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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.

Principle 1: *iAgents* should have a high level of ability for information processing. A huge amount of information, often from different sources, is flowing constantly into financial markets. And delicate patterns are also twinkling in the financial time series. Hence, *iAgents* should be like us human beings who can observe, collect and organize multiple information from the environment and recognize different patterns in the fluctuating time series.

Principle 2: *iAgents* should have a high level of ability for learning. In real markets, traders have to make their investing strategies and then improve the strategies by learning either from the organized information or from their own experience in order to gain profits under the current environment. Correspondingly, *iAgents* should also be able to learn to optimize the internal states of their own decision-making models.

Principle 3: *iAgents* should have a high level of ability to adapt to environmental changes. Unlike common optimization problems, the environment of financial markets is always evolving. A trader's best strategy in one period may become the worst in another. Therefore, in order to realize a steady gain in a long time span, traders have to renew their current strategies from time to time by doing further analyses or by discussion with other people. Similarly, *iAgents* should also have the ability to replace their strategies, either by using self evolutionary algorithms or by taking advice from other agents.

3. The decision-making model

To describe how to realize each of the three principles mentioned above, we show the detailed design process of an example decision-making model for *iAgents*.

3.1. Information processing

Based on Principe 1, *iAgents* should be able to process multiple information. There are many kinds of information, such as fundamental information (e.g., the index of gross domestic product for a country, a company's revenue, etc.), technical information (e.g., stock price returns, trading volumes, market volatilities, etc.), or other special types of information (e.g., search volumes in Google Trends [43], Wikipedia usage patterns [44], or Twitter mood [45]). For our example of *iAgents*, we choose three technical information series for convenience, namely, price change series $\{R_t\}$, trading volume change series $\{V_t\}$ and market volatility change series $\{A_t\}$, where t represents discrete time steps (e.g., minute, hour, day, etc.). The market volatility change is calculated here by $A_t = |R_t| - |R_{t-1}|$, where $|X|$ gives the absolute value of X. To keep the model simple, we further assume that *iAgents*' decisions on their stock positions for the next time step are only affected by the signs of the three technical information series. With this assumption, the amplitude information of the original $\{R_t\}$, $\{V_t\}$, $\{A_t\}$ series is filtered out, resulting in three sign series denoted as $\{M_t\}$, $\{D_t\}$, $\{Y_t\}$ respectively, where $M_t, D_t, Y_t \in \{-1, 0, +1\}, \forall t$. Bit -1 represents for negative values in the original series, 0 for 0, and $+1$ for positive values. Here, we make a second assumption: the same bit value (i.e., -1, 0, or $+1$) at different ticks in a certain information sign series has the same directional influence on the change of an *iAgent*'s stock position. However, the influence strength should decay with the time, which is a common phenomenon observed in the real world [46]. This second assumption can be understood more easily with the following example: suppose that the stock price of Apple Inc. rose consecutively on both Monday and Tuesday this week; if the upward stock price movement on Monday gave an *iAgent* a signal to increase the stock position, the upward price change on Tuesday would direct him/her to do the same thing; the only difference is that the price movement of Apple stock on Tuesday would have a stronger signal influence on the *iAgent*'s decision of position adjustment. We model this decay of information influence in an exponential form. At time step t, the total influence of a certain information (series $\{M_t\}$ is used here for description) on an *iAgent* can be written as

$$I_M(t) = \sum_{\tau=1}^{\infty} M_{t-\tau} \exp\left(-\frac{\tau-1}{T_M}\right), \tag{1}$$

where T_M denotes the half-life time, in the eye of this *iAgent*, of the $\{M_t\}$ information series. Note that half-life time can be different for different information series or for different agents. We further assume that an *iAgent* will neglect completely the information bits which are older than the half-life time he/she chooses. Hence, the normalized expressions for the influence of the three sign series become

$$\begin{aligned}
I_M(t) &= \sum_{\tau=1}^{T_M} M_{t-\tau} \exp\left(-\frac{\tau-1}{T_M}\right) \Big/ \sum_{\tau=1}^{T_M} \exp\left(-\frac{\tau-1}{T_M}\right), \\
I_D(t) &= \sum_{\tau=1}^{T_D} D_{t-\tau} \exp\left(-\frac{\tau-1}{T_D}\right) \Big/ \sum_{\tau=1}^{T_D} \exp\left(-\frac{\tau-1}{T_D}\right), \\
I_Y(t) &= \sum_{\tau=1}^{T_Y} Y_{t-\tau} \exp\left(-\frac{\tau-1}{T_Y}\right) \Big/ \sum_{\tau=1}^{T_Y} \exp\left(-\frac{\tau-1}{T_Y}\right).
\end{aligned} \tag{2}$$

Here, $I_M(t), I_D(t), I_Y(t) \in [-1, +1], \ \forall t$, are named as impact factors of the associated technical information. Note that T_M, T_D, T_Y can also be explained as the information history lengths that an *iAgent* would consider when making decisions on his/her position adjustment.

