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The highly intelligent virtual agents for modeling financial markets

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HIGHLIGHTS

- Designing highly intelligent agents is fundamental for agent-based modeling method.
- 3 principles for high intelligence: information processing, learning and adaptation.
- A specific group of smart agents called *iAgents* are built based on the 3 principles.
- *iAgents* show a great overall performance through trading on real financial indices.

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ABSTRACT

Researchers have borrowed many theories from statistical physics, like ensemble, Ising model, etc., to study complex adaptive systems through agent-based modeling. However, one fundamental difference between entities (such as spins) in physics and micro-units in complex adaptive systems is that the latter are usually with high intelligence, such as investors in financial markets. Although highly intelligent virtual agents are essential for agent-based modeling to play a full role in the study of complex adaptive systems, how to create such agents is still an open question. Hence, we propose three principles for designing high artificial intelligence in financial markets and then build a specific class of agents called *iAgents* based on these three principles. Finally, we evaluate the intelligence of *iAgents* through virtual index trading in two different stock markets. For comparison, we also include three other types of agents in this contest, namely, random traders, agents from the wealth game (modified on the famous minority game), and agents from an upgraded wealth game. As a result, *iAgents* perform the best, which gives a well support for the three principles. This work offers a general framework for the further development of agent-based modeling for various kinds of complex adaptive systems.

1. Introduction

Agent-based modeling has been regarded as a very promising method to explore complex adaptive social or economic systems [1–8]. It resembles microscopic models in statistical physics in the respect that both approaches deal with the emerged complexity in a bottom-up manner [9–14]. The difference is that the micro-units in an agent-based model (ABM)

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are virtual agents typically mimicking the behaviors of human beings or social organizations, while those in microscopic models for a variety of physical systems are defined as interacting entities which have zero intelligence (such as particles, spins, oscillators, etc.). Among different human systems, financial markets are the typical ones vastly studied by researchers in the field of complex adaptive systems [15,16]. There are mainly three roles played by ABMs for modeling financial markets.

1. *A microscopy for underlying dynamics*: ABMs have been used to reproduce the stylized facts of financial markets (fat tails, volatility clustering, etc. [17]) at the aggregated level, meanwhile the microscopic dynamics, structures, as well as behavioral characteristics which cause the emergence of such complex phenomena can be revealed [18–25].
2. *An evaluator for system properties*: An important application of ABMs is to find how the statistics of financial markets (volatility, liquidity, etc.) evolves under the change of macroscopic or microscopic environments. Hence, a class of ABMs have been developed as practical tools for evaluations of leverage limitation, taxation, etc., for financial regulators and policy-makers [26–30].
3. *A forecaster for future states*: Coupled with the algorithms or techniques from the field of artificial intelligence, ABMs are expected to effectively predict the future states of financial markets [31–36], including stock price dynamics, market impact, tipping points for large market movements and prices of financial derivatives. Note that useful trading strategies or risk hedging algorithms may also be extracted, as by-products, from this class of ABMs.

The essential part in the process of building an ABM is the development of a decision-making model for virtual agents, which inevitably involves the concept of intelligence. The intelligence for a human being has been defined in the field of psychology, however, in many different, sometimes controversial ways [37]. For a trader in financial markets, we may define his/her intelligence as the abilities to process information, to learn from information and experience, and to adapt to the changing environment. Correspondingly, an appropriate formulation and a feasible implementation of such intelligence are required for the design of virtual agents for modeling financial markets.

Although there exist zero-intelligence ABMs for financial markets [18,34], usually they are designed for a specific purpose, e.g., to show the qualitative and basic mechanism under fat-tails or order flows. Intuitively, if the above mentioned ABMs' three roles are to be fully played, virtual agents with higher level of intelligence should be recruited. One example to show the importance of agents' intelligence level is the ABM study of the allocation of bias distributed resources [38–40]. In particular, after the heterogeneity in preference was introduced to improve the adaptivity of the agents (hence the intelligence of the agents was improved, according to our definition above), the ABM successfully reproduced the approaching to a balanced state found in the human experiments [38–40]. Another example is the reverse engineering of financial markets using several decision-making models [33]. The study indicates that only if the agents could distinguish different market phases (i.e., bullish trending, bearish trending and non-tending phases) in advance and adjust their strategies accordingly, can the real-world financial time series be well reproduced.

Based on the discussion above, it is clear that the design of highly intelligent agents is one of the key tasks in developing ABMs for financial markets, and even for other human systems as well. However, unlike the model development in the paradigm of statistical physics, there still lack general principles for the design of such intelligent agents. To explain this issue with an example, one may review the development of a well-known discrete kinetic model for fluid flow named lattice gas automata [41]. Correspondingly, conservation laws for mass and momentum, detailed balance for particle interactions, and symmetry in the velocity space were employed as principles for the model building process. The big success of these principles encourages us to propose some principles for building a fine decision-making model for ABMs in the field of financial markets.

Hence, in this study, we will first propose three principles for the design of a class of highly intelligent agents called *iAgents*. These principles are generalized according to our understanding of intelligence needed for a financial agent (e.g., an individual trader, a fund manager, etc.). In the meantime, we will also give a concrete example to detail the realization of these three principles. Methods such as the processing of multiple information, inductive learning and dynamic genetic algorithm (DGA) are used to improve *iAgents*' intelligence in the example. Assessment of the intelligence level for *iAgents* is carried out by letting agents do virtual index trading in different markets. Daily data of Standard & Poor's 500 index (S&P) and Nikkei 225 index (NKY) are used. And three other types of agents, i.e., random traders, agents from the wealth game (WG) [32] which is a model based on the famous minority game [42], and agents from an upgraded WG model (namely, WG implemented with DGA, which is abbreviated as WG-DGA) are also recruited in the assessment. Agents' accumulated profits in the trading are used as a quantity to judge their intelligence level.

The remainder of this work is organized as follows. Three principles for the design of *iAgents* will be introduced in Section 2. Section 3 is for the details on how to build a specific kind of *iAgents* according to these three principles, while assessment of the intelligence level for *iAgents* alongside with the other three types of agents is presented in Section 4. Finally, some discussion and conclusions are given in Section 5.

2. The three principles

Based on the definition of intelligence for an individual or an organization in financial markets, we postulate three principles, with which the design of *iAgents* for modeling the markets can be conducted.