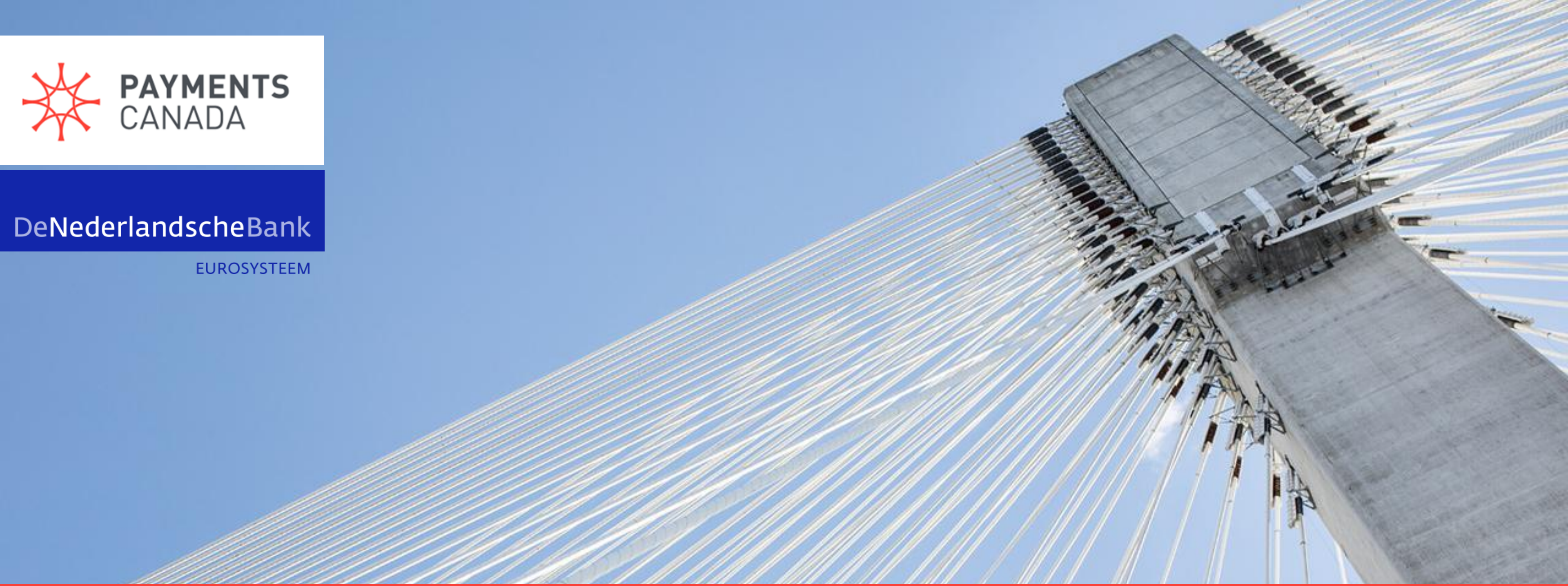

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Assessing financial market infrastructures with neural networks: an application to ACSS

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Outline

- Background
- Research question
- Neural network: Autoencoder
- ACSS Overview and Data
- Model Setup and Results
- Final remarks

