Discussion on

Capturing the Order Imbalance with Hidden Markov Model: A Case of SET50 and KOSPI50

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PIER RESEARCH WORKSHOP
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Summary

- Wu & Siwasarit (2017) use Hidden Markov Model (HMM) to
  - Forecast price movements of liquid stocks (by avg. turnover) in SET 50 and KOSPI 50. (OIR as input)
  - Generate algorithmic trading signals.
- Data
  - Data: intraday (5-min, 10-min, 30-min).
  - Training period: Aug to Sept 2016.
  - Testing period: Nov 2016 to Jan 2017.

Summary and Main Findings

- Hidden Markov Model (HMM)
  - 3-5 States (unobserved) of asset prices
    - Overvalued, Equilibrium, Undervalued
    - Other hidden states
  - Emissions (observed)
    - (+) or (0, –) movement
  - **Discrete** & Continuous Implementation
    - Major findings from discrete case
    - Continuous case – distributions not captured by normal mixture model.

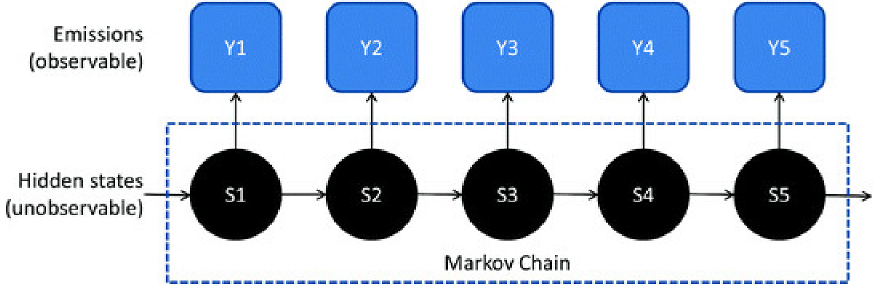


Image Source: Komorowski (2016)

Summary and Main Findings

- Major Findings:
  - Generated signals achieve up to 84% hit ratio (5-min, 5 states)
    - hit ratio $= \dfrac{\#\,\text{correct positive signals}}{\#\,\text{total signals generated}}$
    - SET 50 stocks: hit ratios between 71% (PTTEP) to 89% (BCP)
    - KOSPI 50 stocks: hit ratios between 54% (LG Display Co., Ltd.) to 81% (LG Chem Co., Ltd.)
  - Predictability ↓ as frequency ↓ and liquidity ↑.

Summary and Main Findings

- Major Findings:
  - Profitability measured by Jensen's alpha, assuming 0.05% transaction cost
    - SET 50 stocks: $\alpha = 0.029$ to 0.047
    - KOSPI 50 stocks: $\alpha \approx 0$
  - Profitability has a similar pattern to predictability. Profitability $\downarrow$ as frequency $\downarrow$.

Contribution – Academia

- Provides empirical evidence consistent with
  - Predictability: Chordia, Goyal, and Jegadeesh (2016JFQA) and other Chordia et al. papers.
  - Price efficiency: Rosch, Subrahmanyam, and van Dijk (2016RFS).
  - Components of price impact (inventory-risk, asymmetric information): Muravyev (2016JF).

Contribution – Practitioners' Side

- Algo trading pioneered by IBM researchers in 2001.
- Algo trading is on the rise.
- Example:
  - FX algorithmic trading volume is about 70% of that of dealer-related volume.

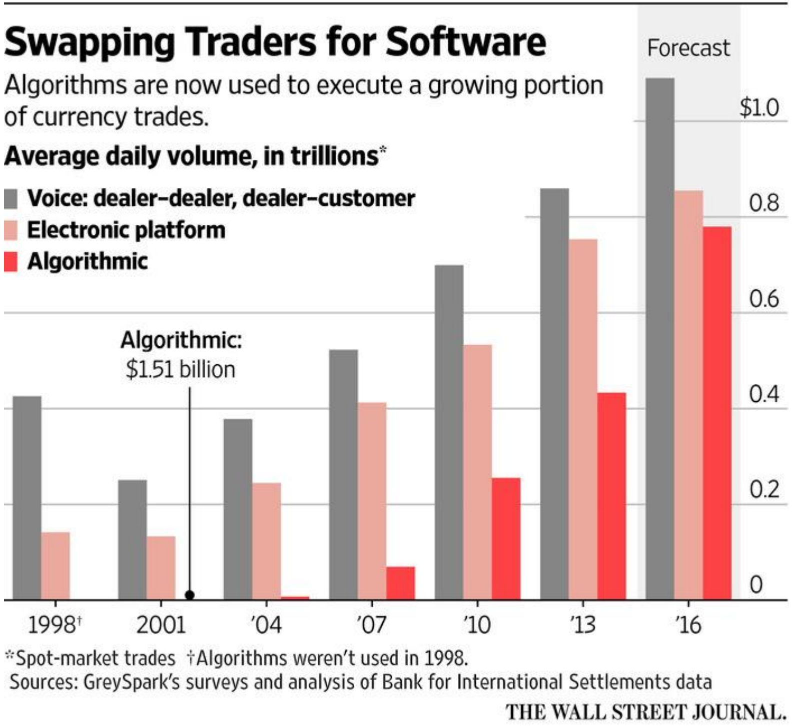


Image Source: Wall Street Journal (2015)

Contribution – Practitioners' Side

- High-frequency trading (HFT) is here to stay.
- Equity volume executed by HFT is about 50% of the total in the US.
- HF trading firms have a 500-microsecond lead for NASDAQ in 2015.

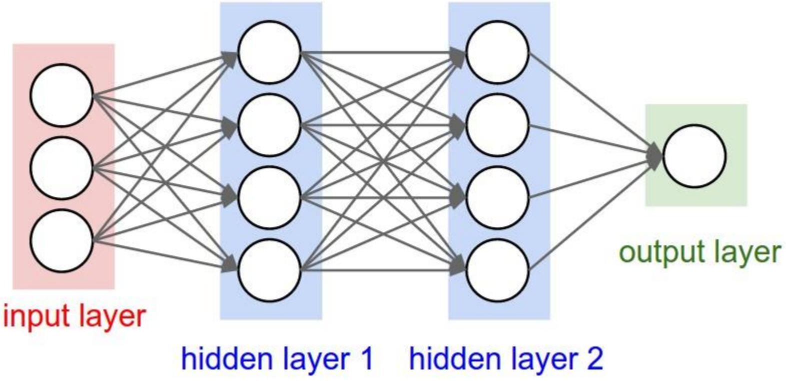
Image Source: Wall Street Journal (2014)

Possible Extensions/Suggestions

- Ensemble Learning (combination of techniques)
  - Zamora-Martinez et al. (*Pattern Recognition*, 2014) find a combination of Neural Networks (NNs) and HMMs improve the performance.
- May allow more trading signal generation in difficult cases (liquid stocks, less frequent data points)

Possible Extensions/Suggestions

- Deep Learning?
  - Di Lena et al. (*Bioinformatics*, 2012) report that Recurrent Neural Networks (RNNs) outperform HMMs and Support Vector Machine (SVM).



Source: CSI231 at Stanford (2017)

Possible Extensions/Suggestions

- Data - possible fine-tuning for performance.
  - Tick data could improve performance.
  - Small-cap stocks.
  - Continuous case
    - Would expanding the training period (currently 2 months) mitigate the coin toss issue?
  - Data challenge: stocks with no trading during selected intervals (5-min, 10-min, 30-min).

Thank You