Detecting intraday financial market states using temporal clustering

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QuERILab
Quantifying Emergence, Risk and Information
in financial markets

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Outline

1. Market microstructure and state representation
2. Identifying temporal system states
   - Unsupervised clustering approach
   - Giada-Marsili proposition with Noh ansatz
   - High-speed cluster configuration identification
   - Financial market intraday times as objects
3. Data and Results
   - Data
   - Temporal states, State Signature Vectors, Cluster size power-law fit, Estimated states, Transition probabilities
4. Conclusion

Market microstructure and state representation

- Financial markets as **complex adaptive systems** (Wilcox & Gebbie, 2015), prices and volumes as **measurable quantities**
- Market microstructure studies the **system evolution**, **behaviour** and consequences for **price formation** at the **lowest scale** (tick-level)
- Motivated by need for **efficient state representation** for automated trading agents in high-frequency markets to enable effective learning
- Agents faced with **high-volume**, **asynchronous** stream of financial market **data** from a real-time datafeed
- Can we find **persistent structure** in this streaming data, such that **meaningful learning** can take place for adaptive trading algorithms?

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Identifying temporal system states

Unsupervised clustering approach

- Clustering involves **grouping objects** according to **metadata** describing objects or their associations
- For unsupervised clustering, apply **super-paramagnetic ordering of q-state Potts model** for cluster identification (Blatt et al., 1996)
- Cost function is a Hamiltonian whose **low energy state** corresponds to a **cluster configuration** most compatible with the sample

$$H_g = -\sum_{s_i, s_j \in S} J_{ij}\delta(s_i, s_j) - \frac{1}{\beta}\sum_i h_i^M s_i$$

  where spins s_i can take on q-states and the short-range ferromagnetic interaction between spins is given by J_{ij}
- To parameterise the model, make Noh (2000) ansatz and use this to develop the **MLE approach** of Giada & Marsili (2001)

Outline

Identifying temporal system states

Giada-Marsili proposition with Noh ansatz

- Objects belonging to the same cluster share a common component,

$$\bar{x}_i = g_{s_i}\bar{\eta}_{s_i} + \sqrt{1-g_{s_i}^2}\,\bar{\epsilon}_i. \tag{1}$$

- If we take this as a **statistical hypothesis**, and assume $\bar{\eta}_{s_i}$ and $\bar{\epsilon}_i$ are Gaussian, this leads to the following probability density,

$$P\left(\{\bar{x}_i\}|\mathcal{G},\mathcal{S}\right) = \prod_{d=1}^{D}\left\langle \prod_{i=1}^{N}\delta\left(x_i(t) - g_{s_i}\bar{\eta}_{s_i} + \sqrt{1-g_{s_i}^2}\,\bar{\epsilon}_i\right)\right\rangle \tag{2}$$

  and the **maximum likelihood** for structure $\mathcal{S}$ can be written as (Giada & Marsili, 2001),

$$\mathcal{L}_c(\mathcal{S}) = \frac{1}{2}\sum_{s:n_s>1}\left(\log\frac{n_s}{c_s} + (n_s-1)\log\frac{n_s^2-n_s}{n_s^2-c_s}\right). \tag{3}$$

- Full derivation in Hendricks, Gebbie & Wilcox (2016b)

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High-speed cluster configuration identification

- Likelihood function in Equation 3 used as **objective function** in metaheuristic optimisation routine (genetic algorithm)
- Systematically **evaluate** candidate **configurations** ($\mathcal{S}$), converging towards **best approximation** of data descriptor
- Hendricks, Gebbie & Wilcox (2016a) demonstrate a high-speed **Parallel Genetic Algorithm** implementation in **CUDA**, using the SPMD architecture to enumerate the GPU thread hierarchy with population members for **concurrent application of genetic operators**
- A **low-cost**, **scalable**, **high-speed** implementation for **unsupervised cluster detection**

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Identifying temporal system states

Financial market intraday times as objects

- **Generic** data generative model **ansatz** conducive to any problem where **Gaussian** object and cluster innovations are reasonable
- Marsili (2002) grouped **days** according to **closing price** performance to identify temporal states
- Propose that **intraday temporal regimes** of financial markets are characterised by feature performance of stocks
- Using **trade price**, **trade volume**, **spread** and **volume imbalance** features of TOP40 stocks on the JSE, we find clusters of **60-min, 30-min, 15-min and 5-min periods**
- Determine whether clustering at varying **calendar time scales** reveals interesting **hierarchy** of system behaviour
- Reduces significant amount of high-frequency information into a **tractable representation** for intraday learning