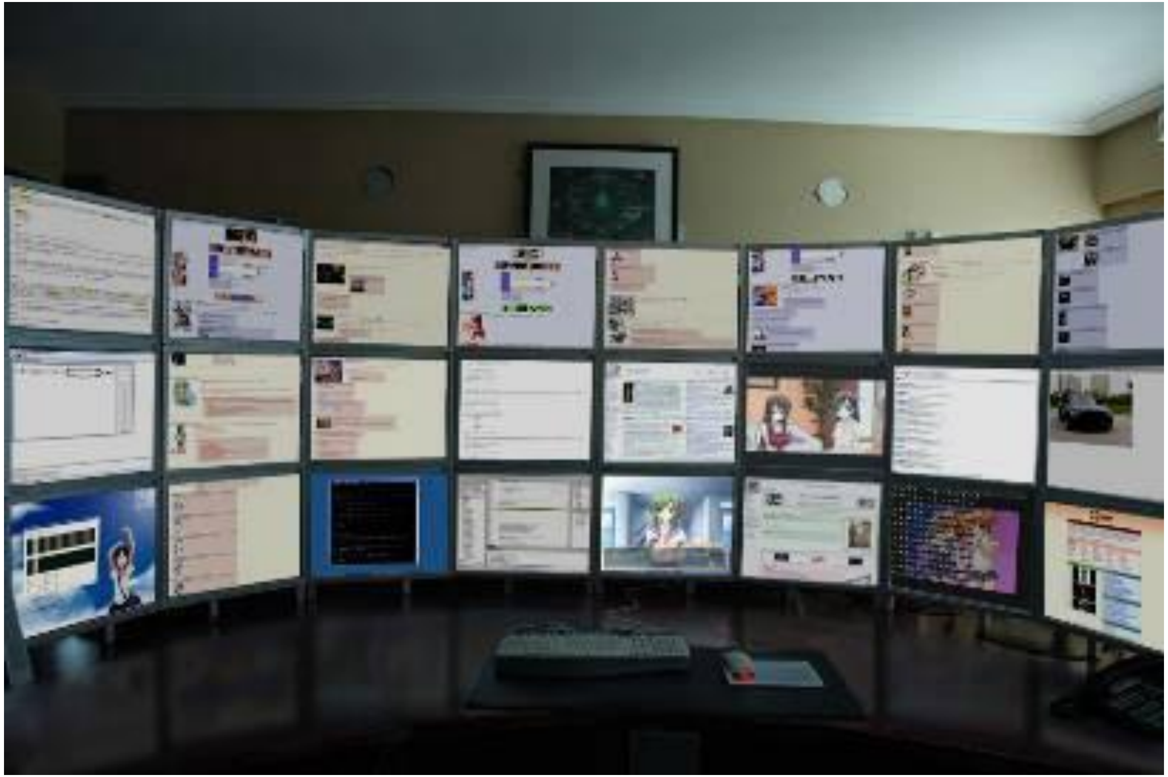
Background

An FMI operator has to be aware of what is happening in its system.

Many aspects to look at (PFMIs)

Automated help is useful

But how to apply AI/ML to FMI data?



Research question & motivation

Can a neural network (auto-encoder) detect bank runs or anomalous payment flows in the Canadian Automated Clearing and Settlement System (ACSS)?

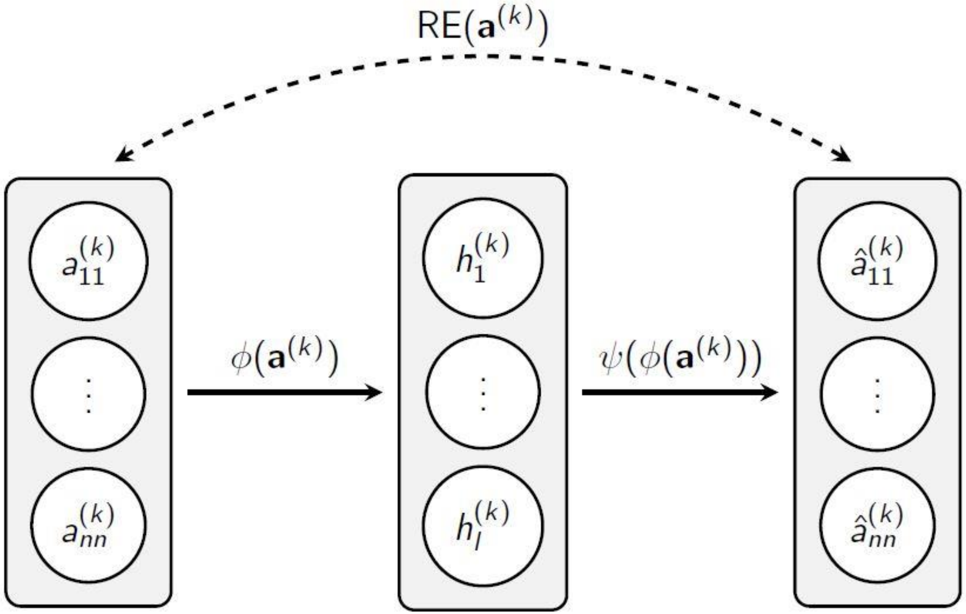
ACSS is a deferred net settlement system operating under a cover-one collateral risk model; no mechanism to limit or cap potential exposures

