Implementation of Actual Data for Artificial Market Simulation

Extended Abstract

Masanori Hirano
The University of Tokyo
Tokyo, Japan
hirano@g.ecc.u-tokyo.ac.jp

Kiyoshi Izumi
The University of Tokyo
Tokyo, Japan
izumi@sys.t.u-tokyo.ac.jp

Hiroki Sakaji
The University of Tokyo
Tokyo, Japan
sakaji@sys.t.u-tokyo.ac.jp

ABSTRACT

This study proposes a new scheme for implementing actual data into artificial market simulations at the level of trader agents. Because humans can introduce bias or overlook the important features of actual traders, we implemented the actual data and automated the strategy learning (imitating) of agents using machine learning (ML). We then ran artificial market simulations in the treader model, which imitates the actual trading behaviors in an ML architecture. Through this study, we demonstrate the potentials and limitations of the proposed scheme.

KEYWORDS

Artificial Market; Social Simulation; Data Mining; Financial Market

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1 INTRODUCTION

Existing artificial market simulations may not be sufficiently reliable, mainly because models are built by humans, who introduce their own biases and might omit some features of actual traders' behaviors. Recently, [4] discussed the differences between actual and simulated data and pointed out that simulation models cannot completely reproduce the essential features of actual markets.

Clearly, the development of models for artificial market simulations needs to be reconsidered. One possible approach is the "reverse engineering" of actual traders. In this study, we build and evaluate a trader model for artificial market simulations, which automatically learns (imitates) the actual behavior of traders.

Our model is aimed at high-frequency-trading market-making traders (HFT–MM). HFT–MM traders were chosen for four main reasons: distinctness in markets; existing well-accepted human-designed model; limitation of computational resources; the increasing shares in markets [6].

2 STUDY OVERVIEW

Figure 1 is an overview of this study. The data in this study is the same as and explained in Hirano et al. [5], which were extracted by a method based on cluster analysis [8].

The data gathered from January to July of 2015 and from August of 2015 were applied as the training and test data, respectively. Then,

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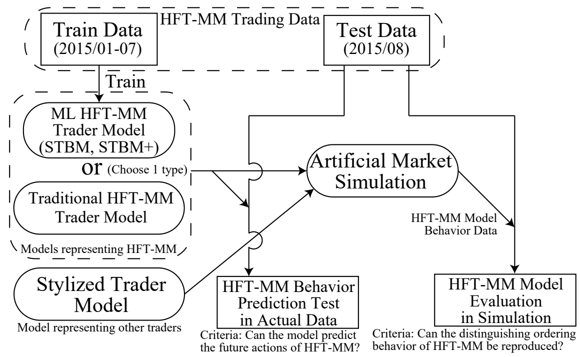

Figure 1: Overview

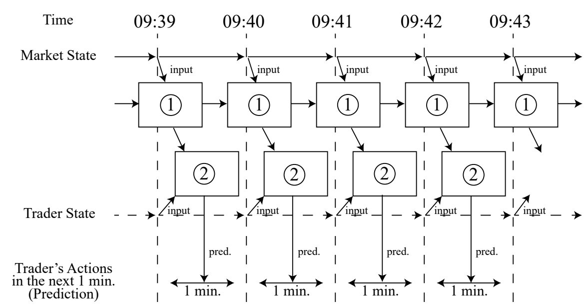

Figure 2: Learning model of the ML HFT–MM trader model (see Table 1 for details)

using the training data, we trained the ML HFT–MM trader models to imitate the actual ordering behavior. Trade models without data were also prepared for two purposes. First was the traditional HFT–MM trader model based on [1], employed for referencing our ML HFT–MM traders. The other model was the stylized trader model based on [7], which simulates traders other than HFT–MM.

In the first evaluation phase, we tested the prediction performances of the ML HFT–MM trader models on the test data to estimate their learning abilities. In the next evaluation phase, we built an artificial market simulation and evaluated the behaviors of the HFT–MM trader models in simulations. This evaluation evaluates how well each HFT–MM trader model could simulate the distinctive ordering behaviors of HFT–MM traders via order distribution comparison based on Kullback–Leibler divergence (KLD).

