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A review on agent-based modeling and simulation

Una breve revisión del Modelado y Simulación basados en agentes

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Resumen

El modelado y simulación basados en agentes, es un enfoque relativamente nuevo para simular sistemas socio-económicos. Su principal ventaja es el uso de entidades autónomas, denominadas agentes, para modelar un sistema, con el que es posible estudiar el comportamiento del mismo y, lo que es más importante, sus propiedades emergentes. Los agentes a menudo representan gente, animales, compañías, entidades naturales, etc., y pueden situarse en un amplio rango de comportamiento que va desde los totalmente autónomos a los básicamente reactivos. La programación de agentes usando reglas de decisión o ciclo de vida, confiere a este enfoque mayor versatilidad y flexibilidad.
Este artículo además de explicar someramente sus principios, muestra el campo de aplicación del mismo, señalando sus ventajas y desventajas.

Palabras clave: Modelado basado en agentes - Simulación socio-económica -sistemas complejos

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Abstract

Agent Based Modeling is a relatively new approach to simulating socio economic systems.
Its main advantage is the use of entities called agents to model a system in order to study the behaviour and, most important, the emergent properties of it. Agents often represent people, animals, companies, natural entities, etc., and could be in a wide range from totally autonomous to basically reactive. The programming of agents using decision rules o life cycles makes the approach more versatile and flexible.

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This article shows the basic concepts underlying the agent based modeling, its advantages and disadvantages, as well as, the wide range of application of it.

Key Words: Agent Based Modeling - Socio-Economic Simulation -Complex Systems

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Introduction

According to Heath and Hill (2009), Agent Based Modeling simulation paradigm emerged from the fields of Complexity, Chaos, Cybernetics, Cellular Automata and Computers, representing a departure from the more classical simulation approaches such as the discrete-event simulation paradigm.

Although computer simulation as an analytical tool has been around since the advent of computers, the ability of the ABM paradigm to simulate complex systems has moved into a breadth of fields ranging from engineering to mathematics to social science and economics. For the first time analysts can use simulation to explore these complex systems at a level of detail that was difficult to achieve before.

Agent-based simulation (ABS), or agent-based modeling (ABM), is a modeling and computational framework for simulating dynamic processes that involves autonomous agents. An autonomous agent acts on its own without external direction in response to situations the agent come across during the simulation.

Modeling a population of autonomous agents, each with its own characteristics and behaviors that extensively interact is a defining feature of an ABS. Agent-based simulation is most commonly used to model individual decision-making, social, and organizational behavior (Bonabeau, 2001).

ABS has gained increasing attention over the past several years as evidenced by the increasing numbers of articles appearing in modeling and applications journals, funded programs that call for agent-based models incorporating elements of human and social behavior, the demand for ABS courses and instructional programs, and the growing number of conferences that feature agent-based modeling, such as the Winter Simulation Conference (WSC) (Macal and North, 2014)

Basic Concepts

Today, computer-simulation in the natural sciences and engineering mostly rely on equation-based modeling (e.g. of the dynamics of gases, fluids, or solid bodies). Such an approach would certainly be hard to transfer to the social sciences, as most system behaviors have not been formalized mathematically. A method that seems to be more suited for the computer simulation of socio-economic systems is agent-based modeling (ABM). The corresponding computational technique is called multi-agent simulation (MAS) or agent-based computational modeling («ABC modeling»). (Helbing and Balietti, 2015)

In the 1990s, Agent-Based Modeling (ABM) began gaining popularity and represents a departure from the more classical simulation approaches, as stated before. This departure, its recent development and its increasing application by non-traditional simulation disciplines indicates the need to continuously assess the current state of ABM and identify opportunities for improvement. (Heath and Hill, 2009)

ABM as a modeling technique and paradigm is really still in development. Two key things are needed to mature the ABM paradigm. First, techniques, philosophies and methods need to be developed specifically for ABM and distinguished from other simulation techniques, philosophies and methods. The second is the teaching of ABM techniques, philosophy and methods must improve for those using ABM improve their models (Heath and Hill, 2009).