Builds on Triepels et al (2018) using data from RTGS

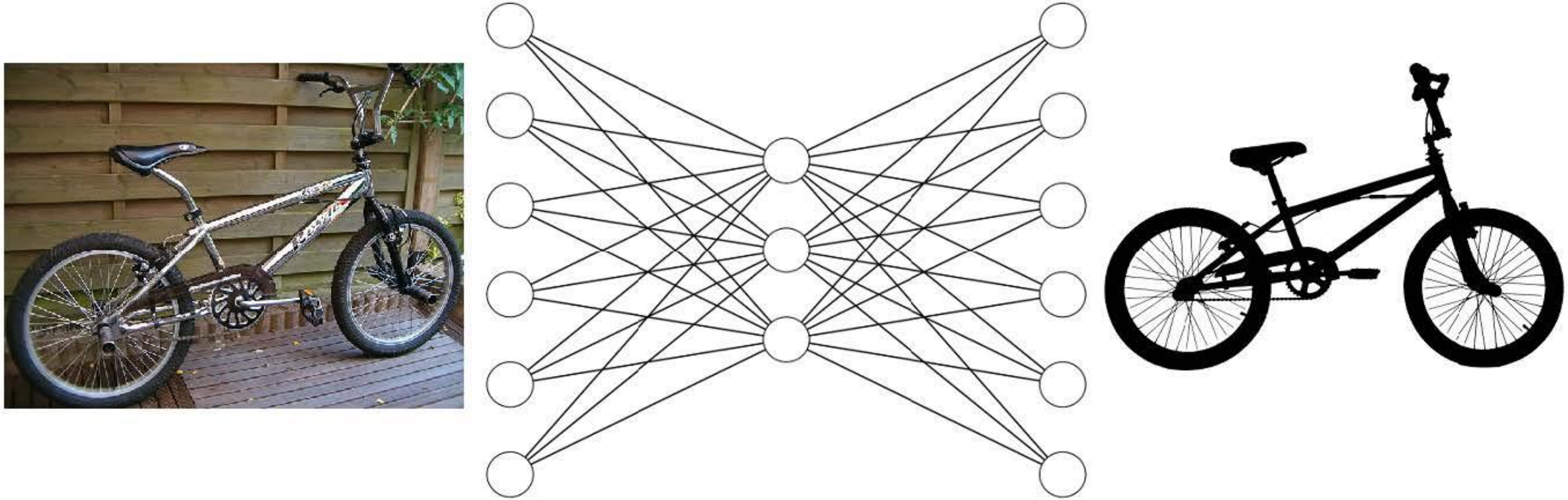
Why a neural network autoencoder?

- No labelled data
- Unsupervised learning
- Number of outliers very small relative to normal situations (e.g. 0.01% vs 99.99%): standard classification does not work.
- Detection of outliers (not predicting)
- Proven to be successful in e.g. credit card fraud detection