The simulation model was based on [4], who focused on HFT–MM traders. For realizing this essential feature of HFT-MM, we set the delay of 100-steps for other agents. This delay affects stylized traders in terms of information and order chance. As an information delay, we set stylized traders to refer 100-step behind information always. On the other hand, stylized agents can put their orders only every 100 steps in terms of ordering chance.

Table 1: ML architecutures

Name	Architecture of ①	Architecture of ②	# of parameters	Note
STBM	LSTM	Dense	378,389	Originally proposed in [5].
LN STBM+	LSTM	Dense w/ Layer Normalization (LN)	379,101	LN was proposed in [2].
RB STBM+	LSTM	4 Residual Blocks (RB) with LN	1,398,685	RB was proposed in [3].
2-layered Tr STBM+	LN	Transformer (2 blocks)	2,654,229	Transformer was proposed in [9]. Transformer encoder, decoder are used for trader and market states respectively.
4-layered Tr STBM+	LN	Transformer (4 blocks)	5,290,005	
6-layered Tr STBM+	LN	Transformer (6 blocks)	7,925,781	
Attn STBM+ I	LN + RB	Attention + 4 × [LN + RB]	875,285	In attention mehanisms, key and value are from ① and query is from trader state.
Attn STBM+ II	LN + RB + Self-attention	Attention + 4 × [LN + RB]	1,204,245	
LSTM Attn STBM+	LSTM	LN + Attention + 4 × [LN + RB]	1,128,453	
Traditional	-	-	-	For comparison. Based on [1].

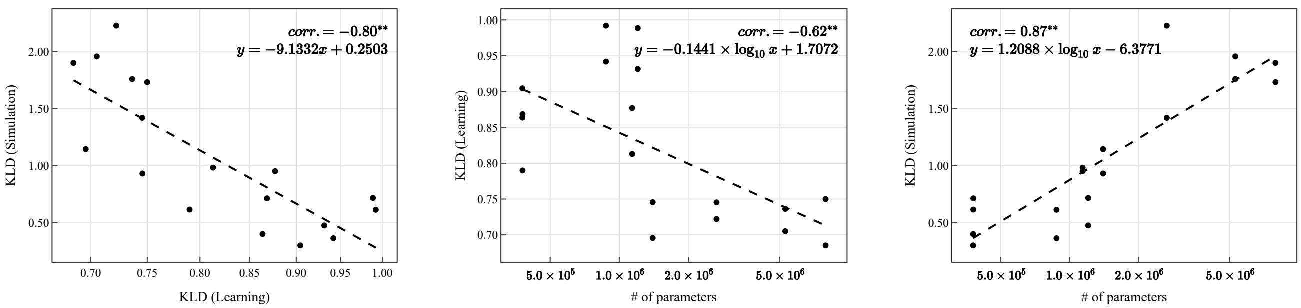

Figure 3: Correlation analysis. For comparison, KLD (Simulation) of the traditional model is 0.4994.

For the HFT-MM model, we made some types of agents. One is the traditional HFT–MM trader model based on [1]. The others are ML models based on STBM [5], whose base architecture is shown in Figure 2. However, in this study, we tested some ML models with different parameters and architectures shown in Table 1.

3 RESULTS & DISCUSSION

Figure 3 shows all the results and the correlations between the evaluation measures in the learning and simulation phases and the number of parameters in each model. Here, KLD is used as the loss function and evaluation measure. According to left-column figures, the better-learned model in behavior prediction tests shows the worse performance in simulation regarding the similarity between actual HFT–MM behavior and HFT–MM models' behavior in simulations. The correlation coefficients for KLD is -0.80, and statistically significant ($p < 0.01$). These values suggest that the tendency of inverse performance between learning and simulation performances is significantly high.

