# Forecasting Intraday Throughput of Large Value Payment System Participants Using Neural Networks: A Preliminary Approach

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## Agenda

- Introduction
- Research Problem
- Machine Learning
  - Artificial Neural Networks (ANN)
- Data Set Used
- Forecast Evaluation
- Experiment Results
- Conclusion
  - Work in Progress

## Introduction

- Recent financial crisis led to new regulatory standards issued by the BCBS
- *Principles for Sound Liquidity Risk Management and Supervision (2008)*
  - Qualitative principles
- *Monitoring Tools for Intraday Liquidity Management (2013)*
  - Quantitative monitoring
  - A key aspect to monitor: **intraday throughput**
    - Percentage of outgoing payments (relative to total value of payments for the day) within each hour of the business day

## BCBS Report Template

- Intraday Throughput

| Time | Cumulative sent | % sent |
|---|---|---|
| 08:00 | 450 | 32.14 |
| 09:00 | 550 | 39.29 |
| 10:00 | 750 | 53.57 |
| 11:00 | 750 | 53.57 |
| 12:00 | 750 | 53.57 |
| 13:00 | 1050 | 75.00 |
| 14:00 | 1050 | 75.00 |
| 15:00 | 1300 | 92.86 |
| 16:00 | 1400 | 100.00 |
| 17:00 | 1400 | 100.00 |
| 18:00 | 1400 | 100.00 |

## Research Problem

- **How to derive and forecast throughput information using LVPS transaction records?**
- Significance
  - Use of derived information for regulatory monitoring
  - Use forecast for estimating liquidity requirements (individual and system-wide)
  - Both derived (actual) and forecast information may be used for further analytical work
    - Simulations
    - Agent-based models

## Machine Learning

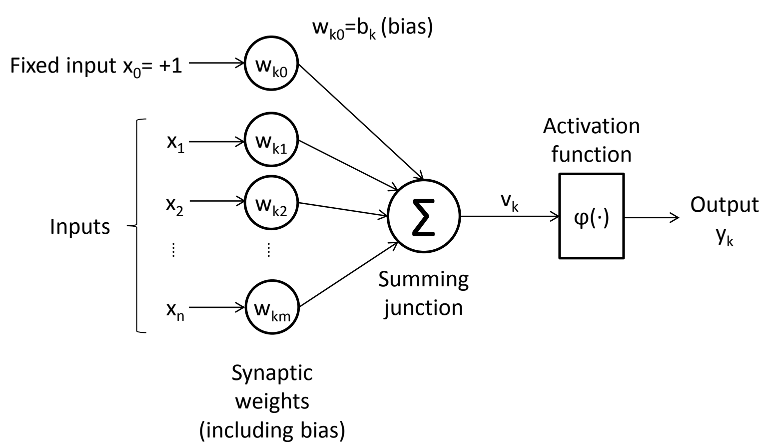
- Mitchell (1997):
  - "A computer program is said to **learn** from experience *E* with respect to some class of tasks *T* and performance measure *P*, if its performance at tasks in *T*, as measured by *P*, improves with experience *E*."
- Problem Breakdown
  - E: LVPS transaction records
  - T: Prediction of throughput information
  - P: Forecast error

## Machine Learning for Time Series Forecasting

- Ahmed et al. (2010)
  - Claimed that machine learning models have been gaining acceptance as an alternative to classical statistical models
  - Compared various machine learning models for time series forecasting and found one of the best results from multilayer perceptron (simple neural network)
- Krollner et al. (2010)
  - Surveyed literature in machine learning and artificial intelligence used to forecast stock market movements
  - Dominant technique found: artificial neural networks

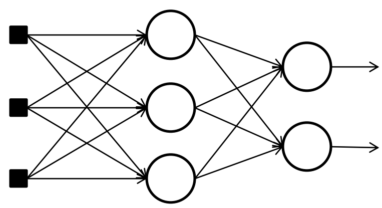
## Artificial Neural Networks

- Model of a Neuron (Haykin, 1999)



