Data Science Research Project

Agent-based Modelling for Market Diffusion Research

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Abstract

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1 Introduction and Research Question

1.1 Introduction

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1.2 Research Question

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2 Literature Review

2.1 Agent-based Modelling and Simulation

2.1.1 Definition and Concept of Agent-Based Modelling

Agent-Based Modeling (ABM) is an innovative and powerful modeling and simulation approach used to study and understand the dynamic behavior of complex systems (Macal & North, 2005). The core concept of ABM is to evaluate the impact on an entire system by simulating the behavior and interactions of numerous autonomous individuals within it, known as agents. The fundamental premise of ABM is that even complex phenomena can be understood and simulated through a series of autonomous agents following specific interaction rules (Zheng et al., 2013).

Unlike traditional equation-based modeling methods, ABM employs a rule-based approach to construct models (Dorri et al., 2018), making it particularly suitable for simulating complex dynamic systems. In ABM, each agent is endowed with the ability to make autonomous decisions (Macal & North, 2009), acting based on its own state, surrounding environment, and interactions with other agents

(Macal, 2016). These agents not only influence their physical and social environment but are also influenced by it, forming an intricate network of interactions.

A key feature of ABM is its capacity to capture heterogeneity within a system, allowing for the simulation of agents with diverse characteristics and behaviors, thus more accurately reflecting the diversity of the real world. Through ABM, researchers can observe and analyze how complex behaviors and patterns at the system level emerge from simple rules at the individual level. This "bottom-up" modeling approach makes ABM a powerful tool for studying emergent phenomena, adaptive behaviors, and the evolution of complex systems.

In ABM, agents are core elements with multiple characteristics, including autonomy, heterogeneity, proactivity, and reactivity. They can make independent decisions, interact with each other, learn and adapt, perceive their environment, and act according to specific rules (Davidsson, 2001). Agents typically possess bounded rationality, goal-oriented behavior, and variable internal states. These features enable ABM to effectively simulate individual behaviors and overall dynamics in complex systems.

2.1.2 ABM modeling process and technical implementation

The ABM models contains three main components: agents, environment, and interaction rules.

ABM Components	Description
Agents	Autonomous individuals with specific attributes and behavioral rules
Environment	The context in which agents operate
Interaction Rules	Governing agent-to-agent and agent-environment interactions

Table 1: Main Components of ABM

Refer to (Badham et al., 2018) and Gilbert's ABM specification sheet (Gilbert, n.d.) for summarizing the ABM modeling process:

1. Define model purpose and scope.
2. Identify and characterize agents.
3. Determine agent behavior theories and decision rules.
4. Establish agent relationships and interaction theories.
5. Design the environment.
6. Choose an ABMS platform and development strategy.
7. Implement learning and evolution strategies.
8. Incorporate security mechanisms (Ramchurn et al., 2004).
9. Develop interaction protocols.
10. Collect relevant agent data.
11. Validate agent behavior models.
12. Run simulations and analyze output results.
13. Link micro-level agent behaviors to macro-level system behaviors.

The setting of interaction rules, the selection of key parameters and the verification of results of ABM are the core links in the modeling process. The interaction rules are usually implemented by setting the behavior and topological structure of the agent, including the "Soup" model, cellular automata, Euclidean space, GIS and network topology (Macal & North, 2009). The key parameters cover the personal characteristics and environmental factors of the agent (Conte & Paolucci, 2014), and may also include specific belief parameters (Ramchurn, Huynh, & Jennings, 2004). The result verification methods include comparing the ABM simulation results with classical models or empirical data, adopting multi-level verification methods (calibrating parameters at the micro level and observing the reality of macro behavior) (Conte & Paolucci, 2014), and using social network analysis and participatory simulation to obtain information about agent behavior and interaction. However, due to the complexity of ABM models, verification and calibration remain one of the main challenges, and the lack of standardized methods makes it difficult to interpret and analyze the results.

2.1.3 Pros and Cons of ABM and its Applications

The main advantage of ABM is its powerful ability to simulate complex systems. It can capture complex interactions between heterogeneous agents, observe macro-emergent phenomena generated by micro-behavior (Conte & Paolucci, 2014), and provide an intuitive and realistic description of the system. The flexibility of ABM enables it to easily adapt to different scenarios and simulate the learning and adaptive behavior of agents (Dorri, Kanhere, & Jurdak, 2018). It supports multi-level modeling that simultaneously considers dynamics at the individual, organizational and system levels. ABM is also spatially explicit, able to simulate the movement and interaction of agents in specific environments (Davidsson, 2001). In addition, it provides generative explanations, can improve efficiency through parallel computing, and can be integrated with other modeling methods to enhance overall modeling capabilities.

However, ABM also faces some significant challenges and limitations. The most prominent one is the difficulty of verification (Zheng, Son, Chiu, Head, Feng, Xi, Kim, Hickman, & University of Arizona, 2013). Due to the complexity of the model, it is difficult to fully verify the accuracy of the results. ABM often requires powerful computing resources, especially for large-scale or complex models (Conte & Paolucci, 2014). It also requires large amounts of detailed process data for calibration and validation, which increases the difficulty of data collection. The complexity of parameter calibration and the highly technical requirements of the model are also important constraints. In addition, the complex interactions and emergent behaviors generated by ABM can be difficult to interpret, running the risk of producing arbitrary and inconsistent models. High computational cost, lack of unified modeling standards, and the possibility of overfitting are important issues to consider when using ABM. Despite these challenges, ABM remains a powerful tool for studying complex systems, but its use requires careful weighing of these advantages and disadvantages.

