European Journal for Philosophy of Science (2021) 11: 63
https://doi.org/10.1007/s13194-021-00382-5

PAPER IN PHILOSOPHY OF TECHNOLOGY AND INFORMATION

Capturing the representational and the experimental in the modelling of artificial societies

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Received: 22 July 2020 / Accepted: 19 May 2021 / Published online: 30 June 2021

Abstract
Even though the philosophy of simulation is intended as a comprehensive reflection about the practice of computer simulation in contemporary science, its output has been disproportionately shaped by research on equation-based simulation in the physical and climate sciences. Hence, the particularities of alternative practices of computer simulation in other scientific domains are not sufficiently accounted for in the current philosophy of simulation literature. This article centres on agent-based social simulation, a relatively established type of simulation in the social sciences, to exemplify this claim. The analysis advanced has a twofold goal. First, it shows that the philosophy of agent-based social simulation, mostly developed by practitioners themselves, is, on one hand, heavily influenced by the methodological features of agent-based modelling and by the loose and fragmented character of social theory and, on the other hand, distinctively shaped by contrasting views of what it implies to do social research with virtual or artificial societies. Second, it suggests ways in which cross-fertilisation could enrich the philosophical understanding of computer simulation both in agent-based social simulation and in the philosophy of simulation.

Keywords Computer simulation · Agent-based modelling · Artificial societies · Representation · Experimentation · Verification - validation

1 Introduction

An increasingly large amount of literature discussing the philosophical aspects of computer simulation has been published over the last two decades, following the progressive popularisation of this practice in different branches of contemporary

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science. This literature seeks to position computer simulation in the wider methodological map through the exploration of the method itself (e.g., how it incorporates elements both of representation (Morrison, 2015; Imbert, 2017; Weinsberg, 2013; Winsberg, 2010) and experimental manipulation (Guala, 2002; Parker, 2008; Saam, 2017)) and of the physical, social and cognitive organisation of the practice of computer simulation (e.g., it is decidedly collective and interdisciplinary (Anzola, 2019b; Galison, 1996; Imbert, 2017; Lenhard, 2017a) and also technology-dependent (Durán & Formanek, 2018; Humphreys, 2004; Lenhard, 2017b; Wolfram, 2002)).

Even though the philosophy of simulation is intended as a comprehensive account of the practice of computer simulation in contemporary science, its output has been disproportionately shaped by research on equation-based simulation in the physical and climate sciences, for the method has been historically more prevalent in these disciplinary areas (Fox Keller, 2003; Lynch, 2008). Hence, the philosophical particularities of alternative practices of computer simulation in other scientific domains have yet to be fully incorporated into the mainstream discussion in the philosophy of simulation (Parker, 2013; Winsberg, 2019). This article discusses the philosophical idiosyncrasy of agent-based social simulation to exemplify the potential benefits of widening the range of computer simulation practices covered by this discussion.

Practitioners of agent-based social simulation have not really engaged in cross-fertilisation with the philosophy of simulation. As a result, their philosophical approach to simulation has been developed, basically, in isolation. The analysis advanced in this article has a twofold goal. First, it shows that the philosophy of agent-based social simulation is, on one hand, heavily influenced by the methodological features of agent-based modelling and by the loose and fragmented character of social theory and, on the other hand, distinctively shaped by contrasting views of what it implies to do social research with virtual or artificial societies. Second, it suggests ways in which cross-fertilisation could enrich the philosophical understanding of computer simulation both in agent-based social simulation and in the mainstream philosophy of simulation.

The discussion focuses on agent-based social simulation, instead of agent-based simulation in general, because the method is not used in a standard manner across disciplines (e.g., while formal verification is quite popular in the wider agent-based modelling literature (Bakar & Selamat, 2018), it is still rare in agent-based social simulation) and because practitioners have historically made sense of agent-based modelling by contrasting it against the methodological tradition in social science, which, as it will be evidenced below, differs from other disciplines in several important regards.

The text is structured around the answers that practitioners of agent-based social simulation have given to key questions in the philosophy of simulation literature. It starts with a brief discussion about the disciplinary nature of the philosophy of agent-based social simulation. The subsequent three sections separately address the following questions: first, what is the connection between the experimental features of the method and its epistemic power?, second, how can a computer simulation be taken to offer a simplified representation of a target phenomenon? and, third, how should knowledge claims provided by computer simulations be evaluated?

2 The philosophy of agent-based social simulation

The increasing interest in the philosophy of simulation derives from the recognition of the distinctive philosophical features of computer simulation as a method and of the scientific practices in which the method is employed. Regarding the latter, agent-based social simulation is used by a relatively small scientific community that began to consolidate around the early 1990s. Because practitioners had diverse disciplinary backgrounds, agent-based social simulation was philosophically made sense of by linking to and comparing against a multiplicity of domains (e.g., social, complexity, computer, and cognitive sciences, engineering and artificial intelligence) and methods (e.g., equation-based modelling, game theory, cellular automata, and traditional quantitative and qualitative social research methods).[1] Even though the practice of agent-based social simulation has not achieved the same level of institutionalisation of traditional social disciplines (e.g., there are no widespread exclusive undergraduate and postgraduate programmes or a well-established labour market), it displays key disciplinary elements, such as differentiated cognitive and social spaces, specialised language, foundational narrative, and agenda (Anzola, 2019a; Macal, 2016; Squazzoni, 2010), that warrant its acknowledgement in the philosophy of simulation. It is a distinctive approach to computer simulation that results, not from the contribution of a few individuals, but from a collective effort of institutionalisation.

Because of the perceived distinctiveness of agent-based social simulation, the foundational narrative in the field includes a somewhat elaborate methodological account. This account is not entirely comprehensive, in part, because the field is decidedly practice-oriented.[2] Yet, it is useful because it is both explicit and, to a large extent, shared. There are, for example, a few core foundational texts addressing philosophical issues that are well-known, extensively cited (Hauke et al., 2017; Macal, 2016; Meyer et al., 2009) and often socialised with new entrants. It is mostly this core foundational philosophy that is analysed in this text. Thus, it is worth considering that, as any other foundational narrative, it is not fully representative of every member of the community, nor entirely reflected by everyday practices.

The methodological narrative developed around agent-based social simulation stresses the fact that this type of computational modelling allows, on one hand, to processually explore social phenomena and, on the other hand, to implement computational models in which objects in the model stand in a one-to-one ontological correspondence with real-world entities. These two features are said to set the method apart both from traditional social research and other types of computer simulation (Axelrod, 1997; Bonabeau, 2002; Epstein & Axtell, 1996; Gilbert & Troitzsch, 2005; Macy & Willer, 2002; North & Macal, 2007; Tesfatsion, 2002): the former tends to centre on the analysis of variables instead of actors and has noticeable limitations for

[1] Much of this discussion precedes the consolidation of the contemporary philosophy of simulation. This might be a factor hindering cross-fertilisation.

[2] ‘Practical’ is used here in the sense of regularly leaning towards model-building rather than philosophical reflection, not in the sense of developing empirical models. The question about whether models should be empirically calibrated has fostered what is, arguably, the most important theoretical disagreement in the agent-based social simulation community (Anzola, 2019a; Sun et al., 2016).

longitudinal research; the latter is still constrained by mathematical formalisms and often struggles to really capture emergence when modelling complex phenomena. Being able to separately represent individuals, physical objects, and the environment as independent computational entities with different characteristics and interaction rules and to account for social phenomena as the bottom-up result of temporally extended micro level interactions leads practitioners to think of agent-based social simulation as a method that permits the creation of fully-fledged virtual worlds.