Autoencoder neural network architecture



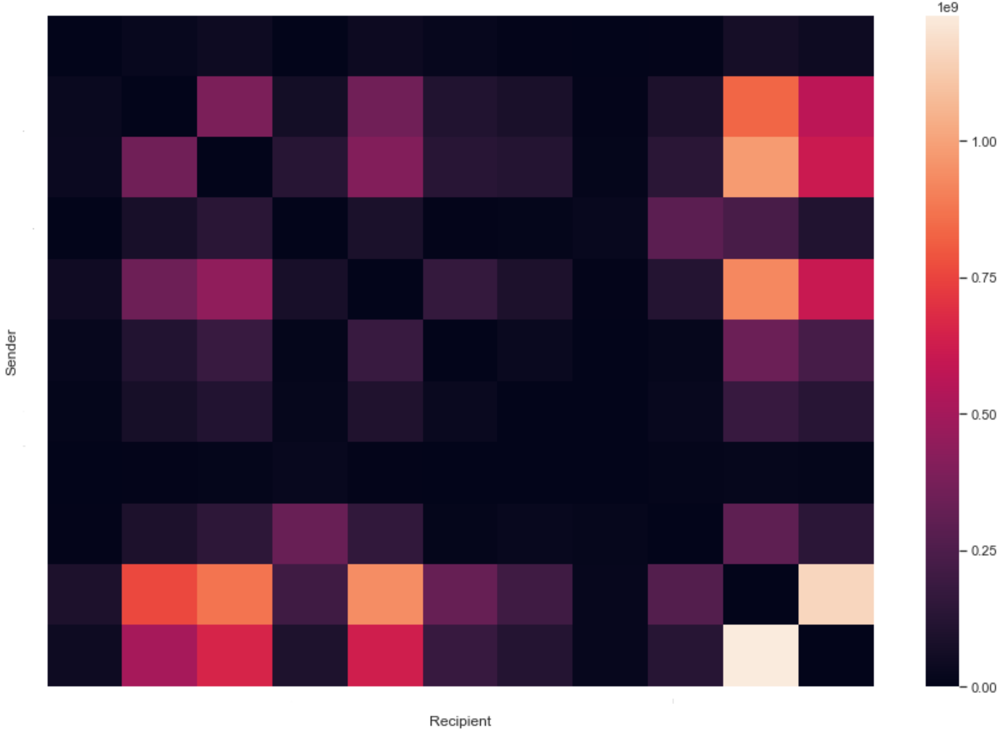
Autoencoder: bike example



ACSS: Overview

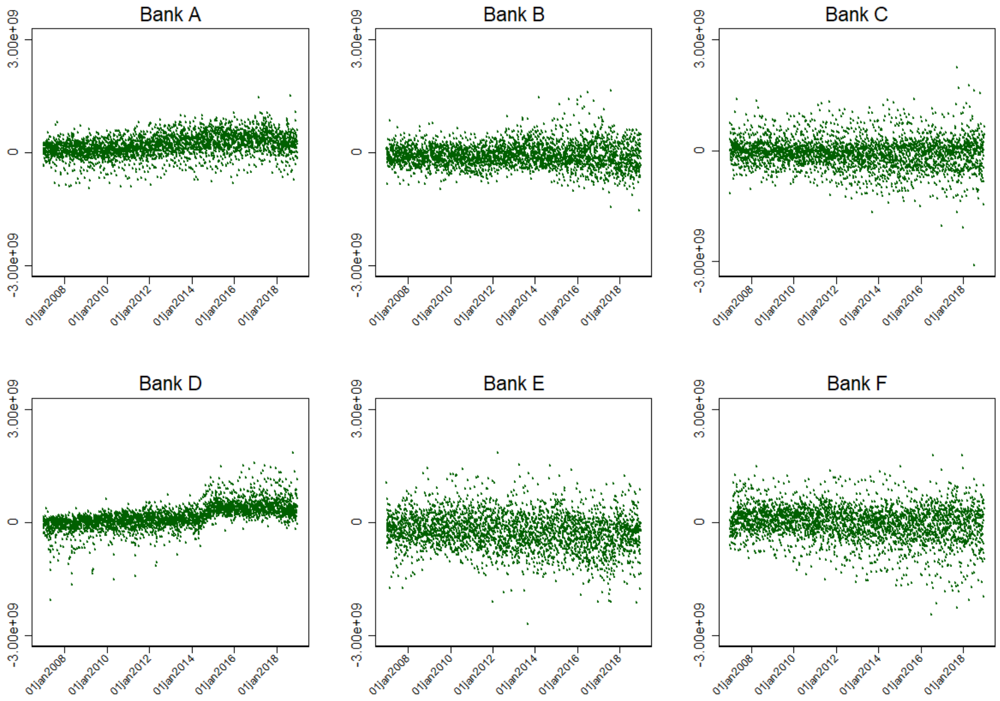
- facilitates clearing and settlement of electronic (automated funds transfer, EDI) and paper-based payments in Canada of primarily low-value (retail);
- statistics:
  - over $6.4 trillion in value
  - roughly 7 billion individual payments
  - 11 direct participants (excluding the central bank)
  - 100+ indirect participants
- decentralized bilateral exchange with multiple exchange window cut-off times; automated funds transfer stream can provide same-day funds availability. Entry into ACSS application for clearing occurs overnight via manual processing for all streams
- application calculates multilateral net positions for settlement by wire payment to the central bank in RTGS (LVTS) due next day

