

Chapter 5

Modelling for the Social Sciences

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5.1 Overview

The examination of the use of ‘artificial worlds’ in the previous chapter seemed to produce some rather damning concerns for those involved in agent-based simulation. While such models can provide a nicely compartmentalised and distilled view of a vastly more complicated real-world system, such a model can create tremendous difficulty when the researcher must begin to analyse the resultant data.

In the context of our overall discussion, however, the examples and analysis presented so far have focused largely on models based upon or inspired by biology. Agent-based modelling is far from confined to this singular area of study, so this chapter will introduce a major theme of this text: the uses and limitations of agent-based models in the social sciences.

As agent-based modelling spreads through various disciplines, there are certain applications which seem particularly promising due to an attendant lack of empirical data underwriting those disciplines. Social science seems an especially relevant example of this situation; by its very nature, the study of social systems makes data-gathering a difficult proposition.

In such an instance, can agent-based models provide a means for developing social theories despite the lack of empirical data to validate the models themselves? This chapter will examine this question in detail, first by describing the current

state-of-the-art in simulation in the field, and second by examining the methodological and philosophical implications of applying simulation techniques to the social sciences.

This chapter forms the first section of Part II of our analysis. The discussion in this chapter places the current state of social science simulation into the context of our analysis of modelling for Alife and the biological sciences. This allows us to develop a contrast between simulation approaches between these two fields, and in turn discover those points at which the unique problems of social science research impact upon the relevance of agent-based models to the social science researcher.

5.2 Agent-Based Models in Political Science

5.2.1 *Simulation in Social Science: The Role of Models*

In the past, models within social sciences such as economics, archaeology and political science have focused on mathematical approaches, though as modelling techniques within the field progressed, some began to criticise this focus. Read (1990) observes that mathematical models within archaeology may have produced sets of modelling assumptions that do not produce useful insights into human behaviour. He posits that the transition of mathematical models to social science from traditional uses in physics and other natural sciences had actually restricted the progression of archaeology by focusing on these inappropriate assumptions.

Similarly, the traditionally statistically-focused discipline of demography has begun to embrace new methodologies as the limitations of these methods for certain types of research questions has become evident (Billari and Prskawetz 2003). The advent of microsimulation in the demographic community has led to some in-depth examination of the foundations of demographic knowledge (e.g., Courgeau 2007), with some suggesting that agent-based modelling could form the foundations of a new, systems-based demography (Courgeau et al. 2017). The development of these modelling methods has been met with significant enthusiasm, though the marriage between data-focused demographic statistical modelling and abstract, individual-based modelling is an uneasy one.

Looking at social sciences more broadly, McKelvey (2001) notes that an increasing number of social scientists and economists propose that the traditional perspective of dynamics in these areas focused upon changing equilibria are outdated, and that the agent-based perspective of interacting autonomous social actors will provide greater insight into social behaviour. Indeed, Billari and Prskawetz (2003) argue that demography may only be able to surpass some of the challenges facing the study of population dynamics by embracing agent-based models. Henrickson and McKelvey (2002) even propose that an increased focus on agent-based methodologies could give social science *greater legitimacy* within the scientific community, allowing for a greater degree of experimentation and analysis across social science as a whole.

5.2.2 *Axelrod's Complexity of Cooperation*

Axelrod's 1997 book "The Complexity of Cooperation" led the charge for this increasing number of social scientists looking towards agent-based models as a method for examining sociological structures. In the same year, Cederman's "Emergent Actors in World Politics" provided an intriguing look at potential applications of such models to the political sciences. In the years that followed, the early mathematical models of political and social problems began to transfer to agent-based modelling methodologies: Epstein et al. (2001) used agent-based models to examine civil violence; Lustick (2002) used similar techniques to study theories of political identity in populations; Kollman et al. (1997) model the movements and shifting alliances of voters; and Schreiber (Donald et al. 1999) modelled the emergence of political parties within a population, to provide just a few examples. Thus, an increasing number of political scientists seem interested in modelling the emergence of social structures and institutions from the level of individuals or small sub-populations; however, the community remains divided as to the usefulness of such methodologies.

5.3 Lars-Erik Cederman and Political Actors as Agents

5.3.1 *Emergent Actors in World Politics a Modelling Manifesto*

Cederman's initial work in his 1997 book-length treatise focused on the simulation of inter-state interactions. Each model represented nation-states as agents, each with differing drives that altered their pattern of interaction with other states in the region. He presents these simulations as a means for building an aggregate-level understanding of the function of political structures by understanding the interactions of micro-level features which produce those effects (although, notably, he did not begin modelling these interactions using smaller units until a few years later, after the publication of *Emergent Actors*).

The excitement apparent in the pages of *Emergent Actors* seemed infectious, bringing other social and political scientists into the fold with an increasing number of agent-based models finding publication in political science journals. Lustick (2000) proposed that agent-based models could alleviate some of the shortcomings of previous modelling approaches:

Difficulties of amassing and manipulating collective identity data into theoretically potent comparisons are among the reasons that agent-based modelling can play an important role in the elaboration, refinement, and testing of the kind of specific and logically-connected theoretical claims that constructivists have been faulted for not producing. Because the models run on computers there is no room for ambiguity in the specification of the model's underlying rules.

