第十一屆 多重代理人基模擬 國際研討會 與會報告

11th International Workshop on Multi-Agent-Based Simulation (MABS 2010)

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- 出國期間:99.5.10-99.5.16
- 報告日期:99.9.15

國立政治大學發展國際一流大學及頂尖研究中心計畫

出國成果報告書(格式)

計畫編號1	99H432	執行單位 ²	經濟系
			99年5月10日至
出國人員	陳樹衡	出國日期	99年5月16日,
			共6日
出國地點3	(MABS 2010)	出國經費4	56000

目的

多重代理人基模擬是一門結合多重代理人基系統(multi-agent system)和代理 人基社會模擬(multi-agent social simulation)相結合的一個領域,基於二個領域的 特性結合與互補,多重代理人基模擬不論在理論發展與應用方面都極受重視,故 此一研討會相當熱門並已持續辦理多屆。

多重代理人基模擬提供許多系統性的研究方法與思維,透過參加本次研討會並與與會學者們討論,實有助於釐清代理人基模擬的經濟學領域的應用議題,而本次投稿的文章是 Microstructure Dynamics and Agent-Based Financial Markets。

過程

本次行程簡要說明如下:

2010/5/10 台北(台灣) 至 多倫多(加拿大) 2010/5/11 多重代理人基模擬國際研討會(AAMAS) 第一天行程 2010/5/12 多重代理人基模擬國際研討會(AAMAS) 第二天行程 2010/5/13~2010/5/15 多倫多(加拿大) 至 洛杉磯(美國)轉機及學者拜訪 2010/5/16 洛杉磯(美國) 至 台北(台灣)

心得及建議

與其他研討會相較,此一研討會的投稿具有較高門檻,必須經由匿名的三名 審稿者所組成的小組通過,綜合三位審稿者對我們投稿文章(Microstructure Dynamics and Agent-Based Financial Markets)的意見後,本文獲選並由本人與會報 告。在審稿與研討的過程中,各方均提出相當多極具參考價值的意見,包含:(1) 在市場交易中,交易者經常相互影響其他交易者的行為,而不能僅參考個人的歷 史出價資訊作為決策的依據;(2)Genetic Programming(GP)與 Boltzmann-Gibbs Distribution 的適用性,雖然已有相關文獻佐證卻仍未能完全說服與會學者;(3) 不同 GP 的形式的影響與自我組織圖(self-organizing map)的建立對於市場研究極

¹ 單位出國案如有1案以上,計畫編號請以頂大計畫辦公室核給之單位計畫編號 + 「-XX(單 位自編2位出國案序號)」型式為之。如僅有1案,則以頂大計畫單位編號為之即可。

² 執行單位係指頂大計畫單位編號對應之單位。

³ 出國地點請寫前往之國家之大學、機關組織或會議名稱。

⁴ 出國經費指的是實際核銷金額,單位以元計。

具討論價值;(4)基於現有研究架構在縱向社會網絡部份的探究等。對於後續研究的延伸層面,或可引入 Dinosaur hypothesis 在市場行為的討論,並進一步應用不同的法則截取機制(例如不同的 GP)加以分析,相信對於財務市場的研究能有更進一步的貢獻。

整體而言,此次研討會的參與情形踴躍,參與者對於報告主題的討論程度極 爲熱烈,更不乏國際知名學者參與。審稿者對我們研究提出的諸多建議,也提供 另一層面的研究發展空間,獲益良多。

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11th International Workshop on Multi-Agent-Based Simulation (MABS 2010): Conference Report

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1 General Description of the Conference

1.1 Multi-Agent-Based Simulation

Multi-Agent-Based Simulation (MABS) is an inter-disciplinary area which brings together researchers active within the *multi-agent systems* (MAS) community and the *agent-based social simulation* (ABSS) community. The focus of MAS is on the solution of complex engineering problems related to the construction, deployment and efficient operation of agent-based systems, while the focus of ABSS is on simulating and synthesizing social behaviors in order to understand real social systems (human, animal and even electronic) via the development and testing of new theories.

As evidenced at previous MABS workshops, the MAS and ABSS communities have much to learn from each other. For example, the MAS community has developed agentbased systems that employ sophisticated and elaborated mechanisms (i.e., rich internal models) to solve complex problems, but these techniques are also useful for addressing sociological issues of cooperation, trust and power hierarchies from the social science viewpoint. In constant, the ABSS community has studied and developed techniques and models for real world societies such as companies or economy and they are tested and validated using experimental data, but these models are also useful for real world applications from the engineering viewpoint. This suggests that the communication between MAS and ABSS communities has a potential of deriving methods that overcome their weak points each other.

