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# **Multi-Agent Applications with Evolutionary Computation and Biologically Inspired Technologies**

Intelligent Techniques for Ubiquity and Optimization



YASUSHI KAMBAYASHI

# Multi-Agent Applications with Evolutionary Computation and Biologically Inspired Technologies: Intelligent Techniques for Ubiquity and Optimization

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Successful decision-making by home-owners, lending institutions, and real estate developers among others is dependent on obtaining reasonable forecasts of residential home prices. For decades, home-price forecasts were produced by agents utilizing academically well-established statistical models. In this chapter, several modeling agents will compete and cooperate to produce a single forecast. A cooperative multi-agent system (MAS) is developed and used to obtain monthly forecasts (April 2008 through March 2010) of the S&P/Case-Shiller home price index for Los Angeles, CA (LXXR). Monthly housing market demand and supply variables including conventional 30-year fixed real mortgage rate, real personal income, cash out loans, homes for sale, change in housing inventory, and construction material price index are used to find different independent models that explain percentage change in LXXR. An agent then combines the forecasts obtained from the different models to obtain a final prediction.

### Chapter 2

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<i>Hisashi Yamamoto, Tokyo Metropolitan University, Japan</i>	

Portfolio optimization is the determination of the weights of assets to be included in a portfolio in order to achieve the investment objective. It can be viewed as a tight combinatorial optimization problem that

has many solutions near the optimal solution in a narrow solution space. In order to solve such a tight problem, this chapter introduces an Agent-based Model. The authors employ the Information Ratio, a well-known measure of the performance of actively managed portfolios, as an objective function. This agent has one portfolio, the Information Ratio and its character as a set of properties. The evolution of agent properties splits the search space into a lot of small spaces. In a population of one small space, there is one leader agent and several follower agents. As the processing of the populations progresses, the agent properties change by the interaction between the leader and the follower, and when the iteration is over, the authors obtain one leader who has the highest Information Ratio.

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Recently, the relation between neuroeconomics and agent-based computational economics (ACE) has become an issue concerning the agent-based economics community. Neuroeconomics can interest agent-based economists when they are inquiring for the foundation or the principle of the software-agent design, normally known as agent engineering. It has been shown in many studies that the design of software agents is non-trivial and can determine what will emerge from the bottom. Therefore, it has been requested for rather a period regarding whether we can sensibly design these software agents, including both the choice of software agent models, such as reinforcement learning, and the parameter setting associated with the chosen model, such as risk attitude. This chapter starts a formal inquiry by focusing on examining the models and parameters used to build software agents.

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<i>Boris Kovalerchuk, Central Washington University, USA</i>	

This chapter models quantum and neural uncertainty using a concept of the Agent-based Uncertainty Theory (AUT). The AUT is based on complex fusion of crisp (non-fuzzy) conflicting judgments of agents. It provides a uniform representation and an operational empirical interpretation for several uncertainty theories such as rough set theory, fuzzy sets theory, evidence theory, and probability theory. The AUT models conflicting evaluations that are fused in the same evaluation context. This agent approach gives also a novel definition of the quantum uncertainty and quantum computations for quantum gates that are realized by unitary transformations of the state. In the AUT approach, unitary matrices are interpreted as logic operations in logic computations. The authors show that by using permutation operators any type of complex classical logic expression can be generated. With the quantum gate, the authors introduce classical logic into the quantum domain. This chapter connects the intrinsic irrationality of the quantum system and the non-classical quantum logic with the agents. The authors argue

that AUT can help to find meaning for quantum superposition of non-consistent states. Next, this chapter shows that the neural fusion at the synapse can be modeled by the AUT in the same fashion. The neuron is modeled as an operator that transforms classical logic expressions into many-valued logic expressions. The motivation for such neural network is to provide high flexibility and logic adaptation of the brain model.