Kenneth Benoit went so far as to argue that ‘because simulations give the researchers ultimate control, simulations may be far better than experiments in addition to being cheaper, faster, and easier to replicate’ (Benoit 2001). In a discipline where solid field-collected data is both complex to analyse and expensive to collect (or even impossible depending on the related political conditions), the prospect of being able to generate useful data from low-level simulated interactions seemed quite promising.

5.3.2 *Criticism from the Political Science Community*

Criticism of agent-based models in political science has come from a number of different sources, but a large portion of those criticisms focus on the difficulty of making sensible abstractions for social and political structures within such a model. As described earlier in relation to Alife models, one can potentially view all of scientific inquiry as reflective of the inherent biases of the experimenter, and this problem of theory-dependence is even more acute in models requiring the level of abstraction that political models necessitate.

Of course, even the most abstract of Alife models may reference both the real-life behaviour of natural biological systems and the wealth of knowledge obtained from many decades of observation and experimentation in evolutionary biology. Political science, however, does not have that luxury. Highly complex social structures and situations, such as Cederman’s models of nationalist insurgency (Cederman 2002, 2008) involve further layers of abstraction, including factors which do not immediately lend themselves to quantification such as cultural and national identities.

Evolutionary Alife simulations also benefit from an extensive backdrop of both theoretical and empirical work on innumerable species, allowing for the basic functions of evolutionary dynamics within biological systems to be modeled fairly competently. In contrast, political systems involve multiple layers of interacting components, each of which is understood primarily as an abstracted entity; frequently only the end results of political change or transition are easily observable, and even then the observer will have great difficulty pinpointing specific low-level effects or drives which may have influenced those results.

As Klüver et al. (2003) describe, sociological theory may not benefit from the micro/macro distinction of levels of analysis that benefits researchers of evolution and other large-scale processes. A micro/macro distinction allows the simulation researcher to create a hierarchical relation between elements, making for simpler analysis. The interacting social levels present in a political system however cannot be so clearly differentiated into a hierarchy of processes, making simulation a difficult, and highly theory-dependent, exercise. Due to these elements, theory-dependence in social simulation becomes a more acute problem than in ALife; Sects. 5.6 and 5.7 examine this difficulty in detail, and propose some possible solutions for the social simulation community based upon the systems sociology approach of Luhmann (1995).

5.3.3 *Areas of Contention: The Lack of 'Real' Data*

Donald Sylvan's review of Cederman's Emergent Actors in World Politics highlights another common complaint leveled at agent-based models by conventional political science:

Moreover, 'data,' in the way this term is understood by most statistically-based modelling procedures, is largely absent from Emergent Actors. This feature is very much in line with the rational-choice modelling tradition, of which the author is so critical. Many readers will find nothing problematic about this feature in a theoretical work such as this. However, it is important that readers understand that the lack of 'data' is a standard feature of CAS simulation as they evaluate the 'results' reported. (Sylvan 1998, p. 378)

As Sylvan points out, Cederman's 'data' only relates to the interactions of virtual states in an idealised grid-world; applying such data to real-life political events or transitions seems suspect. The level of complexity at work in large-scale political events may be very difficult to capture in an agent-based model, and knowing when to draw a specific conclusion from a model of such an inherently difficult-to-analyse situation is quite difficult.

5.4 Cederman's Model Types: Examples and Analysis

Despite these objections, Cederman, as evidenced by his extensive book-length work on agent-based modelling and subsequent methodological papers, sees agent-based modelling as a promising means of investigation for political scientists (Cederman 1997, 2001). His attempt to present a framework to describe the various potential goals of models in this discipline provides an opportunity to contrast this proposed social simulation approach with the other modelling frameworks analysed thus far.

5.4.1 *Type 1: Behavioural Aspects of Social Systems*

Cederman, in describing his three-part categorisation of social simulation (see Table 5.1), credits Axelrod's early work on the iterated prisoner's dilemma as the first major foray into modelling behavioural aspects of social systems (Cederman 2001; Axelrod and Hamilton 1981; Axelrod 1984). Axelrod's work aimed to show the emergence of cooperation, and with the iterated prisoner's dilemma showed that cooperation is possible in social settings as long as the interactions of involved agents are iterated.

This variety of work has continued in the years since, beginning with modifications to Axelrod's original model, such as spatially-embedded versions which show the emergence of cooperative clusters in a social system (Lomborg 1996). By incorporating more complex elements into the original models, researchers have attempted to draw further conclusions about the evolution of cooperative

Table 5.1 Summary of Cederman’s three modelling types

Cederman’s model classification	
C1	Focus on behavioural elements of social systems
C2	Focus on emergence of agent configurations
C3	Focus on emergence of interaction networks between agents

behaviours; such a focus on these aspects of a social system is characteristic of a Type 1 model (hereafter referred to as C1) under Cederman’s classification.