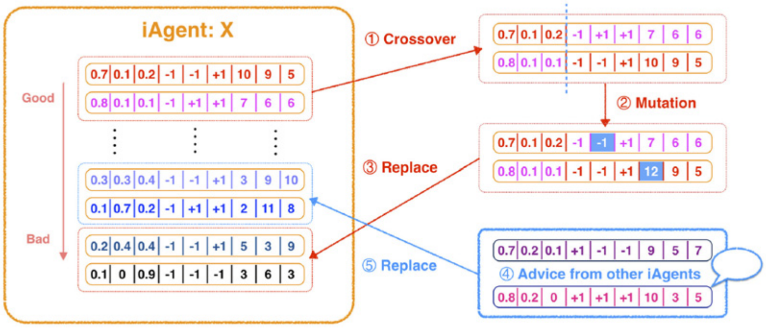

Fig. 1. Sketch of dynamic genetic algorithm (DGA) for the evolution of an *iAgent*'s strategies.

3.2. Learning

First, a basic ability to learn from the organized information is given to *iAgents*. For each *iAgent*, he/she can set different weights $\alpha, \beta, \gamma \in [0, 1]$ $(\alpha + \beta + \gamma = 1)$ and directional parameters e_M, e_D, e_Y (either -1 and $+1$) for the three impact factors. We introduce the position-changing level $L(t)$ for each *iAgent* as

$$L(t) = \alpha e_M I_M(t) + \beta e_D I_D(t) + \gamma e_Y I_Y(t). \tag{3}$$

Hence, $L(t) \in [-1, +1], \forall t$. Let $P_{\max}$ be the stock position limit for an *iAgent*, then his/her position at time t can be expressed by

$$P(t) = [L(t)P_{\max}], \tag{4}$$

where $[X]$ is the operator that rounds X into integers. In Eqs. (3) and (4), it is obvious that the values of e_M, e_D, e_Y determine how an *iAgent*'s stock position is affected by the three impact factors. For example, if factor $I_M(t)$ is positive, $e_M = +1$ will give a positive contribution to an *iAgent*'s stock position, while $e_M = -1$ will give a negative one. Hence, different *iAgents* can have very different judgments when facing the same stock or index in financial markets. Interestingly, we can consider an extreme case. Suppose that the stock market were in a thoroughly static state, so that both of the market index and trading volume would be constant, namely, $I_M(t) = I_D(t) = I_Y(t) \equiv 0, \forall t$. In this static market, no profits could be gained. From Eqs. (3) and (4), all the *iAgents* would keep their stock position as zero, which is a brilliant choice when trading in this environment.

Second, we give *iAgents* an ability to optimize the internal states of their decision-making model. Obviously, the states are controlled by the internal parameters in Eqs. (2)–(4), which are $\alpha, \beta, \gamma, e_M, e_D, e_Y, T_M, T_D$ and T_Y. As discussed above, different sets of these internal parameters could lead to heterogeneous behaviors in stock trading. Therefore, *iAgents* should be able to tune the parameters themselves through an inductive learning process. Here, we define the form of trading strategies for *iAgents* as $\{\alpha, \beta, \gamma, e_M, e_D, e_Y, T_M, T_D, T_Y\}$. Each *iAgent* has S such strategies and these strategies are evaluated continuously. In particular, an *iAgent* will use all the S strategies at every time step to do fake stock trading and record the accumulated virtual profits for each strategy. In the meantime, only the strategy with the highest virtual profits will be selected by the *iAgent* to send real orders for the trading. It can be seen that the design of this learning model for *iAgents* is influenced by the famous minority game [42]. Furthermore, it is obvious that there is no need to worry whether the input information is useful or not for *iAgents*' decision-making. Due to our model design based on Principle 2, if irrelevant time series are included in the information processing, such as sunspot activities, *iAgents* can always adjust the weights of these kinds of information very close to zero through learning from their experience. It is well known that one of the main shortages for ABMs is that there are always too many parameters to be calibrated [2]. Our *iAgent* design based on Principle 2 may offer a solution to this problem, since the internal parameters are of *iAgents*' own concern.

3.3. Adaptation

As stated in Principle 3, no investing strategies in financial markets can be profitable all the time. Hence, for the design of decision-making model for an ABM, the use of a fixed set of strategies cannot be a good representation of a high adaptation ability. To drive the evolution of *iAgents*' strategies, we introduce DGA method to offer *iAgents* a way to seek good strategies and dump bad ones. Crossover, mutation and communication operators of DGA are applied sequentially (in a dynamic way) in every g_a time steps. Here, we call g_a as the DGA period. The detailed process of DGA is sketched in Fig. 1 and described as follows. Step 1, an *iAgent* picks up his/her top-ranked strategies to breed new generations through the crossover of different blocks of internal parameters. Specifically, the type of one-point crossover is used here and the internal parameters are distributed into two blocks, namely, $\{\alpha, \beta, \gamma\}$ and $\{e_M, e_D, e_Y, T_M, T_D, T_Y\}$. Step 2, mutations of the generated strategies occur under a certain rate g_m. Note that if one of the parameters among α, β and γ mutates, the other two will also be adjusted proportionally so that the condition $\alpha+\beta+\gamma = 1$ is satisfied. Step 3, the *iAgent* replaces his/her worst-performing

Table 1
Rank of the agents' intelligence level based on the three principles.

