Methodos Series 13

Eric Silverman

Methodological Investigations in Agent-Based Modelling

With Applications for the Social Sciences

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With contribution by
Daniel Courgeau • Robert Franck
Jakub Bijak • Jason Hilton
Jason Noble • John Bryden

Springer Open

Eric Silverman
MRC/CSO Social and Public Health
Sciences Unit
University of Glasgow
Glasgow, UK

Methodos Series
ISBN 978-3-319-72406-5 ISBN 978-3-319-72408-9 (eBook)
https://doi.org/10.1007/978-3-319-72408-9

Library of Congress Control Number: 2017962298

Printed on acid-free paper

This Springer imprint is published by Springer Nature
The registered company is Springer International Publishing AG
The registered company address is: Gewerbestrasse 11, 6330 Cham, Switzerland

For Takako:
You make it all worthwhile.

Foreword

Following the aims of the *Methodos Series* perfectly, this 13th volume on agent-based models provides a general view of the problems raised by this approach and shows how these problems may be solved.

These methods are derived from computer simulation studies used by mathematicians and physicists. They are now applied in many social disciplines such as artificial life (Alife), political sciences, evolutionary psychology, demography, and many others. Those who introduced them often took care not to consider each social science separately but to view them as a whole, incorporating a wide spectrum of social processes – demographic, economic, sociological, political, and so on.

Rather than modelling specific data, this approach models theoretical ideas and is based on computer simulation. Its aim is to understand how the behaviour of biological, social, or more complex systems arises from the characteristics of the individuals or agents composing the said system. As Billari and Prskawetz (2003, p. 42) said,

> Different to the approach of experimental economics and other fields of behavioural science that aim to understand why specific rules are applied by humans, agent-based computational models pre-suppose rules of behaviour and verify whether these micro based rules can explain macroscopic regularities.

This is, therefore, a bottom-up approach, with population-level behaviour emerging from rules of behaviour of autonomous individuals. These rules need to be clearly discussed; unfortunately, this approach is now used without sufficient discussions in many social sciences. It eliminates the need for empirical data on personal or social characteristics to explain a phenomenon, as it is based on simple decision-making rules followed by individuals, which can explain some real-world phenomena. But how can we find these rules? As Burch (2003, p. 251) puts it,

> A model explains some real-world phenomenon if a) the model is appropriate to the real-world system [. . .] and b) if the model logically implies the phenomenon, in other words, if the phenomenon follows logically from the model as specified to fit a particular part of the real world.

Also, a theoretical model of this kind cannot be validated in the same way as an empirical model with the "covering law" approach, which hinders social research and leads to a pessimistic view of the explanatory power of the social sciences. In Franck's words (Franck 2002, p. 289),

> But, one has ceased to credit deduction with the power of explaining phenomena. Explaining phenomena means discovering principles which are implied by the phenomena. It does not mean discovering phenomena which are implied by the principles.

As the agent-based approach focuses on the mechanisms driving the actions of individuals or agents, it will simulate the evolution of such a population from simple rules of behaviour. It may thus use game theory, complex systems theory, emergence, evolutionary programming and – to introduce randomness – Monte Carlo methods. It may also use survey data, not to explain the phenomenon studied, but only to verify if the parameters used in the simulation lead to a behaviour similar to the one observed in the survey.

As we have already said, such an approach raises many problems which this volume will try to answer. We will present here these main problems, letting the reader see how Silverman has treated it.

The first problem is that these models "are intended to represent the import and impact of individual actions on the macro-level patterns observed in a complex system" (Courgeau et al. 2017, p. 38). This implies that a phenomenon emerging at the aggregate level can be entirely explained by individual behaviour. Holland (2012, p. 48), however, states that agent-based models include "little provision for agent conglomerates that provide building blocks and behaviour at a higher level of organisation." For instance, a multilevel study on the effects of an individual characteristic (being a farmer) and the corresponding aggregate characteristic (the proportion of farmers living in an area) on the probability of internal migration in Norway shows that the effects are contradictory (Courgeau 2007): it seems hard to explain a macro-characteristic acting positively by a micro-characteristic acting negatively. In fact, micro-level rules are often hard to link to aggregate-level rules, and I believe that aggregate-level rules cannot be modelled with a purely micro approach, for they transcend the behaviours of the component agents.

The second problem is that this approach is basically bottom-up. However, it seems important to take into consideration simultaneously a top-down process from higher-level properties to lower-level entities. More specifically, we should speak of a *micro-macro link* (Conte et al. 2012, p. 336) that "is the loop process by which behaviour at the individual level generates higher-level structures (bottom-up process), which feedback to the lower level (top-down), sometimes reinforcing the producing behaviour either directly or indirectly". The bottom-up approach of a standard agent-based model cannot take such a reciprocal micro-macro link into account, given that it only simulates one level of analysis.

The third problem concerns the validation of an agent-based model. Such an approach imitates human behaviour using some well-chosen mechanisms. It may be judged successful when it accurately reproduces the structure of this behaviour.

Determining success, however, requires a method very different from the standard tests used to verify the validity of the effects of different characteristics in the other approaches. Such tests can be performed in the natural sciences but are more difficult in the social sciences. As Küppers and Lenhard observe (Günter et al. 2005, paragraph 1.3),

> The reliability of the knowledge produced by computer simulation is taken for granted if the physical model is correct. In the second case of social simulations in general there is no theoretical model on which one could rely. The knowledge produced in this case seems to be valid if some characteristic of the social dynamics known from experience with the social world are reproduced by the simulation.

To determine if such an exploration has been successful, we need to consider different aspects. First, how do we test that there are no other models offering a better explanation of the observed phenomenon? Researchers often try out different kinds of models so they can choose the one most consistent with empirical data. But this hardly solves the problem, as there is an infinity of models that can predict the same empirical result as well or even better. Second, how do we test that the chosen model has a good fit with the observed data? Unfortunately, there is no clearly defined procedure for testing the fit of a simulation model, such as significance tests for the approaches described earlier. We can conclude that there are no clear verification and validation procedures for agent-based models in the social sciences.

While the agent-based approach appears to resemble event-history analysis, for it focuses on individual behaviour, it nevertheless aims to explain collective behaviour. At that point, the key question is: how do we generate macroscopic regularity using simple individual rules? Conte et al. (2012, p. 340) perfectly describe the difficulties encountered:

> First, how to find out the simple local rules? How to avoid *ad hoc* and arbitrary explanations? As already observed, one criterion has often been used, i.e., choose the conditions that are sufficient to generate a given effect. However, this leads to a great deal of alternative options, all of which are to some extent arbitrary.

Without factoring in the influence of networks on individual behaviour, we can hardly obtain a macro behaviour merely by aggregating individual behaviours. To obtain more satisfactory models, we must introduce decision-making theories. Unfortunately, the choice of theory is influenced by the researcher's discipline and can produce highly divergent results for the same phenomenon studied.

In order to go further, Chap. 9, co-authored by Jakub Bijak, Daniel Courgeau, Robert Franck and Eric Silverman, proposes for demography the enlargement of agent-based models to a model-based research. This will not be a new paradigm in the traditional sense, as with the cross-sectional, the cohort, the event-history and the multilevel approaches, but a new way to overcome the limitations of demographic knowledge. It is a research programme which adds a new avenue of empirical relevance to demographic research. The examples given in the following chapters, despite the simplicity of the models used, give us a glimpse of the importance of model-based demography.

I hope I have given to the reader of this volume a clear idea of its importance for social sciences.

Mougins, France Daniel Courgeau
August 2017

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Acknowledgements

This volume covers more than 10 years of research, stretching back to the start of my PhD in 2003. Over this lengthy period, this work has been supported by a number of institutions and funders. Chapters 1 through 8 are substantially based on my PhD research, completed at the School of Computing at the University of Leeds from 2003 to 2007. Chapters 9 through 11 are based on a work completed at the University of Southampton between 2010 and 2015 during the Care Life Cycle Project, funded by Engineering and Physical Sciences Research Council grant EP/H021698/1. Teesside University supported my work on the manuscript between 2015 and 2017. The completion of the manuscript was also supported by the Complexity in Health Improvement programme at the MRC/CSO Social and Public Health Sciences Unit at the University of Glasgow, with QQR funding code MC_UU_12017/14.

Of course this work has also benefitted from the collaboration, vital input and feedback from a host of colleagues and friends. At Leeds, my thanks go out to Jason Noble for being such a good friend, close colleague and trusted confidant throughout my years in research; Seth Bullock for his supervision and collaboration during my PhD; David Hogg for taking on supervision duties and supporting me during a critical period in my PhD; John Bryden for being a close collaborator and dear friend and for introducing me to Babylon 5; and Roger Boyle and Peter Jimack for being so supportive throughout my PhD studies.

At Southampton, thanks once again go to Jason and Seth, for supporting me throughout my postdoc experience and for fostering a great community within the research group. Special mention must go to Jakub Bijak, close collaborator on key chapters of this volume, trusted friend and a spectacularly talented researcher. Without his support and encouragement, this volume would never have come into being. Part III of this volume came to life thanks to exciting collaborations with Daniel Courgeau, Robert Franck and Jakub, and I feel very privileged to have been part of those conversations. I was also fortunate to be able to discuss the future of model-based demography with Thomas Burch, whose work I hold in very high esteem.

At Teesside, I was lucky to share offices with Ian Wood, who was a great source of support and a great colleague, without whom my time there would have been much poorer. Thanks also to Mark Cavazza for his support during his time there and his dedication to the union. Thanks as well to colleagues Julie Porteous, Fred Charles and The Anh Han – I am glad we will continue working together in the coming years.

For all their encouragement and kindness, I am indebted to my parents, Lewis and Linda Silverman, who have never failed to be a continuous source of inspiration throughout my academic career. Takashi Ikegami has been an inspiration to me since we first met in Boston in 2004; his enthusiasm and belief in Alife and his willingness to break boundaries in research have been a pleasure to experience. A heartfelt thanks also go to my friend and former housemate David Mitchell, who defined my years in Leeds and made my time there a true joy.

Last but certainly not least, thank you to my wife, Takako, who has showed such endless patience with my strange working hours, bizarre sleeping schedule and rambling monologues on obscure topics. Thank you for sticking with me, even when my brain was wandering off somewhere else entirely.

Contents

Acronyms

In general I have attempted to keep this volume free of excessive abbreviations, but the acronyms below will appear at times given their widespread usage in related fields of research.

ABCD Agent-Based Computational Demography. This term describes an approach to the discipline of demography which incorporates agent-based modelling.

ABM Agent-Based Model. These are computer simulations designed to examine the behaviour and interactions of autonomous agents.

ABSS Agent-Based Social Simulation. An approach to social simulation which explicitly focuses on the use of agent-based models.

Part I
Agent-Based Models

This first part of the text examines the theory and practice of computational modelling, much of it viewed through the lens of artificial life. Artificial life, or Alife for short, is a discipline that focuses on 'the simulation and synthesis of living systems', most frequently through the use of simulation. Using agent-based models, evolutionary algorithms, and other recent innovations in simulation and robotics, Alife researchers hope to unravel the mysteries of how life develops and evolves in the real world by studying digital manifestations of 'life as it could be'.

As Alife has itself evolved over the years, researchers have sought closer connections to the real world and to real biology. This has brought about difficult questions concerning the integration of real data into simulated worlds, and the relationship between digital biology and physical biology. As early Alife has slowly given way to a greater desire for empirical relevance, it has become increasingly important to understand the potential role Alife and Alife-inspired approaches can play in understanding real biological systems.

Of course the difficulties inherent in modelling complex biological processes and populations are familiar to population biologists just as much as digital ones – perhaps even more so, given the short history of Alife. We will examine in detail some of the theoretical frameworks developed by population biologists in order to develop their models and position them as a valid form of enquiry, and investigate how we might use these frameworks as a way to understand and categorise computational modelling efforts in disciplines such as Alife. In so doing, we will lay the foundations for Part II, in which we will investigate the additional modelling complexities we encounter when we begin to model social systems.

Chapter 1
Introduction

1.1 Overview

As computer simulation has developed as a methodology, so its range of applications has grown across different fields. Beyond the use of mathematical models for physics and engineering, simulation is now used to investigate fields as varied and disparate as political science, psychology, evolutionary biology, and many other disciplines.

With simulation becoming such a common adjunct to conventional empirical research, debate regarding the methodological merits of computer simulation continues to develop. Some fields, artificial life being the primary example used in this text, have developed using computer simulation as a central driving force. In such a case, researchers have developed theoretical frameworks to delineate the function and purpose of computer simulation within their field of study.

However, the expansion of computer simulation into fields which use empirical study as a central methodology means that new frameworks for the appropriate use of simulation must develop. How might simulation enhance one's use of conventional empirical data? Can simulations provide additions to empirically-collected data-sets, or must simulation data be treated entirely differently? How does theoretical bias influence the results of a simulation, and how can such biases be investigated and accounted for?