Interestingly, although consensus about the distinctive representational capabilities of agent-based modelling is widespread, practitioners do not entirely agree on the implications of this belief. Terms such as ‘artificial society’, ‘virtual world’, ‘culture dishes’ and ‘*in silico*’, ‘generative’ or ‘virtual’ experiment have been used, in a weak sense, to suggest a transition from variables to artificial entities as the form of representation (e.g., Macy & Willer 2002; Manzo 2007; Smith & Conrey 2007; Squazzoni 2010), and, in a strong sense, to suggest a transition in the object of study from real to virtual objects (e.g., Axelrod 1997; Conte & Gilbert 1995; Epstein & Axtell 1996; North & Macal 2007; Tesfatsion 2002). These contrasting views of social simulation, it will be shown, have interesting philosophical implications when considering the experimental and representational features of agent-based modelling.

3 Manipulation

The idea of experimental manipulation is central to the study of artificial societies. Yet, the literature in agent-based social simulation and in the philosophy of simulation approach the link between computer simulations and experiments in different ways. In the latter, the topic has been extensively discussed (Saam, 2017), given the privileged epistemic status that experiments have in the standard conceptualisation of the scientific method. Because experimentation has historically been taken as the hallmark of empirical science, the discussion about the epistemic power of computer simulations revolves around the question of whether a computer simulation counts as an instance of an experiment (Winsberg, 2019).

In social science, conversely, experiments are not as common and, as a method, do not have this higher epistemic status, mainly because they have been historically questioned, on one hand, about the possibility to isolate and properly test the causal effects of experimental manipulations (i.e., internal validity) and, on the other hand, about the generalisability of findings to other populations, experimental settings or phenomena (i.e., external validity). Thus, the discussion about the experimental features of agent-based social simulation does not build upon the belief that experiments are the standard for epistemic power. Rather, practitioners tend to emphasise, in a relatively general way, how artificial societies allow for experimental manipulations that would otherwise be impossible, impractical or unethical. In general, practitioners seem to think of computational models as some sort of surrogates or functional substitutes, although, unlike the mainstream philosophy of simulation (Beisbart, 2018; Boge, 2019; Skaf & Imbert, 2013), they do not address the foundation of this relationship.

Occasionally, simulation is explicitly referred to as a form of experimentation. There are, nonetheless, some noticeable differences in the assumptions underlying this claim and the level of commitment to the simulation-experiment identity thesis. Simulations have been called experiments, among other alternatives, because they could be used to explore the parameter space (Gilbert & Troitzsch, 2005), as a 'virtual' laboratory in which a social phenomenon may be 'virtually grown' (Epstein, 1999) or to test theory (Sawyer, 2004). Sometimes, simulation–experiment identity claims are linked to specific usages. Macy and Willer (2002), for example, argue that a simulation could be considered an experiment or a demonstration, depending on whether it is used to identify differences in the exploration of the parameter space or to test robustness, respectively.

3.1 Simulations as experiments

In the mainstream philosophy of simulation, the discussion about the relationship between simulations and experiments revolves mostly around the clarification of two issues: the epistemic target and the object of manipulation. The former inspires questions regarding what system is intervened in a computer simulation and how manipulating that system can inform about the behaviour of other systems (Guala, 2002; Norton & Suppe, 2001; Peschard, 2012); the latter, regarding the epistemic or ontological features of the system intervened that make acquiring knowledge of other systems possible (Parker, 2009; Barberousse et al., 2008; Winsberg, 2010). This is, overall, a very detailed and complex discussion, with disagreements even for basic aspects, such as the effect of the materiality of a computer simulation (Durán, 2013).

The approach in agent-based social simulation is less elaborate and more standardised among practitioners. Regarding the question about the system intervened, most practitioners argue that computer simulations and experiments differ because, in the former, the researcher is manipulating a model and not the phenomenon itself (Axelrod, 1997; Epstein, 1999; Gilbert & Troitzsch, 2005; North & Macal, 2007; Tesfatsion, 2002). This view has been explicitly criticised in the philosophy of simulation literature on two fronts: it is considered, first, to oversimplify the notion of experiment, for experimentation need not always be directly performed on the phenomenon of interest, and, second, to fail to fully characterise the object of experimentation and the nature of the manipulation (Winsberg, 2010).

While the criticism about oversimplifying scientific experimentation is accurate when reflecting on experiments in general science, it neglects the disciplinary idiosyncrasy of social science, where experimentation has systematically relied on the participation of human subjects. There are likely not many disciplinary areas in which scientific experimentation (and, overall, all research methods) had historically remained so overwhelmingly focused on a single object of manipulation. In this case, it could be argued, if the link between simulations and experiments is explored to understand the source of epistemic power, it is not that much that practitioners of agent-based social simulation are operating with a misguided notion of experiments, but that the philosophy of simulation has yet to robustly account for the influence of methodological pluralism on the connection between computer simulations and experiments, for the epistemological power ascribed to experiments significantly varies across disciplines.

The second criticism, about the object of manipulation and the manipulation itself, does uncover a gap in the approach to the experimental features of agent-based social simulation. In the literature, the object of manipulation is usually underspecified, and, sometimes, also problematic. Some authors, for instance, suggest that computer simulations are an instance of thought experiments (Axelrod, 1997; Troitzsch, 1997; Waldherr & Wijermans, 2013). The claim is not really addressed in much detail. Yet, it seems to be grounded on the assumption that, in comparison to real phenomena, computer simulations are idealised yet useful. In the same way that thought experiments are simplified fictional representations from which conclusions can be drawn in a relatively straightforward manner, agent-based models are also simplified representations that allow for an easier understanding of the cogs and wheels of social phenomena. Because practitioners that support this view of simulations as thought experiments do not seek to articulate a robust account of experimentation, some related issues, such as the question about the nature of manipulations, remain unanswered.

Overall, most practitioners of social simulation would simply argue that manipulations are performed *on* the computational model. Yet, as the literature in the philosophy of simulation evidences, there could be different interpretations for this claim. The belief that computer simulations are thought experiments could equally fit Morgan's (2003) view that computer simulations are non-material experiments because they manipulate mathematical objects or Guala's (2002) view that they are material non-experiments because they deal with physical object that have formal but not material correspondence with the target phenomenon. Each interpretation involves a different conceptualisation of computer simulation as a method of research. Approaching simulations as material non-experiments implies that simulations and experiments require different validation processes. Unlike experiments, simulations would need to solve a problem of representation. In turn, approaching simulations as non-material experiments implies that, due to its non-materiality, the results of a simulation are less powerful than those of an experiment.

A thorough discussion of the nature of experimental manipulation in agent-based social simulation is certainly needed. It is unlikely, however, that this discussion could be carried out mirroring the one in the philosophy of simulation. Aspects such as materiality certainly affect practitioners' assumptions about the epistemic power of an agent-based social simulation, but its effects are better understood in terms of its impact on the execution of a simulation through, among other things, the relationship between power of computation and modelling choices, than in terms of whether there is some sort of causal similarity between the computer and the social world. In spite of the relevance of this latter issue in the mainstream philosophy of simulation (Massimi & Bhimji, 2015), warrants for belief in the results of an agent-based social simulation are evidently not related to the assumption that computers and social systems share some basic causal properties.