ACSS: Heatmap of bilateral flows



Note: Heatmap is based on average daily bilateral gross value sent in dollars from sending participant to recipient over the time period used in our training sample from 2007 to 2018. Diagonal elements are zero.

ACSS: Daily Multilateral Net positions



Note: Scatterplots represent observed daily settlement obligations, or multilateral net positions, in ACSS for select participants. Y-axis is in dollars where a positive value reflects a debit position while a negative value reflects a credit position.

Model setup: Input layer

$F = \{f_1, f_2, \dots, f_n\}$ is a set of n financial institutions

$T = \{t_1, t_2, \dots, t_m\}$ is an orderd set of m time intervals

We extract $D = \{A^1, A^2, \dots, A^m\}$ a set of liquidity matrices from the ACSS system, where A^k is:

$$A^k = \begin{matrix} a_{11}^k & .. & a_{1n}^k \\ : & .. & : \\ a_{n1}^k & .. & a_{nn}^k \end{matrix}$$

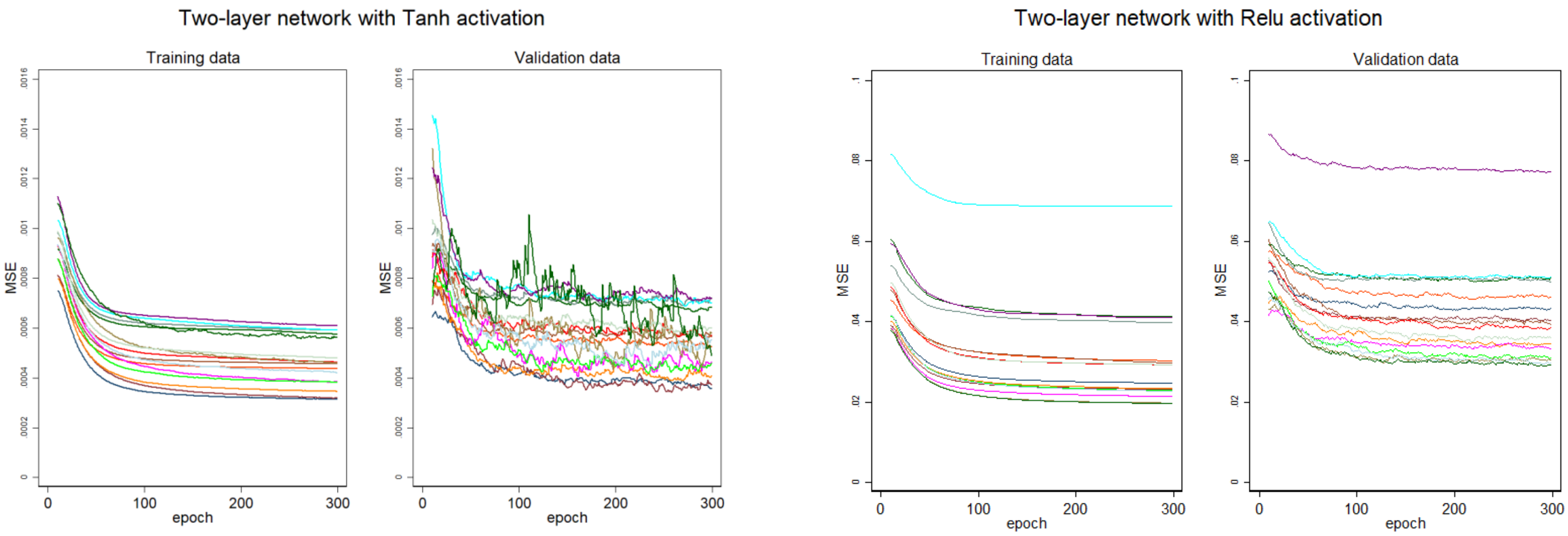
Each element a_{ij}^k **is the liquidity flow** between f_i to f_j over time interval k (daily)