The central goal of this text is to investigate these increasingly important concerns within the context of simulation for the social sciences. Agent-based models in particular have become a popular method for testing sociological hypotheses that are otherwise difficult or impossible to analyse empirically, and as such a methodological examination of social simulations becomes critical as social scientists begin to use such models to influence social policy. Without a clear understanding of the relationship between social simulation and social sciences as a whole, the use of models to explain social phenomena becomes difficult to justify.

E. Silverman, *Methodological Investigations in Agent-Based Modelling*,
Methodos Series 13, https://doi.org/10.1007/978-3-319-72408-9_1

Bearing in mind this central theme, this text will utilise a modelling example which will be revisited regularly in Parts I and II. This example will serve as a means for illustrating the important concepts described in the various modelling frameworks under discussion, and for tying together these frameworks by showing the effect of each upon the construction and implementation of a simulation. This central example takes the form of a model of bird migration; this example seemed most appropriate as this sort of problem can be examined through various modelling means, from mathematical to agent-based computational models. The context and purpose of this hypothetical model will vary from example to example, but the central concern of developing an understanding of the behaviour of migratory birds will remain throughout.

Toward the latter half of Part II, we will use the classic example of Schelling's residential segregation model (Schelling 1971) to discuss some particular methodological points in detail. Part III will delve deeply into specific examples of agent-based modelling work in the field of demography in order to illustrate how the modelling concepts discussed in Parts I and II can influence the practice of modelling in social science.

1.2 Artificial Life as Digital Biology

The field of artificial life provides a useful example of the development of theoretical frameworks to underwrite the use of simulation models in research. The Artificial Life conference bills itself as a gathering to discuss 'the simulation and synthesis of living systems'; with such potentially grandiose claims about the importance of artificial life simulations, theoretical debate within the field has been both frequent and fierce.

In the early days of Alife, Langton and other progenitors of this novel research movement viewed simulation as a means to develop actual digital instantiations of living systems. Beyond being an adjunct to biology, Alife was viewed as digital biology, most famously described as the investigation of 'life-as-it-could-be' (Langton 1992). Ray boasted of his Tierra simulation's explosion of varied digital organisms (Ray 1994), and theorists proposed this sort of digital biology as a means for divining the nature of living systems.

1.2.1 Artificial Life as Empirical Data-Point

Since these heady days Artificial life has sought more conventional forms of methodological justification, seeking to link simulation with more conventional means of data-gathering in biology. This has lead to varying forms of theoretical justification within Alife, ranging from further explorations of Langton's early ideas

(Bedau 1998; Silverman and Bullock 2004) to the use of Alife simulation as a form of 'opaque thought experiment' (Di Paolo et al. 2000).

Within this text, these varying theoretical frameworks for Alife will be examined in turn, both within the context of biology and within Alife itself. Once Alife seeks direct links with conventional biology, theoretical justification becomes correspondingly more difficult, and thus the debate must branch out into more in-depth discussions of biological modelling methodology. An investigation of the use of modelling in population biology, beginning with the somewhat-controversial ideas of Levins (1966, 1968) provides a means for describing and categorising the most important methodological elements of biological models. Having developed an understanding of the complex relationship between biology and Alife, we can then proceed to a discussion of the future of modelling within the social sciences.

1.3 Social Simulation and Sociological Relevance

Social simulation has appeared in the limelight within social science quite recently, starting with Schelling's well-known residential segregation model (Schelling 1978) and continuing into Axelrod's explorations of cooperative behaviour (Axelrod 1984). The development of simple algorithms and rules that can describe elements of social behaviour has led to an increasing drive to produce simulations of social systems, in the hopes that such systems can provide insight into the complexity of human society.

The current state-of-the-art within social simulation relies upon the use of agent-based models similar to those popularised in Alife. Cederman's influential book describing the use of such models in political science has helped to bolster an increasing community of modellers who hope that such individual-based simulations can reveal the emergence of higher-order complexity that we see around us in human society (Cederman 1997). Social science being a field where the empirical collection of data is already a significant difficulty, the prospect of using simulation to produce insights regarding the formation and evolution of human society is an enticing one for many.

1.3.1 Methodological Concerns in Social Simulation

Of course, with such possibilities comes great debate from within the social science community. Proponents offer varying justifications of the potential power of simulation in social science; Epstein echoes the Alife viewpoint by proposing that social simulation can provide 'generative social science,' a means to generate new empirical data-points (Epstein 1999). Similarly, Axelrod stresses the ability of social simulation to enhance conventional empirical studies (Axelrod and Tesfatsion 2006).

Others however are more cautious with their endorsement of social simulation. Kluver and Stoica stress the difficulty in creating models consistent with social theory (Klüver et al. 2003), noting that social systems do not lend themselves to the same hierarchical deconstruction as some other complex systems. Others theorise that social simulation faces the danger of incorporating vast theoretical biases into its models, eliminating one of the potential strengths of social models: a means for developing more general social theory (Silverman and Bryden 2007).

Further examinations of these questions within this text will seek to link such ideas with the methodological frameworks developed within Alife modelling and biology. While both fields display obvious differences in both methodological and theoretical objectives, the philosophical difficulties facing agent-based modelling in these contexts are much the same. In both cases the link between empirical data-gathering and simulated data-generation is difficult to develop, and as a consequence the use of simulation can be difficult to justify without a suitable theoretical justification.

1.4 Case Study: Schelling's Residential Segregation Model

Having developed a detailed comparison between the use of models in biology and social science, this text will use Schelling's residential segregation model as a case study for examining the implications of the theoretical frameworks discussed and outlined in that comparison. Schelling's model is famously simple, its initial version running on nothing more than a chequerboard, but its conclusions had a far-reaching impact on social theory at the time (Schelling 1978). Schelling's ideas regarding the 'micromotives' of individuals within a society, and the resulting effects upon that larger society, sparked extensive discussion of the role of individuals in collective social behaviour.

1.4.1 Implications of Schelling's Model

With this in mind, our investigation will explore the reasons for Schelling's great success with such a simple model, and its ramifications for future modelling endeavours. How did such an abstract formulation of the residential segregation phenomenon become so powerful? What theoretical importance did Schelling attribute to his model's construction, and how did that influence his interpretation of the results? Finally, how does his model illuminate both the strengths and weaknesses of social simulation used for the purpose of developing social theory? All of these questions bear upon our final examination of the most appropriate theoretical framework for social simulation as a whole.

1.5 Social Simulation in Application: The Case of Demography

Having developed some theoretical approaches to social simulation, we will need to move on to discuss the establishment of these methods as a trusted and functional element of the social scientist's toolbox. We will take on this problem by investigating the field of demography, the study of human population change. Demography is a fundamentally data-focused discipline, relying on at times vast amounts of complicated survey data to understand and predict the future development of populations (Silverman et al. 2011). We will investigate the core assumptions underlying demographic research, discuss and analyse the methodological shifts that have occurred in the field over the last 350 years (Courgeau et al. 2017), and develop a framework for a *model-based demography* that incorporates simulation as a central conceit.

1.5.1 Building Model-Based Demography

In order to understand the challenges facing a model-based social science, we will discuss several examples of agent-based approaches to demography. Starting with some inspirational work from the early 2000s (Billari and Prskawetz 2003; Axtell et al. 2002; Billari et al. 2007), we will move on to current work integrating statistical demographic modelling directly into an agent-based approach. We will examine the benefits and the shortcomings of these models, and in the process develop an understanding of the power of a scenario-based approach to the study of future population change. Finally, we will evaluate the progress of model-based demography thus far, and present some conclusions about the lessons we can take from this in our future research efforts.

1.6 General Summary

This text is organised as essentially a three-part argument. In Part I, the theoretical underpinnings of Alife are examined, and their relationship to similar modelling frameworks within population biology. Part II reviews the current state-of-the-art in simulation for the social sciences, with a view toward drawing comparisons with Alife methodology. A subsequent analysis of theoretical frameworks for social simulation as applied to a specific case study provides a means to draw these disparate ideas together, and develop insight into the fundamental philosophical and methodological concerns of simulation for the social sciences. Finally, in Part III we take the specific example of demographic research and attempt to build a cohesive theoretical framework through which social simulation approaches can be integrated productively with empirically-focused social science.

1.6.1 Alife Modelling

This portion of the text aims first to describe the relatively new field of artificial life, and discuss its goals and implications. Once the background and import of Alife is established, then the shortcomings and theoretical pitfalls of such models are discussed. Given the strong association of Alife with biology and biological modelling, the theoretical discussion includes in-depth analysis of a framework for modelling in population biology proposed by Levins (1966, 1968). This analysis allows the theoretical implications of Alife to be placed in a broader context in preparation for the incorporation of further ideas from social science simulation.

1.6.2 Simulation for the Social Sciences

Agent-based modelling in the social sciences is a rather new development, similar to Alife. Social scientists may protest that modelling of various types has been ongoing in social science for centuries, and this is indeed true; however, this more recent methodology presents some similarly novel methodological and theoretical difficulties. This section of the text begins by describing the past and present of agent-based modelling in the social sciences, discussing the contributions and implications of each major development. Then, a discussion of current theoretical concerns in agent-based models for social science proceeds, describing modelling frameworks which attempt to categorise the various types of social simulations evident thus far in the field. Finally, an analysis of the problems of explanation via simulation which are particularly critical for the social sciences allows us to develop a broader understanding of these in a philosophical context.

1.6.3 Schelling's Model as a Case Study in Modelling

Schelling's model of residential segregation is notable for its impact and influence amongst social scientists and modellers (Schelling 1978). Despite the model's simplicity, the illustration it provided of a problematic social issue provoked a great deal of interest, both from social scientists interested in modelling and those formulating empirical studies. This investigation of Schelling will focus on how his model surpassed its simplicity to become so influential, and how this success can inform our discussion of agent-based modelling as a potentially powerful methodology in social science.

1.6.4 Developing a Model-Based Demography

Demography is an old discipline, originating from a major conceptual shift in the treatment of demographic events like birth, death and reproduction in the seventeenth century (Graunt 1662). In the years since, demography has gone through a series of methodological shifts, going from relatively straightforward early statistical work to present-day microsimulation and multilevel modelling approaches (Courgeau 2012). Simulation approaches to demography are now gaining popularity, particularly in areas such as migration, where simulation offers an opportunity to better understand the individual decision-making that plays a vital role in such processes (Anna Klabunde and Frans Willekens 2016). In Part III of this book, we will examine the methodological foundations of demography in detail, and investigate how simulation approaches can contribute to this highly empirical social science. We will present a proposal for a model-based approach to demography which attempts to resolve the conceptual gaps between the empirical focus of statistical demography and the explanatory and exploratory tendencies of social simulation. We will then discuss some applied examples of model-based demographic research and evaluate how these studies can influence our future efforts both in demography and in the social sciences more generally.

1.6.5 General Conclusions of the Text: Messages for the Modeller

By its nature, this text encompasses a number of different threads related to agent-based modelling to bring the reader to an understanding of both the positives and the negatives of this approach for the researcher who wishes to use simulation in the social sciences. Each of the three portions of the text builds upon the previous, with the goal of presenting modellers with both theoretical and practical concepts they can apply in their own work. Part I of the text demonstrates the problems and limitations of biologically-oriented agent-based models; such an approach is inherently theory-dependent, and modellers must be aware of this fact and justify the use of their model as a means to test and enhance their theories.

Part II of the text, focusing on simulation for the social sciences, describes the current state of this field and the various major disputes regarding its usefulness to the social scientist. This new type of modelling approach provides both new possibilities and new problems for the social scientist; the use of simulation can be a difficult balancing act for the researcher who wishes to provide useful conclusions. Thus, the social scientist interested in modelling must be knowledgable regarding these methodological difficulties, as analysed here, and avoid the impulse to produce highly complex models which may fall foul of the guidelines discussed.

In order to reinforce these points, we discuss an example of a powerful, successful, and simple model used within the social sciences: Schelling's residential segregation model (Schelling 1971, 1978). In the context of the modelling frameworks discussed in the previous portions, Schelling's model provides a platform for examining those frameworks in a detailed fashion. Schelling's model demonstrates that the most useful models are not the most complex; simplicity and analysability are much more valuable than complexity for those who wish to understand the phenomena being modelled. In essence, no model can do it all, and a knowledge of the modelling frameworks under discussion here and their implications allows one to understand the necessary balancing act of designing and implementing a model in much greater depth.

Perhaps the most important balancing act related here is the tension between the need for a modeller to provide a theoretical backstory and the desire to minimise a model's theory-dependent nature. This is a common thread running throughout the text, whether the model in question is related to biology or social science. Modellers who create a model without a theoretical backstory that provides a context may find themselves creating a model with no relevance except to itself, while those who create a model with too great a degree of theory-dependence may find themselves warping their model into one restricted by theoretical bias, once again moving the model further from real-world applicability. The notion of balancing acts in model creation and implementation is often practiced intuitively by modellers, but yet this tension between backstory and theory dependence is rarely discussed explicitly by modellers in the literature.