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This chapter investigates the dynamics of trader behaviors using an agent-based genetic programming system to simulate double-auction markets. The objective of this study is two-fold. First, the authors seek to evaluate how, if any, the difference in trader rationality/intelligence influences trading behavior. Second, besides rationality, they also analyze how, if any, the co-evolution between two learnable traders impacts their trading behaviors. The authors have found that traders with different degrees of rationality may exhibit different behavior depending on the type of market they are in. When the market has a profit zone to explore, the more intelligent trader demonstrates more intelligent behaviors. Also, when the market has two learnable buyers, their co-evolution produced more profitable transactions than when there was only one learnable buyer in the market. The authors have analyzed the trading strategies and found the learning behaviors are very similar to humans in decision-making. They plan to conduct human subject experiments to validate these results in the near future.

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<i>Shu G. Wang, National Chengchi University, Taiwan</i>	

This chapter presents agent-based simulations as well as human experiments in double auction markets. The authors' idea is to investigate the learning capabilities of human traders by studying learning agents constructed by Genetic Programming (GP), and the latter can further serve as a design platform in conducting human experiments. By manipulating the population size of GP traders, the authors attempt to characterize the innate heterogeneity in human being's intellectual abilities. They find that GP trad-

ers are efficient in the sense that they can beat other trading strategies even with very limited learning capacity. A series of human experiments and multi-agent simulations are conducted and compared for an examination at the end of this chapter.

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This chapter conducts a comparative study of various traders following different trading strategies. The authors design an agent-based artificial stock market consisting of two opposing types of traders: “rational traders” (or “fundamentalists”) and “imitators” (or “chartists”). Rational traders trade by trying to optimize their short-term income. On the other hand, imitators trade by copying the majority behavior of rational traders. The authors obtain the wealth distribution for different fractions of rational traders and imitators. When rational traders are in the minority, they can come to dominate imitators in terms of accumulated wealth. On the other hand, when rational traders are in the majority and imitators are in the minority, imitators can come to dominate rational traders in terms of accumulated wealth. The authors show that survival in a finance market is a kind of minority game in behavioral types, rational traders and imitators. The coexistence of rational traders and imitators in different combinations may explain the market’s complex behavior as well as the success or failure of various trading strategies.

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This chapter describes advances of agent-based models to financial market analyses based on the authors’ recent research. The authors have developed several agent-based models to analyze microscopic and macroscopic links between investor behaviors and price fluctuations in a financial market. The models are characterized by the methodology that analyzes the relations among micro-level decision making rules of the agents and macro-level social behaviors via computer simulations. In this chapter, the authors report the outline of recent results of their analysis. From the extensive analyses, they have found that (1) investors’ overconfidence behaviors plays various roles in a financial market, (2) overconfident investors emerge in a bottom-up fashion in the market, (3) they contribute to the efficient trades in the market, which adequately reflects fundamental values, (4) the passive investment strategy is valid in a realistic efficient market, however, it could have bad influences such as instability of market and inadequate asset pricing deviations, and (5) under certain assumptions, the passive investment strategy and active investment strategy could coexist in a financial market.

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Artificial evolution has been considered as a promising approach for coordinating the controller of an autonomous mobile robot. However, it is not yet established whether artificial evolution is also effective in generating collective behaviour in a multi-robot system (MRS). In this study, two types of evolving artificial neural networks are utilized in an MRS. The first is the evolving continuous time recurrent neural network, which is used in the most conventional method, and the second is the topology and weight evolving artificial neural networks, which is used in the noble method. Several computer simulations are conducted in order to examine how the artificial evolution can be used to coordinate the collective behaviour in an MRS.

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This chapter presents a framework using novel methods for controlling mobile multiple robots directed by mobile agents on a communication networks. Instead of physical movement of multiple robots, mobile software agents migrate from one robot to another so that the robots more efficiently complete their task. In some applications, it is desirable that multiple robots draw themselves together automatically. In order to avoid excessive energy consumption, the authors employ mobile software agents to locate robots scattered in a field, and cause them to autonomously determine their moving behaviors by using a clustering algorithm based on the Ant Colony Optimization (ACO) method. ACO is the swarm-intelligence-based method that exploits artificial stigmergy for the solution of combinatorial optimization problems. Preliminary experiments have provided a favorable result. Even though there is much room to improve the collaboration of multiple agents and ACO, the current results suggest a promising direction for the design of control mechanisms for multi-robot systems. This chapter focuses on the implementation of the controlling mechanism of the multi-robot system using mobile agents.