	Random traders	WG agents	WG-DGA agents	*iAgents*
Information processing	None	Low	Low	High
Learning	None	Low	Low	High
Adaptation	None	Low	High	High

strategies with these new generations. An additional way for the *iAgent* to better adapt to the changing environment is to allow communications. Thus, at Step 4, the *iAgent* randomly connects with other g_p *iAgents*; if his/her profits are lower than half of the communication group, he/she will take the advice, i.e., the best strategies, from the top-performing agents in the group and then replace his/her bad strategies at Step 5. The total number of strategies of every *iAgent*, namely S, is kept fixed during this strategy evolution process. And the virtual profits of each strategy will be reset to zero after the completion of a round of DGA. Through the design of DGA method, *iAgents*' high level of adaptation ability can be seen clearly. Suppose that one top-ranked strategy of an *iAgent* performs well due to the proper settings of e_M, e_D and e_Y, however its values of α, β and γ are not optimized under the current environment. Then the *iAgent* may obtain an improved strategy simply by a crossover of this strategy with another one whose values of α, β and γ are better, or by mutations that occur in α, β and γ. Note that this is also the reason why we do not try to simplify the form of strategies by using three composite parameters to represent the product of each weight with its associated directional parameter in Eq. (3). A few more parameters are brought into the decision-making model in this part, namely, g_a, g_m, g_p, and S. Since they are not as important as the nine internal parameters in *iAgents*' strategies mentioned above, we leave them to be set externally.

4. Assessment of the intelligence level

In this section, *iAgents*' intelligence level will be assessed through the virtual stock trading on both S&P and NKY indices. Besides, *iAgents*' performance will also be compared with those of three other types of agents, namely, random traders, WG agents [32] and WG-DGA agents.

4.1. Agents for comparison

Needless to say, random traders would choose their stock positions randomly at every time step. Minority game [42] is a very famous game model for resource allocation problems and it has bred many ABMs in econophysics to study a range of complex adaptive systems. For example, the WG model [32] is modified on the minority game in order to apply in financial markets. In the WG model, the strategies used by WG agents take the form of a two-column table. The left column of a strategy contains 2^m different market states represented by binary series in which 1 stands for stock price rising and 0 for price falling. Here, m is explained as the history length of stock price change that WG agents consider at every time step. The right column of a strategy is filled in randomly with trading decision $+1$, -1, or 0, which represents buying a unit of stock, selling a unit of stock, or holding a position respectively in response to each of the market states. Like *iAgents*, each WG agent holds S strategies and the success of a strategy is judged by the virtual profits which the strategy should have gained if it were used from the beginning of the trading. And at every time step, each WG agent will select the strategy with the highest virtual profits to send real orders. Note that the model used here is slightly modified by removing a limitation in the original WG model, which says that each strategy should include at least one pair of buying and selling decisions. The WG-DGA agent is an upgraded WG agent with DGA implemented. Although strategy forms are very different for WG-DGA agents and *iAgents*, the implementations of DGA, namely crossover, mutation and communication, are the same. In Table 1, the information processing, learning and adaptation abilities of the four types of agents are ranked based on the three principles. It is obvious that random traders have zero intelligence. WG and WG-DGA agents only observe the sign series of price movements, while *iAgents* can process more, including trading volumes and price fluctuations. Regarding learning ability, only *iAgents* can calibrate their internal strategy parameters based on the organized information and their experience. Initially, WG and WG-DGA agents and *iAgents* all receive random sets of strategies. Nevertheless, with a high level of adaptation ability, both WG-DGA agents and *iAgents* can update their strategies with DGA. On the other hand, those unlucky WG agents who received poor strategies in the beginning have no chance to make a change.