Part III of the text brings us to the specific example of demography, a discipline where agent-based modelling approaches have begun to take hold in certain areas of enquiry. Building upon the foundations laid in previous chapters, the model-based demography framework described here presents a positive case-study for the integration of simulation with empirically-focused social science. Example models demonstrate how considered choices during model construction, development and implementation produces results that add to demographic knowledge without letting the simulations became unmanageable. The intention is for these models to serve as positive examples of pragmatic, considered modelling practices; each of them has limitations, but are still able to provide insight on the research questions they target.

1.6.6 Chapter Summaries

The analysis begins with an overall review of the philosophical issues and debates facing simulation science in general. Chapter 2 focuses on these general concerns, providing a summation of current thinking regarding issues of simulation methodology. A large portion of this chapter focuses upon the problem of validation of simulation results, which is an issue that is of great importance to the theoretical frameworks under examination. A further discussion of the difficulties inherent in linking the artificial with the natural provides a broader philosophical context for the discussion.

Chapter 3 picks up at this point, focusing on the efforts of Alife researchers to make the artificial become 'real.' After introducing the concepts of 'strong' and 'weak' artificial life, the significance of these two perspectives is discussed in the context of the still-developing philosophical debates of Alife practitioners. A central theme in this chapter is the drive to develop empirical Alife: simulations which can supplement datasets derived from real-world data. Taking into account the problems of validation discussed earlier and the two varying streams of Alife theory, a possible theoretical framework for underwriting empirical Alife is developed.

Chapter 4 moves on to population biology, drawing upon modelling frameworks developed within that discipline to strengthen our burgeoning theoretical backstory for Alife. Levins' three types of models, described in his seminal 1966 paper, provoked a great deal of debate regarding the strengths and weaknesses of modelling in biology, a debate which continues to rage today. After an analysis of Levins' three types, an expanded version of his framework is developed in the hope of providing a more pragmatic theoretical position for the model-builder.

Chapter 5 focuses mainly upon a review of the current state-of-the-art in simulation for the social sciences. Beginning with a look at early models, such as Schelling's residential segregation model (Schelling 1978) and Axelrod's iterated prisoner's dilemma (Axelrod 1984), we move on to more current work including Cederman's work within political science (Cederman 1997). This leads to a review of common criticisms of this growing field and the methodological peculiarities facing social-science modellers. These peculiarities are not limited to social simulation, of course; social science as a whole has unique aspects to its theory and practice which are an important consideration for the modeller.

Chapter 6 then proceeds with an analysis of social simulation in the context of the theoretical frameworks and issues laid out thus far. First, an overall analysis of Alife and related modelling issues in population biology gives us a set of frameworks useful for that particular field. Next, these theoretical concerns are applied to social simulation in the hope of discovering the commonalities between these two varieties of simulation science. This leads to a discussion of the possibility of using social simulation to drive innovations in social theory as a whole; the work of Luhmann is used as an example of one perspective that may prove valuable in that respect (Luhmann 1995). Finally, having placed social simulation within a theoretical framework, the debate regarding the usefulness of social simulation for social explanation is summarised and discussed.

Chapter 7 extends the analysis begun in Chap. 5 by utilising a case study: Schelling's well-known residential segregation model (Schelling 1978). Schelling's model is noted for its simplicity: residential segregation is illustrated by a single rule applied to individual agents on a simple two-dimensional grid. This chapter investigates the reasons behind the powerful impact of Schelling's abstract formulation, placing the model in the theoretical constructs described thus far. The implications of Schelling's model on social theory is also discussed, with reference to the Luhmannian modelling perspective described in the previous chapter.

Chapter 8 offers a conclusion to the arguments laid out in Parts I and II. Having examined Alife modelling, modelling in biology, and social simulation, future directions for substantive modelling works are proposed. In the context of social simulation specifically, the problems of validation and explanation introduced earlier are revisited. The overall questions of methodological individualism in social simulation are investigated as well, with an eye toward developing methods of simulation which can transcend the perceived limitations on the explanatory power of social science models. Having used Schelling as a case study for the modelling frameworks under discussion, this chapter will also discuss how other modelling methodologies may fit cohesively into these frameworks.

Chapter 9 marks the beginning of Part III, in which we delve into the application of agent-based modelling to the specific discipline of demography. This chapter describes the historical evolution of the field, detailing the cumulative development of four successive methodological paradigms. From there we propose a methodological framework for a model-based demography, in which simulation helps demographers to overcome three key epistemological challenges within the discipline and helps avoid the insatiable 'beast' of over-reliance on detailed demographic data.

Chapter 10 moves beyond theoretical aspects of demography and dives into the practice of agent-based modelling in the field. We begin by discussing two examples in brief: Axtell et al.'s model of the decline of the Anasazi (Axtell et al. 2002); and Billari's Wedding Ring model of partnership formation (Billari et al. 2007). For our third, more detailed example, we will examine the Wedding Doughnut – an extended version of the Wedding Ring model which incorporates statistical demographic methods and adds a simple representation of individual health status (Silverman et al. 2013a; Bijak et al. 2013). Sensitivity analysis using Gaussian process emulators is also introduced as a means of understanding the impact of model parameters on their interactions on the final output of interest.

Chapter 11 focuses exclusively on a single model: the Linked Lives model of social care supply and demand (Noble et al. 2012; Silverman et al. 2013b). This model is a significant leap forward in complexity compared to the Wedding Doughnut, incorporating a simple economic system, spatial elements, partnership formation/dissolution, social care need and provision, and migration. We examine the model in detail, including another sensitivity analysis using Gaussian process emulators, and discuss how the strengths of this model can serve as a useful exemplar for future modelling efforts in demography.

Finally, Chap. 12 summarises our findings in Part III and links them to the theoretical discussions presented earlier in the volume. We evaluate the current state of model-based demography, and discuss how the development of this approach can inform efforts to bring agent-based modelling to other areas of the social sciences. Ultimately we will take model-based demography as a positive example of a discipline taking new methods and weaving them gradually and thoughtfully into the broader tapestry of demographic research. Demography benefits particularly from having a cumulative approach to methodology over the last three and a half centuries. Other disciplines can benefit from the insights presented by model-based demography, and in turn develop new approaches to simulation that may strengthen other areas of social science alongside demography's focus on empirical relevance.

1.6.7 Contributions

The major contributions of this text lie within its philosophical and methodological study of modelling within both artificial life and the social sciences. These analyses provide a novel perspective on agent-based modelling methodologies and their relationship to more conventional empirical science. Other elements of the text present a sort of anthropological study of modelling within these areas of science, in the hope of providing a more cohesive view of the use and impact of simulation in a broader context.

Elements of Chap. 3 were based upon a work published in the proceedings for Artificial Life IX; this work aimed to develop a theoretical framework for empirical studies in Alife by providing comparison with other, more established fields of science. Chapter 4 was based substantially on a paper written by myself and Seth Bullock describing the pitfalls of an approach to modelling that relies upon 'artificial worlds'; this work draws upon the papers of Levins, Braitenberg and others. Elements of Chaps. 4 and 5 were drawn from a paper by myself and John Bryden which was published in the proceedings for The European Conference on Artificial Life in 2007. This paper proposed a new means of social simulation which could provide a deeper insight into a fundamental social theory. Chapter 9 is based upon a collaborative paper written with Daniel Courgeau, Jakub Bijak and Robert Franck which was published in an edited volume on agent-based modelling for demography. Chapters 10 and 11 are based largely upon two collaborative papers written with members of the Care Life Cycle Project at the University of Southampton, which ran from 2010 to 2015.

In summary, this text provides a new synthesis of theoretical and practical approaches to simulation science across different disciplines of the social sciences. By integrating perspectives from Alife, biology and social science into a single approach, this text provides a potential means to underwrite the use of simulation within these fields as a means to generate new theory and new insight. Particularly in fields relatively new to simulation, such as social science, the acceptance of this methodology as a valid means of enquiry is a slow process; this text hopes to accelerate the growth of simulation with this field by providing a coherent theoretical background to illustrate the unique strengths of computational modelling, while simultaneously delineating its unique pitfalls. The detailed treatment of simulation modelling in demography will further illustrate how relatively disparate frameworks – in this case the data-centric demographic approach and the explanatory focus of agent-based modelling – can be combined to produce new avenues of productive enquiry.

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Chapter 2
Simulation and Artificial Life

2.1 Overview

Before beginning this extensive analysis of agent-based modelling, the philosophical and methodological background of simulation science must be discussed. Scientific modelling is far from new; conceptual and mathematical models have driven research across many fields for centuries. However, the advent of computational modelling techniques has created a new set of challenges for theorists as they seek to describe the advantages and limitations of this approach.

After a brief discussion of the historical foundations of scientific modelling, both mathematical and computational, some distinctions that characterise modelling endeavours will be described. The distinction between models for science and engineering problems provides a useful framework in which to discuss both the goals of modelling and the difficult problem of validating models. These discussions are framed in the context of artificial life, a field which depends upon computational modelling as a central methodology.

This chapter lays the groundwork for the next two chapters to come, and by extension Part I of this text as a whole. The discussion here of emergence, and the related methodologies of 'bottom-up' modelling, will allow us to understand the major philosophical issues apparent in the field of computational modelling. This, in turn, will prepare us for an in-depth discussion of the field of Artificial Life in the following chapter, which will provide a backdrop for the discussion of general issues in biological modelling in Chap. 4. Similarly, the discussion here of the debate regarding the explanatory capacity of simulation models will be a recurring thread throughout this text, in all three parts of the argument.

E. Silverman, *Methodological Investigations in Agent-Based Modelling*,
Methodos Series 13, https://doi.org/10.1007/978-3-319-72408-9_2

2.2 Introduction to Simulation Methodology

2.2.1 The Goals of Scientific Modelling

The construction of models of natural phenomena has been a continuous feature of human scientific endeavour. In order to understand the behaviour of the systems we observe around us, we choose to construct models to allow us to describe that behaviour in a simplified form. To use our central bird migration example, imagine that a researcher wishes to describe the general pattern of a specific bird species' yearly migration. That researcher may choose to sit and observe the migrations of that species year-on-year for a lengthy period of time, allowing for the development of a database showing that species movement over time.

However, a model of that species' migration patterns could save our researcher a great deal of empirical data collection. A model which takes the collected empirical data and derives from it a description of the bird species' general behaviour during each migration season could provide a means of prediction outside of a constant real-world observation of that species. Further, one can easily imagine models of the migration problem which allow for detailed representation of the birds' environment and behaviour, allowing for a potentially deeper understanding of the causes of these migrations.

Thus, in the context of this discussion, the goals of scientific modelling encompass both description and explanation. A simplified description of a phenomenon is inherently useful, reducing the researcher's dependence on a continuous flow of collected empirical data, but explanation is the larger and more complex goal. Explanation implies understanding: a cohesive view of the forces and factors that drive the behaviour of a system. To develop that level of understanding, we must first understand the nature and limitations of the tools we choose to employ.

2.2.2 Mathematical Models

Throughout the history of science, mathematical models have been a vital part of developing theories and explanations of natural phenomena. From Newton's laws of motion to Einstein's general relativity, mathematical models have provided explicit treatments of the natural laws that govern the world around us. As we shall come to understand, however, these models are particularly well-suited to certain classes of phenomena; the concise description of natural laws that follows from a mathematical model becomes ever more difficult to develop as the phenomena in question becomes more complex.

Even with the appealing simplicity of a mathematical description of a phenomenon however, certain methodological difficulties come into play. Some models may require a very complex system of linked equations to describe a system, creating a vast number of parameters which are not known a priori (see Chap. 4 for discussion of this in relation to population biology). These black-box simulations create difficulties for both theorists and experimentalists; theorists struggle to set values for those parameters, while experimentalists likewise struggle to validate models with such a range of potential parameters.

There is also the question of the accuracy of a given mathematical model, which can be difficult to determine without repeated testing of that model's predictive capacity. For example, the motion of objects in space can be described by Newton's laws of motion; however, for very large bodies which are affected by the tug of gravity, we must use Einstein's general relativity to describe that motion. If we turn the other way and wish to describe the motions of atoms and particles, then we must use quantum mechanics. The intersections of those models, particularly that of Einstein's relativity and quantum mechanics, are far from easy to develop; the fabled union of these two theories has occupied physicists for decades and will likely continue to do so for some time (Gribbin 1992).

2.2.3 Computational Models

The advent of easily-available computing power has revolutionised the process of scientific modelling. Previously intractable mathematical models have been tractable through the sheer brute-force calculating power of today's supercomputers. Supercomputers now allow physicists to run immense n-body simulations of interacting celestial bodies (Cox and Loeb 2007), model the formation of black-hole event horizons (Brugmann et al. 2004) and develop complex models of global climate and geophysics (Gregory et al. 2005).

Beyond the sheer number-crunching power of computational methods, the flexibility of computational modelling has resulted in the development of new varieties of models. While the specific characteristics of each simulated celestial body in a model of colliding galaxies is relatively unimportant, given that each of those galaxies contains billions of massive bodies with similar gravitational impacts on surrounding bodies, certain other phenomena depend on complex individual variation to be modelled accurately. Evolution, for example, depends upon the development of new species through processes of individual mutation and variation mediated by natural selection (Darwin 1859); thus, a model of evolving populations requires a description of that individual variation to be effective.