ABM has been widely used in multiple disciplines, demonstrating its strong potential as an interdisciplinary research tool and its applicability in systems of different scales and complexities, providing researchers with a powerful tool to understand and predict complex social, economic, and natural phenomena (Macal & North, 2005).

Research Field	**Applications**
Social Sciences	• Human behavior and social interactions • Economic systems and artificial financial markets • Political processes and civic behavior • Organizational decision-making • Ancient civilization simulation • Crime analysis • Terrorism network studies
Natural Sciences	• Ecology (animal group behavior, ecosystems) • Biology (cellular behavior, subcellular molecular behavior) • Chemistry

Research Field	**Applications**
Public Health & Medicine	• Infectious disease epidemiology • Non-communicable disease research • Healthcare systems
Engineering & Technology	• Supply chain management • Intelligent/distributed manufacturing • Urban planning and distribution center usage • Transportation systems (air traffic control) • Energy analysis (electricity markets, hydrogen economy) • Complex scalable power grid networks
Business & Economics	• Consumer market analysis • Financial market simulation • Insurance business modeling • Trade network analysis • Marketing strategies
Environment & Energy	• Climate change impacts • Sustainable development strategies • Resource management
Military & Security	• Command and control systems • Force-on-force simulations • Evacuation modeling
Complex Systems Science	• Emergent behavior studies • Adaptive systems analysis • Multi-level system simulations

Table 2: Applications of ABM in Various Fields

2.1.4 Application of ABM in complex systems and social science research

2.1.5 Theoretical contributions and future development of ABM

2.2 Platforms and Building Philosophy of ABM

2.3 Diffusion of Innovation and Bass Model

2.4 Influencers and Opinion Leaders in Diffusion

2.5 Network Structure and Diffusion

2.6 Conclusion of Literature Review

3 Methodology

4 Simulation and Results Analysis

4.1 Design of the Experiment

Index	N	p	q	Agent Proportion	Iter
Sim 1	1000	0.01, 0.02, 0.03	0.3	[0.001, 0.099, 0.009, 0.891]	25
Sim 2	1000	0.02	0.3, 0.4, 0.5	[0.001, 0.099, 0.009, 0.891]	25
Sim 3	1000	0.01	0.3	[0, 0.099, 0.01, 0.891] [0.003, 0.099, 0.007, 0.891] [0.005, 0.099, 0.005, 0.891] [0.007, 0.099, 0.003, 0.891] [0.01, 0.099, 0, 0.891]	25
Sim 4	1000	0.01	0.3	[0, 0.1,0.009, 0.891] [0.003, 0.097, 0.009, 0.891] [0.005, 0.095, 0.009, 0.891] [0.007, 0.093, 0.009, 0.891] [0.01, 0.09, 0.009, 0.891]	25
Sim 5	1000	0.01, 0.015, 0.02 0.025, 0.03	0.3	Prop innovator: 0.1, 0.2, 0.3, 0.4, 0.5 Prop Influencer: 0.01	5
Sim 6	1000	0.01	0.3	Prop innovator: 0.1, 0.2, 0.3, 0.4, 0.5 Prop Influencer: 0.01, 0.02, 0.03, 0.04, 0.05	5

Table 3: The Parameters of the Experiment for Each Simulation

References

Badham, J., Chattoe-Brown, E., Gilbert, N., Chalabi, Z., Kee, F., & Hunter, R. F. (2018). Developing agent-based models of complex health behaviour. *Health & Place*, *54*, 170–177. https://doi.org/10.1016/j.healthplace.2018.08.022

Conte, R., & Paolucci, M. (2014). On agent-based modeling and computational social science. *Frontiers in Psychology*, *5*. https://doi.org/10.3389/fpsyg.2014.00668

Davidsson, P. (2001). Multi Agent Based Simulation: Beyond Social Simulation. In S. Moss & P. Davidsson (Eds.), *Multi-Agent-Based Simulation* (pp. 97–107). Springer. https://doi.org/10.1007/3-540-44561-7_7

Dorri, A., Kanhere, S. S., & Jurdak, R. (2018). Multi-Agent Systems: A Survey. *IEEE Access*, *6*, 28573–28593. https://doi.org/10.1109/ACCESS.2018.2831228

Gilbert, N. *ABM specification sheet.*

Macal, C. M. (2016). Everything you need to know about agent-based modelling and simulation. *Journal of Simulation*, *10*(2), 144–156. https://doi.org/10.1057/jos.2016.7

Macal, C., & North, M. (2005). Tutorial on agent-based modeling and simulation. *Proceedings of the Winter Simulation Conference, 2005.*, 14–15. https://doi.org/10.1109/WSC.2005.1574234

Macal, C. M., & North, M. J. (2009). Agent-based modeling and simulation. *Proceedings of the 2009 Winter Simulation Conference (WSC)*, 86–98. https://doi.org/10.1109/WSC.2009.5429318

Ramchurn, S. D., Huynh, D., & Jennings, N. R. (2004). Trust in multi-agent systems. *The Knowledge Engineering Review*, *19*(1), 1–25. https://doi.org/10.1017/S0269888904000116

Zheng, H., Son, Y.-J., Chiu, Y.-C., Head, L., Feng, Y., Xi, H., Kim, S., Hickman, M., & University of Arizona. (2013). *A Primer for Agent-Based Simulation and Modeling in Transportation Applications* (Issue FHWA-HRT-13-054). https://rosap.ntl.bts.gov/view/dot/36178