4.2. Performance evaluation and parameter settings

We evaluate the four types of agents' performance by letting the agents do index trading with the daily data of S&P and NKY indices. The reason why we choose these two indices is that S&P and NKY represent two general market patterns. As shown in Fig. 2, although there are many turning points in both of the two indices, from the view of a long time run, S&P cycles in an upward direction, while NKY fluctuates downwards gradually. Here we treat the two composite indices as simple stocks given the fact that indices can be traded more easily nowadays via derivative financial instruments, e.g., futures, options, exchange traded funds or synthetic assets. Initially, all the agents have no cash and their stock positions are empty. It is assumed that agents can borrow any amount of cash or short sell any units of stock at any time under the condition

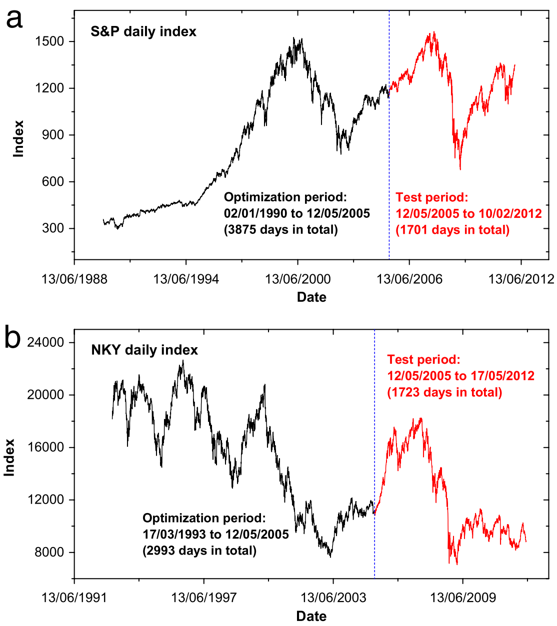

Fig. 2. Two daily indices used to assess agents' intelligence level, namely, (a) S&P 500 index (S&P) and (b) Nikkei 225 index (NKY). Each index is divided into two periods: the optimization period and the test period, as shown in the black line and the red line respectively. And the date format is Day/Month/Year. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

that their positions are kept within the limit $|P(t)| \leq P_{\max}$. So the wealth of an agent, defined as the total current values of both the stock position and the cash account, is also his/her accumulated profits in the trading period. Market impact of the index trading is not considered here, which means that agents can buy or sell stocks at market price at any time. In addition, trading costs are not included either.

Both S&P and NKY indices are divided into two parts as illustrated in Fig. 2: the optimization period and the test period. In the optimization period, 1000 cycles are assigned to both *iAgents* and WG-DGA agents respectively to help them find their optimal strategies. For random traders and WG agents, only 1 cycle is needed, since the former care no experience at all and the latter do not have the ability to change their sets of strategies. After each optimization cycle, the wealth of every agent is reset to zero, while their optimized strategies are inherited. In order to provide a tough test to effectively distinguish the intelligence level for the four types of agents, we choose the beginning and the end dates of the two test periods in a way that significant trend switchings between market's ups and downs are included.

$N = 10{,}000$ agents are employed for each type of agents to do the assessment. The history length of stock price movements considered by WG and WG-DGA agents is set to be 5 trading days, while *iAgents* decide the values of the three information half-life times T_M, T_D and T_Y by their own. The stock position limit $P_{\max}$ is set to 10 universally for the four types of agents. And the strategy number S is set as 8 for WG and WG-DGA agents and *iAgents*. DGA parameters for *iAgents* and WG-DGA agents are set as follows: the DGA period g_a is 60 trading days; the mutation rate g_m is 0.5 for each newly generated strategy through the crossover; and the group size for communication g_p is 8.

As shown in Figs. 3 and 4, wealth distributions of the 10,000 agents of each type are obtained from the trading of the two indices respectively. It can be found that even the best random trader can gain a huge wealth, a phenomenon which could only be explained by an exceptional good luck. Hence, the wealth of the best agent of each type is not an appropriate quantity for comparison. Instead, we use the mean wealth of the 10,000 agents as the quantity to evaluate the intelligence level for each type.

4.3. Performances of agents

In order to be consistent with the agents' stock position limit, the market baseline performance of S&P is defined as the net profits by holding $P_{\max} = 10$ units of position. Reversely, for NKY, it is defined as the profits by short selling the same units $P_{\max} = 10$ at the beginning of the associated period. Performances of the two markets and agents' mean wealth along with the standard deviation (SD) at the end of the optimization and the test periods (as shown in Figs. 3 and 4) are summarized in Tables 2 and 3. Furthermore, time evolutions of agents' mean wealth and averaged position during the test periods of the two indices are plotted in Figs. 5 and 6 respectively.