Take once again our central example. If our hypothetical bird-migration researcher hypothesizes that migration behaviour is due to evolutionary factors that he may be able to represent in a model, then he must be able to represent the effects of biological evolution in some form within that model. If he wishes to represent those effects, the digital birds within his model would require individual complexity that can produce variation within the simulated species. In contrast, if he were modelling only the patterns of the bird movements themselves, then he need only represent the impact of those movements on the other agents in the simulation, as in the colliding galaxy model above; individual variation in those agents is not such a driving force behind the patterns of bird movements as it would be in an evolutionary model of the development of those movements.

2.2.4 The Science Versus Engineering Distinction

As computational modelling has developed, so has a distinction between varying computational approaches. Some models seek to provide predictive power related to a specific physical or natural phenomenon, while others seek to test scientific hypotheses related to specific theories. The first type has been characterised as modelling for engineering, and the second has been described as modelling for science (Di Paolo et al. 2000; Law and Kelton 2000).

Models for engineering are dependent on empirical data to produce predictions. For example, a transportation engineer may wish to examine the most efficient means for setting traffic signals (Maher 2007). To determine this, the modeller will examine current signal settings, note the average arrival time of vehicles at each junction, analyse the anticipated demand for each service, and other similar factors. With this information in hand the engineer can produce a model of the current operating traffic pathways, and alter parameters of those simulated services to attempt to produce an optimum scheduling algorithm for the new signals.

Similarly, to stretch our bird example to the engineering realm, imagine that our migration researcher has decided to model a the dissemination of information via messenger pigeon. If he wishes to find an optimum schedule on which to release and retrieve these pigeons, he could use an engineering-type model to solve this problem. He could examine current and past messenger-pigeon services, note the average transit time for the delivery and retrieval of those messages, and the level of rest and recuperation needed by each bird. With an understanding of these factors, the researcher could develop a model which would provide optimum release schedules, given different potential numbers of birds and varying demand for message delivery.

Models for science, in contrast, focus instead on explanation and hypothesis-testing. A model of the development of animal signalling by its very nature cannot depend on the availability of empirical data; after all, we cannot simply watch random evolving populations in the hope that one of them may develop signalling behaviours while we wait. Instead, the model is based upon a hypothesis regarding the contributing factors that may produce the development of signalling behaviours; if the model produces a simulated population which displays those behaviours, then the modeller may attribute more validity to that hypothesis. This approach is the focus of this text.

Returning to the bird example, our researcher would be taking a similarly scientific modelling perspective if he wished to construct a model which illustrates the influence of individual bird movements on migrating flocks. He hypothesizes that individual birds within the flock assume controlling roles to drive the timeliness of the flock's migratory behaviour. He could test such a hypothesis by developing a simulated population of migrating birds in which certain individual agents within the simulation can affect the movement of multiple other migrating agents; if the presence of those controlling agents appears to confirm the necessity of such individuals to keep migrations moving in an appropriate timeframe, then he may propose that such mechanisms are important to real-world migratory behaviour.

2.2.5 Connectionism: Scientific Modelling in Psychology

The advent of this sort of scientific modelling has produced not only new types of models, but new fields of enquiry within established fields. The development of the connectionist approach to the study of behaviour and cognition provides one example of the scientific modelling perspective, and introduces us to the concept of emergent explanations.

The development of computational modelling techniques together with advances in neuroscience led some researchers to investigate models of neural function. These neural network models consist of simplified neuronal units, with specified activation thresholds and means of strengthening or weakening synaptic connections, which aim to reproduce the neural basis of behaviours (Rumelhart and McClelland 1986). The idea that models of this nature could demonstrate the emergence of cognitive behaviour brought with it related ideas concerning the mind that caused some controversy.

In order for the connectionist to assert that their model can represent cognitive behaviour, one must assume that mental states correspond to states of activation and connection strengths in a given neural network. This concept was derided by some who viewed this as an overly reductionist stance, and that in fact the symbolic manipulation capability of the mind is crucial to understanding cognitive function (Fodor and Pylyshyn 1988). This is related to the perspective espoused by many in the field of artificial intelligence, in which the manipulation of symbols was considered essential to the development of intelligence (Newell and Simon 1976).

The connectionist thus forms scientific models which aim to test the hypothesis that learning mechanisms in neural networks can lead to the development of cognition. While psychologists are certain that the human brain functions via the interaction of billions of individual neurons, the degree of correspondence between these neural-network models and actual brain function is debatable (see Pinker and Mehler 1988 for a damning critique of the unrealistic results of a connectionist model of language, as one example). Many models of this type use idealised neuronal units to investigate possible explanations of behaviour, such as creating non-functional ‘lesion’ areas in a network designed to perform visual search tasks as a means of theorising about possible causes of visual deficits (Humphreys et al. 1992). In this respect, these sorts of connectionist models are designed to test hypotheses and develop theories rather than generate predictions based on empirical data.

2.2.6 Bottom-Up Modelling and Emergence

As noted above, the controversy surrounding connectionist modelling hinged upon one of its base assumptions: the idea that the low-level interaction of individual neuronal units could produce high-level complex behaviour. The cognitivists and computationalists of psychology found this distressing, as reducing cognition to collections of neural activations eliminates the concept of symbolic manipulation as a precursor to thought and cognition; the 'distributed representation' concept proposed by connectionists would remove the necessity for such higher-level concepts of discrete symbol manipulation by the brain (Fodor and Pylyshyn 1988).

Of course, such perspectives need not necessarily be diametrically opposed. One can certainly imagine connectionism forming a useful element of the study of cognition, with the cognitivists continuing the study of mental representation and symbol manipulation in relation to larger concepts of mental behaviour that are less well-suited to the connectionist modelling perspective. Indeed, given that connectionist systems can implement symbol-manipulation systems, these philosophical differences seem minor (Rowlands 1994).

However, the idea of this type of 'bottom-up' modelling is crucial, and as a consequence the debate over this type of modelling bears great relevance to our discussion. The view proffered by connectionists that models of low-level interacting units can produce the emergence of higher-level complexity is a central element of the modelling perspectives being analysed in this text. The particular relevance of this controversy when considering problems of validation and scientific explanation will be examined further both in this chapter and in Chaps. 6 and 7 in particular.

2.3 Evolutionary Simulation Models and Artificial Life

2.3.1 Genetic Algorithms and Genetic Programming

Connectionism was far from the only prominent example of a computational innovation taking cues from biology. The use of genetic algorithms, modelled on the processes of biological evolution, has a long history in the computational sciences. Given the extensive study of natural selection in biological systems as an optimisation process, and the need for increasingly innovative optimisation techniques within computer science, the use of an analogue of that process for computational applications seemed a natural fit. Indeed, as early as the 1950s the computers available were being put to use on just these sorts of problems (Fraser 1957).

Since these early days of experimentation, the genetic algorithm became an established method of optimisation in certain problem spaces. Such algorithms seek to encode potential solutions to the problem at hand in forms analogous to a biological 'genotype'; each solution is then examined to determine its suitability as a solution, and evaluated according to a specified fitness function. The most fit solutions can then be combined, individual mutations can be generated if desired, and the next generation of potential solutions is subjected to the same process. Over many generations, the genetic algorithm may find a solution suitable for the problem, and in some cases the solution comes in an unexpected and novel form due to the influence of this selection pressure. Such systems came into the spotlight quite prominently in the 1970s, when John Holland's book on the topic provided a strong introduction (Holland 1975); later works by Goldberg (1989), Fogel (1988), and Mitchell (1996) cemented the position of genetic algorithms as a useful method for optimisation and search problems.

Genetic algorithms do suffer from methodological difficulties, of course; certain problems are not well-suited to genetic algorithms as a means of finding appropriate solutions. In addition, the design of a useful fitness function can be extremely difficult, as the programmer must be careful to avoid solutions which cluster around local optima (Mitchell 1996). Incorporating an appropriate amount of variation in the generated population can be vital for certain applications as well, as the right level of random mutation can provide a useful means to escape those local optima.

2.3.2 Evolutionary Simulations and Artificial Life

While genetic algorithms became popular amongst certain elements of the computer science community, they also drew great interest from those interested in the biological function of evolution. As the artificial intelligence community sought to model the fundamentals of human intelligence and cognition, others sought to use computational methods to examine the fundamentals of life itself.

The field of artificial life, or ALife, has complex beginnings, but is most often attributed to Langton (2006) who first christened the field with this title. ALife however has strong links with the artificial intelligence community (Brooks 1991), as well as with the earlier modelling traditions of ecology and population biology. The influence of the artificial intelligence community, the interest in bottom-up modelling as alluded to earlier in our review of connectionism, and the development of new techniques to produce adaptive behaviour in computational systems all seem to have had a hand in the development of ALife.

ALife work to date has revolved around a number of related themes, but all of them share some method of reproducing the mechanics of biological adaptation in computational form. Genetic algorithms as described above are perhaps the most prominent example, with a great number of evolutionary simulations using such algorithms or some version thereof to provide that element of adaptation. While the members of this growing research community moved forward with these methods of simulating evolutionary systems, a related set of new challenges faced that community.

2.3.3 Bedau and the Challenges Facing ALife

Mark Bedau's 2003 (Bedau 2003) summary of the field of artificial life provides one view of the array of potential challenges facing the ALife researcher. In Bedau's view, ALife clearly displays the potential to enhance our understanding of the processes of life, and numerous fundamental questions that spring from those processes:

How does life arise from the non-living?

1) Generate a molecular proto-organism in vitro.
2) Achieve the transition to life in an artificial chemistry in silico.
3) Determine whether fundamentally novel living organisations can arise from inanimate matter.
4) Simulate a unicellular organism over its entire lifecycle.
5) Explain how rules and symbols are generated from physical dynamics in living systems.

Bedau begins his extensive list of ALife challenges with a look at the potential for these new methods of simulation to simulate the origins of life. Of course there is great debate over the best means to simulate such early beginnings. Simulating the development of cell structures has been an important theme in ALife (e.g., Sasahara and Ikegami 2004), as well as the development of simple self-replicating structures (Langton 1990). This is not entirely surprising, given that Von Neumann's self-replicating cellular automaton was clearly an influence on those seeking to understand the development of such forms in silico (Von Neumann and Burks 1966).

However, at what point might we agree that such self-replicating digital organisms have achieved a 'transition to life' as proposed by Bedau? At what point does that simulated organism become an instantiation of the laws governing the development of natural life? Agreement here is hard to come by; some argue that the status of 'alive' is best conferred on organisms that can self-reproduce (see Luisi (1998) for an evaluation of this and other definitions), while others argue that self-motility[1] is a more important determining factor (Hiroki et al. 2007), and still others appeal to the concepts of self-organisation and autopoiesis[2] (Maturana and Varela 1973). This issue hinges upon the theoretical perspective of the modeller to a large degree: if one believes that the properties of life are just as easily realised in the digital substrate as they are in the biological substrate, then an ALife simulation can easily achieve life (given an appropriate definition of such) regardless of its inherent artificiality. The issue of artificiality in ALife research and its import for the theorist and experimentalist are explored in detail in Chap. 3.

[1]The ability to move spontaneously or non-reactively. This is considered a vital capability for biological life – self-motility allows living things to move in pursuit of food sources, for example. See Froese et al. (2014) for a detailed exploration.

[2]Autopoietic systems are systems that can produce and sustain themselves through their own internal processes, such as the biological cell. The concept was originally described in relation to biological systems, but has since been adapted to characterise cognitive and social systems as well.

What are the potentials and limits of living systems?

6) Determine what is inevitable in the open-ended evolution of life.
7) Determine minimal conditions for evolutionary transitions from specific to generic response systems.
8) Create a formal framework for synthesizing dynamical hierarchies at all scales.
9) Determine the predictability of evolutionary manipulations of organisms and ecosystems.
10) Develop a theory of information processing, information flow, and information generation for evolving systems.

Bedau's next set of challenges are reminiscent of one of Chris Langton's more famous descriptions of artificial life, in which he stated that ALife could seek to examine 'life-as-it-could-be' rather than simply 'life-as-we-know-it' (Langton 1992). In other words, given that the ALife researcher can construct an enormous variety of possible models, and thus living systems if we agree that life can be realised in silico, then ALife can be used as a platform to understand the vast variety of potential forms that life can create, rather than only examine the forms of life we currently perceive in the natural world.

Bedau is alluding to similar ideas, proposing that ALife researchers can use their work to probe the boundaries of the evolution of life. By simulating evolutionary systems, he posits that we may be able to investigate the mechanics of evolution itself in a way impossible in conventional biology. The researcher is able to freely tweak and direct the evolutionary processes at work in his simulation, and if we accept that the simulation adequately represents the function of evolution in the real world, then such research may allow for a greater understanding of the limits of the evolutionary process.

How is life related to mind, machines and culture?