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This chapter investigates the use of agile program design techniques within an online game development laboratory setting. The proposed game concerns the prediction of early Paleo-Indian hunting sites in ancient North America along a now submerged land bridge that extended between Canada and the United States across what is now Lake Huron. While the survey of the submerged land bridge was being conducted, the online class was developing a computer game that would allow scientists to predict where sites might be located on the landscape. Crucial to this was the ability to add in gradually different levels of cognitive and decision-making capabilities for the agents. The authors argue that the online component of the courses was critical to supporting an agile approach here. The results of the study indeed provided a fusion of both survey and strategic information that suggest that movement of caribou was asymmetric over the landscape. Therefore, the actual positioning of human artifacts such as hunting blinds was designed to exploit caribou migration in the fall, as is observed today.

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*Thillainathan Logenthiran, National University of Singapore, Singapore*

*Dipti Srinivasan, National University of Singapore, Singapore*

The technology of intelligent Multi-Agent System (MAS) has radically altered the way in which complex, distributed, open systems are conceptualized. This chapter presents the application of multi-agent technology to design and deployment of a distributed, cross platform, secure multi-agent framework to model a restructured energy market, where multi players dynamically interact with each other to achieve mutually satisfying outcomes. Apart from the security implementations, some of the best practices in Artificial Intelligence (AI) techniques were employed in the agent oriented programming to deliver customized, powerful, intelligent, distributed application software which simulates the new restructured energy market. The AI algorithm implemented as a rule-based system yielded accurate market outcomes.

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The multiagent reinforcement learning approach is now widely applied to cause agents to behave rationally in a multiagent system. However, due to the complex interactions in a multiagent domain, it is difficult to decide the each agent's fair share of the reward for contributing to the goal achievement. This chapter reviews a reward shaping problem that defines when and what amount of reward should be given to agents. The author employs keepaway soccer as a typical multiagent continuing task that requires skilled collaboration between the agents. Shaping the reward structure for this domain is difficult for the following reasons: i) a continuing task such as keepaway soccer has no explicit goal, and so it is hard to determine when a reward should be given to the agents, ii) in such a multiagent cooperative task, it is difficult to fairly share the reward for each agent's contribution. Through experiments, this chapter finds that reward shaping has a major effect on an agent's behavior.

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In open multiagent systems, individual components act in an autonomous and uncertain manner, thus making it difficult for the participating agents to interact with one another in a reliable environment. Trust models have been devised that can create level of certainty for the interacting agents. However, trust requires reputation information that basically incorporates an agent's former behaviour. There are two aspects of a reputation model i.e. reputation creation and its distribution. Dissemination of this reputation information in highly dynamic environment is an issue and needs attention for a better approach. The authors have proposed a swarm intelligence based mechanism whose self-organizing behaviour not only provides an efficient way of reputation distribution but also involves various sources of information to compute the reputation value of the participating agents. They have evaluated their system with the help of a simulation showing utility gain of agents utilizing swarm based reputation system.

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Exploitation-oriented Learning XoL is a new framework of reinforcement learning. XoL aims to learn a rational policy whose expected reward per an action is larger than zero, and does not require a sophisticated design of the value of a reward signal. In this chapter, as examples of learning systems that belongs in XoL, the authors introduce the rationality theorem of profit Sharing (PS), the rationality theorem of reward sharing in multi-agent PS, and PS-r\*. XoL has several features. (1) Though traditional RL systems require appropriate reward and penalty values, XoL only requires an order of importance among them. (2) XoL can learn more quickly since it traces successful experiences very strongly. (3) XoL may be unsuitable for pursuing an optimal policy. The optimal policy can be acquired by the multi-start method that needs to reset all memories to get a better policy. (4) XoL is effective on the classes beyond MDPs, since it is a Bellman-free method that does not depend on DP. The authors show several numerical examples to confirm these features.

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Keiji Suzuki, Hokkaido University, Japan*

Pheromones are the important chemical substances for social insects to realize cooperative collective behavior. The most famous example of pheromone-based behavior is foraging. Real ants use pheromone trail to inform each other where food source exists and they effectively reach and forage the food. This sophisticated but simple communication method is useful to design artificial multiagent systems. In this chapter, the evolutionary pheromone communication is proposed on a competitive ant environment model, and the authors show two patterns of pheromone communication emerged through co-evolutionary process by genetic algorithm. In addition, such communication patterns are investigated with Shannon's entropy.