A major benefit of this type of model is computational simplicity. The prisoner’s dilemma example noted here is a well-known problem in game theory, and has been implemented and studied countless times over the past few decades. For the modeller, reproducing such a game computationally is a relatively simple task compared to more complex models, due to the lack of excessive numbers of parameters and the inherent compartmentalised nature of the interactions between players of the game.

To use our bird migration example, imagine that a certain bird species has demonstrated a social behaviour which can produce greater nest productivity between cooperating females, but at the expense of more frequent reproduction. In this case a C1 model might be useful, as a game-theoretic model could be designed to probe the ramifications of this behaviour in different situations. While our researcher would be pleased in one sense, given the greater simplicity of model-construction in this case, the model would also be quite narrow in its focus, and the abstractions made in such a model would be significant.

5.4.2 Type 2: *Emerging Configurations*

Cederman identifies Type 2 models (C2) as those which attempt to explain the emergence of particular configurations in a model due to properties of the agents (or ‘actors,’ to use Cederman’s terminology) involved (Cederman 2001). Models of cultural evolution, fit this description, as they rely upon the interaction and exchange of agent properties (often identified as ‘arguments or ‘attitudes’) and examine the resultant configurations of agents (March 1991; Axelrod 2001).

Ian Lustick’s Agent-Based Identity Repertoire Model (ABIR) is a suitable example of a modern C2 model, as it provides agents with potential ‘identities’ relating to different groups of agents which can be modified through interactions between those agents (Lustick 2006). C2 models such as ABIR focus on demonstrating the emergence of larger configurations within the social systems they simulate; in this case, the properties of each agent in the ABIR model have been used to study the development of clusters of ethnic and religious groups under various social situations.

These C2 models offer greater complexity for the modeller than C1 models, but they also offer the possibility of examining another category of questions about

social systems. To use our bird migration example, imagine that our researcher wished to examine the interactions of members of a flock upon arrival at a destination and reaching a suitable colony site. A C2 model may be a useful approach in this context, as our researcher could construct a model which assigns each agent certain properties (such as gender, behaviour mode, and so on) which could then allow the agents to interact using these properties and delegate roles and responsibilities in establishing a colony.

Of course, this model is far more complex than the C1 example above, but the problem in question is also very different. Not all problems are easily broken down into variations or extensions of highly-studied game-theoretic situations, so in this case our bird researcher may prefer to construct a novel model in the C2 style which suits this problem, despite the greater difficulties inherent in doing so.

5.4.3 Type 3: Interaction Networks

Cederman classifies Type 3 models (C3) as perhaps being the most ambitious: this type of system attempts to model both the individual agents themselves and their interaction networks as emergent features of the simulation (Cederman 2001). Interestingly, Cederman cites the field of artificial life as one likely to inform this area of computational work in political science, given that ALife focuses on such emergent features. He also acknowledges that some overlap can occur between C1 and C3 models by allowing agents more latitude in choosing interaction partners for example (Cederman 2001; Axelrod 2000).

Cederman argues that C3 models may provide very powerful tools for the political scientist, allowing for profound conclusions to be drawn regarding the development of political institutions. This approach does seem the most methodologically difficult of the three types in this classification, however, as the already significant abstractions necessary to create C1 and C2 models must be relaxed even further to allow for such ambitious examinations of emergent features at multiple levels.

To once again use our bird migration example, we could imagine any number of possible ALife-type models which would fall under the C3 categorisation. Our bird researcher would encounter the same difficulties with these models that we have described in previous chapters. The C3 classification as provided by Cederman is quite broad indeed – presumably due to the relatively recent appearance of this type of model within political science.

5.4.4 Overlap in Cederman's Categories

As mentioned above, Cederman acknowledges that there is some overlap between his C1 and C3 categories (Cederman 2001). However, given the complex nature

of social interaction, none of his categories provide a hard distinction that makes categorisation of simulations obvious in every case.

Cederman points to the possibility of a C1 model straying into C3 territory by simply allowing its agents more greater choice in choosing interaction partners. In a sense, C3 seems to be a superset of C1 and C2; a C3 model could provide insight into similar issues to those examined by a C1 or C2 model. Given that the C3 approach is naturally more broad, then the border separating either of the other types from C3 becomes more fuzzy.

Thus, the utility of Cederman's categories is slightly different from the pragmatic nature of Levins' modelling dimensions (Levins 1966). Defining the position of a model along Levins' dimensions is difficult due to the problems inherent in specifying the exact meaning of generality, realism and precision, but the framework as a whole remains useful as a pragmatic guideline for modellers (see Chap. 4 for further discussion). Cederman's framework is not intended to serve this same purpose, but does provide a means to classify and discuss models in terms of social science research questions. For this reason, Cederman's framework will be useful to us as we investigate modelling in the social sciences in greater detail in the remainder of the text.