11) Demonstrate the emergence of intelligence and mind in an artificial living system.
12) Evaluate the influence of machines on the next major evolutionary transition of life.
13) Provide a quantitative model of the interplay between cultural and biological evolution.
14) Establish ethical principles for artificial life. (Bedau 2003, p. 506)

Finally, Bedau closes his list of ALife 'grand challenges' with more speculative notions of relating the development of life with the development of mind and society. He posits that cognition originates from similar roots as life, in that such mental activity is a biological adaptation like any other seen in evolving systems, and that in this context artificial life may provide insight into the origins of mind as well as life.

The idea that mind and culture follow similar rules of adaptation to life is not a new one; the field of evolutionary psychology is well-established, if controversial (Buss 2004), and Dawkin's discussion of the 'meme' in relation to cultural evolution is one of the more prominent examples of such thinking in sociology (Dawkins 1995). The question of whether simulation can become sufficiently sophisticated to allow for the emergence of these higher-order phenomena is critical to our upcoming examination of simulation in the social sciences; in fact, the same philosophical difficulties that face modellers of cognition have been linked with similar difficulties in using simulation to model the roots of society and culture (see Sawyer 2002, 2003, 2004 and the accompanying discussion in Chap. 5).

2.4 Truth in Simulation: The Validation Problem

2.4.1 Validation and Verification in Simulation

While Bedau has provided a useful summary of the possible challenges facing artificial life in the research realm, numerous other challenges also loom in the area of methodology for ALife modellers. The difficulty of tying simulation results to the system being simulated is one not confined to ALife, but instead is common to all varieties of simulation endeavour.

The validation and verification of simulations is often most troublesome for modellers of all types. Once a model is designed and run, the researcher must be able to express confidence that the results of that model bear a direct relation to the system of interest. This is validation, and in relation to computational models specifically, Schlesinger's description of this process as a 'substantiation that a computerized model within its domain of applicability possesses a satisfactory range of accuracy consistent with the intended application of the model' (Schlesinger et al. 1979) is often cited. In other words, the modeller must demonstrate that the model displays a measure of accuracy within the domain to which the model has been applied.

Going hand-in-hand with validation is the concept of verification. A verified model is one in which the construction of the model is known to be accurate according to the framework in which that model is designed (Law and Kelton 2000). In relation to computational models specifically, this means that the model must be programmed appropriately to produce results that reflect the intent of the model's construction; given the inherent complexity of the software design process, this is not necessarily a simple task to complete.

2.4.2 The Validation Process in Engineering Simulations

Validation in simulations for engineering purposes, as described earlier, would tend to follow a certain pattern of verifying assumptions and comparing model predictions to empirical data (Sargent 1982, 1985). To illustrate these concepts we may return to the bird migration example. If our migration researcher wished to construct a model which provides an illustration of the migration behaviour of a certain bird species, he would first need to discuss the assumptions inherent in the conceptual model leading to the simulation's construction. For example, the speed and direction of movement of his simulated migrating populations should match those values gleaned from empirical observation; in general, his conceptual model should be informed by the available data. This verification of the conceptual model provides confidence that the assumptions made to produce the model have a solid foundation in theory related to the migrations observed in that bird species.

Having verified the conceptual model, the researcher would then need to verify the model itself. While confidence in the assumptions in the conceptual model has been established, the researcher must confirm that these assumptions have been implemented appropriately in the model itself. Has the code for the simulation been written correctly? Are the correct parameters in place in the model, given the parameters required by the conceptual model? If the researcher can demonstrate that the simulation has been implemented correctly, then validation can proceed.

The validation step is the most difficult, requiring a comparison of model data with real data. With our model migrating birds in place, the simulation should provide predictions of the behaviour of those birds when it is run. Do these simulation runs provide data that correlates appropriately with observational studies of that bird species' migration? Does empirical data related to bird migrations in general imply that the model's results are believable? Such questions can be complicated to answer, but nevertheless can be answered with access to appropriate empirically-collected data (see Law and Kelton 2000 for more discussion).

2.4.3 Validation in Scientific Simulations: Concepts of Truth

The procedure outlined above is undoubtedly complex, but achievable for the engineer. For the scientist, however, the procedure becomes more complex still. In a simulation which is designed to test hypotheses, and in which a clear relation to empirical data is not always obvious are indeed possible, the prospect of validating the results of that simulation depends on different sorts of relations between theory, data and model.

Appealing to the philosophy of science, Alex Schmid describes three theories of truth for simulations in science: the correspondence theory, the consensus theory, and the coherence theory (Alex Schmid 2005). The correspondence theory holds that the simulation must correspond directly with facts in reality; the consensus theory holds that the simulation must be acceptable under idealised conditions; and the coherence theory holds that the simulation must form a part of a coherent set of theories related to the system of interest.

The correspondence theory of truth relates closely to the methods of validation discussed in relation to engineering: our example bird migration simulation must display results that correspond directly to empirical data regarding migrating birds, otherwise the predictions of that simulation are of little use. Such a view coincides with the prevailing views of validation present in engineering models: validated models in the engineering perspective must demonstrate a close relationship to known empirical data about the problem under study.

The consensus theory, however, is much less defined, depending as it does on a more communal evaluation of the truth of the model. Our bird migration model may not provide entirely accurate predictions for future migration behaviours, but under this view we may still consider the simulation to be validated if the model is generally illustrative of bird migration behaviour. A more general version of our migration simulation, one developed as an abstract model not tied to any particular bird species, could fall into this category.

The coherence theory moves even further from the concept of truth most applicable to engineering, requiring only that the model in question fit into a given set of coherent beliefs. If our bird migration model fits cohesively into the general body of animal behaviour theory relating to migrating populations, then the model may provide a useful and valid addition to that theory. However, as Schmid points out, there is no reason that a coherent system of beliefs cannot also be completely false (Alex Schmid 2005); a model of our migrating birds travelling across a flat planet may be accurate given the belief structures of the Flat Earth Society, but is nevertheless completely separate from the truth of birds migrating over a round planet.

2.4.4 Validation in Scientific Models: Kuppers and Lenhard Case Study

Kuppers and Lenhard's evaluation of validation of simulation in the natural and social sciences sought to demonstrate the relation between theory and validation in models (Günter et al. 2005). As a case study, they focused upon the infamous scenario in climate modelling of 'Arakawa's trick.'

Norman Phillis' model of atmospheric dynamics (Phillips 1956) was a very ambitious step toward climate modelling on a grand scale. The results of his simulation were viewed with respect by the research community of the time, demonstrating as they did a direct correspondence to empirically-observed patterns of airflow in the atmosphere, but his results were hampered by an unfortunate consequence of the equations: numerical instability prevented the model from making any long-term predictions.

Arakawa sought to solve this problem, and eventually did so by virtue of his notable trick: he altered the equations of state, incorporating assumptions that were not derived from conventional atmospheric theory, and in the process ensured long-term stability in the model. Understandably this technique was met with substantial skepticism, but eventually was accepted as further empirical data showed the accuracy of Arakawa's revised model despite the theoretical inadequacies.

Kuppers and Lenhard use this as a demonstration that 'performance beats theoretical accuracy' (Günter et al. 2005). In other words, a simulation can provide successful data without having a completely accurate representation of the phenomenon at hand. This certainly seems to spell trouble for Schmid's descriptions of relating truth in simulation to the theoretical background of that simulation. If we agree that simulations may achieve empirical accuracy despite theoretical inaccuracy, how does this affect our view of truth in simulation?

A different approach to the relation between model and theory seems required. The status of a successful, validated model relies on more than a simple correspondence between the model and the research community, or the model and its surrounding theoretical assumptions, as Arakawa's computational gambit demonstrates.

2.5 The Connection Between Theory and Simulation

2.5.1 Simulation as 'Miniature Theories'

The relations described thus far between theory and simulation clearly lack important elements. For example, while the coherence theory of truth is appealing in that, say, an evolutionary model may find validation by fitting cohesively into the existing theory of biological evolution, how that model relates to theory itself remains an open question. Likewise, if a model must fit into an existing set of beliefs, are we suddenly restricting the ability of simulation to generate new theory? Is there room for innovation in such concepts of validation?

One means to escape from this difficult connection between simulation and theory is to reform our definition completely: we may consider a simulation as a theory in itself. Within the simulation community this view is not uncommon:

> The validation problem in simulation is an explicit recognition that simulation models are like miniature scientific theories. Each of them is a set of propositions about how a particular manufacturing or service system works. As such, the warrant we give for these models can be discussed in the same terms that we use in scientific theorizing in general. (Kleindorfer et al. 1998, p. 1087)

Similarly, Colburn describes simulation as a means to 'test a hypothesis in a computer model of reality' (Colburn 2000, p. 172). In the context of Arakawa's trick, this perspective is attractive: in this view Arakawa's model can serve as a miniature theory of its own, and the perceived disconnect between the assumptions of his model and the accepted atmospheric theory are of no consequence to the validity of the model.

2.5.2 Simulations as Theory and Popperian Falsificationism

If we accept that simulations can take the form of such 'miniature theories,' then perhaps the question of validation becomes instead a question of the validity of scientific theories. Herskovitz suggests that the process of validating simulation models is at its root a Popperian process of falsification (Herskovitz 1991). In essence, given that a simulation model is considered validated if its results correspond to the behaviour of real-world systems, then a system must likewise be falsified if its results do not correspond to the real-world system.

However, Arakawa's trick once again throws this view into question. Arakawa's model by its very nature incorporates assumptions that are contrary to physical theory: as one example, he assumes that energy is conserved in his model of the atmosphere, while the real atmosphere does not display such conservation (Günter et al. 2005; Arakawa 1966). In this respect, is his model subject to Popperian falsification? If a central assumption of this model, one which informs every calculation of that model, is demonstrably false, does his model likewise lose all validity?

Kuppers and Lenhard argue that it does not: that the theory presented by Arakawa's model stands apart from the physical theory upon which it was initially based, and its performance speaks more to its validity than the accuracy of its conceptual assumptions. Likewise, we might imagine an evolutionary model falling victim to the same Popperian plight: assumptions made to simplify the process of evolution within the model may contradict observed facts about evolving species in nature. However, if those assumptions allow the model to display accuracy in another respect, either theoretical or empirical in nature, should we still decry the assumptions of that model?

2.5.3 The Quinean View of Science

In this context the Popperian view of falsification seems quite at odds with the potential nature of scientific models. In contrast to what Herskovitz seems to believe, simulations are far more than mere collections of assumptions designed to imitate and calculate the properties of natural phenomena. Indeed, simulations can often contain a rich backdrop of internal assumptions and theories, and the measure of a simulation's success seems likewise more rich than a simple comparison with accepted data and theory.

The Quinean view of science seems much more suited to the simulation endeavour (and indeed, many would argue, more suited to science of all varieties). The Duhem-Quine problem stands famously at odds with the Popperian view, asserting that scientific theories can in fact never be proved conclusively false on their own (Quine 1951, 1975). Given that theories depend on one or more (often many) related auxiliary assumptions, theories can be saved from definitive falsification by adjusting those auxiliary assumptions.

For example, Newton's laws of gravitation were able to explain a great deal of natural phenomena, and are still used extensively in modern physics. However, Newton's laws could not explain some clearly evident and anomalous behaviours in astronomical bodies: the perihelion of Mercury's orbit being a prime example. Yet, rather than simply disposing of Newton's theory as inadequate, scientists instead strove for another explanation in addition to Newton's theories, which later arrived in the guise of Einstein's general relativity. Now Newton's laws are presented as essentially a subset of Einstein's theory, displaying correct results within a certain set of reference frames. Likewise, points where Einstein's theories break down (i.e., at the Big Bang or at the event horizon of a singularity) are not taken as a falsification of Einstein's views, but rather an indication of the need for additional theories and assumptions to explain those anomalies in detail.

2.5.4 Simulation and the Quinean View

Having rightly discarded the Popperian view of simulation and embraced Quine's notion of flexible and interconnected scientific theories, we can revise our initial view of simulation in the context of this understanding. Noble (1998) provides a summary of one view of simulation in a Quinean context, specific to artificial life: he argues that the Quinean view implies that new models are generated according to a requirement to incorporate new information in an existing theory without completely reorganising that theory.

As an example Noble posits that a new simulation in artificial life may seek to explain a behaviour in biology as a consequence of an emergent process (Noble 1998). The modeler may then implement a model incorporating appropriate low-level assumptions with the intention of running the simulation to determine whether the expected behaviour does indeed emerge. In this respect the model is based upon pre-existing conceptual frameworks concerning the high-level behaviour, and contributes to the addition of this new behaviour into the overall biological theory by providing an explanation of that behaviour in terms of an emergent phenomenon.

More generally, we may add to this characterisation by referring back to the earlier discussion of simulation-as-theory. When constructing a model to allow for the integration of new information into an overall conceptual framework, a simulation model can function as an auxiliary hypothesis in and of itself: that simulation forms a theory, and thus is subject to the same standards as the larger conceptual framework. In this case, even if the model does not achieve validation in comparison to empirical data, all is not lost; in the appropriate Quinean fashion, the auxiliary hypotheses linked to that simulation may be revised to present a new version of the simulation-theory (perhaps by revising certain parameter values or similar).

