Detecting outliers in LVPSs using neural networks: Does memory improve performance?

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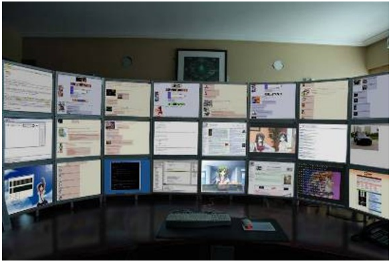
Outline

- Desire to monitor financial sector closely
- At system and individual bank level
- Monthly reporting for long term trends ...
- ...., but disruption happen quickly (days/weeks)

- e.g. corona crisis, global financial crisis, Nashdaq power trader shock, etc.

Can ML detect liquidity problems in LVPS?

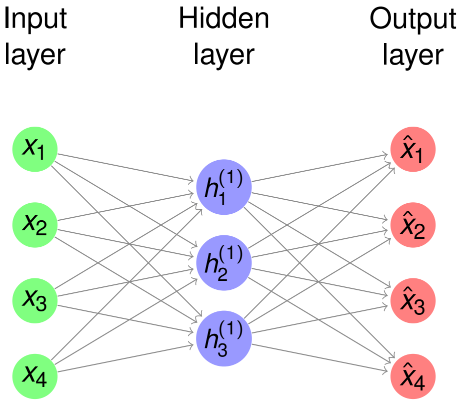
- Unlabelled data
  $\Longrightarrow$ unsupervised learning
- Number of outliers very small relative to normal situations (e.g. 0.01% vs 99.99%):
  $\Longrightarrow$ standard classification does not work
- How to create an unambigious outlier definition? $\Longrightarrow$ augmented scenarios
- Detection NOT prediction of outliers.

- Outlier detection proven to be successful in e.g. stock market and credit card fraud detection
- see e.g. Kim and Sohn (2012), Leangarunet (2016), Ghosh and Reilly (1994) or Maes et al. (2002)

Do memory enabled neural networks have enhanced efficiency in detecting liquidity problems in contrast with traditional autoencoders?

- builds on:
  1. Triepels, Daniels and Heijmans (2018) in lecture note in computer science (TARGET2).
  2. Sabetti and Heijmans (2020) DNB Working Paper 681 (ACSS).

basic 3-layer autoencoder

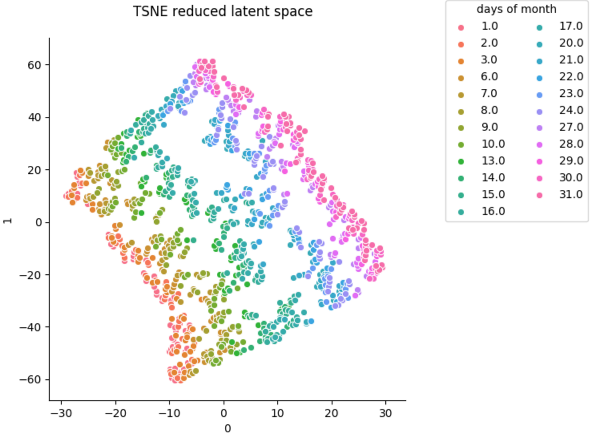


- Loss function: MSE
- Hidden layer creates latent space

source: Sabetti and Heijmans (2020)

How does it work?

- Trained on raw data (hopefuly) without outlier
- Evaluation on scenario augmented data
- Evaluation metrics: Reconstruction error, latent space distance

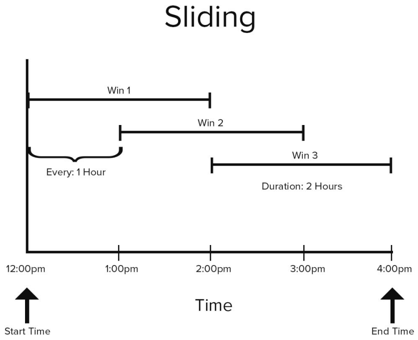


Main limitation

- Deals with static input without concept of memory (e.g no timeseries)
  - No history
  - Only looks at outlier in isolation (at a certain point in time)
  - Need for aggregation, one transaction holds little features