5.5 Methodological Peculiarities of the Political Sciences

5.5.1 *A Lack of Data: Relating Results to the Real World*

As Sylvan's review of Cederman emphasizes, Cederman's 'data' only relates to the interactions of virtual states in an idealised grid-world; applying such data to real-life political events or transitions seems suspect at best. The levels of complexity at work in large-scale political events may be very difficult to capture in an agent-based model, and knowing when to draw a specific conclusion from a model of such an inherently difficult-to-analyse situation is quite difficult.

In essence the lack of real 'data' produced by such simulations is an issue critical to the acceptance of such models in mainstream political science. While some accept the potential for social simulations to illuminate the emergence of certain properties of political structures (Epstein et al. 2001; Axelrod 2001), the difficulty in connecting these abstracted simulations to real-world political systems is significant. Weidmann and Gerardin, with their GROWLab simulation toolkit, have attempted to sidestep these concerns by making their framework compatible with GIS (geographic information system) data in order to allow 'calibration with empirical facts to reach an appropriate level of realism' (Weidmann and Girardin 2006). They also emphasize the relational and spatially-embedded aspects of GROWLab simulations, presumably a nod to the importance of spatial considerations and social interactions in a real-world political context.

5.5.2 A Lack of Hierarchy: Interdependence of Levels of Analysis

While even abstract Alife models may reference the real-life behaviour of natural biological systems, and the wealth of related empirical data, political models do not necessarily have that luxury. Highly complex social structures and situations, such as Cederman's models of nationalist insurgency and civil war (Cederman and Girardin 2005; Cederman 2008) involve further layers of abstraction, often involving factors which do not immediately lend themselves to quantification, such as cultural and national identities.

In addition, sociological theory is notoriously difficult to formalise, incorporating as it does a number of both higher- and lower-level cognitive and behavioural interactions. In fact, sociological theory may not benefit from the micro/macro distinction of levels of analysis that benefits researchers of evolution and other large-scale processes (Klüver et al. 2003). These interacting social levels cannot be clearly differentiated into a hierarchy of processes, making simulation a very difficult, and highly theory-dependent, exercise.

5.5.3 A Lack of Clarity: Problematic Theories

Doran (2000) identifies a number of problems facing social scientists who wish to 'validate' their simulation work. He maintains that social scientists need not provide 'specific validation,' a direct connection to a target system, but instead face a more nebulous difficulty in demonstrating relevance of the assumptions within that simulation to social systems at large. He notes the immediate difficulties of finding an appropriate parameter space and method for searching that space, of analysing the simulation results in a way that does not produce an 'intractable level of detail,' and the problem of instability in simulations and the necessity of detailed sensitivity analyses. In his conclusion he argues convincingly for sensible constraints in social simulations which do not add confounding cultural biases to the behaviour of agents within the simulation. While Doran's examples provide a useful illustration of this concept, simulation architects may find great difficulty in ensuring that such biases are absent from their work, particularly in more complex multi-agent simulations.

5.6 In Search of a Fundamental Theory of Society

5.6.1 The Need for a Fundamental Theory

As we have seen, social science presents a few particularly thorny methodological problems for the social simulator. Despite this, can social simulation be used to

illuminate the underlying factors which lead to the development and evolution of human society? Social simulation certainly presents a new approach for examining societal structures, and perhaps could serve as a novel method for testing hypotheses about the very origins of society itself.

However, using social simulation for this purpose seems fraught with difficulties. Human society is an incredibly complex system, consisting as it does of billions of individuals, each making hundreds of individual decisions and participating in numerous interactions every day. There are vast numbers of factors at play and many of them are inherently unanalysable given that we cannot examine the contents of a human's brain during a decision or interaction which appears to make the already monumental task of the social simulator nearly impossible in such a case.

The problem of how life has evolved on Earth would seem also to be one of insurmountable complexity as well if it weren't for the theories of Charles Darwin (1859). Perhaps there is hope for a theory in social science of similar explanatory power to evolution, not necessarily one that fully explains society, but instead provides us with a holistic framework to push forward our understanding of society – in a similar way that evolution does for biology.

5.6.2 Modelling the Fundamentals

While Cederman describes a broad framework in which social simulation can operate, a fundamental social theory seems difficult to develop under his description of C1, C2, and C3 models (Cederman 2001). C3 models are designed to allow for the development of broad-stroke models which can illuminate more fundamental theories about political systems; however, to extend that to societal structures and interactions as a whole requires a new level of abstraction.

In essence an extension of the C3 categorisation becomes necessary when seeking a fundamental theory. In the context of political science, agents would be operating under a framework developed from that particular field of social science; while political decisions amongst agents will by their nature require the incorporation of elements of psychology and sociology, a more fundamental approach requires an even more abstract method for allowing all varieties of social behaviour to emerge from the simulated system.

As part of this new approach, we also need a new perspective on the development of human society. How do individual actors grow to communicate? How does that communication then become structured? How do these structured communications then grow into a societal-level framework guiding interactions between members of a population? To see the fundamentals of human society develop, the model would need to set a stage upon which society may grow without a pre-set communicative framework already in place.

