Classifying Payment Patterns with Artificial Neural Networks: An Autoencoder Approach

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Introduction

Motivation: Manage systemic risk in the high-value payments systems

- Objective: Model to detect potential anomalies stemming from payments patterns in the SPI (Ecuador's payments systems)
- Data: Aggregated intraday data structured in three time-intervals
- Model: Autoencoder (type of artificial neural network used to learn data codings)

Outcome: Model is useful to support the monitoring of payments systems' functioning, but need to be accompanied by the expert judgement of payments overseers:

- Unsupervised learning: no need of prior examples of anomalies in the data
- Can detect a wide range of anomalies: the unusual behavior of individual banks to systemic changes in the overall structure of the payments network.

Comments/Questions

Objective: It's a worthy objective and such model could be very useful for early identification of anomalous transactions and monitor HVPS. Also they perform alert analysis to investigated which of the flows caused these anomalies

- The developed tool is tested on artificial data only. Although, that is worthwhile exercise, it would be really useful to test such tool for some observed anomalous flows (such as operational incidents)
- It would be also interesting to see some in-sample analysis: what type of flows are hard to reconstruct? is there a threshold below/above which the reconstruction errors is high? or may be some FI's flow are predictable than others. etc.
- Can such tool deals with the shocks to the system: the payments patterns during the global financial crisis or COVID-19 shock could be classified as anomalous? It is valuable to investigate and discuss the limitations of such tools in practice

Comments/Questions

Data:

- SPI settlement data from 2018: Why only one year? May be yearly repetition of pattern using more years of data could be valuable for training?
- Could including time stamp feature along with the flow add value to the model?

Model:

- Autoencoders are hard to interpret: it could be useful to see how model is conceptualizing the input feature and on what basis it is learning. That could be valuable for operators to understand why any given flow is anonymous or usual?
- Although it is not constrains, it is common practice to use symmetric architecture in autoencoders: 1 or 3 hidden layers (why 2?) symmetry could be advantageous
- If the interest is to find rare events (a needle in a haystack), then something like isolation forest could be more useful, which works on basis of isolating anomalies. The autoencoder works on the basis of profiling normal points (compare them?)

Thank you!