## Artificial Neural Networks

- Architecture
  - the manner in which the neurons in the network are connected to each other
  - several types are available, but the most commonly used is **multilayer feedforward networks** (or **multilayer perceptrons**)




## Artificial Neural Networks

- Designing a Neural Network (Haykin, 1999)
  - Selection of a neural network **architecture**
  - Phase 1: Subset of examples are used to train the network by means of suitable algorithm (**learning**)
    - Using a training data set
    - The network ‘learns’ every time it is presented with new input through forward activation flow and weight adjustments through backward error propagation (Josef, 1996)
  - Phase 2: Tested with data not seen before and its performance evaluated (**generalization**)
    - Using a test (out of sample) data set

## ANN Implementation Used

- R Environment
- **nnetar** from **forecast** package by R. Hyndman
  - Relies on **caret** package by M. Kuhn
    - Relies on **nnet** package by B. Ripley
  - Feed-forward neural network with a single hidden layer and lagged inputs for forecasting single-variable time series
- Experiments varied **number of lagged inputs** and **number of nodes** within the hidden layer between experiments

## Data Set Used

- Philippine Payments and Settlement System
  - **PhilPaSS**: real-time gross settlement system used in the Philippines
  - 161 participants as of February 2013 (BSP, 2013)
    - (universal/commercial banks, thrift banks, rural banks, quasi-banks, 3rd party system providers)
- Used **1 month** of transaction data
  - Selected **5 participants** with the highest value of outgoing payments for the month
  - Transaction data per participant aggregated and cast as **hourly cumulative outflows** from 9:00 AM to 6:00 PM
    - 9 time buckets per day
  - Included transactions for **21 business days**
    - 189 data points per participant
  - Data set divided into **80% training set** and **20% test set**
    - Training – 17 days Test – 4 days

## Forecast Evaluation

- Mean Absolute Scaled Error (MASE)
  - proposed by Hyndman and Koehler (2005)
  - scales the absolute error based on the mean absolute error (MAE) from a benchmark method
  - using a naïve method as benchmark, the scaled error is computed as follows:

$$q_t = \frac{e_t}{\frac{1}{n-1}\sum_{i=2}^{n} |Y_i - Y_{i-1}|}$$

  - scaled error is less than one if it arises from a better forecast than the average one-step benchmark forecast

## Forecast Evaluation

- Mean Absolute Scaled Error (MASE) (cont'd)
  - the MASE is simply computed as

$$MASE = mean(q_t)$$

  - when MASE is less than 1, the proposed method gives, on average, smaller errors than the one-step errors from the benchmark method

## Experiment Results

| Participant | Number of Lagged Inputs | Number of Hidden Units | MASE |
|---|---|---|---|
| A | 27 | 4 | 0.91 |
| B | 18 | 3 | 0.45 |
| C | 36 | 10 | 0.89 |
| D | 36 | 26 | 0.78 |
| E | 18 | 3 | 0.50 |

**First iteration**

| Participant | Number of Lagged Inputs | Number of Hidden Units | MASE |
|---|---|---|---|
| A | 27 | 1 | 0.44 |
| B | 36 | 3 | 0.44 |
| C | 36 | 7 | 0.82 |
| D | 45 | 1 | 0.40 |
| E | 27 | 1 | 0.42 |

**Second iteration**

| Participant | Number of Lagged Inputs | Number of Hidden Units | MASE |
|---|---|---|---|
| A | 27 | 1 | 0.44 |
| B | 36 | 3 | 0.44 |
| C | 36 | 9 | 0.79 |
| D | 45 | 1 | 0.40 |
| E | 27 | 1 | 0.42 |