In Table 2, the mean wealth of random traders is found to be almost zero comparing with the market performance of S&P, a result which well reflects the nature of zero intelligence. And both WG and WG-DGA agents do not perform better than

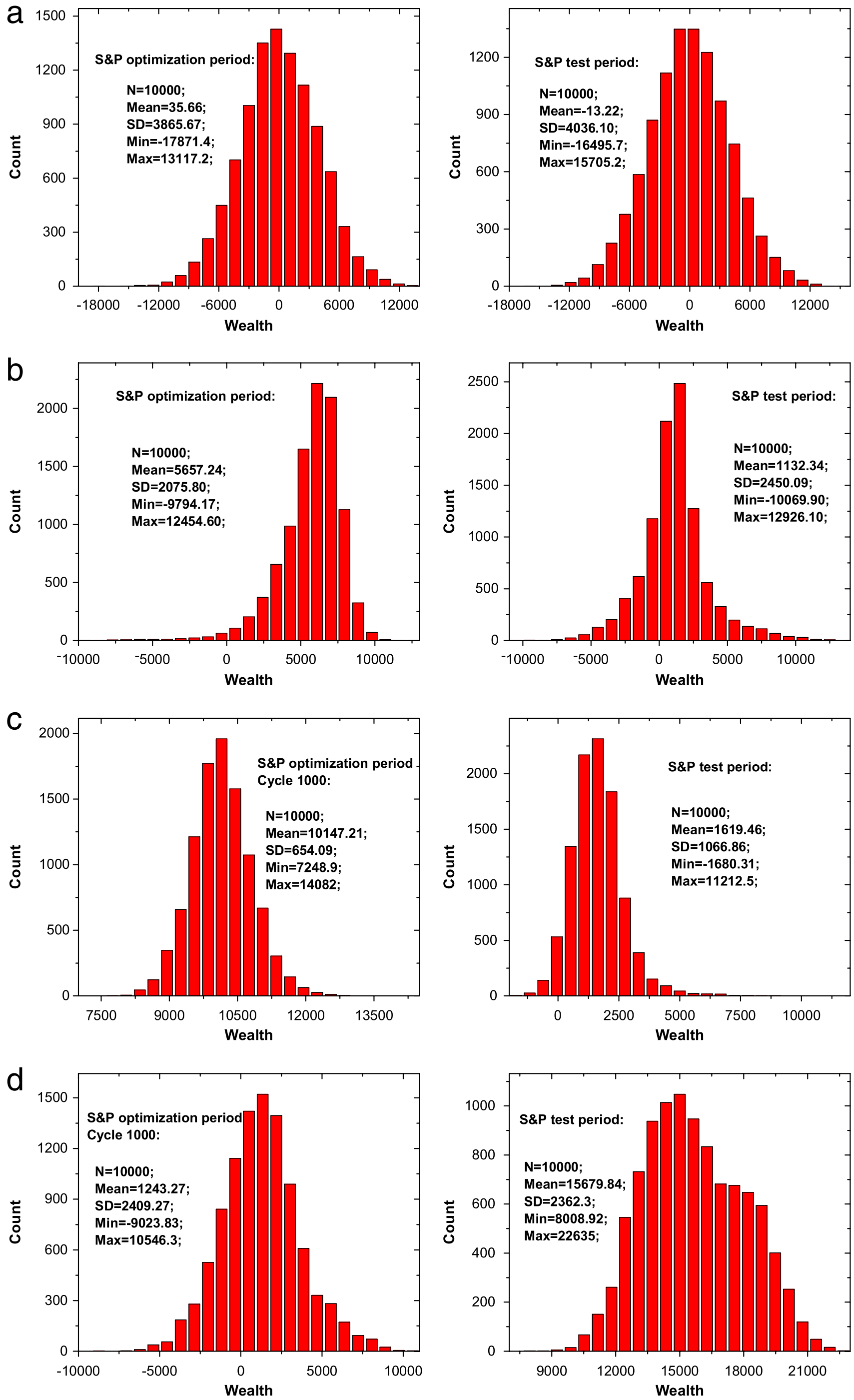

Fig. 3. Wealth distributions of the 10,000 agents from each of the four types, namely, (a) random traders, (b) WG agents, (c) WG-DGA agents, and (d) *iAgents*, on S&P 500 index (S&P) respectively. The graphs in the left column analyze the agents' wealth at the end of the optimization period (for random traders and WG agents, it is at the end of Cycle 1, while for WG-DGA agents and *iAgents*, it is at the end of Cycle 1000). The ones in the right are for the agents' wealth at the end of the test period.

the market in the test period. In fact, as shown in the top parts of Fig. 5(a) and (b), both the two types of agents behave more like passive fund managers whose main goal is to follow the market movements. This passive investing behavior can also be verified from the lower parts of Fig. 5(a) and (b) where the time evolution of agents' averaged position is shown accordingly. One can see that WG and WG-DGA agents send long orders and increase their stock positions fast at the beginning, and from then on they just keep their positions in a small oscillating range. In contrast, as shown in Table 2, the mean wealth