To promote these cross-influence, the MABS workshop focuses on both the ideas coming from *computer science* as a new technology to provide insights into ABSS community and the ideas coming from *social sciences* as new metaphors to provide insights into MAS community. For this purpose, the workshop provides a forum for social scientists, agent researchers and developers and simulation researchers to assess the current state of the art in the modelling and simulation of MABS, identify where existing approaches can be successfully applied, learn about new approaches and explore future research challenges.

1.2 This Eleventh Event

The Multi-Agent-Based Simulation (MABS) workshop is the eleventh of a series than began in 1998. This year MABS is co-located with the *9th International Joint Conference on Autonomous Agents and Multiagent Systems* (AAMAS 2010), held in Toronto, Canada, May 10-14, 2010. Its scientific focus lies in the confluence of *social sciences* and *multi-agent systems*, with a strong applicational/empirical vein, and its emphasis is stressed on

- 1. *exploratory agent based simulation* as a principled way of undertaking scientific research in the social sciences and
- 2. using social theories as an inspiration to new frameworks and developments in multi-agent systems.

The excellent quality level of this workshop has been recognised since its inception, and so its proceedings have always been published by Springer-Verlag, in the Lecture Notes series. Our paper submitted to the conference last year "*Does Cognitive Capacity Mater When Learning Using Genetic Programming in Double Auction Markets*?" has just been published in the latest volume (Chen, Tai and Wang, 2010).

1.3 Submission and Acceptance

MABS 2010 attracted a total of 26 submissions from 16 different countries (Canada, France, India, Ireland, Israel, Italy, Japan, Luxembourg, the Netherlands, New Zealand, Sweden, Switzerland, Taiwan, Tunesia, UK, USA). Every paper was reviewed by three anonymous referees. 11 papers were accepted for presentation. This is an acceptance rate of 42.3%.

Not only was our submission "*Microstructure Dynamics and Agent-Based Financial Markets*?" accepted, we also benefited very much from the four referee reports. Among the three referee reports, one is negative (rejection), the other two are all positive (one weak acceptance and one acceptance). Some reflections on the referee reports and the comments received from the workshop will be detailed in Section 4.

1.4 Structure of the Workshop

The one-day workshop is composed of four sessions, namely,

- Session 1: Models and Frameworks for MAS Development
- Session 2: Exploring MAS Behaviors
- Session 3: Game Theory and Information Sharing
- Session 4: MAS in Economics and Negotiation

2 Culture-Sensitive Agents

Among the eleven papers presented at this conference, I have been benefitted most from the presentation given by Catholijn Jonker, who, from Delft University of Technology, is one of the three organizers for MABS'2010. She presented a paper entitled "Computational

Modeling of Culture's Consequences." The two other co-authors are Gert Hofstede and Tim Verwaart, both from Wageningen University. Gert Hofstede is the son of the Dutch organizational sociologist Geert Hofstede, who is famous for his *five dimension theory of culture* (Hofstede, 2001). Hofstede studied the effect of culture on work-related values, and tries to find dimensions in order to describe the differences between cultures for work-related values. The significance of his work in in cross-culture studies has been compared to the work of Darwin in evolutionary theory.¹

Hofstede (2001) defines culture as "the collective programming of the mind that distinguishes the members of one group of people from another" (Ibid, p.9) Culture gives individuals a mode of thinking and behaving that can be adopted in different groups and social contexts. Culture includes and is related to, at least, concepts such as norms, rituals, practices, values, shared meaning, shared judgments of good and bad, groups, institutions and so forth. One of the key issues of culture is how these collective concepts are related to individual minds, and how collective norms, values and behavior, on the one hand influence, and on the other hand, arise from, interactions of socially and culturally sensitive agents. There have been very few attempts at analyzing, from a computational point of view, how culture may arise, develop and evolve through time. Computational models of culture are valuable for designing complex open systems such as serious games, social simulations, virtual reality environments, personal assistants, collective intelligence and social network software, etc. What Hofstede, Jonker and Verwaart attempted to do in their series of studies is to construct the culture-sensitive software agents. They have incorporated four of these five dimensions of culture into agent-based models of trade negotiation. The four are power distance (Hofstede, Jonker, and Verwaart, 2009), individualism (Hofstede, Jonker, and Verwaart, 2008a), uncertainty avoidance (Hofstede, Jonker, and Verwaart, 2008b), and long-term orientation (Hofstede, Jonker, and Verwaart, 2008c).

Gert Hofstede also co-authored with his father Geert Hofstede on the book *Software of the Mind*. This book has come to the third edition, and in this edition, they have introduce the sixth dimension of culture.