## Chapter 17

Evolutionary Search for Cellular Automata with Self-Organizing Properties  
toward Controlling Decentralized Pervasive Systems ..... 308

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Cellular Automata (CAs) have been investigated extensively as abstract models of the decentralized systems composed of autonomous entities characterized by local interactions. However, it is poorly understood how CAs can interact with their external environment, which would be useful for implementing decentralized pervasive systems that consist of billions of components (nodes, sensors, etc.) distributed in our everyday environments. This chapter focuses on the emergent properties of CAs induced by external perturbations toward controlling decentralized pervasive systems. The authors assumed a minimum task in which a CA has to change its global state drastically after every occurrence of a perturbation period. In the perturbation period, each cell state is modified by using an external rule with a small probability. By conducting evolutionary searches for rules of CAs, the authors obtained interesting behaviors of CAs in which their global state cyclically transited among different stable states in either ascending or descending order. The self-organizing behaviors are due to the clusters of cell states that dynamically grow through occurrences of perturbation periods. These results imply that the global behaviors of decentralized systems can be dynamically controlled by states of randomly selected components only.

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# Preface

## ABSTRACT

From a historical viewpoint, the development of multi-agent systems demonstrates how computer science has become more social, and how the social sciences have become more computational. With this development of cross-fertilization, our understanding of multi-agent systems may become partial if we only focus on computer science or only focus on the social sciences. This book with its 17 chapters intends to give a balanced sketch of the research frontiers of multi-agent systems. We trace the origins of the idea, a biologically-inspired approach to multi-agent systems, to John von Neumann, and then continue his legacy in this volume.

## 1. GENERAL BACKGROUND

Multi-agent system (MAS) is now an independent, but highly interdisciplinary, scientific subject. It offers scientists a new research paradigm to study the existing complex natural systems, to understand the underlying mechanisms by simulating them, and to gain the inspiration to design artificial systems that can solve highly complex (difficult) problems or can create commercial value. From a historical viewpoint, the development of multi-agent systems itself demonstrates how computer science has become more social, and, in the meantime, how the social sciences have become more computational. With this development of cross-fertilization, our understanding of multi-agent systems may become partial if we only focus on computer science or only focus on the social sciences. A balanced view is therefore desirable and becomes the main pursuit of this editing volume. In this volume, we attempt to give a balanced sketch of the research frontiers of multi-agent systems, ranging from computer science to the social sciences.

While there are many intellectual origins of the MAS, the book “Theory of Self-Reproducing Automata” by von Neumann (1903-1957) certainly contributes to a significant part of the later development of MAS (von Neumann, 1966). In particular, it contributes to a special class of MAS, called cellular automata, which motivates a number of pioneering applications of MAS to the social sciences in the early 1970s (Albin, 1975). In this book, von Neumann suggested that an appropriate principle for designing artificial automata can be productively inspired by the study of natural automata. Von Neumann himself spent a great deal of time on the comparative study of the nervous systems or the brain (the natural automata) and the digital computer (the artificial automata). In his book “The Computer and the

Brain”, von Neumann demonstrates the effect of interaction between the study of natural automata and the design of artificial automata.

This biologically-inspired principle has been further extended by Arthur Burks, John Holland and many others. By following this legacy, this volume has this biologically-inspired approach to multi-agent systems as its focus. The difference is that we are now richly endowed with more natural observations for inspirations, from evolutionary biology, and neuroscience, to ethology and entomology. The main purpose of this book is to ground the design of multi-agent systems in biologically-inspired tools, such as evolutionary computation, artificial neural networks, reinforcement learning, swarm intelligence, stigmergic optimization, ant colony optimization, and ant colony clustering.

Given the two well-articulated goals above, this volume covers six subjects, which of course are not exhaustive but are sufficiently representative of the current important developments of MAS and, in the meantime, point to the directions for the future. The six subjects are multi-agent financial decision systems (Chapters 1-2), neuro-inspired agents (Chapters 3-4), bio-inspired agent-based financial markets (Chapters 5-8), multi-agent robots (Chapters 9-10), multi-agent games and simulation (Chapters 11-12), and multi-agent learning (Chapters 13-15). 15 contributions to this volume are grouped by these subjects into six sections of the volume. In addition to these six sections, a “miscellaneous” section is added to include two contributions, each of which addresses an important dimension of the development of MAS. In the following, we would like to give a brief introduction to each of these six subjects.