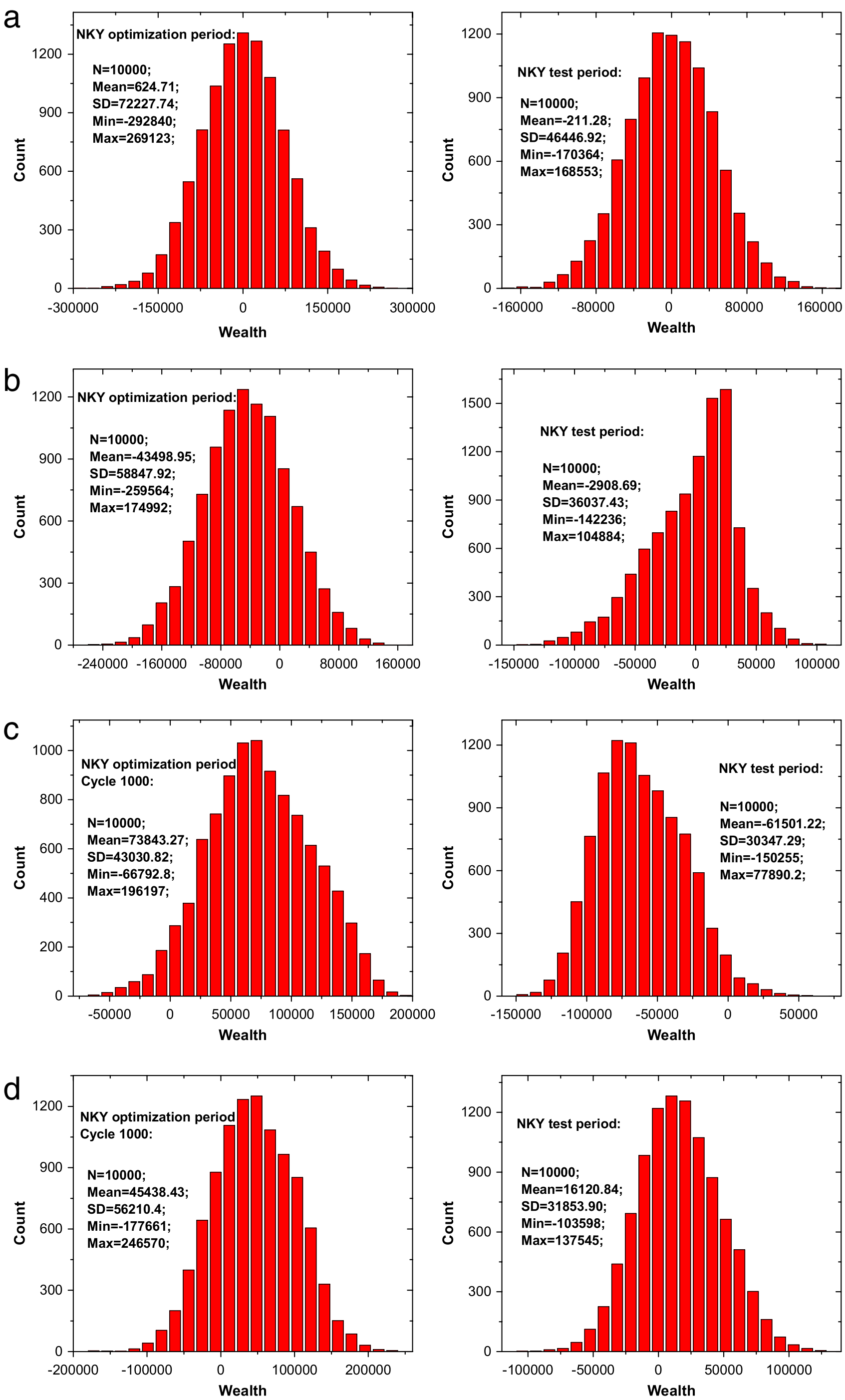

Fig. 4. Wealth distributions of the 10,000 agents from each of the four types, namely, (a) random traders, (b) WG agents, (c) WG-DGA agents, and (d) *iAgents*, on Nikkei 225 index (NKY) respectively. The graphs in the left column analyze the agents' wealth at the end of the optimization period (for random traders and WG agents, it is at the end of Cycle 1, while for WG-DGA agents and *iAgents*, it is at the end of Cycle 1000). The ones in the right are for the agents' wealth at the end of the test period.

of *iAgents* is 8.56 times larger than the market performance of S&P in the test period, which well demonstrates that *iAgents* can behave much better than the other three types of agents. Interestingly, time evolution of *iAgents*' mean wealth in the top part of Fig. 5(c) shows that they can even make a correct prediction for the tipping point of the market around June of 2007. In addition, the clustering phenomenon emerges in the time series of the averaged position of *iAgents*, see the lower part of Fig. 5(c), which will be further discussed in the next section.

Table 2
Comparison of agents' mean wealth from index trading of S&P at the end of the optimization and the test periods respectively.

Market performance	Optimization period		Test period	
	7996.7		1832.8	
	Mean wealth	SD	Mean wealth	SD
Random traders	35.66	3865.67	−13.22	4036.10
WG agents	5657.24	2075.80	1132.34	2450.09
WG-DGA agents	10 147.21	654.09	1619.46	1066.86
iAgents	1243.27	2409.27	15 679.84	2362.30

Table 3
Comparison of agents' mean wealth from index trading of NKY at the end of the optimization and the test periods respectively.