3 Spatial Agent-based Models of Human/Environment Interactions

Dawn Parker from George Mason University is the keynote speaker of this year. She introduced the project "Spatial Land Use Change and Ecological Effects" which is funded through the US National Science Foundation's *Coupled Natural and Human Systems program*. This is a collaborative, multi-institution, interdisciplinary research project involving six faculty members in the area of *coupled human-natural systems*. The project links agent-based modeling of human behaviors driving land use change and land cover change, preferences for vegetation cover and vegetation management, land market modeling, field work, remote sensing, and ecosystem modeling of landscape carbon balance in low-density human-dominated landscapes. Her main task is to develop *agent-based land market models*, whose effects will be compared to the non-market land allocation mechanism. The model involves bilateral trading between heterogeneous buyer and seller

¹Of course, his work is still very controversial, see, for example, McSweeney (2002).

agents. Her work also includes a simple combined cellular automaton and agent-based model designed to study the joint influence of distance-dependent spatial externalities and transportation costs on patterns of land use.

4 What Do We Learn? Comments to Our Work

My paper, "*Microstructure Dynamics and Agent-Based Financial Markets*", co-authored with Michael Kampouridis and Edward Tsang at University of Essex at UK, was presented at Session 4 "**MAS in Economics and Negotiation**". This paper received well discussion during the conference. This is probably the biggest gain of attending this conference. Hence, I want to be humbly to documents what I have learned from those feedbacks.

4.1 Fundamental Criticisms on the Proposed Methodology

I want to start with some concerns of the key idea and the specific methodology which we apply to the study of it. The key idea is the *market fraction hypothesis* (MFH). There may be some merit in the MFH, but only in a proper market simulation, that is, one in which *the behavior of the traders affects and influence each other*. Useful strategy *A* appears, and soon everyone starts using it, which suddenly makes strategy *B* interesting, so then people move to that. Some argued that *historical prices are simply not enough to show this kind of thing*. This is the fundamental challenge to our methodology. Nevertheless, the audience with this kind of arguments are not familiar with the *agent-based financial econometrics*, which basically are all using historical data to do *this kind of thing*, for example, see Chen, Chang, and Du (2010). Studies in the agent-based financial econometrics are all concerned with *reverse engineering* which is to discover traders' behavior using historical prices.

To one extreme, some audience have difficulties accepting our proposed approach to the *empirical microstructure dynamics*. Some consider the procedures which we followed are not well-motivated or subjected to proper sceptical appraisal by the authors. Specifically, they are not convinced that genetic programming is appropriate, because it is not clear how traders can imitate each others' rules by having a sample of behavior but not the rules underlying it. In fact, this question is highly legitimate and, in fact, has been addressed in Chen and Yeh (2001), where they proposed a mechanism called *business school* to show how the seemingly unobservable rules can be imitated. On the other hand, imitation and social learning, as opposed to individual learning, plays a central role in social sciences (Rendell et al., 2010). In fact, agent-based financial economic models have used the idea of social learning substantially through the devise of the *Boltzmann-Gibbs distribution*, an idea borrow from statistical physics.

Using the Boltzmann-Gibbs distribution, one can precisely give a prediction of the *copy dynamics* at an aggregate level. However, it is exactly because of this preciseness we have to humbly admit the possible weakness or limitation of the Boltzmann-Gibbs model. For example, the fitness function (utility, rewards, profits) is an essential ingredient of the Boltzmann-Gibbs social leaning models, but it is not clear what would be the nature choice of the fitness function. This issue can be further complicated if one also take into account *memory*, since quite likely agents can be heterogeneous in memory. This kind of heterogeneity may not been well captured by this model. Finally, the

Boltzmann-Gibbs model was built upon interactions of particles. Hence, the interaction scheme can be another important part of this model. Its validity can crucially depend on the assumed network topologies, and so far there are very few studies on the effect of network topologies on this kind of social learning models.

4.2 Generalizability with Different Designs

Right next to the above the fundamental criticisms is whether the tools which we apply and the results which we derive accordingly can be generally interest in the sense if people try different tools in similar vein. Can any features which we obtained using genetic programming or self-organizing maps be valid if different rule-inference machines or simply just different settings of genetic programming (GP) or self-organizing maps (SOM) are tried?

As to the GP part this question, later on we have modified our program and prepare a manuscript entitled "*The Market Fraction Hypothesis under different GP algorithms*." But, of course, this has not been done enough. As to the SOM part, audience have questioned why we used the SOM approach for clustering and not others? What was recommended to us is *standard hierarchical clustering* (Xu and Wunsch, 2008), for example, the growing hierarchical self-organizing map (Dittenbach, Rauber, and Merkl, 2001). We consider this a very good suggestion to work with and believe that it would provide much finer details in the structure of the market.

4.2.1 Longitudinal Social Networks

On a similar note, audience also pointed out that the clustering longitudinal data sets and comparing clusters find for different time slices is a known problem. Recently, it has surfaced with regards to community detection in *dynamic* (*longitudinal*) *social networks*. We are suggested to consult with this literature as well. During the conference, we, therefore, spent some time to think about the relevance of longitudinal social networks to our work. Snijders (2005), as a review article, provides a good start for us. We found this idea very interesting, almost like a serendipity for us. In this kind of framework, the connection is no longer static and are evolving with time; so sometimes it is on, and sometime it is off. In a simple way, we have a binary matrix to characterize the connection of all agents in the society, but based on the some underlying dynamics, this binary matrix is not stationary but time-variant.