It might be that, after further theorising on the simulation-experiment connection in alternative types of computer simulation, the possibility of a generalising or monolithic account of this connection should be renounced. Although, as some suggest

(Beisbart, 2018; Imbert, 2017), it might be undesirable to have a conceptualisation of experiments in which these are used to understand a different system from the one being manipulated, this is what regularly happens in social science.[3] Hence, the relevance that the internal-external validation distinction has in social experiments. Researchers often use human decision-making as a proxy to understand social phenomena, and, even when experiments focus on simple decision-making heuristics, there are always concerns that the participants are a representative and relevant sample of the larger population i.e., that they are not, in fact, part of another system or a subsystem with behavioural traits that cannot be generalised.

The literature in the philosophy of simulation has established conceptual distinctions that can be widely agreed upon, such as that between the object of manipulation and the target system or that between the epistemic target and the epistemic motivation (Peschard, 2010). While conceptually clear, the concepts seem to instantiate in different disciplinary areas in ways that might be not easily commensurable. There is, for example, no concept in social science that bears the same weight in out-of-sample inferences as the notion of model organism in biological sciences. Likewise, other disciplinary areas might not have the theoretical-methodological diversity that is found in social sciences. Social scientists might disagree on aspects such as whether laboratory experiments provide inter- or intra-system inferences based on their position about naturalism in social research i.e., whether social sciences should study individual in their natural environments.

3.2 Simulations as virtual laboratories

In the agent-based social simulation literature, there is a second view of the computer simulation–experiment relationship in which the link is established, not over methodological similarities and differences, but over the general idea of ‘control’. Historically, there has been an idealised conception of the laboratory as the place for controlled manipulations. Following this idealised conception, computer simulations are conceived as an artificial or virtual laboratory that bypasses internal validity issues that are typical of field or natural experiments. In this context, to put it simply, computer simulation is not a method, but a place.[4] This additional view of the simulation—experiment connection is not advanced as an alternative to the one described in the previous section. Rather, it reflects variations in the way in which the experimental features of computer simulations are approached, depending on the sense of artificial societies that is favoured. For instance, those practitioners that lean towards the weak sense find it easier to conceive simulations as virtual laboratories.

This view of simulations as virtual laboratories does not really have a correlate in the philosophy of simulation, for it is grounded, first, on the unformalised character of most social theory and, second, on the epistemological meaning given to execution of a simulation in agent-based social simulation. These two factors are not equally

[3] Unless it is claimed that the entire social world can be reduced to individual decision-making.

[4] It is important to clarify that ‘place’, in opposition to ‘space’, has more to do with the meaning and value than with the physical embeddedness of social practices.

emphasised in the literature. In fact, it could be argued that there are two relatively independent versions of this view, differing in how the simulation as a virtual laboratory allows for controlled manipulations. The first version is not exclusive of practitioners or agent-based social simulation but inherited from mainstream social science. With the popularisation of personal computers at the end of the twentieth century, social scientists became increasingly interested in the possibility of using programming languages for theory building and testing. They are sufficiently flexible syntactically and semantically to accommodate the conceptual richness of social theory, while still operating algorithmically, thus, providing an interesting middle ground between natural languages and mathematics (Hanneman, 1988; Markovsky, 1997; Ostrom, 1988). Following this trend, many practitioners suggest that agent-based simulation is a tool that permits the development of formal theory in social science (Axelrod, 1997; Conte et al., 2001; David et al., 2007; Edmonds & Hales, 2005; Klüver et al., 2003).

The rationale behind this version of the view of simulations as virtual laboratories is relatively straightforward: using computer simulations adds rigour to the process of theory building and testing. To program the computational model, the researcher needs, on one hand, to make explicit concepts and relations, eliminating the vagueness and ambiguity of natural languages, and, on the other hand, to work out or correct logical gaps or mistakes in the unformalised theory. The resulting computational model, then, would be an axiomatic or formal theory of the system of interest; the execution of the simulation, an artificial dataset to test such theory. While, at first, this approach might resemble Beisbart's (2012) argumentative view of computer simulation, there is an important difference: in the agent-based social simulation literature, it is the comparison of the simulation output with external data that constitutes the test. Running the simulation is important, not because it implies executing the argument, but because artificial data is rigorously produced by processes that are easily reproducible and could be, if needed, backtracked to the initialising conditions.

The second view of simulations as virtual laboratories also builds on the idea that a computational model produces data in a rigorous and reproducible manner. It, however, attaches additional epistemological meaning to the execution of the simulation. In the philosophy of simulation, the processual nature of computer simulation is often considered a distinctive feature of the method (Guala, 2002; Hartmann, 1996), although, it is acknowledged, practitioners need not commit to the belief that a simulation explicitly represents the time evolution of the system of interest (Humphreys, 2004; Winsberg, 2019). In those cases where time matters, due to the overemphasis on equation-based simulation, the time evolution of the systems of interest has been approached mostly in an operational manner: in terms of the philosophical implications of discretisation. In the agent-based social simulation literature, conversely, there is a widespread commitment to the belief that there is an explicit representation of the time evolution of the system. There is, as well, a distinctive disciplinary belief that computer simulations account for processes of generation.

The notion of generation has significantly informed the approach to explanation in agent-based social simulation. The concept was first introduced by Epstein and Axtell (1996), who claimed that "[a]rtificial society modeling allows us to "grow" social structures *in silico* demonstrating that certain sets of microspecifications are *sufficient to generate* the macrophenomena of interest" (p. 20, emphasis in the original). The dynamics of representation in agent-based social simulation will be explored in more detail in next section. At this point, however, it is worth mentioning that practitioners of social simulation, following complexity science, understand social phenomena as an emergent of individuals interacting with each other and with the environment. The laboratory metaphor is, in this case, used to describe a place where the controlled testing of potential explanations of social phenomena can take place. While the connection is metaphorical, this approach to computer simulation has far-reaching methodological implications: a successful computational implementation of a phenomenon is considered a sufficient but not necessary explanation, yet, generativism, as a theory of explanation, is necessary but insufficient for explanation of social phenomena. Hence, the popular motto in agent-based social simulation: "If you didn't grow it, you didn't explain its emergence" (Epstein 1999, p. 43).

Although Epstein and Axtell first introduced the generative account inspired by the idea of generative grammars in linguistics, subsequent authors have further developed this explanatory account by linking it to the theory of social mechanisms (Macy & Flache, 2009; Manzo, 2010; Sawyer, 2005; Hedström & Ylikoski, 2010). From an explanatory point of view, the turn to social mechanisms incorporates a more explicit concern with production in processes of social emergence (in the sense of the mechanism being responsible for *causally producing* the macropattern) and circumscribes the question of competing explanations to the domain of alternative explanatory mechanisms. It also relaxes the epistemic role of generation: growing a phenomenon is not considered a necessary condition for explanation, partly, because mechanism is an overarching theory of explanation that is not limited to agent-based social simulation (nor social science). Yet, the overall view of a computer simulation as a virtual laboratory that permits growing the phenomenon of interest remains.

Overall, the two views of computer simulations, as experiments and as virtual laboratories, evidence that practitioners of agent-based social simulation have extensively addressed philosophical concerns about the experimental features of computer simulation and their relationship with traditional experiments. The difference with the mainstream philosophy of simulation is noticeable, nonetheless. In some cases, it could be argued, this difference might be due to relatively trivial issues, such as the lesser amount of epistemic resources employed by the community to discuss the philosophical underpinning of its practices. For these cases, appropriating prior developments in the philosophy of simulation could certainly be of help. There are some instances, however, where the differences are more likely attributable to particular constraints in the disciplinary context in which these practices are carried out. It is difficult, among other things, to consider that the discussion about the epistemic power of a simulation in agent-based social simulation should not be affected by the peripheral methodological role that experiments have historically had in social science. In aspects such as this, a more robust independent exercise of philosophical reflection is probably needed. Eventually, the outcome of this reflection will yield benefits both for agent-based social simulation and the philosophy of simulation.