Market performance	Optimization period		Test period	
	70 954.3		22 013.5	
	Mean wealth	SD	Mean wealth	SD
Random traders	624.71	72 227.74	−211.28	46 446.92
WG agents	−43 498.95	58 847.92	−2908.69	36 037.43
WG-DGA agents	73 843.27	43 030.82	−61 501.22	30 347.29
iAgents	45 438.43	56 210.40	16 120.84	31 853.90

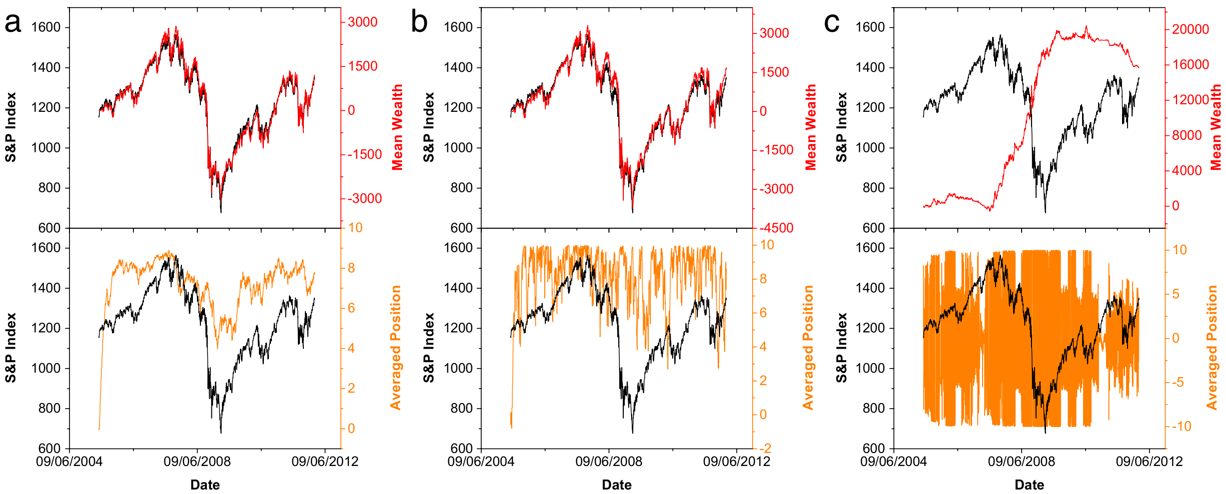

Fig. 5. Average test period performance of the 10,000 agents from (a) WG agents, (b) WG-DGA agents, and (c) *iAgents* respectively on S&P 500 index (S&P). The sub-figures show the mean wealth (red line, first row) and averaged stock position (orange line, second row) for each type of agents at each time step of the test period. The associated test period index (black line) is also drawn in each sub-figure. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Moreover, the standard deviation (SD) of WG-DGA agents' wealth shown in Table 2 is the smallest among the others. Note that the DGA evolution can update agents' strategies towards a small partition of good strategies, hence the trading results are less diversified for both WG-DGA agents and *iAgents*. However, although the same DGA evolution for *iAgents* makes the standard deviation (SD) lower than those of random traders and WG agents, the complicated structure makes it higher than that of WG-DGA agents.

Main results of NKY trading are similar to those of S&P, which can be confirmed in Table 3 and Fig. 6. Both WG and WG-DGA agents are still passive traders, however, the former hold short positions longer while the latter hold long positions most of the time. As NKY index is declining, WG-DGA agents' overall long positions make them behave poorer. For *iAgents*, though unable to beat the market, they still trade actively and have the best performance comparing with the other types of agents.

5. Discussion and conclusions

There are a few more aspects which we want to discuss deeply in this section. We have seen that WG and WG-DGA agents trade both indices passively in the test periods. When comparing Fig. 6 with Fig. 5, it can be clearly seen that the