5.7 Systems Sociology: A New Approach for Social Simulation?

As we have seen, the advent of social simulation has proved influential in the social sciences, provoking new questions regarding the origin and nature of society. While the examples discussed thus far demonstrate the potential impact of social simulation, they also illustrate the inherent difficulties involved in generalising the conclusions drawn from a social simulation. More generalised models of society may provide a means for investigating aspects of society which elude the empirical data-collector and in turn inform our search for a fundamental social theory, but in order for this to occur we need to establish a method of examining society on a broad theoretical scale through simulation.

5.7.1 *Niklas Luhmann and Social Systems*

The well-known social systems theory of Niklas Luhmann provides one example of an attempt to develop an understanding of the foundations for social behavior. Luhmann classifies social systems as systems of communication which attempt to reduce complexity by presenting only a fraction of the total available information (Luhmann 1995).

One of the fundamental issues facing the systems sociology theorist is solving the problem of double contingency, an issue Luhmann describes as central to the development of social order. Put simply, if two entities meet, how do they decide how to behave without a pre-existing social order to govern their actions? How might these entities decide to develop a common means of interaction, and through those interactions develop a shared social history?

As Dittrich, Kron and Banzhaf describe, Luhmann described a method for resolving this contingency problem which was far more elemental than previous approaches, relying as it does on 'self-organization processes in the dimension of time' rather than through more standard social processes. The entities in question would perform initial contingency-reducing actions during an encounter to allow for each to develop an understanding of the expectations of each party in the interaction (Dittrich et al. 2003).

In Luhmann's view, the social order develops as a consequence of these contingency-reducing actions on a large scale. As elements of the developing society develop their expectations about the social expectations of others (described as 'expectation-expectation' by Luhmann), a system of social interaction develops around this mutual social history. This system then produces as a consequence the social institutions which can further influence the development of the social order. These social institutions perform a similar function by reducing the amount of information disseminated amongst the members of a society, essentially providing contingency-reducing services on a much larger scale.

Agent-based models in the context of artificial life have certainly proved useful in the examination of other autopoietic systems; however, recent attempts to formalize Luhman's theories into a usable model, while producing interesting results, have highlighted the inherent difficulties of encapsulating the many disparate elements of Luhman's theories of social systems into a single model (Fleischmann 2005).

5.7.2 *Systems Sociology vs. Social Simulation*

As we can see from Luhman's analysis, while there may indeed be a lack of 'data' inherent to the study of artificial societies, there still exists a theoretical framework for understanding the fundamental mechanisms which drive the creation of a larger social order. While some social simulation researchers may seek to strengthen their models through establishing direct connections with empirically-collected data from social science, the systems sociology perspective could provide a different path to more useful examinations of human society.

The social simulation stream is oriented towards specific elements of social behaviour; simulations of cooperation (Axelrod 1997), nationalist insurgency (Cederman 1997), or the spatial patterning of individuals or opinions within a society (Lustick 2006). Social simulation's stronger links with empirical data may make validation of such models much easier, but further restricts the domain of those models to focus on social problems for which usable data exists. Given the difficulties inherent in collecting social science data, these problems tend to be a subset of those social problems for which models could prove potentially illuminating.

This very restriction into particular domains prevents the social simulation approach from reaching a more general perspective; this approach is constrained by approaching social phenomena from the top-down. These top-down approaches are necessarily rooted in the societies they model. In essence, looking for a feature in society and then attempting to reproduce it in a model is not sufficient to develop a fundamental theory.

In contrast, the systems sociology stream abstracts outside of the standard view of society. Luhmann's perspective aims to describe interactions which can lead to the development of social order, in a sense examining the development of human society through an 'outside perspective.' Luhmann essentially moves beyond standard sociology, attempting to describe what occurs prior to the existence of social order, rather than operating within those bounds as with social simulation.

Returning for a moment to our bird migration example, imagine that our migration researcher wishes to construct a model to investigate the beginnings of migration behaviour. One obvious approach may be to model individual agents, each of which is given the choice of moving to follow changing resources or environmental conditions. However, in a Luhmannian context, we could remove that element of pre-existing ideas concerning the origins of migration. A model which features individual agents which can move of their own accord, and have

basic requirements for survival in the simulated environment, may provide differing explanations of migration behaviour if that behaviour is seen to emerge from this very basic scenario. In this way, we allow for the possibility of other means for migration to emerge: perhaps through a developing social structure which drives movement of groups of birds, for example. In essence we would seek to move the migration model to a stage in which we assume as little as possible about the origins of migration behaviour, rather than assuming that certain factors will produce that effect.

Similarly, by viewing society from its earliest beginnings prior to the existence of any societally-defined modes of interaction and communication, the systems sociology approach hopes to develop a theoretical understanding of the fundamental behavioural characteristics which lead to the formation of social order. In many ways this approach is reminiscent of the Alife approach to modelling 'life-as-it-could-be' (Langton et al. 1989); the systems sociology perspective leads us to examine society-as-it-could-be.