Identifying temporal system states

State Signature Vectors

- Temporal clustering reveals *ex-ante* grouping of periods
- How do we incorporate this into an **online learning algorithm**? i.e. determine the state we are **currently** in
- Analyse **average feature performance** of stocks within identified temporal clusters and extract *State Signature Vector* (SSV) as state descriptor
- Online feature vectors are **easy to compute** from streaming market datafeeds in financial markets, conducive to near-real-time detection
- Need to determine which identified states are **significant**, i.e. likely to persist such that meaningful learning is possible
- Use best **power law fit** to cluster size to identify likely persistent states
- Use **Euclidean distance** of (current) online feature vector to set of SSVs for state index assignment

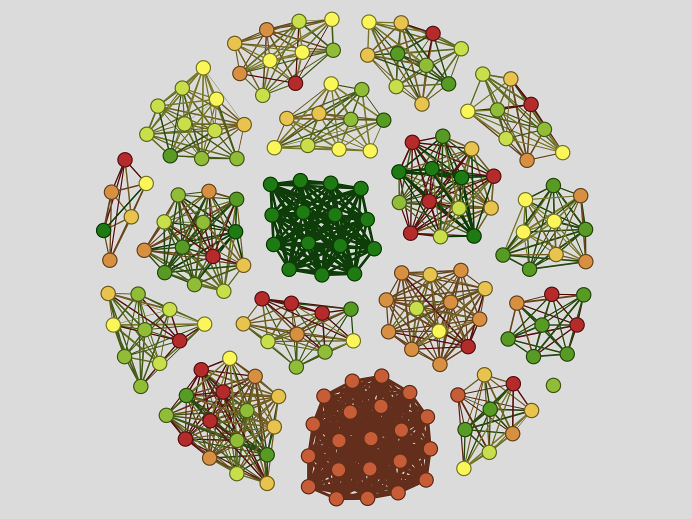
Outline

- Tick-level **trades** and top-of-book **quotes** for **42 stocks** on the **Johannesburg Stock Exchange** (JSE) from **1 November 2012 to 30 November 2012**
- Raw data sourced from Thomson Reuters Tick History
- Stored in **MongoDB noSQL database** on QuERILab server and integrated into MATLAB development environment

Outline

Identifying temporal system states

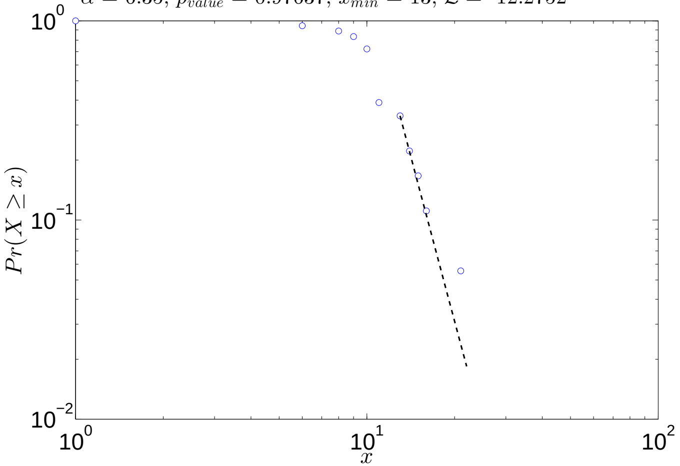
60-min clusters (TOP40 stocks; price, volume, spread, volume imbalance), 01-Nov-2012 to 30-Nov-2012, GREEN=morning, YELLOW=lunch, RED=afternoon



Power law fit for cluster size

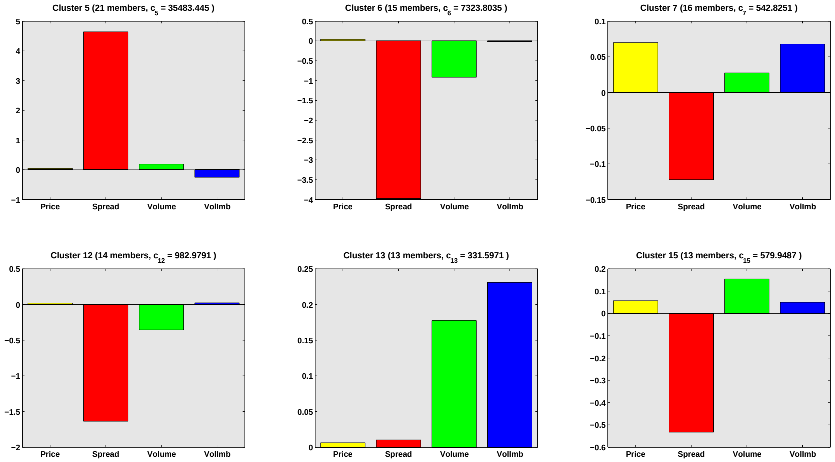
60-min clusters (TOP40 stocks; price, volume, spread, volume imbalance), 01-Nov-2012 to 30-Nov-2012