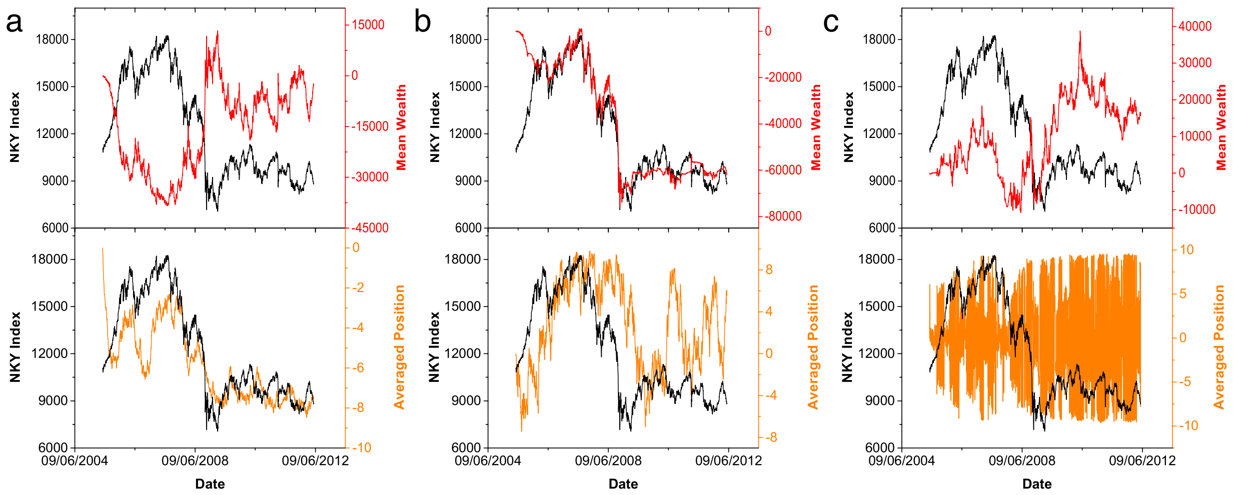

Fig. 6. Average test period performance of the 10,000 agents from (a) WG agents, (b) WG-DGA agents, and (c) *iAgents* respectively on Nikkei 225 index (NKY). The sub-figures show the mean wealth (red line, first row) and averaged stock position (orange line, second row) for each type of agents at each time step of the test period. The associated test period index (black line) is also drawn in each sub-figure. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

averaged positions of WG and WG-DGA agents in the test period of NKY undergo larger fluctuations than in that of S&P. This phenomenon implies that the market environment of NKY is more complex than that of S&P. Due to this complexity, even *iAgents* are unable to outperform the NKY market. Additionally, as shown in Tables 2 *and* 3, WG-DGA agents in average gain much higher profits than WG agents in both markets at the end of optimization period, which well demonstrates the effectiveness of DGA. However, WG-DGA agents' mean wealth becomes much worse in the test period of NKY. To test the effect of overlearning, a few more simulations of NKY index trading with reduced optimization cycles are conducted for WG-DGA agents. We find that even though the optimization cycles are cut down to 100 or 50 times so that WG-DGA agents' mean wealth is comparable with that of *iAgents* at the end of the optimization period, they still trade passively in the test period. Since the time evolutions of mean wealth and averaged positions of these less optimized WG-DGA agents are very close to the ones in Fig. 6(b), we can conclude that their poor performance in the test period of NKY is not caused by overlearning. Comparing with the performance of *iAgents*, now we can say that although WG-DGA agents' strategies can evolve with DGA, the agents' intelligence is still limited by the strategy form so that they have no ability to trade actively.

In the lower parts of Figs. 5(c) and 6(c), where *iAgents* alter their positions heavily, the clustering phenomenon has been observed. This clustering suggests a sort of swarm intelligence [47], considering of the small number of strategies and group members an *iAgent* has in the simulations. Additionally, clustering in *iAgents*' averaged positions may imply that the market environment undergoes some kinds of state changes from time to time. Therefore, by comparing the properties of the indices with the clustering patterns, one may find some correlations so that trading strategies could be extracted from the *iAgents*' overall behaviors.

Talking about algorithmic trading that may be constructed on *iAgents*' intelligence, we want to have some further discussion. The strategy number S for each *iAgent* is set to a rather small value in order to reduce the computation time. Increase of S may further improve *iAgents*' averaged performance. In addition, the evolutionary strength of *iAgents*' strategies is controlled by the DGA period g_a, mutation rate g_m, communication group size g_p, and the optimization cycles. It should be noted that an extremely high strength of optimization can lead to the overlearning of *iAgents* which may cause them a huge loss when the market undergoes a drastic state change. Therefore, a diversity of *iAgents*' strategies should be kept in mind for the calibrations of the associated parameters. Due to the advantage of our *iAgent* design, the parameters mentioned above may also be integrated into *iAgents*' strategies in future researches so that the agents can decide the values on their own.

To sum up, through our own study of agent-based modeling and by reviewing literatures on ABMs of financial markets, we found that a higher intelligence level of virtual agents is one of the key factors which could enable such models to achieve greater accomplishments in both academic and engineering aspects. Borrowed from related research fields, we re-defined the concept of intelligence for traders in financial markets, namely, the abilities of information processing, learning and adaptation. Based on this definition, we further proposed three principles for the design of highly intelligent agents called *iAgents* in the modeling of financial markets. The effectiveness of these three principles were shown through the detailed formulation of *iAgents* and with the comparison of mean profits obtained by *iAgents* and other three different types of agents from virtual index trading. We found that *iAgents* are the best performers and sometimes they can even outperform the market greatly. Finally, it is worth mentioning that the three principles we proposed in this work may also be applied to the modeling of intelligence in other human complex adaptive systems, since most of them have multiple information flows and fast-changing environments as well.

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