Simulation then is not simply a means to simplify calculations within a pre-existing theoretical framework, it is a means to modify that theoretical framework. The validity of a simulation is not easy to determine by any means, but a simulation based in an existing framework that adds sensible assumptions to that framework may go a long way toward justifying its existence as a substantive part of the overall theory. Unlike in the Popperian view, an invalidated simulation need not be discarded, but instead revised; assumptions used in a simulation are pliable, and an alteration of same could allow that model to produce insights it originally appeared to lack.

2.6 ALife and Scientific Explanation

2.6.1 Explanation Through Emergence

Having established that simulation can perform a valuable role in the development of scientific theory, this analysis now turns to the role of simulation in scientific explanation specifically. The ability of simulation to provide complete and coherent scientific explanation will impact the strength with which this methodology can develop scientific theories; bearing this in mind, we require an understanding of the limits of simulation in developing explanations. This explanatory role for simulation is often hotly debated, particularly in the case of scientific models as described here (see the exchange between O'reilly and Farah 1999 and Burton and Young 1999 for one example, as the authors debate the explanatory coherence of distributed representations in psychological models).

Within ALife, which depends upon frequently abstract simulations of complex emergent systems, the explanation problem takes on a new dimension. As Noble posits (Noble 1998), ALife models provide the unique mechanism of emergence which can provide new elements of an explanation of a phenomenon; however, debate continues as to whether explanations of higher-order phenomena through emergence can capture a complete explanation of those phenomena. This debate is exemplified once more by the debate within cognitive science regarding connectionism and distributed representations: the reductive character of connectionist explanation of mental phenomena is seen as overly restrictive, removing the possibility of higher-order explanations of mental states.

As noted earlier in our discussion of connectionism, this debate is easily avoidable in one sense: if we accept that consciousness, for example, is a natural emergent property of neuronal activity, then the acceptance of this fact does not preclude the use of higher-order discussions of mental states as a means to explain the characteristics of that emergent consciousness. This does, however, seem to preclude the notion of that emergent explanation being a complete explanation; even if one can show that consciousness does indeed emerge from that lower-level activity, by the nature of emergent phenomena that consciousness is not easily reducible to those component activities.

2.6.2 *Strong vs Weak Emergence*

The variety of emergence discussed in the previous section is often referred to as 'strong emergence': the concept that not only is an emergent phenomenon difficult to reduce directly to its component parts, but in fact the emergent phenomenon can display downward causation, or supervenience (influencing its own component parts), thus making the cause of that emergent phenomenon very difficult to define. In essence, the whole is a consequence of its component parts, but is irreducible to the actions of those components (see O'Conner 1994; Nagel 1961).

Weak emergence, by contrast, is a means proposed by Mark Bedau to capture the emergent character of natural phenomena without the troublesome irreducibility (Bedau 1997). Bedau defines weak emergence thus:

> Macrostate P of S with microdynamic D is weakly emergent iff P can be derived from D and S 's external conditions but only by simulation. (Bedau 1997, p. 6)

Thus, similar to strong emergence, the macro-level behaviour of the emergent system cannot be predicted merely by knowledge of its micro-components. Crucially however, those macro-level properties can be derived by allowing those micro-components to perform their function in simulation. Under strong emergence, an evolutionary simulation constructed in bottom-up ALife fashion would be unable to capture the complete behaviour of the resultant emergent phenomenon. Under weak emergence, that simulation could indeed provide a derivation of that higher-level behaviour.

Bedau takes great pains to point out however that such weakly emergent behaviours are still, much like strongly emergent behaviours, essentially autonomous from their micro-level components. While in theory one could predict exactly the behaviour of a weakly emergent system with a perfectly accurate simulation of its micro-level components, in practice such simulations will be impossible to achieve. Instead, the micro-level explanation via simulation provides a means to observe the general properties of the macro-level weakly emergent result.

In this sense there appears to be a certain circularity to weak emergence: simulation can provide a micro-level explanation of an empirical phenomena, but in practice 'we can formulate and investigate the basic principles of weak emergent phenomena only by empirically observing them at the macro-level' (Bedau (1997), p. 25). Some may argue in fact that this constitutes an explanation in only a weak sense: one could point to a simulation of this type and note that the given micro-components lead to the specified macro-behaviour, but the level of insight into that macro-behaviour is still fundamentally limited despite intimate knowledge of the behaviour of its components.

This objection becomes important once more in the context of social simulation and the concept of non-reductive individualism, which is explored in Chaps. 5, 6 and 7. While Bedau's concept of weak emergence is less metaphysically tricky than classical strong emergence, the difficulties that remain in explanation by simulation despite this new categorisation of phenomena still allow for criticism of the simulation approach. Such criticisms will inform our discussion of social simulation in the second section of this text as well as our discussion of Alife in the current section.

2.6.3 Simulation as Thought Experiment

Unsurprisingly these difficulties in using simulation for scientific explanation have generated much discussion within the research community. Di Paolo, Noble and Bullock approach this thorny issue by proposing that simulations are best viewed as opaque thought experiments (Di Paolo et al. 2000). This proposal draws upon Bedau's earlier description of ALife models, describing them as 'computational thought experiments.'

A traditional thought experiment in this view constitutes 'in itself an explanation of its own conclusion and its implication' (Di Paolo et al. 2000, p. 6). In other words a thought experiment provides a self-contained means with which to probe the boundaries of the theory which informs that experiment. A successful thought experiment can provoke a reorganisation of an existing theory as it brings previously-known elements of that theory into a novel focus.

Simulation experiments, it is argued, can fulfill a similar purpose. However, simulations suffer from an inherent opacity: as noted in our discussion of emergence, the modeler's knowledge of the workings of the simulation do not imply an understanding of the simulation's results. Unlike in a conventional thought experiment, the modeler must spend time unraveling the result of his simulation, probing the consequences to determine the implications for theory.

As a result of this view, the authors propose a different methodology in simulation research than the conventional view. Firstly, they contend that the successful replication of a result given some mechanism described in the simulation does not constitute an explanation (a misconception common to simulation work, and clearly debunked by the characteristics of emergence mentioned earlier). In consequence the explanation which may be drawn from simulation work is likely to incorporate an 'explanatory organisation,' in which some elements of the problem are explained through micro-level behaviour, others may be explained at the macro-level, and still others in relations between the two.

In essence, they advocate an additional step in the modelling process in which the modeler performs experiments on the simulation, as one might do in a laboratory environment. The systematic exploration of the model itself is intended to provide a greater understanding of its inner workings, and in turn this theory of the model's behaviour must then be related to theories about the natural world which provide the inspiration for the model. So the ALife researcher can accept the view that emergent behaviours are difficult to explain via simulation, but at the same time forming theories about the simulation that relate to theories about those behaviours may produce a new insight into pre-existing theories, as with a successful thought experiment.

2.6.4 Explanation Compared: Simulations vs Mathematical Models

Taking the thought-experiment perspective into more depth, Bryden and Noble (2006) contrast the explanatory capacity of simulation models with that of mathematical models. They seek to explore what is required of an explanation derived from simulation, noting that the unfortunately commonly accepted view that a simple qualitative similarity between the simulation result and the behaviour of the real system is sufficient to provide any sort of explanation.

Bryden and Noble note another element of the inherent opacity of simulation research: the analytical incompleteness of such models. Mathematical treatments, when flawed, are easily revealed as such. Simulations in contrast can be run many times, with different parameter values, and flaws in the coding of the simulation may not be immediately apparent. Similarly, those simulation runs represent only isolated data points in the entire possible space of runs allowable in that model; since no researcher can spare the time to browse the entire space of parameter values for a simulation, the results we see are only a fraction of what is possible.

The authors go on to advocate a means for decomposing a simulation system into component mechanistic subsystems which are more amenable to mathematical explanation. A working model which is decomposed in this way may still not provide the complete analytical package of an exclusively mathematical treatment, but it is argued that this brings the researcher closer to a full analytical solution of the target system. Thus the computational model is seen as a means to generate the tools necessary to reach a cohesive mathematical explanation of the phenomenon under study.

In a broader context this approach is quite close to that proposed by Di Paolo, Noble and Bullock (Di Paolo et al. 2000). In both cases the modeler spends time exploring the confines of the model in question, probing its inner workings to define the parameters in which that model operates. Having done this, the modeler may begin to relate those theories about the model to theories about the world; in Bryden and Noble's view, for maximum explanatory power those relations should take the form of mathematical treatments. From both however we draw the conclusion that models which are able to replicate an emergent behaviour through the simulation of a system's micro-level component interactions is still very far from providing an explanation of that system. The simulation itself must be further deconstructed, its parameters understood, and its workings probed in order to relate that model successfully to the real system to which it relates. Thus simulation becomes a valuable tool in the scientist's repertoire, but one that must be supplemented by more traditional means of enquiry as well.

2.7 Summary and Conclusions

The problems facing the simulation methodology are clearly far from philosophically transparent. From mathematical models to evolutionary simulations, these tools display potential explanatory power and are quick to develop in comparison to traditional empirical studies. However, with that relative ease of use comes a correspondingly high difficulty of analysis.

The type of simulation discussed here, particularly in the context of ALife, focuses on the investigation of emergent phenomena in the natural world. These phenomena by their very nature are difficult to explain; simulation provides a means to view the origin of these phenomena from the behaviour of low-level component parts, but still lacks in its ability to explain the overall behaviour of that higher-level emergent order.

A number of researchers and philosophers have attempted to justify the use of simulation as a means for scientific explanation in a variety of ways; our synthesis up to this point indicates that simulation is certainly a useful element in the explanatory toolbox. Simulation however cannot stand alone: a simulation which displays an emergent behaviour still requires a theoretical framework to describe that behaviour.

Within ALife, different streams of thought have developed in response to these difficulties; questions surrounding the appropriate use of simulation in the field have led to extensive debate on the validity of simulation as a means to generate data. A further investigation into the theoretical underpinnings of ALife in the following chapter will provide insight into the fundamental aspects of this debate, and lead us further into this analysis of simulation methodology. This investigation will also provide important theoretical background for future discussion of Alife models and their relation to more general methodological concerns in modelling amongst the broader biology community.

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Chapter 3
Making the Artificial Real

3.1 Overview

Having established in Chaps. 1 and 2 a working understanding of the philosophical underpinnings of computer simulation across disciplines, we turn now to a relatively new field which has created a stir throughout the computer science community to investigate questions of artificiality and its effect upon this type of inquiry. Can a simulation create novel datasets which allow us to discover new things about natural systems, or are simulations based on the natural world destined to be mere facsimiles of the systems that inspire them?

For a possible answer we turn to Artificial Life, a field which jumped to prominence in the late 1980s and early 1990s following the first international conferences on the topic. Proponents of 'Strong' Alife argue that this new science provides a means for studying 'life-as-it-could-be' through creating digital systems that are nevertheless alive (Langton et al. 1989; Ray 1994).

Of course, such a bold claim invites healthy skepticism, so in this chapter we will investigate the difficulties with strong Alife. By discussing first the nature of artificiality in science and simulation, then investigating related theoretical and methodological frameworks in Artificial Intelligence and more traditional sciences, we attempt to uncover a way in which the strong Alife community might justify their field as a bona fide method for producing novel living systems.

This discussion bears significant importance in the further discussion to come. Providing a theoretical background for any given simulation can greatly impact the modeller's ability to link a simulation to conventional empirical science, and also serves to illuminate the assumptions inherent in the model and their possible impacts. These issues will be discussed further in the following chapter, in which this first section of the text incorporates broader concerns regarding modelling from the biological community in preparation for creating a framework that incorporates social science in the second section.

E. Silverman, *Methodological Investigations in Agent-Based Modelling*, Methodos Series 13, https://doi.org/10.1007/978-3-319-72408-9_3

3.2 Strong vs. Weak Alife and AI

3.2.1 Strong vs. Weak AI: Creating Intelligence

The AI community has often been characterised as encompassing two separate strands of research: Strong AI, and Weak AI. Strong AI aims to develop computer programmes or devices which exhibit true intelligence; these machines would be aware and sentient in the same way as a human being. Weak AI, in contrast, aims to develop systems which display a facsimile of intelligence; these researchers do not attempt to create an intelligent being electronically, but instead a digital presence which displays the abilities and advantages of an intelligent being, such as natural language comprehension and flexible problem-solving skills.

3.2.2 Strong vs. Weak Alife: Creating Life?

The title of the first international artificial life conference immediately identified two streams of Alife research: the synthesis of living systems as opposed to their simulation. Perhaps designed to echo the distinction made between strong and weak artificial intelligence, this division has been readily adapted by the Alife community in the following years. While strong Alife attempts to create real organisms in a digital substrate, the weak strand of Alife instead attempts to emulate certain aspects of life (such as adaptability, evolution, and group behaviours) in order to improve our understanding of natural living systems.