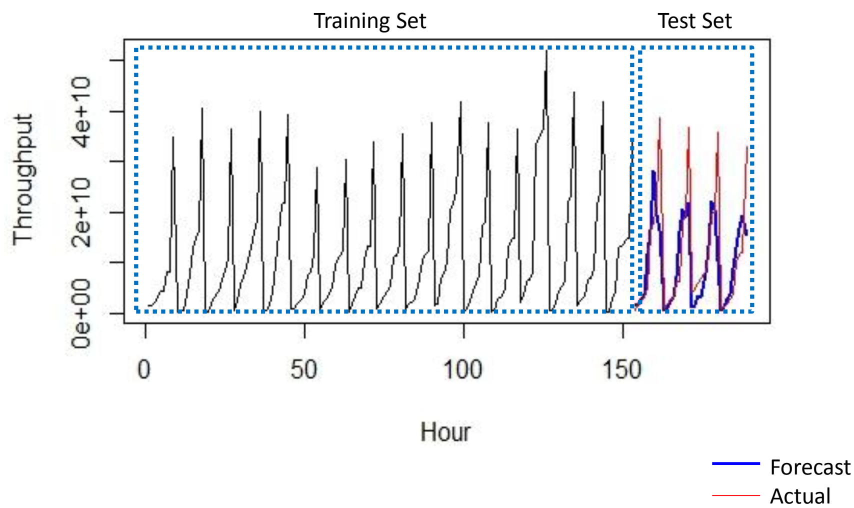
**Third iteration**

## Experiment Results

- Additional runs were performed to examine performance for longer forecast windows (2 to 4 days)

| Participant | 1-Day Forecast | 2-Day Forecast | 3-Day Forecast | 4-Day Forecast |
|---|---|---|---|---|
| A | 0.44 | 0.83 | 0.75 | 0.73 |
| B | 0.44 | 0.52 | 0.62 | 0.69 |
| C | 0.79 | 0.61 | 0.90 | 0.79 |
| D | 0.40 | 0.63 | 0.63 | 0.70 |
| E | 0.42 | 0.43 | 0.47 | 0.56 |
| Average | 0.50 | 0.60 | 0.67 | 0.69 |

# Actual vs. Forecasts

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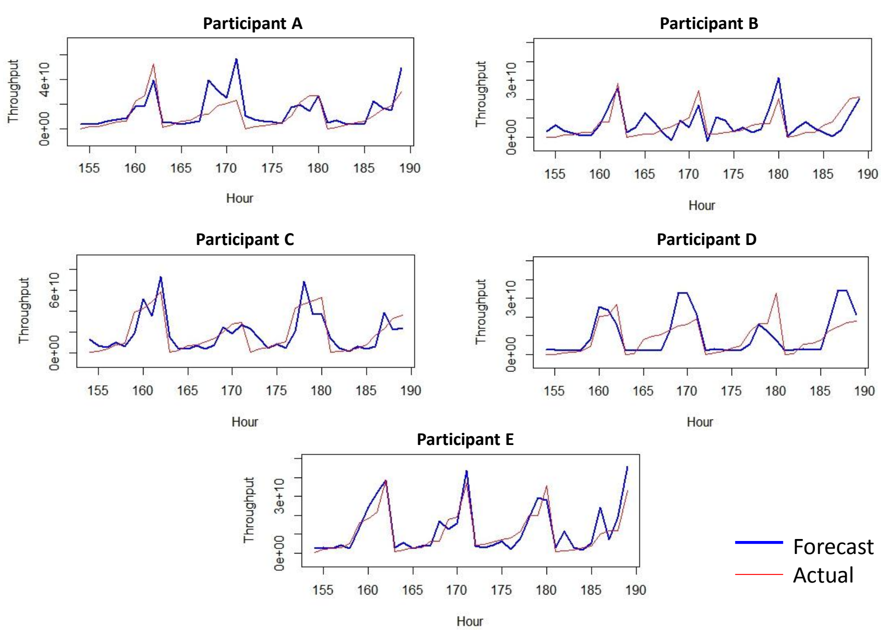

## Conclusion (So Far)

- ANNs show potential for forecasting throughput information of individual participants
- Some participants easier to model than others
  - Contributory factors may include variety of services offered, diversity of client base, and volume of transactions
- Generally approximates the cycle of the throughput data but forecast errors remain significant
- … more work to be done!

## Work in Progress

- Continuous model refinement
- Determining effect of training data size
- Predicting total transaction per hour vs. cumulative (throughput) values
- Determining features other than lagged values (time of day, day of week, etc.)
- Use of other neural network architectures

**Thank you for listening.**