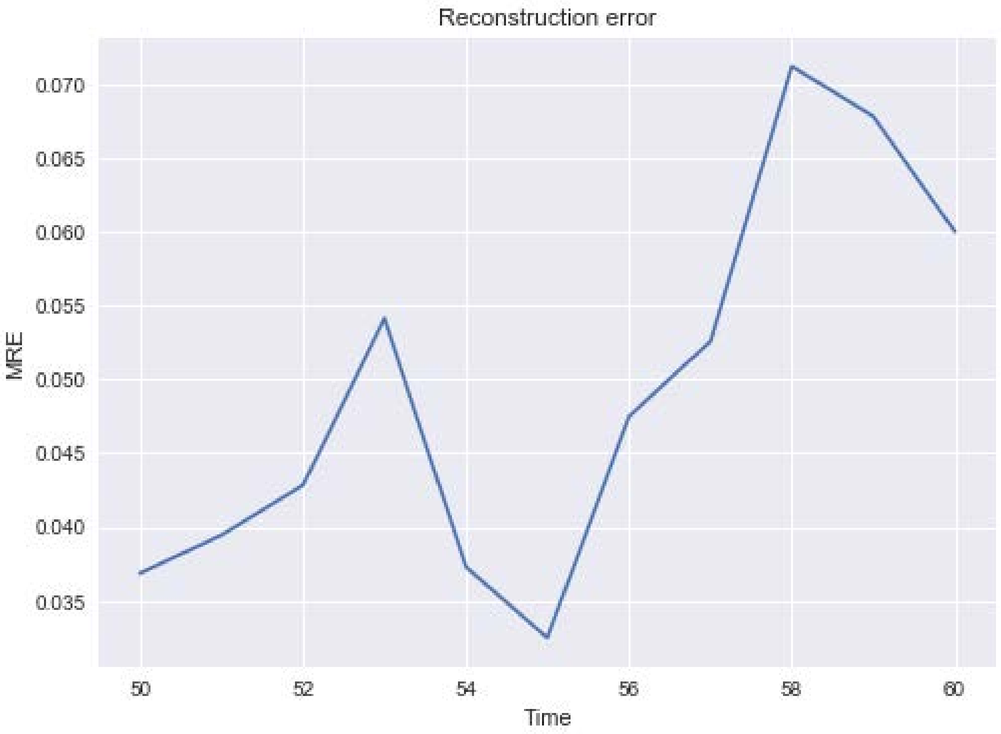
Model assessment





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Conclusions

- Results on autoencoders for detecting anomalous payments has showed that liquidity vectors contain distinctive features of a payment network which an autoencoder is able to capture very well (Triepels, 2017).
- Further investigation is needed in order to explore new architecures for the improvement of the model performance. Also, the autoencoder could be compared with other unsupervised techniques as clustering or PCA.
- In next steps seasonality should be considered so that different models can be trained in accordance.
- Bank run simulations may be more helpful to present performance of the models proposed.