Test for **cluster size** power law fit: *60-min periods*
Power law distributional form ($p(x) \sim x^{-\alpha}$) vs empirical data
$\alpha = 6.35$, $p_{value} = 0.97637$, $x_{min} = 13$, $\mathcal{L} =$ -12.2752



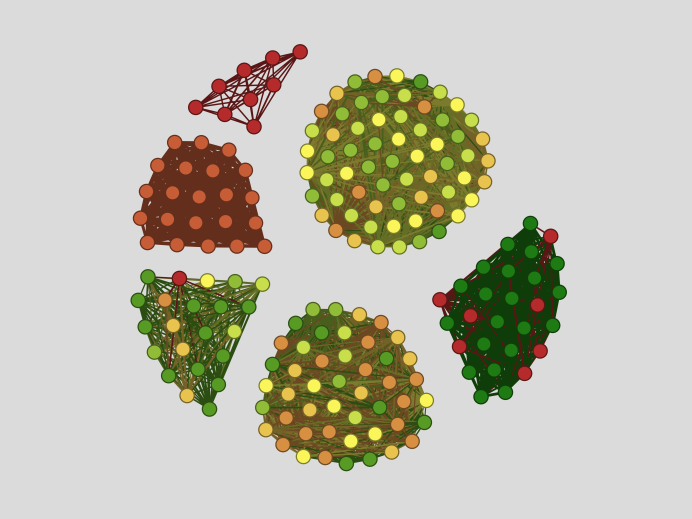
State Signature Vectors

60-min clusters (TOP40 stocks; price, volume, spread, volume imbalance), 01-Nov-2012 to 30-Nov-2012



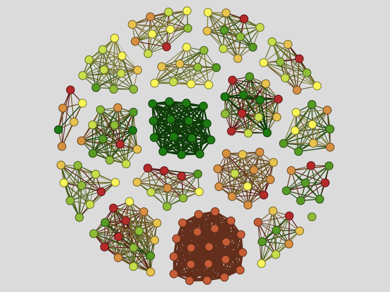
Estimating temporal states using feature vectors

60-min clusters (TOP40 stocks; price, volume, spread, volume imbalance), 01-Nov-2012 to 30-Nov-2012

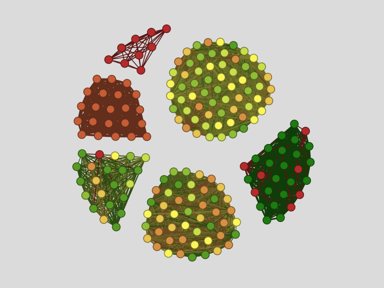


Actual vs Estimated temporal states

60-min clusters (TOP40 stocks; price, volume, spread, volume imbalance), 01-Nov-2012 to 30-Nov-2012