- A^k: daily data covering the period 2007 to 2018 inclusive
- a_{ij}^k daily bilateral liquidity flow from one participant i to j

Model setup: network architecture

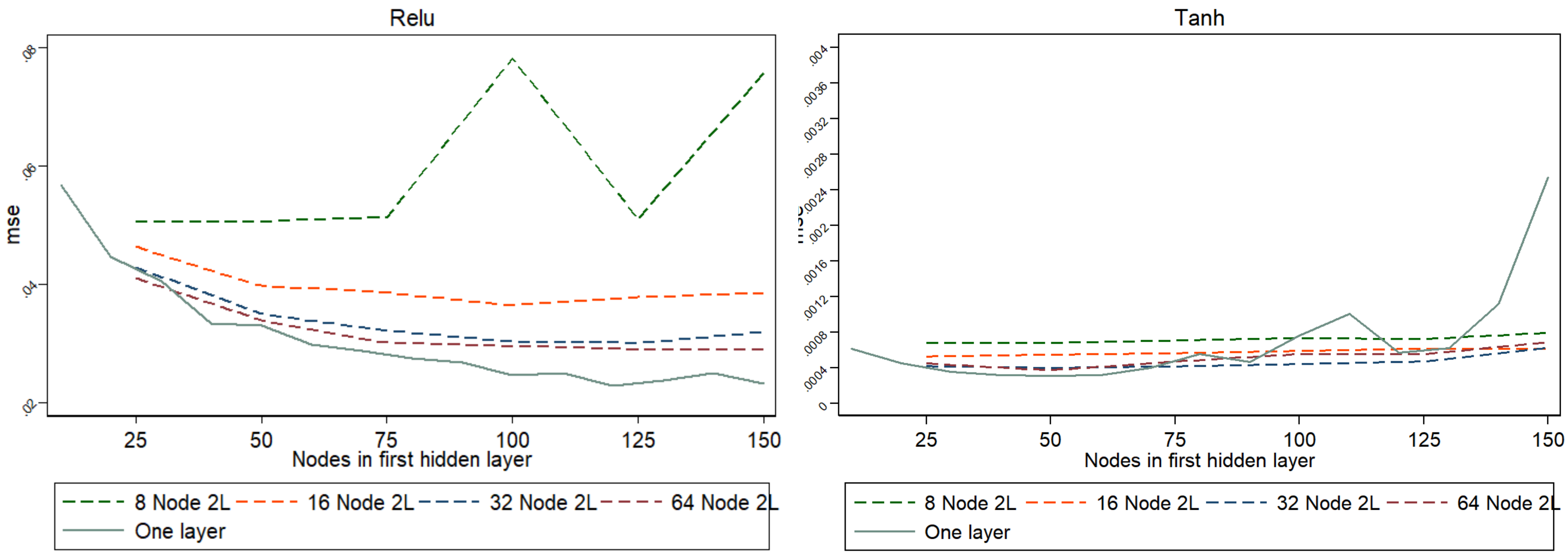
- Sequential network architecture: 3 layers (input, hidden, and output)
- input/output layer have 110 (11*10) nodes
- First hidden layer node size ranges from 10 to 150
- Add second hidden layer of node size 8, 16, 32, 64
- Compare two common activation functions: relu, tanh

