AGENT-BASED MODELLING

OVERVIEW

Social sciences often aspire to move beyond exploring individual behaviours and seek to understand how interaction between individuals leads to large-scale outcomes. In this process, understanding complex systems requires more than understanding their parts. Agent-based modelling (ABM) is a bottom-up modelling approach in which macro-level system behaviour is modelled through the behaviours of micro-level autonomous, interacting agents. ABM can generate deep quantitative and qualitative insights into complex socioeconomic, natural and man-made systems through simulating interacting processes, diversity and behaviours at different scales. Social interventions are generally designed to influence micro-level behaviour (e.g. the behaviour of an individual or household). Similarly, evaluations are mostly interested in explaining micro-level behavioural changes. ABM, in contrast, allows macro-level mechanisms to be represented, which makes it well-suited to evaluate complex programmes and policies, for example, evaluating multi-intervention outreach programmes.

The use of ABM expanded in the social sciences during the early 1990s to simulate large-scale social phenomena such as pollution, migration and disease (Epstein, & Axtell, 1996). Later, many ABM studies turned their focus to designing effective teams and exploring the behaviours of social networks. According to a more recent survey of ABM practices (Heath et al., 2009), the method became widely used in a range of fields, including traffic, public policy and the military, yet the most popular domains of study using ABM are still economics, social science and biology.

Recent applications of ABM have been made possible by advances in the development of specialized agent-based modelling software, more granular and larger data sets and advancements in computer performance (Macal & North, 2010). However, ABM is a complex and resource-intensive method: the implementation process requires expert modellers, the results can be difficult to understand and communicate, and the application of ABM can be costly.

KEY ELEMENTS OF METHODOLOGY

The underlying premise of ABM is its 'complex system-thinking'. That is, the complex world comprises numerous interrelated individuals, whose interactions bring about higher-level features. In ABM, such emergent phenomena are generated from the bottom up (Bonabeau, 2002) by seeking to unfold underlying rules that govern the behaviours of whole systems. ABM presumes that simple rules behind individual action can lead to coherent group behaviour, and that even a small change in those rules can radically change group behaviour. ABM characterises individual behaviour as being nonlinear and defined by thresholds and if-then logic. It can capture discontinuity in individual behaviour that is difficult to describe with structural statistical models (Bonabeau, 2002). Furthermore, ABM – unlike other modelling approaches – does not assume equilibrium within the social realm. Instead, systems are understood as dynamic and adaptable, consisting of the complex interaction of autonomous, decision-making agents, who influence each other, learn from their experiences and adapt their behaviour to better fit the environment (Macal & North, 2010).

A typical ABM has three main elements:

1. Agents (with their attitudes and behaviour)
2. The relationships between agents
3. Environments (with which agents also interact; Macal & North, 2010)

In ABM the most essential property of *Agents* is their autonomy. They are 'active, initiating their actions to achieve their internal goals, rather than merely passive, reactively responding to other agents and the environment' (Macal & North, 2010, p. 153). From a practical standpoint, agents have the following characteristics:

- They are *self-contained* (they have a distinct boundary that differentiates them from other agents)
- They have a *state* that varies over time (an agent's behaviour is conditioned on its state, which is conditioned by the agent's attributes as well as the state of other interacting agents and the state of the environment)
- They are social, meaning their behaviour is influenced by their dynamic interactions with their social environment
- They may also be *adaptive* (i.e. they may modify their behaviour as a result of learning), and *heterogeneous* (their behaviours and characteristics are diverse and may vary in terms of their extent and sophistication).

Agent relationships and interactions are just as important for ABM as their behaviours. ABM is concerned with two principle questions: who interacts with whom (as agents only connect to a subset of agents – termed as *neighbours*), and how these neighbours are connected (which is referred to as the *topology* of connectedness). Regarding the former: ABM understands (social) environments as decentralised systems, where information is gained from an agent's interactions with its neighbours and the local environment – both can change rapidly as the agent moves. The topology of connectedness refers to the spatial (or social) network of agents and their relationships. Topology also models the direction of information. The neighbourhood in which agents interact can be specified spatially as well as socially. For instance, in the event of a pandemic, infection may be transmitted during physical activities that emerge through daily activities (special network) but also through interactions with friends and family (social network).