4 Representation

The philosophy of simulation is strongly linked to the philosophy of modelling, for a *computer simulation* implies the execution of a *computational model* on a physical machine. While there is not a widespread consensus about the core features of computational models and the similarities and differences with other types of scientific models (Durán, 2020; Winsberg, 2019), several of the most important topics in the philosophy of modelling are equally addressed in the philosophy of simulation. The most important of these topics is, perhaps, the question about in virtue of what do these models represent.

Even though some authors have previously established some links between the philosophy of modelling and agent-based social simulation (e.g., Gräbner 2018; Phan & Varenne 2010), the foundational philosophy has yet to incorporate a sufficiently robust account of representation. Most practitioners use general definitions from simulation studies that address modelling in a very broad way, for example, as "[...] a representation or abstraction of something such as an entity, a system or an idea" (Balci 2003, p. 150). In simulation studies, this 'abstraction' has been conceptualised minimalistically i.e., as the formalisation of a problem into a system of equations; in agent-based modelling, it has been left underspecified i.e., as a form of simplification. While simplification is, indeed, a key feature of modelling, this underspecified approach to representation has prevented practitioners of agent-based social simulation from actively engaging with the contemporary discussion of *models as* (e.g., mediators (Morrison & Morgan, 1999), autonomous agents (Morrison, 1999), fables and parables (Cartwright, 2010) make-believe (Toon, 2010), surrogates (Contessa, 2007), credible world (Sugden, 2009), artefacts (Knuuttila, 2017)), which addresses the reasons and mechanisms behind the simplifying character of scientific models.

The lack of discussion about the nature of modelling has eventually fostered some disagreements about the representational features of agent-based models. Regarding the connection between theory and models, for instance, both Edmonds and Hales (2003) and Troitzsch (2004) take models to be cases of theory instantiation. Yet, the former suggest that the instantiation is grounded on a Simulation—Conceptual model—Target phenomenon relationship, where the conceptual model is an abstract representation of a social process, generally expressed in natural language. This model, they argue, "[...] mediates between the simulation and the phenomena, the purpose of the simulation is to inform the conceptual model, but it is only the conceptual model which directly *represents* the phenomena" (Edmonds and Hales 2003, emphasis in the original). Troitzsch, in turn, has an interpretation conforming to the principles of philosophical structuralism. According to him, "a simulation model "of a theory" is "analogous to a structuralist reconstruction of this theory"" (Troitzsch 2004, p. 269). The relationship in this case is Theory—Simulation—Target phenomenon, and it is the simulation that carries the representational burden.

Regarding the target of representation, in turn, it has been argued, among other things, that the artificial society is not a model of something else but the very target of inquiry (Conte & Gilbert, 1995), that computer simulations are models to inquire about social processes through the exploration of possible worlds (Epstein & Axtell,

1996) and that computational models are tools for thinking that allow answering how-possibly questions, only some of which apply to the real world (Grüne-Yanoff, 2013). Overall, the approach to representation in the agent-based social simulation literature is not standardised because there is no consensus about the nature and connection between the representing object that is manipulated: the source, and the object represented for which knowledge is desired: the target. The ambiguity regarding the source and target of representation partly depends on the sense of artificial societies favoured. The belief that the simulation is the target, for example, is only compatible with the strong sense of artificial societies.

4.1 The representation of time

While the weak and strong senses of artificial society might lead to different conceptualisations of the source and target of representation, practitioners on both sides agree that the temporal character of a computer simulation is fundamental for representation. As a form of modelling, as mentioned, agent-based modelling relies on a view of social phenomena as bottom-up emergents of entities interacting at the micro level. Underlying this view are two principles. The first one is the principle of non-redundancy, which aims to avoid adding unnecessary entities to the computational model; the second principle, of levels of reality, differentiates between the level of individual action and the level of social properties or entities (Anzola, 2015). The principle of non-redundancy noticeably led the foundational philosophy to incorporate a modelling style that is closer to the principles of methodological individualism in social science, in which higher-level properties or objects are expected to appear as emergents, rather than being directly incorporated into the model entities and interaction rules (Macy & Flache, 2009; Epstein, 2006).

The effects of the principle of levels of reality on the modelling process is not as clear. The relationship between levels is not extensively discussed, although it seems to be generally interpreted as supervenient (it is uncertain, though, whether practitioners believe this supervenience to be causal, mereological or epiphenomenal, among others). Overall, however, in combination with the first principle, the notion of a layered reality seems to lead most practitioners, first, to localise non-local properties of individuals and, second, to endogenise social structures (Epstein, 2011). Aspects such as formal roles are often incorporated as individual properties in agent-based models, even though a role is not a property of the individual holding that role, but of the relational context for which the role is devised. Likewise, turn-taking in models of iterated games is an endogenised social structure that is built into the model prior to any interaction and is rarely affected by it.

Although the application of the principles of non-redundancy and levels of reality has a distinctive reductive nature, agent-based social simulation, practitioners argue (Axelrod, 1997; Conte & Gilbert, 1995; Conte et al., 1997; Epstein & Axtell, 1996; Gilbert & Troitzsch, 2005; Macy & Willer, 2002), avoids becoming a reductionist method by the incorporation of dynamics. Whereas, as mentioned, computer simulations need not commit to representing time or representing it in a realistic manner, agent-based social simulation commits to an explicit representation of a temporal asymmetry between the initial and final states of the simulation. More than simply a representation of time passing, though, the execution is believed to account for the micro to macro transition.

This belief that the execution represents a micro to macro transition bears a significant epistemological weight. It sets agent-based social simulation apart from other types of simulation, not only because of its commitment to the explicit representation of time, but, more importantly, because it links the epistemic power of a computer simulation to a sense of surprise. In the philosophy of simulation, surprise has been used as a criteria to claim the epistemic privilege of experiments over computer simulations (Parke, 2014). Conversely, the literature in agent-based social simulation, following emergence and complexity theory, argues that computer simulations are epistemologically powerful, for they unveil micro to macro transitions that are often unexpected, unpredictable and counterintuitive.[5] Some models, such as Schelling's (1971) model of segregation or Axelrod's (1984) model of cooperation, have achieved a canon status partly because of the surprising nature of their results.

Interestingly, in spite of its epistemic relevance, the literature in agent-based social simulation has yet to robustly theorise about the impact of the temporal features of a simulation on warrants for belief. Since agent-based models are not computational implementations of systems of formal equations, the discussion about dynamics is not only different e.g., the temporal evolution of the simulation does not depend on how equations are discretised, but also more difficult to pin-down than in traditional equation-based simulation. Given the lack of a background formal framework, much of what practitioners of agent-based social simulation have to say about time has a decidedly narrative component.

Not enough epistemic resources have been used by practitioners to address the effects of time on representation, partly, because of technical aspects of agent-based social simulation. Event- and period-oriented simulations, two temporally different simulation approaches, are usually implemented in different software. Likewise, specialised software regularly has specific temporal framework already built in. Practitioners seem to defer to software architecture on technical aspects that might affect representation, such as concurrency. For example, Netlogo (Wilensky, 1999), a popular software among the agent-based social simulation community, simplified the set of primitives that were initially available to determine the temporal structure of interaction due to some researchers getting unexpected results with simulated concurrency. Now, every model built using the software has agents executing actions serially. The overemphasis on the algorithmic nature of a computer simulation might also have diverted attention from the conceptualisation of time: because of the belief that generation is a type of formal deduction, a macro output, some argue (Axelrod, 1997; Epstein, 1999; Conte et al., 2001), could always, in principle, be logically reduced to the micro initialising conditions from which it emerges.