An agent is a general concept having broad applicability. Agents often represent people, or groups of people. Agent relationships represent processes of social interaction (Gilbert and Troitzsch, 2005).

Fundamental social structures and group behaviors emerge from the interaction of individual agents operating on artificial environments under rules that place only bounded demands on each agent's information and computational capacity (Epstein and Axtell, 1996).

Applications

Applications range from modeling agent behavior in supply chains and the stock market, to predicting the success of marketing campaigns and the spread of epidemics, to projecting the future needs of the healthcare system. Progress in the area suggests that ABS promises to have far-reaching effects on the way that businesses use computers to support decision-making and researchers use agent-based models as electronic laboratories to aid in discovery (Macal and North, 2014).

A broad classification of applications can be obtained from (Helbing and Balietti, 2015):

- social influence and opinion formation (Mäs, 2010),
- coalition formation (Sichman 1998), (Gaston and Jardins, 2005)
- collective intelligence (Bonabeau, 2000),
- social networks (Szabo and Fath, 2007), (Carrington et al., 2005), (Holme and Ghoshal ,2006)
- group dynamics (Sierhuis et al., 2003),
- social cooperation (Axelrod 1997), (Bowles and Gintis, 2004)
- social norms (Helbing et al., 2010), (Helbing and Johansson, 2009) (Rauhut and Junker, 2009)
- social conflict (Cederman, 1997), (Cederman, 2003)
- financial markets (Hommes, 2006),(LeBaron, 2002), (Raberto et al., 2001)
- competition and cooperation between firms (Zhang, 2005), (Axtell, 1999)
- micro-economic models(Kaihara, 2003), (Preist, 1999)
- macro-economic models (Lebaron et al., 2008), (Tesfatsion, 2002)
- organization and managerial decisions (Harrison et al., 2007)
- migration (Onggo , 2008)
- agglomeration and segregation (Mansury et al., 2002), (Osullivan et al., 2003)
- urban and regional development (Batty, 2007), (Helbing and Nagel, 2004), (Killer et al., 2010)
- traffic dynamics (Binder et al., 2004), (Dia, 2002)
- crowd dynamics (Henein and White, 2005), (Batty, 2003)
- systemic risks in socio-economic systems (Delli, 2008), (Aoki and Yoshikawa, 2006)
- others (Conte et al., 1997), (Sun, 2008), (Gilbert, 2007), (Grimm et al., 2005), (Axelrod, 2005)

Principles of Agent Based Modeling

Authors like Helbing and Balietti (2015) define several steps or principles for ABM Modeling.

First, one should clearly describe the evidence to be explained by the respective study. What are the empirical or experimental data or observations to be reproduced, or what are the «stylized facts», i.e. the simplified, idealized properties of the system under consideration?

Second, one should explain what the purpose of the simulation is. To understand a phenomenon?. To get a more accurate description?. To make predictions?. To develop an application? (e.g. a new traffic control). In the social sciences, it is common to formulate a scientific puzzle, i.e. to describe a problem that is hard to understand and why. This could be an unexpected or even paradoxical individual or system behavior. Emergent system behaviors are particularly interesting candidates for the formulation of such a puzzle («scientific mystery»).

Next, one needs to decide how to choose the agents in the model. For example, when the competition of companies shall be studied, it may not be necessary to simulate all employees of all companies. It may be sufficient to choose the companies as the agents of the model. In fact, it can be shown mathematically (e.g. by eigenvalue analysis) that mutually coupled agents may jointly behave like one entity, i.e. one agent. An example for this is the quasi-species concept in the theory of evolution (Eigen, 1978).

After specifying the agents, one should formulate hypotheses regarding the underlying socio-economic processes or fundamental mechanisms leading to the particular system behavior that needs to be explained. Ideally, these mechanisms should be sociologically or economically justified, i.e. there should be some empirical evidence for the mechanisms on which the agent based model is based. The transfer of models from other sciences (such as spin, epidemic, or synchronization models) requires particular justification beyond saying that the resulting system behavior is reminiscent of features that have been observed elsewhere.