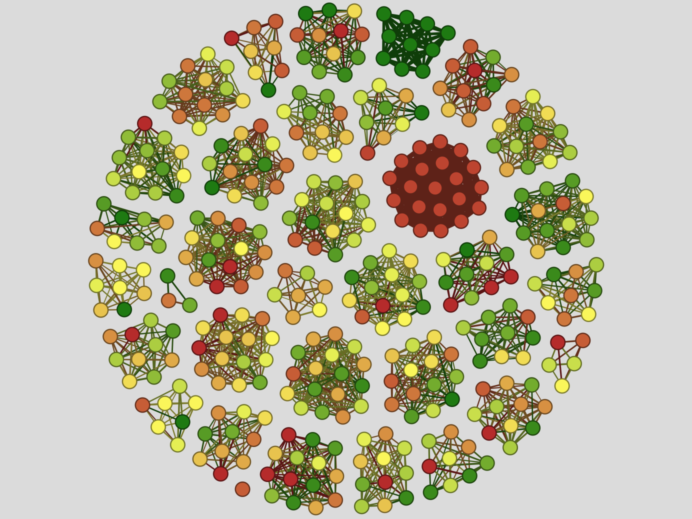
(a) Actual 60-min states



(b) Estimated 60-min states

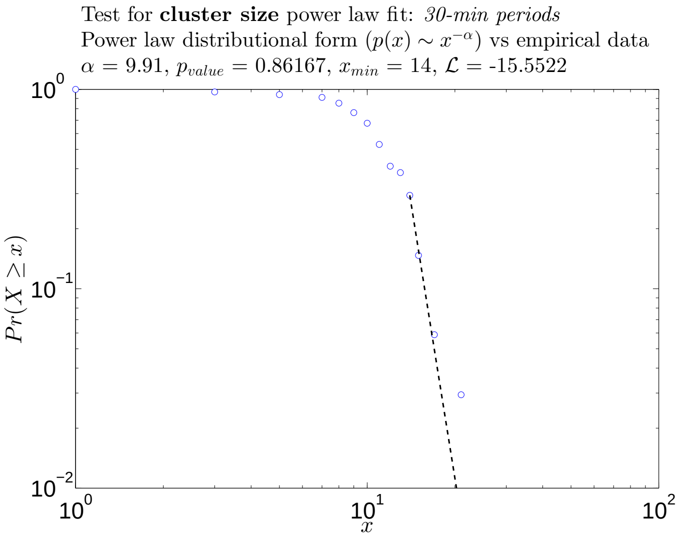
Identifying temporal system states

30-min clusters (TOP40 stocks; price, volume, spread, volume imbalance), 01-Nov-2012 to 30-Nov-2012, GREEN=morning, YELLOW=lunch, RED=afternoon



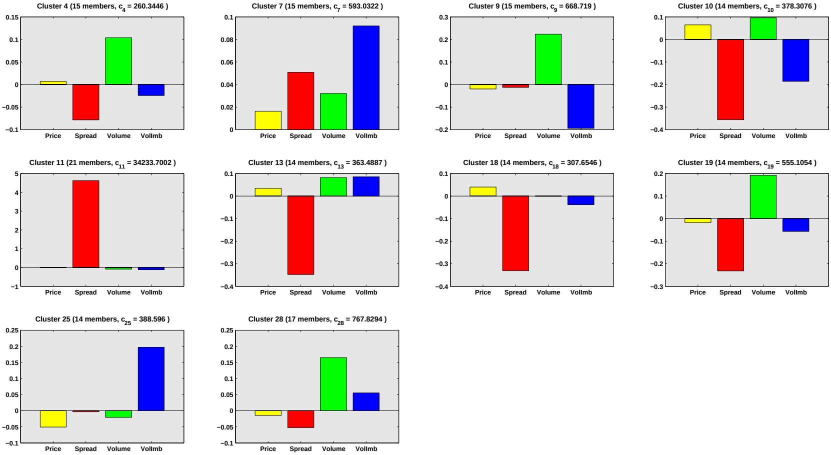
Power law fit for cluster size

30-min clusters (TOP40 stocks; price, volume, spread, volume imbalance), 01-Nov-2012 to 30-Nov-2012



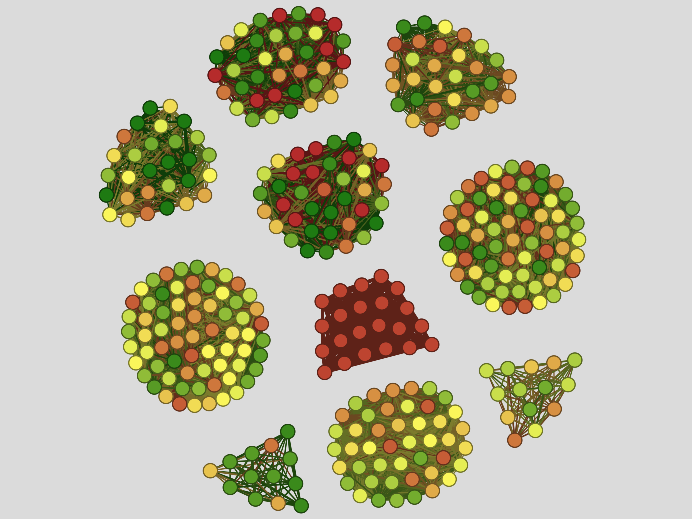
State Signature Vectors

30-min clusters (TOP40 stocks; price, volume, spread, volume imbalance), 01-Nov-2012 to 30-Nov-2012



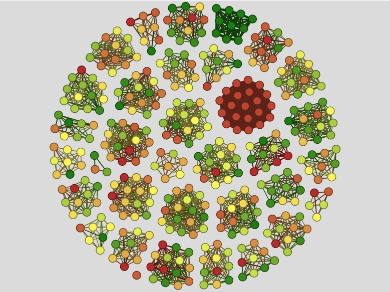
Estimating temporal states using feature vectors