The mid and right columns in Figure 3 show the impact of the number of ML models' parameters on the performances. The mid-column figures show the relational analysis between learning performance and the number of parameters for each ML HFT–MM model. Moreover, the right-column figures show the relational analysis between simulation performance and the number of parameters for each ML HFT–MM model. According to these figures, we confirm the following tendencies: (1) ML HFT–MM trader model with more parameters shows a better performance in model learning; (2) ML HFT–MM trader model with more parameters shows a worse performance in simulations; These tendencies are statistically significant. Figures in the right column in Figure 3 show the comparison between the number of parameters in each ML HFT–MM model and each ML HFT–MM model's performance in simulations in terms of the similarity of their ordering behavior in actual data and simulations. According to these figures, the more model parameters ML HFT–MM models have, the more dissimilar the ordering behaviors in simulations compared to the actual behaviors became. The correlation coefficients is more than 0.85 and are statistically significant. Thus, this tendency (tendency (2)) is very strong.

Moreover, comparing the results that KLD (Simulation) of the traditional model is 0.4994, some outperforming models in simulations, which have a comparatively small number of parameters, outperformed the traditional model.

Summarizing these results, we can estimate the dynamics of the model performances: (1) Including more parameters in the ML HFT–MM trader models improved the performance of model learning; (2) Including more parameters in the ML HFT–MM trader models worsened the performance in the simulations; (3) Points (1) and (2) imply that a strong learning ML model is a weak simulation model, and vise versa; (4) The most primitive ML HFT–MM trader model displayed the best performance in the simulations and outperformed the traditional model without ML learning.

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REFERENCES

[1] M. Avellaneda and S. Stoikov. 2008. High-frequency trading in a limit order book. *Quantitative Finance* 8, 3 (2008), 217–224. https://doi.org/10.1080/14697680701381228

[2] J. Ba, J. Kiros, and G. Hinton. 2016. Layer Normalization. (2016). arXiv:1607.06450 http://arxiv.org/abs/1607.06450.

[3] K. He, X. Zhang, S. Ren, and J. Sun. 2016. Deep residual learning for image recognition. In *Proc. of IEEE CVPR*. 770–778. https://doi.org/10.1109/CVPR.2016.90

[4] M. Hirano, K. Izumi, H. Matsushima, and H. Sakaji. 2020. Comparing Actual and Simulated HFT Traders' Behavior for Agent Design. *J. of Artificial Societies and Social Simulation* 23, 3 (2020), 6. https://doi.org/10.18564/jasss.4304

[5] M. Hirano, H. Matsushima, K. Izumi, and H. Sakaji. 2020. STBM : Stochastic Trading Behavior Model for Financial Markets Based on Long Short-Term Memory. In *34th Annu. Conf. of Japanese Soc. for Artificial Intelligence*. Kumamoto, Kumamoto, Japan, 1K4–ES–2–04. https://doi.org/10.11517/pjsai.JSAI2020.0_1K4ES204

[6] Go Hosaka. 2014. Analysis of High-frequency Trading at Tokyo Stock Exchange. (2014). https://www.jpx.co.jp/english/corporate/research-study/working-paper/b5b4pj000000i468-att/E_JPX_wp_No4.pdf

[7] T. Torii, K. Izumi, and K. Yamada. 2015. Shock transfer by arbitrage trading: analysis using multi-asset artificial market. *Evolutionary and Institutional Economics Review* 12, 2 (2015), 395–412. https://doi.org/10.1007/s40844-015-0024-z

[8] J. Uno, K. Goshima, and R. Tobe. 2018. Cluster Analysis of Trading Behavior: An Attempt to Extract HFT [in Japanese]. In *12th Annu. Conf. of Japanese Association of Behavioral Economics and Finance*.

[9] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. Gomez, L. Kaiser, and I. Polosukhin. 2017. Attention is all you need. In *Advances in NeurIPS*. 5999–6009. arXiv:1706.03762 http://arxiv.org/abs/1706.03762