Information about the *environment* in which agents interact may be needed beyond providing spatial location: whilst interacting with the environment, agents are constrained in their actions by the infrastructure, resources, capacities or the links the environment can provide.

These elements need to be identified, modelled and programmed to create an ABM. The model developer then must use a computational engine to simulate the behaviours and interactions of agents. This step is executed using general software or programming language, or specifically designed toolkits. The underlying mainspring of ABM is that these behaviours and interactions are repeatedly executed by agents, and the resulting processes can be modelled to run in different structures: they can be activity-based, time-speed or discrete events, or they may operate over a timeline (Macal & North, 2010).

ABM is not purely inductive, nor deductive, and is often referred to as a third way of doing science (Axelrod & Tesfatsion, 2021). Deduction is used to specify a set of assumptions (about agents and the environment) and derive theorems about the system of interest; but induction is applied to identify patterns in the empirical data. Furthermore, as Axelrod and Tesfatsion claims,

> *'simulation does not prove theorems with generality. Rather, simulation generates data suitable for analysis by induction. In contrast to typical induction, however, the simulated data comes from controlled experiments rather than from direct measurements of the real world.'*

(2021: Online)

Given these strengths, ABM is typically applied for three purposes:

- Theory development: theory is implemented in a model and tested to assess whether it can generate observed outcomes (Castellini et al., 2019)
- Analysis of real-world issues: ABM can draw on empirical research results to simulate future scenarios, potential interventions and counterfactuals to inform decision-making
- Engaging stakeholders in discussions and thinking: modellers and stakeholders work in collaboration to design various models by editing and changing parameters. Such experimentation in the virtual world can trigger discussions about agent behaviours or about the potential effects of different interventions (Gilbert et al., 2018).

ABM has been used in a variety of fields including the physical, biological, social, and management sciences. According to Axelrod, (1997), applying ABM can be especially beneficial in systems that rely upon competition and collaboration of its agents. Thus, the application of ABM may be beneficial in higher educational settings, where complex interactions might be difficult to understand using conventional analytic techniques (Triulzi et al, 2011).

MULTI-METHOD APPROACHES

ABM is most typically combined with other modelling approaches, such as social network analysis (for a recent review, see Will et al., 2020) and activity-based modelling (Muller et al., 2021)

ABM is commonly treated methodologically incompatible with case-based methods (CBM). The reasons being that (1) there is a conceptual difference between 'agent' and 'case', (2) ABM focuses on simulating process for theory testing or scenario analysis while CBM is looking for patterns in real data, and (3) the ingrained distance between those grounded in quantitative versus qualitative methodologies. However, recent studies discussed the possibility of combining ABM with other small *n* case-based methods, such as using in tandem with Qualitative Comparative Analysis (Castellini et al., 2019).

RESOURCES REQUIRED

Evaluator skills and experience

ABM requires expert modellers and facilitators, as the system needs to be captured in sufficient detail, otherwise findings may not be meaningful. Computer scientists will be involved in building the complex computational models that underpin ABM. Findings are likely to be complex, hence results are often difficult to comprehend and communicate. However, it is argued that the complexity captured reflects the complexity found in human behaviours and interactions.

Resource implications

In addition to assembling a team with the necessary skills to build complex computational models based on a detailed understanding of social phenomenon, ABM is likely to also require specialist software and high-performance computers able to run simulations.

CASE STUDY

A study by Reardon et al. (2013) implemented ABM to simulate how socioeconomic background influences university application choices and enrolment. The goal of the simulation was to 'build intuition about the relative strength of some of the resource-based mechanisms that shape the distribution of students among more- and less-selective colleges and universities' (Reardon et al., 2013). The related mechanisms include: (1) prior educational performance (high-resources student have a disproportionate ability to enhance their apparent academic preparation for university); (2) the quality of information used when selecting university; (3) the number of submitted applications; (4) the perceived utility of university enrolment, and (5) the differences in high- and low-resources students in valuing higher/lower profile universities.