[5] The epistemic opacity of computer simulation is a major factor in the conceptualisation of this sense of surprise (although practitioners of agent-based social simulation have not discussed the issue as extensively as philosophers of simulation). It is partly what made the concept of emergence popular in agent-based social simulation (Gilbert, 1995) and, curiously, also one reason for which some social scientists do not fully trust the results of agent-based models (Lehtinen & Kuorikoski, 2007; Waldherr & Wijermans, 2013).

Along with the technical aspects of computer modelling, the lack of theorisation on time seems to be linked to the way in which the agent-based social simulation literature incorporates prior developments in social theory. Despite the existence of several temporally rich interdisciplinary (e.g., theory of practice) or disciplinary (e.g., relational or figurational sociology) theoretical accounts in social science, practitioners often rely on theoretical accounts of social processes that are compatible with the notion of a layered reality, such as Coleman's boat (1990) (Fig. 1). This is due, in part, to the reliance on complexity science rather than social science during the early conceptualisation of agent-based social simulation as a scientific practice (Anzola, 2019b). The conceptual apparatus of interlevel emergent transitions that practitioners took from complexity theory could be more easily accommodated by Coleman's boat, and, overall, the micro-macro tradition, than by theory of practice or relational and figurational sociology.

There are, however, a few issues with using micro-macro accounts such as Coleman's boat to tackle temporality. Coleman's boat is not a model of processes, but of causal efficacy or explanatory sufficiency (Little, 2012). In addition, contemporary social theory usually reinterprets the model to incorporate elements from philosophy of mind, moving the discussion away from processes to centre, instead, on levels (Ylikoski, 2016). Finally, and more importantly, the model does not really account for time, for it never addresses the question of temporal individuation of nodes. As a representation of a social phenomenon, the edges might be equally interpreted as atemporal, instantaneous or temporally extended (Anzola, 2015). The theoretical approach to the micro-macro dualism in the agent-based social simulation foundational narrative, thus, contributes to the neglect of time because it shifts the focus from the process itself to its outcomes.

From a representational point of view, using the execution of a simulation to separate the micro from the macro is, to a certain extent, inconvenient, for it does not entirely conform to explanatory practices in the field. The micro-macro dualism originated in a context where micro and macro data were clearly separable and led to

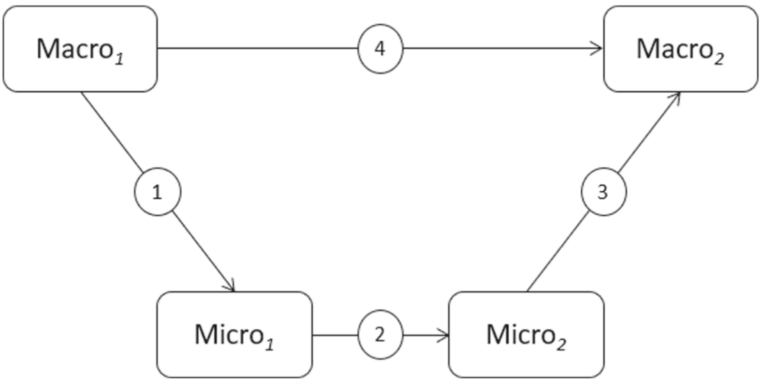

Fig. 1 Basic conceptualisation of Coleman's boat. Adapted from Coleman (1990). In his text, Coleman uses the diagram in a couple of examples to argue that 4) is not causally efficacious i.e., a change in the macro must always be preceded by a change in the micro

distinct operational procedures and narratives. There is, for example, a clear separation between concepts such as individual income and GDP. Income data could be directly collected from individuals through surveys and is conceptually straightforward; GDP data requires additional mathematical transformations of raw data, has more intricate underlying theoretical assumptions and requires more complex collection processes. Computer simulation, however, produces its own (artificial) data that, on one hand, is made sense of with theoretical constructs that do not necessarily fit into the traditional micro-macro distinction or lose some their explanatory power when reduced to a single level (e.g., attractors or network measurements such as centrality) and, on the other hand, involves its own processes of observation and measurement (Parker, 2017).

4.2 Social mechanisms, patterns and entities

Making sense of emergence not only requires conceptualising time, but also the outcome of the bottom-up process of transition. Again, the disciplinary particularities of agent-based social simulation seem to limit the usefulness of prior developments in the philosophy of simulation. In comparison to equation-based simulation in formalised disciplines, there is a significant amount of contextual and subjective elements that are incorporated into the design, operation, analysis and socialisation of an agent-based model in the social domain. Equation-based models are certainly not simply a formalised derivation of theory that is computed by a physical machine (Lenhard, 2007; Winsberg, 2010). Yet, it is undeniable that having a common underlying formalism helps the delimitation of what the computational model is about, since it makes it easier to link the simulation output to specific terms and operators defined by background theory.

In social science, ‘phenomenon’ is an umbrella term for a diverse set of objects, such as processes, events, structures, institutions, individual cognitive states, perceptions and attitudes. Because of its dynamic character, as mentioned, practitioners tend to highlight the role of computer simulation in the understanding and explanation of social processes or mechanisms. None of these concepts, however, has a clear and univocal conceptualisation, neither in agent-based social simulation or mainstream social science. ‘Process’ is usually used informally. Practitioners rely on the folk understanding of the term i.e., as something that is temporally extended. ‘Mechanism’, conversely, does have a large amount of underlying theorisation, but it is far from uniform. In terms of their metaphysical properties, for instance, the wider social science literature considers social mechanisms to be real and observable, real and unobservable, abstract conceptualisations based on observation, among other alternatives (Mahoney, 2001; Ylikoski, 2018).

In the specific case of agent-based social simulation, practitioners, overall, tend to use the concept of mechanism to incorporate into the explanation of dynamics a sense of production or generation of the resulting macropattern. Mechanisms are meant to causally connect the micro with the macro, providing metaphysical identity to the entire process. Beyond this general purpose, however, the use of ‘mechanism’ in social simulation evidences the same lack of consensus of mainstream social science. An initial source of disagreement is the sense of artificial societies a researcher subscribes to. Those closer to the strong sense of artificial societies need not conceive mechanisms as real, either because they are abstract conceptualisations incorporated into the model (as the object of study) (Conte & Gilbert, 1995) or because the model does not necessarily refer to real-world phenomena (Grüne-Yanoff, 2013). Alternatively, those closer to the weak sense seem to accept the realism of mechanisms, especially because many of these practitioners conform to the notion of mechanisms that has become popular in contemporary analytical accounts of social sciences (Manzo, 2007; Macy et al., 2011).

The conceptualisation of a mechanism is affected, as well, by other aspects of the general practice of social simulation, such as the well-known disagreement concerning the level of abstraction that better guarantees explanatory success. This disagreement, often referred to as the KISS-KIDS (Keep it simple, stupid; Keep it descriptive, stupid), sides those that have a preference for simple abstract models, against those that favour intricate empirically calibrated models, respectively (Anzola, 2019b). It is easier for those on the KISS camp to adopt a realistic approach to social mechanisms, for, traditionally, it has been thought that simple abstract models can better individuate trajectories or mechanisms in a computer simulation (Axelrod, 1997; Gilbert & Troitzsch, 2005; Macy & Willer, 2002).