3.2.3 Defining Life and Mind

Both intelligence and life suffer from inherent difficulties in formalisation; debate has raged in psychology and biology about what factors might constitute intelligent or living beings. AI has attempted to define intelligence in innumerable ways since its inception, resulting in such notable concepts as the Turing Test, in which a computer programme or device which can fool a blind observer into believing that it is human is judged to be genuinely intelligent (Turing 1950).

Meanwhile, prominent philosophers of mind have pointed out the flaws in such arguments, as exemplified in the oft-cited Chinese Room dilemma posed by Searle (1980). In this thought experiment, an individual is locked inside a room with an encyclopaedic volume delineating a set of rules allowing for perfect discourse in Chinese. This individual engages in a dialogue with a native Chinese speaker outside the room merely by following his rulebook. Searle contends that since the speaker himself does not have any innate knowledge of Chinese, his ability to speak Chinese fluently and convincingly through his rulebook does not prove his intelligence. Counter-arguments to Searle's Chinese Room have attempted to evade this apparent conundrum by claiming that, while the individual inside the room has no comprehension of Chinese, the entire system (encompassing the room, rulebook, and individual) does have an intelligent comprehension of Chinese, thus making the system an intelligent whole; Searle of course offered his own rejoinder to this idea (Searle 1980, 1982), though the controversy continues with connectionists and other philosophers continuing to weigh in with their own analyses (Churchland and Churchland 1990; Harnad 2005).

Similarly life as a phenomenon is perhaps equally difficult to define. While most researchers in relevant fields agree that living systems must be able to reproduce independently and display self-directed behaviour, this definition can fall apart when one is presented with exceptional organisms such as viruses, which display that reproductive component but consist of a bare minimum of materials necessary to for that action. Are such organisms still alive, or are they no more than self-reproducing protein strands? Alternatively, are even those protein strands in some way 'alive'? Researchers and philosophers alike continue to dispute the particulars. Alife researchers' claims that they can produce 'real,' digital life become more problematic in this regard, as under such a nebulous framework for what constitutes life, those researchers have quite a lot of latitude under which to make such statements.

3.3 Levels of Artificiality

3.3.1 The Need for Definitions of Artificiality

The root of the problem of strong Alife is hinted at by the suggestion of unreality or falsity that can be connoted by the terms thus far used to characterise Alife: synthetic or simulated. A clarification of the type of artificiality under consideration could provide a more coherent picture of the type of systems under examination in this type of inquiry, rather than leaving Alife researchers mired in a morass of ill-defined terminology.

Silverman and Bullock (2004) outline a simple two-part definition of the term 'artificial,' each intended to illuminate the disparity between the natural system and the artificial system under consideration. First, the word artificial can be used to denote a man-made example of something natural (hereafter denoted Artificial^1). Second, the word can be used to describe something that has been designed to closely resemble something else (hereafter denoted Artificial^2).

3.3.2 *Artificial^1: Examples and Analysis*

Artifical^1 systems are frequently apparent in everyday reality. For example, artificial light sources produce real light which consists of photons in exactly the same manner as natural light sources, but that light is indeed manufactured rather than being produced by the sun or bioluminescence. A major advantage for the 'strong artificial light' researcher is that our current scientific understanding provides that researcher with a physical theory which allows us to combine phenomena such as sunlight, firelight, light-bulb light, and other forms of light into the singular category of real light.

Brian Keeley's example of artificial flavourings (Keeley 1997) shows the limitations of this definition. While an artificial strawberry flavouring might produce sensations in human tastebuds which are indistinguishable from real strawberry flavouring, this artificially-produced compound (which we shall assume has a different molecular structure from the natural compound) not only originates from a different source than the natural compound, but is also a different compound altogether. In this case, while initially appearing to be a real instance of strawberry flavouring, one can make a convincing argument for the inherent artificiality of the manufactured strawberry flavour.

3.3.3 *Artificial^2: Examples and Analysis*

Artificial^2 systems, those designed to closely resemble something else, are similarly plentiful, but soon show the inherent difficulties of relating natural and artificial systems in this context. Returning to the artificial light example, we could imagine an Artificial^2 system which attempts to investigate the properties of light without producing light itself; perhaps by constructing a computational model of optical apparatus, for example, or developing means for replicating the effects of light upon a room using certain architectural and design mechanisms. In this case, our Artificial^2 system would allow us learn about how light works and why it appears to our senses in the ways that it does, but it would not produce real light as in an Artificial^1 system.

Returning to the case of Keeley's strawberry flavouring, we can place the manufactured strawberry flavouring more comfortably into the category of Artificial^2. While the compound is inherently useful in that it may provide a great deal of insight into the chemical and biological factors that produce a sensation of strawberry flavour, the compound itself is demonstrably different from the natural flavouring, and therefore cannot be used as a replacement for studying the natural flavouring.

3.3.4 *Keeley's Relationships Between Entities*

In an effort to clarify these complex relationships between natural and artificial systems, Brian Keeley (1997) describes three fundamental ways in which natural and artificial entities can be related:

> ... (1) entities can be genetically related, that is, they can share a common origin, (2) entities can be functionally related in that they share properties when described at some level of abstraction, and (3) entities can be compositionally related; that is, they can be made of similar parts constructed in similar ways. (Keeley 1997, p. 3, original emphasis)

This description seems to make the Alife researcher's position even more intractable. The first category seems highly improbable as a potential relationship between natural systems and Alife, given that natural life and digital life cannot share genetic origins. The third category is more useful in the field of robotics perhaps, in which entities could conceivably be constructed which are compositionally similar, or perhaps even identical, to biological systems. The second category, as Keeley notes, seems most important to Alife simulation; establishing a functional relationship between natural life and Alife seems crucial to the acceptance of Alife as empirical enquiry.

3.4 'Real' AI: Embodiment and Real-World Functionality

3.4.1 *Rodney Brooks and 'Intelligence Without Reason'*

Rodney Brooks began a movement in robotics research toward a new methodology for robot construction with his landmark paper 'Intelligence Without Reason' (Brooks 1991). He advocated a shift towards a focus on embodied systems, or systems that function directly in a complex environment, as opposed to systems designed to emulate intelligent behaviours on a 'higher' level. Further, he posited that such embodiment could produce seemingly intelligent behaviour without high-level control structures at all; mobile robots, for example, could use simple rules to walk which when combined with the complexities of real-world environments may produce remarkably adaptable walking behaviours.

For Brooks and his contemporaries, the environment is not something to be abstracted away in an AI task, but something which must be dealt with directly and efficiently. In a manner somewhat analogous to the Turing Test, AI systems must in a sense 'prove' their intelligence not through success in the digital realm but through accomplishments rooted in real-world endeavour.

3.4.2 Real-World Functionality in Vision and Cognitive Research

While embodiment may appear to be less of a concern in AI research related to vision and cognition, as these behaviours can be separated from the embodied organism more readily, such research is often still rooted in real-world environments. Winograd's well-known SHRDLU program (Winograd 1972) could answer questions addressed in natural language that related to a 'block world' that it was able to manipulate; the program could demonstrate knowledge of the properties of this world and the relationships of the various blocks to one another. While the 'block world' itself was an artificial construct, the success of SHRDLU was based upon its ability to interact with the human experimenter about its knowledge of that virtual world, rather than just its ability to manipulate the virtual blocks and function within that world.

Computer vision researchers follow a similar pattern to the natural-language community, focusing on systems which can display a marked degree of competence while encountering realistic visual stimuli. Objection recognition is a frequent example of such a problem, testing a system's ability to perceive and recognize images culled from real-world stimuli, such as recognising moving objects in team-sports footage (Bennett et al. 2004). Similarly, the current popularity of CCTV systems has lead to great interest in cognitive systems which can analyse the wealth of footage provided from many cameras simultaneously (Dee and Hogg 2006). In the extreme, modern humanoid roboticists must integrate ideas from multiple disciplines related to human behaviour and physiology as well as AI in order to make these constructions viable in a real-world environment (Brooks et al. 1999).

Within the AI research community, the enduring legacy of the Turing Test has created a research environment in which real-world performance must be the end goal; merely understanding basic problems or dealing exclusively in idealised versions of real-world situations are not sufficient to prove a system's capacity for intelligent behaviour. The question of artificiality is less important than that of practicality; as in engineering disciplines, a functional system is the end goal.

3.4.3 The Differing Goals of AI and Alife: Real-World Constraints

Clearly, real-world constraints are vital to the success of most research endeavours in AI. Intelligent systems, Strong or Weak, must be able to distinguish and respond to physical, visual, or linguistic stimuli, among others, in a manner sufficient to provide a useful real-world response. Without this, such systems would be markedly inferior next to the notable processing abilities of even the most rudimentary mammalian brain.

For Alife, however, the landscape is far more muddled. Most simulations take place in an idealised virtual context, with a minimum of complex and interacting factors, in the hopes of isolating or displaying certain key properties in a clear fashion. Given the disparity between the biological and digital substrates, and the difficulties in defining life itself, the relationship between the idealised virtual context of the simulated organisms and any comparable biological organism seems quite wide.

In this sense, artificial intelligence has a great advantage, as 'human' intelligence and reasoning is a property of a certain subset of living beings, but can be viewed as a property apart from the biological nature of those living beings to a degree. Artificial life, by its very nature, attempts to investigate properties which depend upon that living substrate in a much more direct fashion.

3.5 'Real' Alife: Langton and the Information Ecology

3.5.1 Early Alife Work and Justifications for Research

The beginnings of Alife research stemmed from a number of examinations into the properties of life using a series of relatively recent computational methods. Genetic algorithms, which allow programs to follow a process of evolution in line with a defined 'fitness function' to produce more capable programs, were applied to digital organisms which attempted to compete and reproduce rather than simply solve a task (Ray 1994). Similarly, cellular automata displayed remarkable complexity despite being derived from very simple rules; such a concept of 'emergent behaviour' came to underwrite much of Alife in the years to come. Creating simulations which display life-like behaviours using only simple rule-sets seemed a powerful metaphor for the complexity of life deriving from the interactions of genes and proteins.

3.5.2 Ray and Langton: Creating Digital Life?

Ray (1994) and Langton (1992) were early proponents of the Strong Alife view. Ray contended that his Tierra simulation, in which small programs competed for memory space in a virtual CPU, displayed an incredible array of varied 'species' of digital organisms. He further posited that such simulations might hail the beginnings of a new field of digital biology, in which the study of digital organisms may teach researchers about new properties of life that may be difficult to study in a natural context; he argued that his digital biosphere was performing fundamentally the same functions as the natural biosphere:

> Organic life is viewed as utilising energy, mostly derived from the Sun, to organize matter. By analogy, digital life can be viewed as using CPU (central processing unit) time, to organize memory. Organic life evolves through natural selection as individuals compete for resources (light, food, space, etc.) such that genotypes which leave the most descendants increase in frequency. Digital life evolves through the same process, as replicating algorithms compete for CPU time and memory space, and organisms evolve strategies to exploit one another. (Ray 1996, p. 373-4)

For Ray, then, an environment providing limited resources as a mechanism for driving natural selection and an open-ended evolutionary process is sufficient to produce 'increasing diversity and complexity in a parallel to the Cambrian explosion.' He goes on to describe the potential utility of such artificial worlds for a new variety of synthetic biology, comparing these new digital forms of 'real' artificial life to established biological life.

Langton (1992), in his investigation of cellular automata, takes this idea one step further, describing how 'hardware' computer systems may be designed to achieve the same dynamical behaviours as biological 'wetware.' He posits that properly organised synthetic systems can provide these same seemingly unattainable properties (such as life and intelligence), given that each of these types of systems can exhibit similar dynamics:

> ...if it is properly understood that hardness, wetness, or gaseousness are properties of the organization of matter, rather than properties of the matter itself, then it is only a matter of organization to turn 'hardware' into 'wetware' and, ultimately, for 'hardware' to achieve everything that has been achieved by wetware, and more. (Langton 1992, p. 84)

For Langton, life is a dynamical system which strives to avoid stagnation, proceeding in a series of phase transitions from one higher-level evolved state to the next. This property can be investigated and replicated in computational form, which in his view seems to provide sufficient potential for hardware to develop identical properties to wetware in the appropriate conditions (such as an appropriately-designed cellular automata space).

3.5.3 Langton's Information Ecology

Langton (1992) and Langton et al. (1989) attempted to justify his views regarding artificial life by proposing a new definition for biological life. Given that natural life depends upon the exchange and modification of genetic information through natural selection, Langton suggests that these dynamics of information exchange are in fact the essential components of life:

> ...in living systems, a dynamics of information has gained control over the dynamics of energy, which determines the behavior of most non- living systems. (Langton 1992, p. 41)

Thus, the comparatively simple thermodynamically regulated behaviours of non-living systems give way to living systems regulated by the dynamics of gene exchange. From this premise, Langton proposes that if this 'information ecology' were accepted as the defining conditions for life, then a computer simulation could conceivably create an information ecology displaying the same properties.