The model shows how the link between socioeconomic inequality and student performance drives observed patterns of resource stratification in university enrolment.

The study builds upon a very basic framework, and it– admittedly – over-simplifies the realms of university enrolment, therefore, it cannot substitute policy evaluation. Yet it is a useful method to explore the dynamic interdependent processes underlying the apparent patterns of stratification, and it can 'develop intuition about how student characteristics and behaviour influence the sorting of students into colleges of varying quality' (Reardon et al., 2013: online).

Reference

Reardon, S., Kasman, M., Klasik, D., & Baker, R. (2016). Agent-based simulation models of the college sorting process. *Journal of Artificial Societies and Social Simulation*, 19(1), 8. DOI: 10.18564/jasss.2993. Download at: https://www.jasss.org/19/1/8.html

RESOURCES

Web resources

The following website provides a good introduction to Agent-based modelling:

Axelrod, R. and Tesfatsion, L. (2021) *On-Line Guide for Newcomers to ABM*. [online] Available at: <http://www2.econ.iastate.edu/tesfatsi/abmread.htm> [Accessed 24 August 2021].

Key reading

An introductory tutorial into background and application of Agent-base modelling:

Macal, C., & North, M. (2014). *Introductory tutorial: Agent-based modeling and simulation*. In Proceedings of the Winter Simulation Conference 2014, pp. 6-20. IEEE.

An early book that is regarded as launching the field of social ABM in a sustained way:

Epstein, J. M. and Axtell, R. (1996). *Growing Artificial Societies: Social Science From The Bottom Up*. Cambridge, MA:MIT Press.

A widely read book that provides a simple overview of the methodology including how to construct simple ABM:

N Gilbert and K. Troitzsch (2005). *Simulation for the Social Scientist*, McGraw-Hill.

Exemplary ABM applications are scattered across disciplines. There is no single publication outlet for studies applying ABM, but the following journal is considered a high-quality source for many years:

Jasss.org. 2021. JASSS. [online] Available at: <https://www.jasss.org/JASSS.html> [Accessed 24 August 2021].

Further references

Axelrod, R. (1997). *The complexity of cooperation*. Princeton university press.

Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the national academy of sciences*, 99(3), 7280-7287.

Castellani, B., Barbrook-Johnson, P., & Schimpf, C. (2019). Case-based methods and agent-based modelling: bridging the divide to leverage their combined strengths. International Journal of Social *Research Methodology*, 22(4), 403-416.

Gilbert, N., Ahrweiler, P., Barbrook-Johnson, P., Narasimhan, K. P., & Wilkinson, H. (2018). Computational modelling of public policy: Reflections on practice. *Journal of Artificial Societies and Social Simulation*, 21(1).

Heath, B., Hill, R., & Ciarallo, F. (2009). A survey of agent-based modeling practices (January 1998 to July 2008). *Journal of Artificial Societies and Social Simulation*, 12(4), 9.

Macal, C.M., & North, M.J. (2010). Tutorial on agent-based modelling and simulation. *Journal of Simulation*, 4(3), 151–162. doi: 10.1057/jos.2010.3

Müller, S. A., Balmer, M., Charlton, W., Ewert, R., Neumann, A., Rakow, C., ... & Nagel, K. (2021). Predicting the effects of COVID-19 related interventions in urban settings by combining activity-based modelling, agent-based simulation, and mobile phone data. *medRxiv*. doi: https://doi.org/10.1101/2021.02.27.21252583

Triulzi, G., Pyka, A., & Scholz, R. (2014). R&D and knowledge dynamics in university-industry relationships in biotech and pharmaceuticals: an agent-based model. *International Journal of Biotechnology 6*, 13(1-3), 137-179.

Will, M., Groeneveld, J., Frank, K., & Müller, B. (2020). Combining social network analysis and agent-based modelling to explore dynamics of human interaction: A review. Socio-Environmental Systems Modelling, 2, 16325-16325.