Learning curves over training and validation data



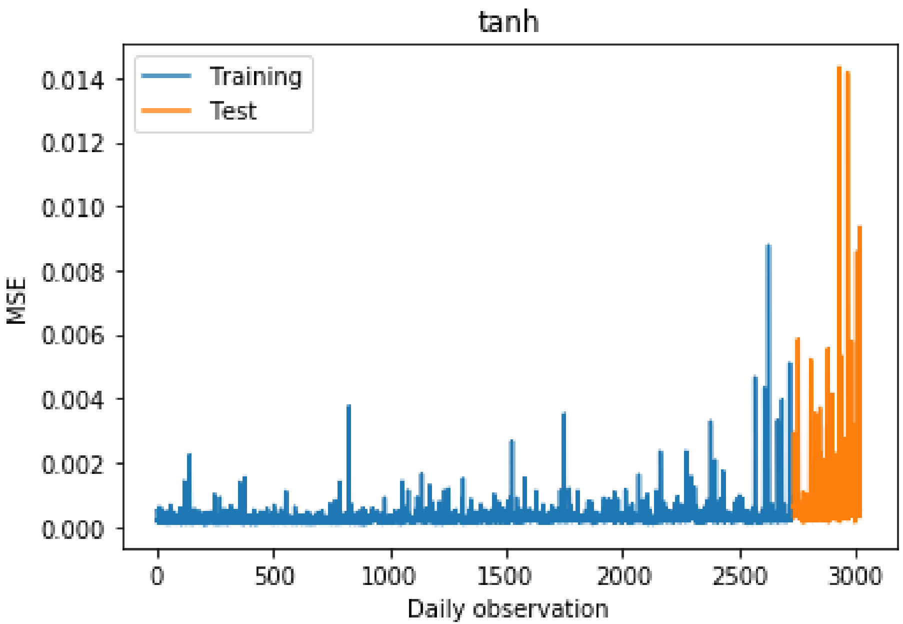
Note: Training data is drawn from daily gross bilateral flows between participants from the period 2007 to 2018 inclusive excluding days where any participant exhibits a MNDP greater than its 99^{th} historical quantile. Validation data is based on k-fold cross validation where k=5. Tanh activation function used for the case where input data is normalized to lie between 0 and 1. Relu activation function is used for the case where input data is normalized to be mean 0, sd 1.

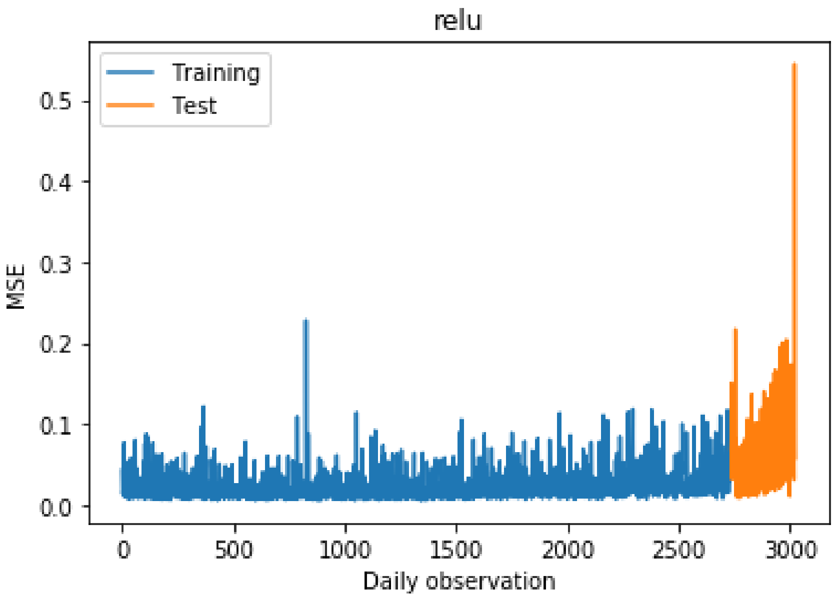
Choosing optimal network architecture



Note: MSE results shown for epochs = 200 on validation data.