5.8 Promises and Pitfalls of the Systems Sociology Approach

5.8.1 *Digital Societies?*

Having established this relatively promising outlook on the future prospects of social-science simulation using Luhmann's approach, a certain resemblance to the early philosophy of artificial life becomes apparent. As in Alife, we may have simply replaced one troubling set of methodological and philosophical concerns with another. Strong Alife's contention that computer simulations can be repositories for real, digital life provides an escape route for theorists to develop a suitable theoretical backstory for Alife. As discussed in Chap.3, such a backstory can underwrite these computer simulations as a new method for gathering empirical data, a means for examining processes like evolution in a method that is otherwise completely impractical. As long as we maintain that a computer simulation can potentially produce life, then our experiments on that digital biosphere can proceed apace. However, such a backstory for this 'artificial society' approach to social science seems a great deal more tenuous. Potentially, we could harken back to Silverman and Bullock's Physical Symbol System Hypothesis for Alife (Silverman and Bullock 2004):

1. An information ecology provides the necessary and sufficient conditions for life.
2. A suitably-programmed computer is an example of an information ecology.

Then, if we further argue that society is a property of living beings, we may contend that such an information ecology would also provide the necessary and sufficient conditions for the development of a society.

5.8.2 *Rejecting the PSS Hypothesis for Society*

Ignoring for a moment the philosophically and ethically troubling nature of the potential theoretical backstory outlined above, those who might find such an account appealing will be forced once again to face the artificial-world problem. Additionally, the vastly increased complexity of a population of organisms capable of developing a society would also increase the troubling aspects of this artificial-world approach, creating ever more complex artificial societies that are increasingly removed from real-world societies.

As discussed in Chap. 4, the greatest difficulty with developing an artificial world in which to study such complex systems is the problem of connecting that artificial world to the natural one on which it is based. The Strong Alife community may argue that probing the boundaries of what constitutes life in a virtual world is inherently a valuable pursuit, allowing for the creation of a new field of digital biology.

For the social scientist, however, the possibility of creating a further field of ‘digital sociology’ is less than appealing. In a field where empirical data in relation to the natural world is far more lacking than in biology, and in which simulation seems to be viewed as a means for enhancing the ability of social scientists to produce and test sensible theories, then producing and testing those theories in relation to a virtual society without direct connection to real society is quite a wasteful pursuit. Indeed, Burch (2002) contends that computer simulations in social science will revolutionise the field by *embracing* this theoretical complexity and tying it directly to empirically-relevant questions.

With the appeal of Luhmann’s approach deriving from the potential for examining the earliest roots of societal development, and from that developing a fundamental theory of society analogous to evolution in biology, a theoretical backstory along the lines of strong Alife seems inappropriate. Instead, the Luhmann-influenced social simulator would strive for a theoretical framework which emphasizes the potential role for simulation as a means for social explanation and theory-building, rather than allowing for the creation of digital forms of society.

5.9 Social Explanation and Social Simulation

The problem of explanation in social science, as in most scientific endeavours, is a difficult one. In a field with such various methods of data-gathering, prediction, and theory-construction, developing a method for providing social explanation is no mean feat.

Proponents of social simulation regard the agent-based simulation methodology as one potential method for providing an explanation of social phenomena. Before we establish the veracity of this opinion, however, we must establish the ground rules for our desired form of social explanation. With social systems involving

potentially many millions of participants, we must determine how we will focus our social explanations to derive the greatest possible theoretical understanding of the processes underlying human society.

5.9.1 Sawyer's Analysis of Social Explanation

As noted by R. Keith Sawyer, 'causal mechanistic accounts of scientific explanation can be epistemically demanding' (Sawyer 2004). A causal mechanistic explanation of a social system would require a detailed analysis of the large-scale elements of the system, and their related elements, but also of the individual actions and interactions of every member of that society.

Of course, this explanation may still be insufficient. On a macroscopic scale, the behaviour of a human society may be identical despite significant variations in the microscopic actions of individual members of that society. In that case, the causal mechanist account fails to encompass the larger-scale elements of a social explanation which could describe these effects.

Oddly enough, this description echoes that of many current agent-based models. Most of the models discussed thus far in this chapter have displayed a clear mechanistic bent; agents interact in ways reminiscent of societal actors and produce complex dynamical behaviour, but there is little to no incorporation of larger-scale structures such as social institutions. Therefore such models are not only causal mechanistic accounts, but they are also methodologically individualist (Sawyer 2004; Conte et al. 2001).

With this in mind, Sawyer implies that the current state-of-play in social simulation is incapable of providing true social explanation. He states that 'an accurate simulation of a social system that contains multiply-realised macro-social properties would have to represent not only individuals in interaction, but also these higher-level system properties and entities' (Sawyer 2003, 2004).

5.9.2 Non-reductive Individualism

Revisiting Klüver and Stoica for a moment, we recall their concerns regarding agent-based models and the difficulty of capturing the multi-leveled complexity of social phenomena within such a structure (Klüver et al. 2003). They argue that social phenomena do not adhere to a strictly hierarchical structure in which micro-scale properties result in macro-scale behaviour; in fact, these levels are intertwined, and separating social systems into that sort of structure as is common in agent-based models may be extremely difficult.