## 2. MULTI-AGENT FINANCIAL SYSTEMS

We start with the multi-agent financial system. The idea of using multi-agent systems to process information has a long tradition in economics, even though in early days the term MAS did not even exist. In this regard, Hayek (1945) is an influential work. Hayek considered the market and the associated price mechanism as a way of pooling or aggregating the market participants’ limited knowledge of the economy. While the information owned by each market participant is imperfect, the pool of them can generate prices with any efficient allocation of resources. The assertion of this article was later on coined as the Hayek Hypothesis by Vernon Smith (Smith 1982) in his double auction market experiments. The intensive study of the Hayek hypothesis in experimental economics has further motivated or strengthened the idea of prediction markets. A prediction market essentially generates an artificial market environment such that forecasts of crowds can be pooled so as to generate better forecasts. Predicting election outcomes via what is known as political future markets becomes one of the most prominent applications.

On the other hand, econometricians tend to pool the forecasts made by different forecasting models so as to improve their forecasting performance. In one literature, this is known as the combined forecasts (Clement 1989). Like prediction markets, combined forecasts tend to enhance the forecast accuracy. The difference between prediction markets and combined forecasts is that agents in the former case are heterogeneous in both data (the information acquired) and models (the way to process information), whereas agents in the latter case are heterogeneous in models only. Hybrid systems in machine learning or artificial intelligence can be regarded as a further extension of the combined forecasts, for example, Kooths, Mitze, and Ringhut (2004). Their difference lies in the way they integrate the intelligence of the crowd. Integration in the case of a combined forecast is much simpler, most of the time, consisting of just the weighted combination of forecasts made by different agents. This type of integration can function well

because the market price under certain circumstances is just this simple linear combination of a pool of forecasts. This latter property has been shown by the recent agent-based financial markets. Nevertheless, the hybrid system is more sophisticated in terms of its integration. It is not just the horizontal combination of the pool, but also involves the vertical integration of it. In this way, heterogeneous agents do not just behave independently, but work together as a team (Mumford and Jain, 2009).

Chapter 1 “*A Multi-Agent System Forecast of the S&P/Case-Shiller LA Home Price Index*” authored by Mak Kaboudan provides an illustration of the hybrid systems. He provides an agent-based forecasting system of real estate. The system is composed of three types of agents, namely, artificial neural networks, genetic programming and linear regression. The system “aggregates” the dispersed forecasts of these agents through a competition-cooperation cyclic phase. In the competition phase, best individual forecasting models are chosen from each type of agent. In the cooperation phase, hybrid systems (reconciliatory models) are constructed by combining artificial neural networks with genetic programming, or by combining artificial neural networks with regression models, based on the solutions of the first phase. Finally, there is a competition again for individual models and reconciliatory models.

Chapter 2 “*An Agent-based Model for Portfolio Optimization Using Search Space Splitting*” authored by Yukiko Orito, Yasushi Kambayashi, Yasuhiro Tsujimura and Hisashi Yamamoto proposes a novel version of genetic algorithms to solve the portfolio optimization problem. Genetic algorithms are population-based search algorithms; hence, they can naturally be considered to be an agent-based approach, if we treat each individual in the population as an agent. In Orito et al.’s case, each agent is an investor with a portfolio over a set of assets. However, the authors do not use the standard single-population genetic algorithm to drive the evolutionary dynamics of the portfolios. Instead, the whole society is divided into many sub-populations (clusters of investors), within each of which there is a leader. The interactions of agents are determined by their associated behavioral characteristics, such as leaders, obedient followers or disobedient followers. These clusters and behavioral characteristics can constantly change during the evolution: new leaders with new clusters may emerge to replace the exiting ones. Like the previous chapter, this chapter shows that the wisdom of crowds emerges from complex social dynamics rather than just a static weighted combination.

