Agent-Based Models: The Balance between Validity and its *Raison d'Être*

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1 Definition

The increasing volume, velocity and variety of data and increasing computer power has enabled the penetration of modeling in most domains of science. Modeling can be described as the development of a model as a representative of a system. Its resulting product, the execution of those models, is defined *simulation* (Klügl & Bazzan, 2012, p. 30).

Although simulation can be used as a tool for prediction (Gilbert & Troitzsch, 2005, p. 4), outside of the exact sciences and engineering, such as in social sciences, the adoption of simulation methods is rather new and is mainly used as a tool for theory development (Gilbert & Terna, 2000). Theories, expressed in textual form, are formalized in into a specification which can be programmed in a computer. "In this respect," Gilbert & Troitzsch (2005, p. 5) write that "computer simulation has a similar role in the social sciences to that of mathematics in the physical sciences."

The idea behind modeling is to use and experiment with a model instead of the real world in order to gain knowledge of the underlying real-world causal structure (Fagiolo et al., 2007, p. 207). This is not different from the use of statistical methods. To explain a phenomenon, a theory-driven abstraction is made. The result of this abstraction, an equation of a model, is compared to the real world. If it behaves in a similar way, it is used to validate the model. If one does not want to be stuck in self-referential formalizations, generalization

from the model to the real world is desirable and validity of the model is a very important requirement. With regards to the real world, Terna (2017, p. 170) writes that "simulation models act as a sort of magnifying glass that may be used to better understand reality."

According to Klügl & Bazzan (2012, p. 30), contrary to equation-based models that describe an overall, global phenomenon, an agent-based model (ABM) generates phenomena "from the actions and interactions of the multiagent system." Agents are heterogeneous and their behaviour inside the model is theory-driven. In a neoclassical world, driven by micro-macro models the entire set of objects in the world is known (Fagiolo et al., 2007, p. 196-197). In ABMs, the agents engage in a pen-ended search for new objects. Ormerod & Rosewell (2009, p. 136) call the process of building an ABMs "a discovery process, of discovering the types of behavioural rules for agents which appear to be consistent with the phenomena we observe."

ABMs focus on providing a generative explanation for complex dynamics and phenomena by growing them in the model (Conte & Paolucci, 2014, p. 1). Each agent starts in a particular state and as the system updates over time, the macroproperties of the model can be consulted by reading them off the microstates (B. Epstein, 2011). Goldthorpe (2001) even goes so far as to saying that this generative process "appears to offer the best basis [...] on which statistical and substantive concerns can be related in causal analysis in sociology."

2 Features

Gilbert (2008, p. 14) identifies 6 core features of agent-based models: ontological correspondence, heterogeneous agents, representation of the environment, agent interactions, bounded rationality and learning.

2.1 Ontological Correspondence

Properties of agents are usually intrinsic and their behaviour internally driven. But they can be triggered by changes in the object with which they are causally connected (B. Epstein, 2011). However, it is important that there is a direct correspondence between the agents in the model and the real-world actors that they resemble. This makes it easier to design the model than would be the case with macroscopic approaches such as equation-based models (Gilbert, 2008, p. 14). However, there is no restriction on the complexity of the agents reasoning, internal structure and interaction (infra) abilities (Klügl & Bazzan, 2012).

2.2 Heterogeneous Agents

Most theories in economics and organisation science simply assume that all actors are identical or similar in most important respects (Gilbert, 2008, p. 15). For example: the 'typical firm' or the 'representative agent'. In that sense, ABMs are starkly juxtaposed to equation-based models, as "they are the only known approach apt to model and reproduce sets of heterogeneous agents interacting and communicating in different ways." (Conte & Paolucci, 2014, p. 2)

2.3 Representation of the Environment

Agents act within a certain environment (Gilbert, 2008, p. 6). This environment can be simply neutral and have no effect on the agents, or it can be an important actor in the model. Models that represent a geographical space are called *spatially explicit*. Another option is to have no spatial representation and link agents together, like in a social network.

2.4 Agent Interactions

Very important is that *interactions between agents* can be simulated. This ensures that agents decisions depend on the past choices made by other agents in the population (Fagiolo et al., 2007, p. 196-197). It is very likely that the existence of structures such as subgroups or local networks in combination with heterogeneity and bounded rationality (infra) generate aggregation processes

that are non-trivial and that structurally new objects emerge from it. "A phenomenon is emergent if it requires new categories to describe it which are not required to describe the behaviour of the underlying components." (Gilbert, 2008)

2.5 Bounded Rationality

"Many models implicitly assume that the individuals whom they model are rational, that is, that they act according to some reasonable set of rules to optimize their utility or welfare." (Gilbert, 2008) Nonetheless, many social scientists proposed that people should be modeled with *bounded rationality*, e.g. their cognitive abilities and the degree to which they optimize their utility is limited. Because agents in ABMs are defined by a limited set of functions and parameters, their behaviour is *boundedly rational* by design.

2.6 Learning

As Klügl & Bazzan (2012, p. 30) point out: "ABMs are particularly suitable for the analysis of complex adaptive systems." That is because ABMs are able to simulate learning at both the individual and population levels. According to Gilbert (2008), *learning* can be modeled in three different ways. (1) Agents learn from their own experience; (2) evolutionary learning, as unadapted agents die out and (3) social learning as agents interact with each other.