30-min clusters (TOP40 stocks; price, volume, spread, volume imbalance), 01-Nov-2012 to 30-Nov-2012

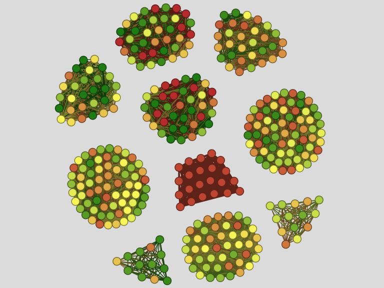


Actual vs Estimated temporal states

30-min clusters (TOP40 stocks; price, volume, spread, volume imbalance), 01-Nov-2012 to 30-Nov-2012



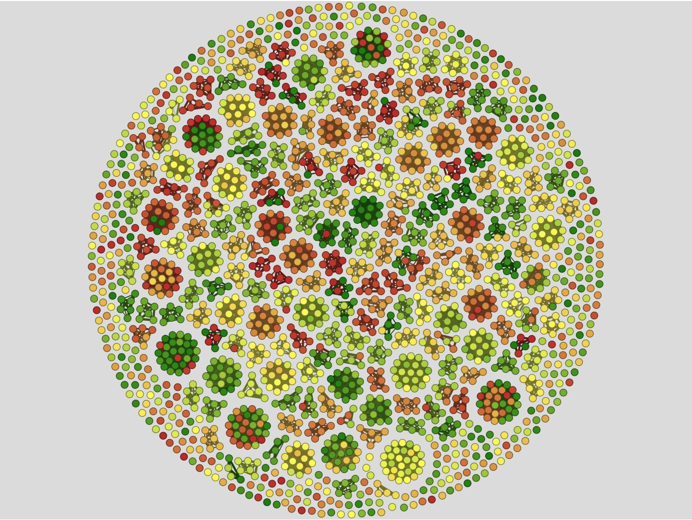
(a) Actual 30-min states



(b) Estimated 30-min states

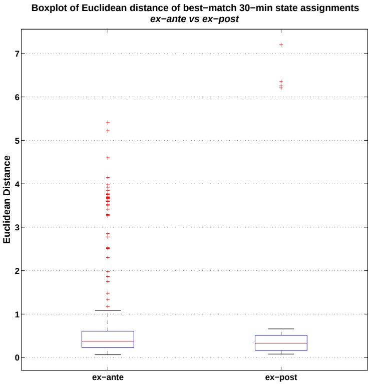
Identifying temporal system states

5-min clusters (TOP40 stocks; price, volume, spread, volume imbalance), 01-Nov-2012 to 30-Nov-2012, GREEN=morning, YELLOW=lunch, RED=afternoon

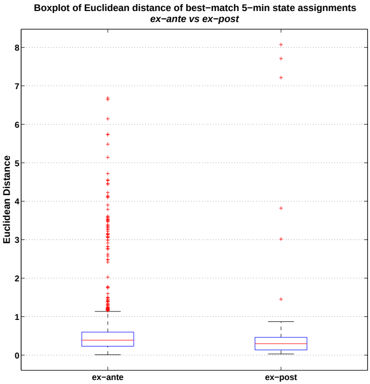


Stability of the online state assignment out-of-sample

ex-ante (01-Nov-2012 to 30-Nov-2012, same period used for SSV estimation) vs *ex-post* (03-Dec-2012 to 07-Dec-2012, one week after SSV estimation window)



(a) 30-min states



(b) 5-min states

Conclusion

- Provided a scheme for **unsupervised** determination of intraday financial market **states** and **online** state **detection** using **SSVs**
- Tractable **state representation** for learning agents in high-frequency trading domain
- Non-trivial **hierarchy** of clustering **behaviour** at varying time-scales reveals **scale-specific information** for learning
- One application is the online enumeration and refinement of an **empirical transition probability matrix**
- States appear to persist **long enough** to be exploited - needs to be verified
- Will consider clustering in **machine time** in further work

For Further Reading I

- D. Hendricks, D. Wilcox, T. Gebbie. *Detecting temporal financial market states using clustering*. Quantitative Finance (accepted, to appear 2016). (Pre-print: http://arxiv.org/abs/1508.04900)
- D. Hendricks, D. Wilcox, T. Gebbie. *High-speed detection of emergent market clustering via an unsupervised parallel genetic algorithm*. South African Journal of Science, vol. 112, no. 1/2, 2016.
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- D. Wilcox, T. Gebbie. *Hierarchical causality in financial economics*. Working paper, QuERILab, 2015 (Available at SSRN: http://ssrn.com/abstract=2544327)