Memory as solution

- Memory gates allow for detecting (complex) relations between points in time (timeseries).
- Memory gates considered: GRU and LSTM



Data

- LVPS (TARGET2 and LVTS) bilateral flows (1ms-60 min aggregates) between participants
- leads to a Matrix $A^{(k)}$

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

Scenario's

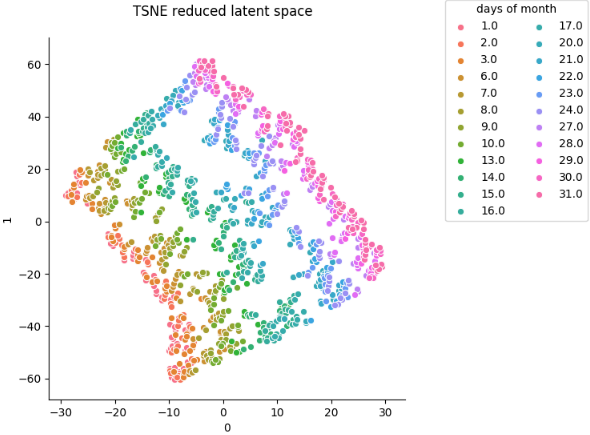
- Augment known transactions to simulate liquidity problems
- Parameterized exponential growing function
- Different selected large and medium banks
- (Dis)continuous outflows
- Multi/single participant outflows
- Different systems: TARGET2 and LVTS

Challenges

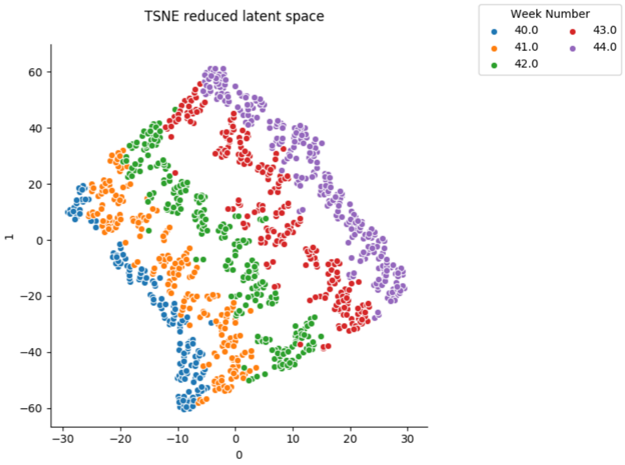
- Cloud computing within CB environment (security)
- Very few historical examples of liquidity issues.
- Large variety of possible liquidity issues

- Autoencoder seems to be learning
- Latent space shows clusters by Days and Weeks

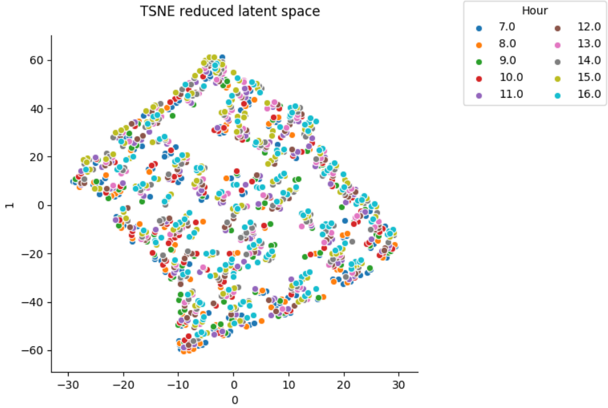
Latent space: Days



Latent space: Weeks



Latent space: Hours



- Autoencoder seems to be learning
- Intermediate analysis done with subset of data need to expand to full set
- Memory (GRU, LSTM) has not yet been extensively tested
- LVTS data have not been incorporated yet

WARNING!!!

"The Terminator" (Arnold Schwarzenegger) warns us for modern AI

Whether or not this statement holds true for out research remains to be seen