Sawyer's take on social explanation and social simulation expands on this topic, describing the difficulty of applying the concept of emergence (familiar to us from artificial life) to the social sciences. While the idea that lower-level simplicity leads

to higher-level complexity seems intuitively appealing within Alife and other related fields, Sawyer presents the idea that in fact social systems do not necessarily obey this relation (Sawyer 2003, 2004).

In this view, there is a fundamental conflict between emergence and the social sciences. If social systems can display properties are ‘irreducibly complex,’ then those properties cannot be the result of individual actions or properties, and thus could not have emerged from those actions or properties. This is clearly quite a dangerous possibility for the social simulator, as then the causal mechanistic method of simulating low-level agent interaction to produce high-level complexity would be a fundamentally flawed approach.

In order to escape this potentially troubling theoretical conflict, Sawyer proposes his own version of emergence for the social sciences which he dubs non-reductive individualism (see Sawyer 2002, 2003, 2004). In this view, Sawyer concedes to individualists that their fundamental assumptions about the roles of individuals in society are correct (i.e., that all social groups are composed of individuals, and those groups cannot exist without the participation of individuals). However, he also contends that some social properties are not inherently reducible to the properties of individuals; in this case, there is reason to present new ideas and theories which treat the properties of social groups or collectives as a separate entity.

Returning to our bird example, imagine a model which addresses the social behaviour of a bird species, perhaps the development of birdsong for use in signalling between individuals or something similar. We could choose to model these social developments using an agent-based model, which Sawyer would not find objectionable; after all, the actions of individuals do drive society in Sawyer’s perspective as much as for any other social scientist. We then choose to model the development of these birdsong behaviours by allowing these agents to signal one another before performing an action, then observing if those signals begin to find use amongst the simulated population in different circumstances.

However, Sawyer might argue that our model would be insufficient to ever display the richness inherent in bird social behaviour; the development and spread of new songs, the separation of songs into differing contexts among different social groupings and other such factors may be difficult to capture in a simple agent-based model. As with human society, he might argue that the complexity and variation of birdsong development requires another layer of simulation beyond the simple agent-based interactions underlying the drive to communicate between agents. Perhaps vindicating this perspective, some modelling work has shown that birdsong grammars and their development can be represented as evolving finite-state automata (Sasahara and Ikegami 2004).

Sawyer names this perspective quite appropriately, drawing as it does upon the philosophy of mind perspective of non-reductive materialism. Non-reductive materialists accept the primacy of matter in driving the brain, and thus mental phenomena, but reject the idea that only low-level discourse regarding this brain matter is valid in the context of studying the mind. In other words, non-reductive materialists are not dualists, but argue that mental phenomena are worthy of study

despite the primacy of matter; or, in Sawyer's words, 'the science of mind is autonomous from the science of neurons' (Sawyer 2002).

Thus, in the case of social science, Sawyer essentially argues that the science of society is autonomous from the science of individuals. This leads to his contention that individualist agent-based models are insufficient to provide social explanation. Without incorporating both individual effects and irreducible societal effects, the model would not provide the complete picture of societal complexity, as described in our example above.

Interestingly, Sawyer does leave one potential door open for individualist modellers. As he admits, one cannot be certain whether a given social property can be given an individualist mechanistic explanation, or whether that property will be proven irreducible to such explanations (Sawyer 2004); presumably, individual-based models could be used to fill that gap. A suitably rich model of interacting individuals could possibly provide a testing ground to determine whether a certain system does display properties independent of individual properties. However, under this view those simulations would only be able to provide explanation in such limited cases, and given that not all social systems will display such reducibility to individual properties, simulating every possible social construct to find such systems is presumably a rather inefficient way to utilise agent-based models in social science.

5.9.3 Macy and Miller's View of Explanation

While Sawyer points out some potentially troubling methodological difficulties for social simulators, and also proposes entirely new simulation methods to circumvent those difficulties, he does still maintain that social simulation provides a means for social explanation when implemented appropriately (Sawyer 2004). Macy and Miller also argue that simulation provides a remarkably useful tool for social science, and lament the lack of enthusiasm for agent-based models within the social science community (Macy and Willer 2002).

Macy and Miller propose that agent-based models can provide a perspective particularly well-suited to sociology, arguing that this methodology 'bridges Schumpeter's (1909) methodological individualism and Durkheim's rules of a non-reductionist method' (Macy and Willer 2002, p. 7). Thus, agent-based models can produce groups of agents which produce novel and complex higher-level behaviour, and in this respect reflect a potentially appealing method of investigation for the social scientist seeking to understand the origin of certain societal properties.

However, Macy and Miller join Sawyer in his caution regarding the application of such bottom-up methods to all social phenomena. Stepping away from the excitement of the artificial life theorists, they admit that these methods are not always inherently useful. In fact, they constrain the application of individualist models to 'studying processes that lack central coordination, including the emergence of institutions that, once established, impose order from the top down' (Macy and Willer 2002, p. 8).