The difficulties with the delimitation of the target of representation in agent-based social simulation is a consequence of both the theoretical diversity in social disciplines and the manner in which practitioners interact with data. Differences with those types of simulation regularly considered by philosophers of simulation start with the way in which data for social simulation is acquired. Certainly, computer modellers in formal disciplines struggle with aspects such as data availability. Yet, social science has a comparatively lower amount of longitudinal data that can be used for verification, calibration and validation. Data collection processes, in turn, pose distinctive or more profound difficulties e.g., ethical concerns are heightened when dealing with human subjects. Finally, because of the focus on emergence, there is a need in social simulation to acquire both micro and macro data, which, as mentioned, follow different collection procedures and interpretation processes.

Practitioners of social simulation also set themselves apart from equation-based modellers in formalised disciplines because of the role played by qualitative data in their everyday practices. Since the modelling process is in several instances informed by qualitative data, practitioners of agent-based social simulation were required to tackle the questions, first, of how to use qualitative data for design, calibration and validation of a computational model (Yang & Gilbert, 2008), second, of where computer simulation, as a method, stands with relation to the qualitative-quantitative dichotomy in social science (Anzola, 2019a), and, third, of how to use computer simulation in a mixed-methods research design with other qualitative and quantitative techniques (Polhill et al., 2010).

In answering the third question, about using agent-based modelling together with other qualitative and quantitative tools, practitioners of social simulation have progressively developed a more explicit and comprehensive framework of interaction with stakeholders, which is often referred to in the literature as 'participatory modelling' (Barreteau et al., 2013). While knowledge elicitation from external stakeholders is not uncommon in computer simulation, the participation of these stakeholders is mostly limited to issues of quality assurance e.g., expert knowledge and risk management (Rougier & Crucifix, 2018; Winsberg, 2018). Conversely, in agent-based social simulation, partly because the design and operation of the computational model is not as cognitively demanding (since there is not a background formal framework and the simulation process need not be data-intensive), practitioners have articulated interaction structures that can range from simple expert knowledge elicitation to the co-construction of the computational model and the phenomenon of interest (Barreteau et al., 2013).

A more robust engagement with stakeholders is needed in agent-based social simulation because of the nature of social phenomena. Among other things, individuals are highly reflexive and might decide to significantly change their behaviour in response to their perception of the phenomenon of interest, leading, subsequently, to complex dynamics of second order emergence or downward causation. The popular notion of self-fulfilling prophecy, where a macrophenomenon changes to fit prior, initially erroneous, individual expectations or perceptions, is a paradigmatic example. This reflexive behaviour might also influence measuring processes. For instance, criminals might iteratively switch between diverse activities depending on their risk perceptions, and perhaps with the deliberate intention to mislead policing agencies, which could lead to underreporting or misrepresentation of crime, unless measuring tools and procedures are constantly adapted to respond to these deliberate decisions.

Overall, the approach to representation in the agent-based social simulation literature is less developed and shows less consensus than the one to the experimental. To an extent, this is because conceptualising computer simulations as models requires to engage more explicitly with social theory and data, which are both significantly diverse and fragmented, and because practitioners of social simulation have yet to appropriate the developments in the contemporary discussion about model-based science. It is clear, though, that both practitioners and philosophers of simulation could greatly benefit from further explore how social theory and data affect the conceptualisation of the representational features of an agent-based social simulation, especially when it comes to understanding the kind of temporally extended social phenomena computer simulations are meant to account for.

This philosophical exploration, as evidenced by the discussion, is unlikely to extensively benefit from prior developments in the philosophy of simulation, first, because of the methodological difference between agent- and equation-based models, second, because of the particular way in which practitioners of social simulation interact with theory and data, and, third, because it is likely that no other account of computer simulation has the same commitment and pressure, both theoretical and methodological, to ground its explanatory account on the notion of emergence.[6] The results, however, should significantly enrich the contemporary understanding of computer simulation as a secondary source of knowledge.

[6]Theoretically, because the micro-macro dualism is, arguably, the most important theoretical distinction in social science (Alexander & Giesen, 1987); methodologically, because agent-based modelling is, perhaps, the type of computer simulation that is better equipped to deal with emergence, due to the possibility to explicitly model entities and interactions (Davidsson et al., 2017).

5 Evaluation

In spite of the idiosyncratic way in which the experimental and the representational are theorised in the agent-based social simulation literature, practitioners follow standardised procedures in general simulation studies for the testing of knowledge claims. Evaluation activities rely on a dual evaluation scheme divided in two processes: verification and validation. The former focuses on whether the conceptual model has been correctly transformed into a computational model; the latter, on whether the computational model correctly represents the target phenomenon. The dual evaluation scheme was originally developed in software engineering and later adopted by general computer science. Agent-based social simulation, and, overall, simulation studies, incorporated the scheme through knowledge transfer processes with computer science (Anzola, 2019b).

The dual evaluation scheme is useful because it is transversal to many areas of research. It provides a common language and method across different disciplinary interests and objects of study. Nonetheless, it is problematic, for it was devised with a view of computer programming as a formal activity that does not entirely fit the use of computer simulation as a method in empirical research. Although it has been pointed out in the philosophy of simulation literature that there are some limitations when the scheme is applied to computer *modelling*, rather than computer *programming* e.g., full verification of a model is not entirely possible (Oreskes et al., 1994) or verification and validation are not always easily separable in everyday practices (Winsberg, 2010), the foundational narrative in agent-based social simulation has yet to systematically address the effects of using the dual evaluation scheme on its conceptualisation of the experimental and the representational.

5.1 Computer models as empirical experiments

When computer scientists first started inquiring about the scientific status of computer programming, the overall consensus was that computer science and software engineering could be more adequately described as exact sciences. This view was challenged in the late twentieth century, following the acknowledgement that everyday practices of computer programming have some evident empirical underpinnings i.e., that algorithm implementation and execution is more than a formal process of algorithm analysis.

The recognition of the empirical in computer programming has fostered some changes in the philosophy of computation, such as the separation between virtual and physical machines and the revision of the nature of the knowledge being tested and the selection processes experienced by this knowledge. Regarding the former, virtual machines are said to deal exclusively with formal and syntactic aspects of computation (e.g., the Turing machine), whereas physical machines require reflecting on additional issues associated with implementation and execution e.g., the connection between low- and high-level programming languages or computing efficiency. Regarding the latter, computer scientists, taking insights both from the syntactic and semantic view of theories, have questioned aspects such as whether computer programs are theories (and, if so, what kind of theories) and whether these programs are falsified, as in empirical science, rather than verified, as in exact sciences (Northover et al., 2008).

While there is a growing awareness among practitioners of computer science and software engineering that their activities could be more adequately described as empirical, there is not a univocal consensus about how this 'empirical' should be conceptualised. For example, 'empirical' is sometimes taken as synonymous with 'experimental' (Tedre & Moisseinen, 2014). The conflation is misleading, however. 'Empirical' is a broader concept, for it relates to the nature of inquiry and of evidence. It determines the type of phenomena being studied, the methods and the overall philosophical underpinnings of everyday scientific practices. Experiments, conversely, are just one in a collection of several available methods.

In part, the conflation between 'empirical' and 'experimental' occurs because there is no consensus either about whether computer science and software engineering use experimental testing, the hallmark of empirical science. In the literature, algorithms, programs and simulations have all been taken as object or target of experimentation (Colburn, 2000). The justification for any given combination hinges on whether the notion of experimental is attached to the practice of computer programming as a whole, to the execution of a specific program, or to particular stages of the execution e.g., debugging (Tedre & Moisseinen, 2014). In the first case, the notion of experimentation is linked to the process of comparing different programs executing the same task; in the second, to the connection between algorithms and programs; finally, in the third, to the performance of the program.