When specifying the mechanisms underlying the multi-agent simulation, one should not put into the model assumptions what one wants to explain. The mechanisms on which the multi-agent simulations are based should be (at least) one level more elementary than the evidence to be understood. For example, the rich-gets-richer effect (Merton 1968) may be used as an ingredient, if class formation shall be described. Moreover, «homophily» (Miller, 2001) may be assumed in models of coalition formation or solidarity. Moreover, social network characteristics may be used to explain the spreading of behaviors (Christakis 2007, 2008), (Smith, 2008). However, if the income distribution is to be explained, it is favorable not to start with the rich-gets-richer effect, but instead with a mechanism that is purely random and not biased in favor of anybody in the beginning. Moreover, even if this is not realistic, it would be interesting to start the computer simulation with identical wealth of everybody (Chadefaux, 2010). Furthermore, if social segregation is to be explained, one should not assume «homophily» already, but to let it evolve in a system that starts off with identical and non-segregated individuals (Helbing and Yu 2009, 2011). Finally, if group formation is to be explained, social network characteristics should not be assumed as an input (Mäs, 2010). They should, for example, result from certain rules regarding the formation and deletion of social ties (Granovetter, 1982), (Fiske, 1991).

Last but not least, one should compare the computer simulation results with the empirical

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evidence. Here, one should avoid to be selective, i.e. one should state what are the features that are correctly reproduced, and which ones are not. Pointing out the limitations of a model is equally important as underlining its explanatory power.

Differences with other types of simulation

Helbing (2012) shows some differences with other types of simulations:

Today, computer-simulation in the natural sciences and engineering mostly rely on equation-based modeling (e.g. of the dynamics of gases, fluids, or solid bodies). Such an approach would certainly be hard to transfer to the social sciences, as most system behaviors have not been formalized mathematically. A method that seems to be more suited for the computer simulation of socio-economic systems is agent-based modeling (ABM). The corresponding computational technique is called multi-agent simulation (MAS) or agent-based computational modeling («ABC modeling»). Depending on the problem of interest, agents may for example represent individuals, groups, companies, or countries and their interactions. The behaviors and interactions of the agents may be formalized by equations, but more generally, they may be specified through (decision) rules, such as if-then kind of rules or logical operations. This makes the modeling approach much more flexible.

Besides, it is easily possible to consider individual variations in the behavioral rules («heterogeneity») and random influences or variations («stochasticity»).

To give a clearer picture, let us provide below a list of properties, which may be given to an agent representing an individual:

- Birth, death, and reproduction
- Individual needs of resources (e.g. to eat and drink)
- Competition and fighting ability
- Toolmaking ability (e.g. the possibility to grow food, hunt etc.)
- Perception
- Curiosity, exploration behavior, ability for innovation
- Emotions
- Memory and future expectations
- Mobility and carrying capacity
- Communication
- Learning and teaching ability
- The possibility of trading and exchange
- The tendency to have relationships with other agents (e.g. family or friendship ties etc.)

Criticisms of ABM simulation

Despite all the virtues of mathematical modeling, one should not forget some possible problems (Helbing, 2012). So far, it is not known what phenomena agent-based models, can understand, and what the fundamental limits of this approach are. It is conceivable that there exist phenomena, which are irreducibly complex (Helbing, 2010). For example, the method of physics to reduce most observations to the behavior of individual particles and pair interactions may not be fully appropriate in socioeconomic systems. Some phenomena require a more integrated treatment of the interactions between many agents. Public good games are just one example (Olson, 1971).

Recent models of pedestrian interactions are also turning away from pair interaction approaches in favor of heuristics that respond to an integrated visual pattern (Moussaýd, 2009).

The corresponding behaviors can still be treated by agent-based models, but one must be aware that they may have fundamental limitations as well.

Conclusion

Due to its characteristics and abilities, some claim that ABM represents a revolution in modeling and simulation. However, this statement is based primarily on the *potential* of ABM rather than *current results* (Bankes, 2002).

Nevertheless, there is no reason why analyzing these complex systems using ABM should not eventually always produce meaningful, model-based results.

By extension meaningful results regarding these complex systems will be consistently gained when the proper tools and models are in place, and ABM is, at least for the moment, the most suitable tool for analyzing these types of the complex systems.

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