3 Validation of Agent-Based Models

Since ABMing is a fairly recent innovation there is no consensus on the appropriate way to verify or validate the resulting models. A fundamental critique of ABMs is that in many cases they are solved by simulation, which blurs the line between verification and validation (Ormerod & Rosewell, 2009, p. 133) where verification is the process of determining if the equations are correctly solved and that the software implementation correctly represents a model of a process (Ormerod & Rosewell, 2009). Validation, on the other hand, is the process of determining if we are using the right equations and that the computer model is an accurate representation of the world, given the model's intended application.

The central focus of the next paragraphs is the latter.

The central feature of ABMs is that they work bottom-up (J. M. Epstein, 2007): they provide a generative theory that explains phenomena by growing them (Conte & Paolucci, 2014, p. 1) from microfoundational properties. Consequently, it is essential that macroentities are explicitly excluded from the model (B. Epstein, 2011). Nevertheless is it absolutely crucial that the microparameters that are obtained through simulation, are thorougly substantiated by existing theories, expert views and experiments. However, theories only are not capable of providing "knife-edge" (Izquierdo & Polhill, 2006) parameters. Ergo, it is very likely that parameters that drive the behaviour of the agents implicitly include macroscopic factors just because model developers fit or finetune microscopic foundations on in-sample macro-level real-world data to validate the model. *In nuce*, the model becomes auto-referential.

Gilbert (2004, p. 285) acknowledges "that the mere reproduction of expected macro-level patterns leads modelers to conclude that their model is correct, not realizing that many models could give rise to the same patterns." Nevertheless is the finetuning of microfoundations to macro-level data a popular practice regarding validation of ABMs. It is known as calibration. Fagiolo et al. (2007, p. 208-210) provide a step-by-step guideline how to build an ABM using the indirect calibration approach. (1) In a first step, the researcher identifies a set of stylised facts that should be reproduced or explained by the model. (2) The model is built in a way that it matches the microeconomic description - built on empirical and experimental evidence - of the agents. (3) The empirical evidence on stylised facts is used to restrict the space of the parameters. (4) The researcher investigates the causal mechanisms that underlie the stylised facts which the model can validate ex post. Fagiolo et al. (2007) acknowledge that the microfoundational parameters are not calibrated on their empirical counterparts. They give two reasons for this: the model exclusively addresses in-sample exercises and it is very difficult to compare the variables and parameters of a model to empirically-observable ones. Nevertheless, even if the data is available they "are invariably biased. Data sets are constructed according to

criteria that reflect certain choices and, as a consequence, have builtin biases." (Fagiolo et al., 2007, p. 222) In this light, ABMs do not differ from equation-based research methods.

Since models are built up from the bottom, a macro-level phenomenon can occur in multiple ways, with different behaviour on the lower levels. In other words: in ABMing, phenomena are multirealisable (Conte & Paolucci, 2014, p. 2), one can fit parameters for an infinite amount of models with an infinite amount of agent properties to an existing real-world data set. This can be an unsettling property of ABMs because it weakens the validating power of a sensitivity analysis. A sensitivity analysis gives insight in how a model behaves across all specific combinations of values of the parameters (Manzo, 2014). The amount of simulations that result from a sensitivity analysis grow exponentially as the amount of parameters increases. One can pick the values or from a specified simulation range in order to have the model simulation match the data from the macrophenomenon as close as possible. As Ormerod & Rosewell (2009, p. 139) point out: "testing the range of model outcomes provides a test only in respect to a prior judgment on the plausibility of the potential range of outcomes. In that sense, verification blends into validation."

For example, in their research on technology diffusion Guerzoni et al. (2017) provide a theoretical model of technology adoption "based on the idea that the diffusion of information about a technology depends both on the social structure of the adopters and their degree of assortativity." To justify levels of assortativity of the agents in the model they use proxy indicators based on available religion and ethnicity studies which no more than hint an order of magnitude. Yet the authors claim that "the accurate replication of the observed diffusion curves validate the model". Problematic is that this accurate replication has been acquired by calibrating the microfoundational parameters through a brute-force sensitivity analysis on macro-level real-world data. Implicitly, macroscopic data has entered the model. Consequently, it does not provide a generative theory as the parametrised model has become the result of circular reasoning: technology adoption is the result of assortativity levels which are the

result of how well they explain for technology adoption. The model loses its explanatory power and the end result of the model is the model itself. Which is unfortunate as in ABMs, "the essential move is conceptual, not technological. [...] The computer is not the point." (J. M. Epstein, 2007)

4 Conclusion

In this paper I have acknowledged that parametrising agent-based models is a very burdensome task. Although calibrating the microfoundations of the model on real-world macro-level data as a technique of validation is a very popular practice among many agent-based modelers, they internalize the end-result, the macrophenomenon, in the agent's decision making. Like zombies attracted to brains, the agents are forced towards the macrophenomenon the researcher tries to understand. They are no longer in a pen-ended search for new objects and no theory is generated inside the model. In this light, they suffer from the same curve-fitting properties of many equation-based models. But for ABMs this is especially troubling because its distinguishing feature is that phenomena emerge bottom-up. For prediction purposes, one could argue that out-of-sample validation is an adequate approach to test the model's assumptions. But if ABMs are used as a tool of knowledge discovery, what good is a model where agent behaviour towards a macrophenomenon is the result of a self-referring loop? What is the scientific community discovering? How does this not reduce ABMing to a time-expensive visualisation technique?

To conclude, if the core business of ABMing is growing an explanation of a phenomenon inside the model, claiming validity of the microfoundations by calibrating them on macro-level data goes by on its *raison d'être*.

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