### 3. NEURO-INSPIRED AGENTS

Our brain itself is a multi-agent system; therefore, it is natural to study the brain as a multi-agent system (de Garis 2008). In this direction, MAS is applied to neuroscience. However, the other direction also exists. One recent development in multi-agent systems is to make software agents more human like. Various human factors, such as cognitive capacity, intelligence, personality attributes, emotion, and cultural differences, have become new working dimensions for software agents. Since these human factors have now been intensively studied in neuroscience with regard to their neural correlates, it is not surprising to see that the design of autonomous agents, under this influence, will be grounded deeper into neuroscience. Hence, the progress of neuroscience can impact the design of autonomous agents in MAS. The next two chapters are written to feature this future.

Chapter 3 “*Neuroeconomics: A Viewpoint from Agent-Based Computational Economics*” by Shu-Heng Chen and Shu G. Wang gives a review of how the recent progress in neuroeconomics may shed light on different components of autonomous agents, including their preference formation, alternatives valuation, choice making, risk perception, risk preferences, choice making under risk, and learning. The

last part of their review covers the well-known dual system conjecture, which is now the centerpiece of neuroeconomic theory.

Chapter 4 “*Agents in Quantum and Neural Uncertainty*” authored by Germano Resconi and Boris Kovalerchuk raises a very fundamental issue: does our brain fuzzify the received signals, even when they are presented in a crispy way? They then further inquire into the nature of uncertainty and propose a notion of uncertainty which is neural theoretic. A two-layered neural network is proposed to be able to transform crisp signals into multi-valued outputs (fuzzy outputs). In this way, the source of fuzziness comes from the conflicting evaluations of the same inputs made by different neurons, to some extent, like Minsky’s society of minds (Minsky, 1998). Using various brain image technologies, the current study of neuroscience has already explored various neural correlates when subjects are presented with vague, incomplete and inconsistent information. This mounting evidence may put the modal logic under a close examination and motivate us to think about some alternatives, like dynamic logic.

#### **4 BIO-INSPIRED AGENT-BASED ARTIFICIAL MARKETS**

The third subject of this volume is bio-inspired agent-based artificial markets. Market is another natural demonstration of multi-agent systems. In fact, over the last decade, the market mechanism has inspired the design of MAS, known as the market-based algorithm. To some extent, it has also revolutionized the research paradigm of artificial intelligence by motivating the distributed AI. However, in a reverse direction, MAS also provides economists with a powerful tool to explore and to test the market mechanism. This research helps them to learn when markets may fail and hence learn how to do market designs. Nevertheless, the function of markets is not just about the institutional design (the so-called structuralism); a significant number of studies of artificial markets have found that institutional design is not behavior-free or culture-free. This behavioral awareness and cultural awareness has now also become a research direction in experimental economics and agent-based computational economics.

The four chapters contributing to this section all adopt a behavioral approach to the study of artificial markets. Chapter 5 “*Bounded Rationality and Market Micro-Behaviors: Case Studies Based on Agent-Based Double Auction Markets*” authored by Shu-Heng Chen, Ren-Jie Zeng, Tina Yu and Shu G Wang can be read as an example of the recent attempt to model agents with different cognitive capacities or intelligence. It is clear that human agents are heterogeneous in their cognitive capacity (intelligence), and the effect of this heterogeneity on their economic and social status has been found in many recent studies ranging from psychology and sociology to economics; nevertheless, conventional agent-based models paid little attention to this development, and in most cases agents were explicitly or implicitly assumed to be equally smart. By using genetic programming parameterized with different population sizes, this chapter provides a pioneering study to examine the effect of cognitive capacity on the discovery of trading strategies. It is found that larger cognitive capacity can contribute to the discovery of more complex but more profitable strategies. It is also found that different cognitive capacity may coordinate different matches of strategies of players in a co-evolutionary fashion, while they are not necessarily the Nash equilibria.

Chapter 6 “*Social Simulation with both Human Agents and Software Agents: An Investigation into the Impact of Cognitive Capacity on Their Learning Behavior*” authored by Shu-Heng Chen, Chung-Ching Tai, Tzai-Der Wang and Shu G Wang. This chapter can be considered to be a continuation of the cognitive agent-based models. What differs from the previous one is that this chapter considers not only