The underlying dynamics can be quite complex and it depends on our models of agents. Are they optimizing agents, or are they bounded-rational agents? Will they be clothed with cultural influence, personality traits, and cognitive capacities. This and that can make this system extremely rich and complex. It is certainly interesting to see what has been done within this general framework.

However, we have to say that this dynamics (longitudinal) social networks have little to do with our analysis. While the self-organizing map which we constructed does involve the idea of evolution (changing in time), but it is not a network. It is purely a statistical way to cluster the agents. Of course, one can always ask the relation between these agents in the same clusters or in different clusters. Presumably the agents in the same cluster may have a link or closed connected, but our work does not make reference to any underlying network topologies and their dynamics. As a further study, one can actually construct a more general framework such that the dynamics of self-organizing maps or the dynamics of the growing hierarchical self-organizing maps are coupled with the underlying dynamics of social networks. This hybridization seems to be gigantic enough for a separate research project.

4.3 Extensions

Being inspired by the heated discussion received from the conference, we also consider to develop the paper into several directions. First, we consider the extension what we call it the *dinosaurs hypothesis*. The nub of the issue is really understanding the dynamics of the market. Does the market have a number of "typical states" (in which case past rules may become useful again) or is the "future" slightly different every time. It would be interesting to see whether the former can be the case: *dinosaurs can return*. Hence, market behavior can actually repeat itself, and have a number of typical states, where past rules may become useful again.

This hypothesis derive the following statements which form the basic constituents of the dinosaurs hypothesis: (1) The market behavior never settles down; (2) The population of predictors continuously co-evolves with the market. This observation had been made and tested under artificial data by the Santa Fe Institute (Ehrentreich, 2010). What we can do is to formalize this hypothesis and also test it using empirical data. We, first, test the hypothesis based on a GP system in vein of our paper in this conference (MABS). However, as what we have seen above, many may argue that results may be dependent on the specific design of the rule extraction machine. Hence, the second step is to test the dinosaur hypothesis by varying the rule extraction machines, e.g., different GP algorithms, in order to assure the insensitivity of the previous results to the choice of GP.

4.4 Specific Technical Comments

Other comments are very specific and technical, which are listed as follows.

- 1. In Section 3 the authors discuss the "dynamics" of their results, i.e., how the clusters found change over time. One starts wondering, however, how much of this is dependent on the sensitivity of the clustering method to *small changes in the input data set*? Some kind of validation (null hypothesis checking) would be useful here.
- 2. The determination of the number of the clusters, be three or nine, is not well justified. It is not clear whether the "clusters" and their various features are *spurious*. A cure for this problem is to test whether, for example, a completely random set of strategies, or a set evolved in a different way, or the set used grouped randomly into clusters, would give different results.
- 3. Regarding footnote #5: since the system considered is a closed system, does not that mean that some agents are bound to loose money? So is not that some agents must evolve "bad strategies"? Or, at least, the system definitely has to evolve heterogeneous strategies for keeping it working...

- 4. it might be convenient to use a form of a temporal language to be able to express the change of these values over time.
- 5. The one thing the paper lacks is a little bit more details on the eventual behavior of the agents.
- 6. Our paper presents an overview of the genetic algorithm, however, we do not express how good the last generation used has learned to behave well (what's their fitness), furthermore, it would have been nice to show an example of a behavior tree that showed to be a successful one. And how do mutation and crossover work here? And what is the precise specification of the fitness function?

4.5 Acknowledged Contributions

As to the significance of our paper, the following is directly cited from the referee reports.

- the paper describes the ideas well, and the results shown in the simulation runs shown are interesting.
- This paper deals with a novel computational approach to analyze empirical data about stock market behavior. Computational finance is one of the important application areas of computational (agent-based) simulation that has been flourishing in the past decade. The bulk of the work so far was concerned with replicating the global statistical properties of empirical observations (c.f., stylized facts). The given paper belongs to a more recent direction that aims at understanding/reproducing the market microstructure from empirical data.
- While the work presented in the paper is not based on simulation in the classical meaning of the word (a completely artificial system producing "in silico" data sets), it applies computational multi-agent systems to fine-tune its parameter array to observed data. I think, while borderline in scope, the papers merits (relevance, new insight, etc.) makes it worth for acceptance.

5 Achievable Documents

• Proceedings (Electronic Version in UBS)

6 Acknowledgements

The author is grateful for the financial support by the NCCU Top University Project sponsored by the Ministry of Education, Taiwan, R.O.C.

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