Regardless of the different possible interpretations, what is central to these efforts to determine how computer programming can be empirically characterised is the belief that the *actual* implementation and execution of an algorithm on a physical machine involves several elements that go beyond the algorithm itself and its solution. These elements, it is believed, may be more adequately conceptualised by paying attention to the physical, social and cognitive organisation of the practice of computer programming.

Although the literature in agent-based social simulation has not remained completely uncritical of the dual evaluation scheme (e.g., Anzola Forthcoming; Augusiak et al. 2014), and, in practice, researchers approach evaluation processes in a multiplicity of ways (e.g., Barreteau et al. 2013; Gräbner 2018; Lee et al. 2015; ten Broeke et al. 2016), the methodological narrative has yet to incorporate a discussion about whether this conceptual transition in computer science and software engineering warrants a revision of how the dual evaluation scheme captures the empirical and the experimental in social simulation. Practitioners reserve the concept 'empirical' for external data with which the models are verified, calibrated and validated. Yet, this other sense of empirical that computer scientists and software engineers attach to the practice of computer modelling as such affects evaluation processes and warrants for belief in the adequacy of a simulation.

Unlike the mainstream philosophy of simulation, as mentioned, the literature in agent-based social simulation has not sufficiently addressed the materiality of computer simulation as a practice and of the computer as an artefact. Reflecting on materiality could help practitioners, among other things, to more explicitly incorporate issues of evaluation that are strongly linked to the distinction between physical and virtual machines,[7] and also to renounce an ambiguous approach to empirical confirmation that simultaneously includes views of computer simulation as empirical and formal testing.

Explicitly accounting for how empirical testing is tackled in the practice of computer simulation should also allow practitioners to better define domains of evaluation. Following the traditional interpretation in computer science and software engineering, the foundational narrative in agent-based social simulation conceptualises verification and validation as two different procedures with well-defined areas of application: the former deals with a *formal* problem of translation; the latter, with a *representational* problem of commensuration (David, 2009; Edmonds, 2000; Gilbert, 2008; Rand & Rust, 2011). Taking verification as a matter of formal translation makes sense under the view of computer programming as an exercise in algorithm analysis. However, it might be an oversimplification of the diverse ways in which practitioners implement agent-based models of social phenomena.

The literature in the philosophy of simulation does not forcefully challenge the dual evaluation scheme because, in the verification of equation-based simulations, there are, indeed, some formal issues associated with the computational implementation of a system of equations that can, at least in principle, be separated from the experimental manipulation of the computational model. Rather, this literature has centred on clarifying how the formal and the empirical interact in computer simulation to show, contrary to Frigg and Reiss (2008), that the empirical aspects of computer simulation are one reason for which the method cannot be philosophically reduced to a form of mathematical modelling.

The same, however, is not the case with agent-based social simulation. Even though there are some technical/formal issues associated with the implementation of the computational model, the lack of a background mathematical framework requires practitioners to engage in informal sense-making of the experimental manipulation of the model from very early in the implementation process (Anzola, Forthcoming). These sense-making processes, however, are noticeably absent from the agent-based social simulation literature. Conceptual modelling, for instance, is not reported in academic publications and barely accounted for theoretically. To a certain extent, this neglect is surprising, considering, first, the recognised effects of the conceptual model on the implementation process and, second, the attention that the literature in other closely linked types of social simulation, such as micro and discrete event, has paid to conceptual modelling from a practical and theoretical point of view (e.g., Brooks & Wang 2015; Robinson 2020).

There seems, then, to be some knowledge about evaluation that remains tacit in the field due to the reliance on the traditional conceptualisation of the dual evaluation scheme. Along with the definition of the domains of evaluation for verification and validation, incorporating the discussion about empirical testing in computer

[7] For example, based on concerns about computation, some large-scales model e.g., the popular TRANSIMS (Smith et al., 1995) model, deliberately trade off features, such as agents' reactivity for population size. In turn, Netlogo's processing power upper bound is determined by the way the software incorporates Java.

programming, even if computer scientists and software engineers have not entirely agreed on it, might benefit the foundational narrative in agent-based social simulation by providing a framework in which, first, the interdisciplinarity of computer simulation is acknowledged, second, the differences in evaluation with other types of computer simulation are recognised and, third, several other elements that are fundamental from an experimental point of view are better accommodated. For example, even though it is a ubiquitous activity in computational modelling, calibration is not explicitly included in the dual evaluation scheme. It can be found in the literature subordinated both to verification and validation, without clear and standardised criteria for the decision. As a result, there is some evident theoretical ambiguity regarding its scientific status and role in the experimental exploration of the computational model.

5.2 Computer models as a source of knowledge

Practitioners of agent-based social simulation, in comparison to philosophers of simulation, have not sufficiently tried to clarify the way in which the dual evaluation scheme is meant to account for representation. Albeit the process of implementation in equation-based modelling has a decidedly large technical component, the literature in the philosophy of simulation does not entirely disregard matters of representation. The system of equations, it is acknowledged, has a relatively well-defined representational meaning derived from the background formal theory that is independent of any given computational implementation (which is why a computer simulation is sometimes defined as a numerical implementation of a mathematical model). The process of implementation does not itself create representational meaning, but, instead, changes or adds to this already existing meaning through conceptual and practical activities e.g., discretisation or parametric experimental exploration.

Due to the lack of a background formal theory and the neglect of conceptual modelling, it is difficult to assess whether practitioners believe agent-based social simulation follows an analogous procedure. It seems, however, that most practitioners believe it is the computational model that carries the entire representational burden. This view makes it easier to keep the formal-empirical separation between verification and validation, but does it at the expense of circumscribing the evaluation process within what is known in the philosophy of simulation as the narrow view of computer simulation i.e., centred mostly around the implementation and execution of the computational model, rather than the surrounding practice of computer simulation (Winsberg, 2019).

This narrow view of agent-based social simulation not only leads to philosophically overlook the effects of multiple modelling strategies that practitioners employ in everyday practices (because of the larger syntactic and semantic flexibility of both social theory and agent-based modelling), but also to theoretically oversimplify the process of validation. The agent-based social simulation literature on evaluation tends to suggest there is a direct representational relationship between the computational model and the target phenomenon during validation practices (Anzola, 2019b). This view, however, does not sufficiently account for the diversity in approaches to representation. In academic reporting, practitioners describe a multiplicity of activities involving additional elements such as theory, data, visualisations or interaction with stakeholders, that are carried out, among other things, to put together a non-fragmented picture of the source and target of representation.

In spite of the representational intricateness of social simulation described in the previous section, practitioners of agent-based social simulation have yet to develop an account of modelling that successfully explains how simple models such as Schelling's (1971) can be taken to provide useful knowledge about social phenomena. This model is often referred to as a paradigmatic agent-based model despite not including a realistic spatial representation or any kind of cognitive assumption regarding the actors' motivations for segregation. The overall evaluation of this model clearly favours the fact that it offers simple straightforward evidence of the macroconsequences of microbehaviour (the spatial clustering typical of residential segregation emerges as a result of local individual decision-making on neighbourhood similarity), over the possibility to realistically model agents decision-making heuristics and the space. Yet, criteria on which to judge it partially remain tacit.[8]

While in the philosophy of simulation, just like in the philosophy of modelling, there is not a generalised consensus around the best way to approach representation, it is widely acknowledged that representation is not simply a two-place relationship that is validated through a first-order comparison. As a result, several of the physical, social and cognitive aspects of the organisation of computer simulation that influence judgements about representation are extensively addressed in the literature (Imbert, 2017; Parker, 2013; Winsberg, 2019). In the agent-based social simulation literature, conversely, the role of the modelling context is often mentioned, but rarely systematically addressed. The prevalence of the notion of a two-place representation in the philosophy of social simulation is certainly puzzling, given, on one hand, the historically critical approach to objectivity and generalisability in social science and, on the other hand, the reservations that the literature on social simulations expresses about variable-based and linear methods (Axelrod 1997; Conte et al. 1997, 2012; Epstein & Axtell 1996; Gilbert 2008; Macy & Willer 2002), with which much of the data used for the validation of agent-based models is produced.