Evaluation on Training vs Test sets





Note: Based on two-layer network of size 50,64 for tanh and 125, 64 for relu using 200 epochs. Test data drawn from days where any participant exhibits a MNDP greater than its 99th empirical quantile.

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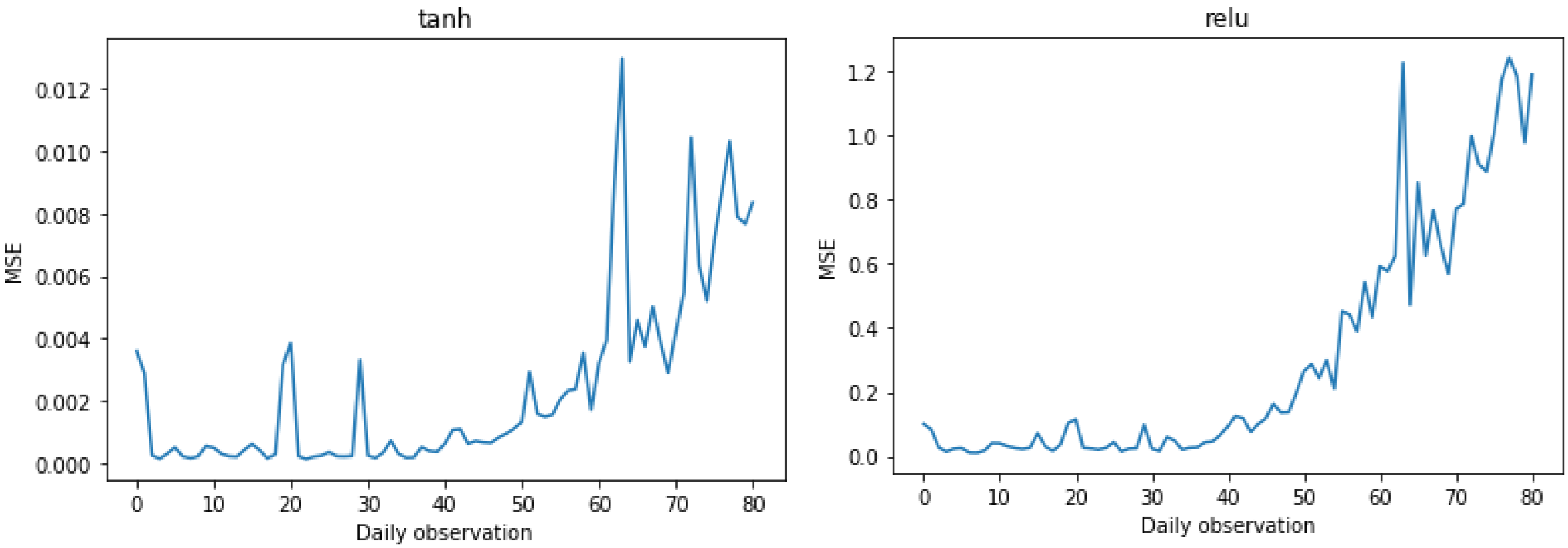
Evaluation on experimental bank run data



Note: Based on two-layer network of size 50,64 for tanh and 125, 64 for relu using 200 epochs. Participant experiences cumulative 1/2 standard deviation +(-) shift in outflow (inflow) weekly from n=40 to n=80.

Next steps, future work

- Compare results and efficacy of autoencoder to traditional methods
- Evaluate alternate network architectures and activation functions
- Evaluate sensitivity, robustness to training, validation data composition and overfitting
- Develop and simulate alternate bank run scenarios as in Triepels et al (2018)
- Neural network for time-series data that take into account memory, time dependence

Final remarks

- We setup a first autoencoder for detecting anomalous payment flows for ACSS data
- Promising initial results but additional testing and fine tuning is necessary
- Can we add other features (augmented data) or work with more advanced methods to improve performance
- Compare findings/approaches with others in the literature such as Triepels et al (2018) who work with RTGS data

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