5.9.4 *Alife and Strong Emergence*

Sawyer and Macy and Miller's points are more than reminiscent of the debate over strong emergence discussed in Chap. 2. In the *Alife* context, strong emergence contends that emergent phenomenon can show downward causation, influencing the behaviour of its own components. Just as Sawyer discusses, this would result in a situation in which that strongly emergent behaviour cannot be reduced to the actions of those component parts (O'Conner 1994; Nagel 1961).

Bedau attempted to get around this restriction by proposing weak emergence, in which the macro-components of a system, allowed to run in simulation, can demonstrate the general properties of a weakly-emergent phenomenon (Bedau 1997). As noted in the previous discussion, however, Bedau's categorisation requires a certain circularity of reasoning; Bedau himself states that only empirical observations at the macro-level of a given system can allow us to develop a means to investigate them through simulation.

In essence, Bedau alters the problem slightly by contending that a simulation can provide a general understanding of the properties of a system's macro-behaviour, but Sawyer would argue that such an explanation is still incomplete. Bedau's method, after all, does not actually propose a means for the simulation researcher to avoid the difficulties caused by downward causation posited by the strong emergence theorists. Macy and Miller, despite being more positive about simulation than Sawyer, argue that this very difficulty fundamentally limits the utility of simulation of this type. Without a means for capturing this downward causative influence of macro-level social institutions and similar structures, they contend that more traditional empirical methods would remain more useful in some cases.

Thus, for the simulation researcher who wishes to illuminate some potential influencing low-level factors in a given social system, the issues of non-reductive individualism or strong emergence do not make an enormous difference. Even if such objections are true, the researcher can still produce results which are indicative of the importance of those low-level factors in the emergence of the high-level behaviours under investigation, particularly with the assistance of an appropriate theoretical backstory. However, for the researcher wishing to use simulation as an explanation, and thus as a means for generating more powerful social theory, such objections create more difficulty.

5.9.5 *Synthesis*

Macy and Miller go on to identify two main streams in social simulation: studying the self-organisation of social structure and studying the emergence of social order (Macy and Willer 2002). The second stream is quite relevant to our earlier discussion of the implications of Luhmann's theories regarding social order to the agent-based modelling methodology.

As described in our discussion of Luhmann, a central difficulty in social simulation is the issue of heavily-constrained agent interaction. While agent interactions can provide an explanation of social behaviours at the individual level, those interactions may be far too limited to provide a useful explanation of larger-scale social structures. Sawyer and Macy and Miller provide an affirmation of this idea, arguing that most agent-based models are inherently individualist and thus limited in their ability to explain many social structures.

As we describe, the theories of Luhmann provide an intriguing means for studying the emergence of social order at the most fundamental level. However, while these models might provide insight into the earliest beginnings of certain societal interactions and structures, if we believe Sawyer and Macy and Miller then we would still be lacking critical elements of a complete social explanation.

5.10 Summary and Conclusion

Having taken a tour through the issues of social explanation that bear upon our proposed uses of agent-based models in the social sciences, we have a more complete picture of the possible empirical niche that such models may fill within this field. In particular our look at the explanatory deficiencies inherent to agent-based models draws us toward some specific conclusions regarding their most promising uses.

First, as indicated by our analysis of Luhmann's theories, we see that agent-based models suffer from some inherent constraints due to their status as artefacts of a society themselves. Given that models constructed based upon our own understanding of societal structure to date will naturally have certain fundamental assumptions about the operating parameters of a society, using such models to draw conclusions about a possible fundamental theory of society is fraught with potential difficulties.

In addition, most agent-based models seen thus far in this analysis have been individualist constructions which seek a mechanistic explanation for societal properties. As Sawyer and others have shown, individualist models may lack another essential portion of information needed to produce a full social explanation. If we accept the non-reductive individualist contention that some social groups or collectives may have non-trivial behaviour that cannot be reduced to the actions of individuals, then we would be unable to model such social constructions using conventional agent-based modelling techniques.

Thus, our analysis points toward a synthesis between Luhmann-style modelling of fundamentals combined with top-down elements. However, these elements seem rather disparate. Is it possible to combine models of the earliest beginnings of social interaction together with the influence of established top-down social structures? Does not the Luhmann view by its very nature preclude the inclusion of such preset structures, filled as they are by tacit assumptions regarding the functioning of society and its structures?

Clearly these two views would not mesh particularly well within a single model, but a combination of these two approaches when looking at different aspects of society may contribute to the development of the fundamental theory of human society that we seek. The next chapter will examine the current and future state of social simulation in relation to the theoretical frameworks elucidated in our analysis thus far. These comparisons will give us a more nuanced view of the issues facing agent-based modelling, with the addition of the social science perspective providing some new considerations. With these elements in mind, and with a view toward the issues of social explanation discussed in this chapter, we shall begin a more complete synthesis of theoretical frameworks that may drive future work in social simulation.

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