It is possible that practitioners of agent-based social simulation are closer to the narrow view of computer simulation because it is the one that most closely fits the original streamlined approach to verification and validation in software engineering and computer science. Interestingly, it is, perhaps, in social simulation where practitioners should be more critical of it. Take, for example, the notion of benchmark. Benchmarking was devised in computer programming as a functional evaluation of performance. It tests levels of satisfaction in the execution of a task, depending on predetermined standards. This testing, however, was initially framed within a problem-solving epistemology that does not entirely fit a representational approach to computer modelling. The representational component of validation is not inherent to the dual evaluation scheme but was added with the turn to the empirical in computer

[8]Interestingly, Schelling's model is extremely popular in the philosophy of simulation literature that discusses the usefulness of simple models.

programming. Originally, validation was not defined representationally, but functionally. Software was meant to do things, to perform certain task for which truthness predicates might be secondary or totally irrelevant.

When transferred to the context of computer simulation, benchmarking has been used in equation-based modelling in formal disciplines to describe processes of commensuration against known theory or data (Parker, 2008; Winsberg, 2010; Saam, 2019). While there is a change in meaning, the overall foundation for the notion of benchmark still remains.[9] The same does not happen in social science. Benchmarks could hardly be employed in agent-based social simulation, for their application depends on the possibility to produce accurate and reliable empirical estimations (Saam, 2019).

The turn to the empirical in computer modelling requires a revision of the normative elements that affect warrants for belief in the adequacy of a model, for representation cannot be functionally reduced to some sort of parallelism between simulation output and external data. In part, this requires revising the dual evaluation scheme from the perspective of confidence-building. In empirical science, a crucial question concerns the identification of the point at which enough confidence is built in the robustness of the results so as to end the experimental phase (Galison, 1987). The dual evaluation scheme, however, provides a definition of 'adequate' representation that is more easily reconstructed retrospectively. It is likely that agent-based social simulation will face a bigger challenge for this revision, taking into account the loose and fragmented nature of social theory, the diversity and insufficient amount of social data, the popularity of the KISS approach to computer simulation and the difficulties for commensuration due to the larger semantic and syntactic flexibility of agent-based models (Anzola & Rodríguez-Cárdenas, 2018; Conte et al., 2012; Axtell et al., 1996; Davis et al., 2018; Gilbert et al., 2018; Squazzoni, 2010).

The evaluation process is a topic that, again, evidences the philosophical idiosyncrasy of agent-based social simulation. Unfortunately, as with representation, much of the relevant knowledge pertaining to evaluation in social simulation remains tacit. Although the dual evaluation scheme is standard in general simulation studies, it would be worthwhile for practitioners and philosophers of simulation to explicitly address evaluation practices in agent-based social simulation, for developments in the mainstream philosophy of simulation could only have limited explanatory scope. First, because, in its approach to the testing of knowledge claims, the foundational philosophy in agent-based social simulation seems to have incorporated a functional account of the scheme that is closer to the original formulation in computer science and software engineering than to the one in other types of computer simulation; second, because of the particular philosophical implications of using agent-based simulation in social science.

[9] Conceptually, the notion of benchmark is more consistent with a logic of justification than of discovery. To an extent, the entire dual evaluation scheme is devised this way, since both verification and validation are formulated as success terms. Furthermore, knowledge and benchmarks proper experience completely different certification processes and are also not contested in the same way. Benchmarks could be deliberately and institutionally established and, at the same time, cannot really be falsified.

This philosophical reflection will probably yield an alternative view on how warrants for belief in the adequacy of computer simulation are produced, given the different approach that practitioners of social simulation have taken to the experimental and representational features of computer simulation. Even though, currently, the evaluation scheme is where the agent-based social simulation literature more closely conforms to the literature in other disciplinary areas, over time, this topic might become the one where the effects of disciplinary and methodological pluralism will be more easily noticeable.

6 Conclusion

This article analysed the extent to which the philosophy of agent-based social simulation, developed by practitioners themselves, diverges from the mainstream discussion in the philosophy of simulation. It identified some topics for which practitioners can resort to prior developments in the philosophy of simulation to achieve a better understanding of their practices, as well as some other topics for which paying attention to the particularities in agent-based social simulation could enrich the discussion in the philosophy of simulation.

Three major areas were selected for the analysis: manipulation, representation and evaluation. The first one is the most extensively addressed by practitioners of social simulation. There, it was argued, the weak and strong sense of artificial societies have led to alternative interpretations of the experimental features of agent-based social simulation. Practitioners see the method both as a sort of experiment and virtual laboratory. Experimentation, however, is not conceptualised in the same way as in the mainstream philosophy of simulation, probably because of the different methodological role that experiments have historically played in social science.

Regarding representation, agent-based social simulation sets itself apart from other types of computer simulation due to its commitment, first, to explicitly represent the dynamics of target phenomenon and, second, to conceptualise these dynamics under the lenses of complexity and emergence theory. In spite of the important philosophical effect of these commitments, it was claimed, the philosophy of agent-based social simulation is still missing a robust account of representation that adequately accommodates the theoretical-methodological diversity about the source and target of representation in social science.

Finally, when it comes to evaluation, even though the dual evaluation scheme is a standard framework for different types of simulation and disciplines, the foundational narrative in agent-based social simulation has incorporated a version of the scheme that hinders the correct conceptualisation of computer simulation as a tool for social research. It, on one hand, uses a narrow sense of 'empirical' that keeps some knowledge about the experimental use of simulations tacit and, on the other hand, grounds the evaluation process on a view of simulation as functional problem-solving, rather than as a type of modelling.

The overall discussion evidences the opportunity to further advance the philosophical conceptualisation of agent-based social simulation, especially regarding those aspects related to the distinctive physical, social and cognitive organisation of simulation practices. While some theoretical-methodological similarities can be found with other areas of research, the combination of social science and agent-based modelling involves enough idiosyncratic elements to make this philosophical exploration worthwhile. Subsequent theorisation on the philosophy of agent-based modelling will also offer some insights into how different elements might be prioritised depending on whether a philosophical account is developed by practitioners or philosophers. The article did not elaborate on this issue. Yet, it seems that the philosophical distinctiveness of the agent-based social simulation literature can be partly attributed to the multiplicity of issues beyond philosophy that practitioners are concerned with in their everyday use of computer simulation.

In the future, it is also worth exploring in more depth the differences among practitioners. This article suggests that the foundational methodological narrative in agent-based social simulation cannot be easily accommodated by the mainstream discussion in the philosophy of simulation. However, agent-based social simulation, as it is common with other social sciences, is decidedly multiparadigmatic. There are clear theoretical and practical divisions among practitioners e.g., the KISS-KIDS debate, that have fostered contrasting approaches to computational modelling.

The interdisciplinary and collaborative nature of agent-based social simulation raises equally important philosophical questions. In this practice converge researchers with expertise in social, computational, biological, natural and artificial sciences. A comprehensive philosophical account will need to consider how, historically, all these disciplinary areas have developed their own warrants for belief in the epistemic power and relevance of computer simulation as a method of research.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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