3.6 Toward a Framework for Empirical Alife

3.6.1 A Framework for Empirical Science in AI

If we seek the construction of a theoretical framework to underwrite empirical exploration in Alife, we can gather inspiration from Newell and Simon's seminal lecture (Newell and Simon 1976). The authors sought to establish AI as a potential means for the empirical examination of intelligence and its origins. They argue that computer science is fundamentally an empirical pursuit:

> Computer science is an empirical discipline.... Each new machine that is built is an experiment. Actually constructing the machine poses a question to nature; and we listen for the answer by observing the machine in operation and analyzing it by all analytical and measurement means available. (Newell and Simon 1976, p. 114)

However, the argument that computer science is fundamentally empirical due to its experimental interactions with replicable, physical systems is not sufficient to claim that an AI can be used as a means to study intelligence empirically. Newell and Simon address this by proposing a definition of a physical symbol system, or 'a machine that produces through time an evolving collection of symbol structures' (Newell and Simon 1976, p. 116). The details of the definition and its full import are beyond the scope of this text, but in essence, the authors argue that physical symbol systems are capable of exhibiting 'general intelligent action' (Newell and Simon 1976, p. 116), and further, that studying any generally intelligent system will prove that it is, in fact, a physical symbol system.

Newell and Simon then suggest that physical symbol systems can, by definition, be replicated by a universal computer. This leads us to their famous Physical Symbol System Hypothesis – or PSS Hypothesis – which we can summarise as follows:

1. 'A Physical Symbol System has the necessary and sufficient means for general intelligent action.' (Newell and Simon 1976, p. 116)
2. A computer is capable of replicating a Physical Symbol System.

Thus, by establishing general intelligence as a process of manipulating symbols and symbol expressions, and that computers are capable of replicating and performing identical functions – and indeed are quite good at doing so – Newell and Simon present AI as an empirical study of real, physical systems capable of intelligence. AI researchers are not merely manipulating software for the sake of curiosity, but are developing *real examples* of intelligent systems following the same principles as biological intelligence.

3.6.2 Newell and Simon Lead the Way

Newell and Simon's PSS Hypothesis (Newell and Simon 1976) largely succeeded in providing a framework for AI researchers at the time, and one that continues to be referenced and used today. Such a framework is notably absent in Alife, however, given the difficulties in both defining Alife and in specifying a unified field of Alife, which necessarily spans quite a few methodologies and theoretical backgrounds. With Langton's extension of the fledgling field of Alife into the study of 'life-as-it-could-be,' a more unified theoretical approach seems vital to understanding the relationship between natural and artificial life:

> Artificial life is the study of artificial systems that exhibit behavior characteristic of natural living systems. It is the quest to explain life in any of its possible manifestations, without restriction to the particular examples that have evolved on Earth. This includes biological and chemical experiments, computer simulations, and purely theoretical endeavors. Processes occurring on molecular, social and evolutionary scales are subject to investigation. The ultimate goal is to extract the logical form of living systems. (Langton, announcement of Artificial Life: First International Conference on the Simulation and Synthesis of Living Systems)

By likening Alife to the study of the very nature of living systems, Langton appeals to the apparent flexibility and power of computer simulations. The simulation designer has the opportunity to create artificial worlds that run orders of magnitude faster than our own and watch thousands of generations of evolution pass in a short space of time, and thus seems to provide an unprecedented opportunity to observe the grand machinery of life in a manner that is impossible in traditional biology.

This, in turn, leads to an enticing prospect: can such broad-stroke simulations be used to answer pressing empirical questions about natural living systems? Bedau (1998), for example, sees a role for Alife in a thought experiment originally proposed by Gould (1989). Gould asks what might happen if we were able to rewind evolutionary history to a point preceding the first developments of terrestrial life. If we changed some of those initial conditions, perhaps merely by interfering slightly with the 'primordial soup' of self-replicating molecules, what would we see upon returning to our own time? Gould suggests that while we might very well see organisms much the same as ourselves, there is no reason to assume that this would be the case; we may resume life in our usual time frame to discover that evolutionary history has completely rearranged itself as a result of these manipulations.

For Bedau, this thought experiment presents an opening for Alife to settle a question fundamentally closed to traditional biology. By constructing a suitable simulation which replicates the most important elements of biological life and the evolutionary process, and running through numerous simulations based on variously-perturbed primordial soups, we could observe the resultant artificial organisms and see for ourselves the level of diversity which results.

Other authors have proposed Alife simulations that fall along similar lines (Bonabeau and Theraulaz 1994; Ray 1994; Miller 1995), noting that evolutionary biologists are burdened with a paucity of evidence with which to reconstruct the evolutionary course of life on Earth. The fossil record is notoriously incomplete, and our vanishingly small time on Earth has allowed precious few opportunities to observe even the species which exist around us today. In addition, as Gould's thought experiment highlights, we only have the opportunity to observe those organisms which have evolved on Earth, leaving us entirely uncertain of which properties we observe in that life are particular to life on Earth, and which are particular to life in any form.

Quite obviously such an experiment could be potentially revolutionary, and yet the methodological problems are vast despite the inherent flexibility of computer simulation. How could we possibly confirm that these artificial organisms are Artificial^1 rather than Artificial^2? Given our lack of a definition for biological life, determining whether a digital organism is alive seems a matter of guesswork at best. Further, how detailed must the simulation be to be considered a reasonable facsimile of real-world evolutionary dynamics? Should they select on the level of individuals, or genes, or perhaps even artificial molecules of some sort? If by some measure we determine the simulation to be Artificial^2 rather than Artificial^1, can we truly claim that this simulation in any way represents the development of natural living systems, or is it merely a fanciful exploration of poorly-understood evolutionary dynamics?

3.6.3 Theory-Dependence in Empirical Science

Beyond these methodological considerations, some troubling philosophical issues appear when considering such large-scale applications of the Alife approach. Some have argued that Alife simulations should not, and in fact cannot, be considered useful sources of empirical data given that they are loaded with inherent biases from their creators (Di Paolo et al. 2000). Simulations must necessarily adopt varying levels of abstraction in order to produce simulations which are both computable and analysable; after all, simulations which replicate the complexities of real biology in exacting detail would gain the experimenter very little time-saving and eliminate one of the major benefits of computational modelling. These abstractions are tacitly influenced by the experimenter's own biases, relying upon the simulation creator's perception of which aspects of the biological system can be simplified or even removed from the simulation entirely. Similarly, the parameter settings for that simulation will come with their own biases, resulting in simulations which could produce vastly different results depending on the theoretical leanings of the programmer.

While one might claim that conventional empirical science suffers from very similar shortfalls, Chalmers points out that biases within such fields must necessarily end when the results of an experiment contradict those biases:

> …however informed by theory an experiment is, there is a strong sense in which the results of an experiment are determined by the world and not by theories… we cannot make [the] outcomes conform to our theories. (Chalmers 1999, p. 39–40)

In the case of computer simulations this conclusion seems more difficult. After all, we are in essence adding an additional layer – in addition to the two layers of the physical world and the theory that describes it, we now have a model layer as well, which approximates the world as described by our theory. Clearly this adds additional complications: when not only the experiment but the very world in which that experiment takes place are designed by that biased experimenter, how can one be sure that pre-existing theoretical biases have not completely contaminated the simulation in question?

To return to our central bird migration example, one can imagine various ways in which our migration researcher could introduce theoretical bias into the simulation. That researcher's ideas regarding the progression of bird migration, the importance of individual behaviours or environmental factors in migration, and other pre-existing theoretical frameworks in use by the researcher will inform the assumptions made during construction of the model. In such a scenario, removing such biases is difficult for the modeller, as on some level the model requires certain assumptions to function; the researcher needs to develop a theoretical framework in which this artificial data remains usable despite these issues.

3.6.4 *Artificial Data in Empirical Science*

An examination of more orthodox methods in empirical science may shed some light on how some methodologies use artificially-generated data to answer empirical questions. While these methods are more based in the natural world than an Alife simulation, they still rely upon creating a sort of artificial world in which to examine specific elements of a process or phenomenon.

Despite the artificiality of this generated data, such disciplines have achieved a high degree of acceptance amongst the research community. A brief look at some examples of the use of such data in empirical research will provide some insight into possible means for using artificial data derived from simulation.

3.6.4.1 Trans-Cranial Magnetic Stimulation

Research into brain function often employs patients who have suffered brain damage through strokes or head injuries. Brains are examined to determine which areas are damaged, and associations between these damaged areas and the functional deficits exhibited by the patients are postulated. The technique of trans-cranial magnetic stimulation, known as TCMS or TMS, has allowed psychology researchers to extend the scope of this approach by generating temporary artificial strokes in otherwise healthy individuals.

TMS machinery produces this effect through a set of electrodes which are placed on the outside of the subject's skull. The researcher first maps the subject's brain using an MRI scan, and then begins using the TMS apparatus to fire brief magnetic pulses at the surface of the brain. These pulses in effect overstimulate the affected neurons, causing small areas of the brain to 'short-circuit,' which replicates the effects of certain types of brain injury. TMS researchers have managed to replicate the effects of certain types of seizure (Fujiki and Steward 1997), and have examined the effects of stimulation of the occipital cortex in patients with early-onset blindness (Kujala et al. 2000). TMS has even produced anomalous emotional responses; after inhibition of the prefrontal cortex via TMS, visual stimuli that might normally trigger a negative response were much more likely to cause a positive response (Padberg 2001).

Such methods provide a way for neuroscientists and psychologists to circumvent the lack of sufficient data from lesion studies. Much of cognitive neuropsychology suffers from this paucity of raw data, forcing researchers to spend inordinate amounts of time searching through lengthy hospital records and medical journals for patients suffering from potentially appropriate brain injuries. Even when such subjects are found, normal hospital testing may not have revealed the true nature of the subject's injury, meaning that potentially valuable subjects go unnoticed as some finely differentiated neurological deficits are unlikely to be discovered by hospital staff. Assuming that all of these mitigating factors are bypassed, the researcher is still faced with a vanishingly small subject pool which may adversely affect the generalisability of their conclusions.

TMS thus seems a remarkable innovation, one which suddenly widens the potential pool of subjects for cognitive neuropsychology to such a degree that any human being may become a viable subject regardless of the presence or lack of brain injury. However, there are a number of shortcomings to TMS which could cause one to question the validity of associated results. The inhibition of neural activity produced by TMS causes neurons to explode into such activity that normal firing patterns become impossible; while this certainly effectively disrupts activity in the brain area underneath the pulse, TMS is not necessarily capable of replicating the many and varied ways in which brain injuries may damage the neural tissue. Similarly, the electromagnetic pulse used to cause this inhibition of activity is only intended to affect brain areas which are near to the skull surface; the pulse does penetrate beyond those areas, but the effects of this excess inhibition are not fully understood. Despite these shortcomings, and the numerous areas in which standard examinations of brain-injury patients are superior, TMS has continued to become a rapidly-growing area of research in cognitive neuropsychology.

The data derived from TMS is strongly theory-dependent in nature, in a similar fashion to computer simulation. In order to use this data as a reasonable method of answering empirical questions requires that TMS researchers adopt a theoretical 'backstory.' This backstory is a framework that categorises TMS data and lesion data together as examples of 'real' brain-damage data. Despite the fact that TMS brain damage is generated artificially, it is deemed admissible as 'real' data as long as neuroscientists consider this data Artificial^1 rather than Artificial^2 in classification.

3.6.4.2 Neuroscience Studies of Rats

Studies of rats have long been common within the field of neuroscience, given the complex methodological and ethical difficulties involved in studying the human brain. Though such studies allow much greater flexibility due to their more uncontroversial participants, certain fundamental limitations still prohibit certain techniques; while ideally, researchers would prefer to take non-invasive, in situ recordings of the neural activity of normal, free-living rats, such recordings are well beyond the current state of the art.

Instead, neuroscientists must settle for studies of artificially prepared rat brains or portions thereof; such a technique would be useful if the researcher wishes to determine the activity of specific neural pathways given a predetermined stimulus, for example. One study of the GABA-containing neurons within the medial geniculate body of the rat brain required that the rats in question were anaesthetised and dissected, with slices of the brain then prepared and stimulated directly (Peruzzi et al. 1997). Through this preparatory process, the researchers hoped to determine the arrangement of neural connections within the rat's main auditory pathway, and by extension gain some insight into the possible arrangement of the analogous pathway in humans.

Given how commonplace such techniques have become within modern neuroscience, most researchers in that community would not question the empirical validity of this type of procedure; further, the inherent difficulties involved in attempting to identify such neural pathways within a living brain makes such procedures the only known viable way to take such measurements. However, one might argue that the behaviour of cortical cells in such a preserved culture, entirely separate from the original brain, would certainly differ significantly from the behaviour of those same cells when functioning in their usual context. The entire brain would provide various types of stimulus to the area of cortex under study, with these stimuli in turn varying in response to both the external environment and the rat's own cognitive behaviour.

With modern robotics and studies of adaptive behaviour focusing so strongly upon such notions of embodiment and situatedness, the prevailing wisdom within those fields holds that an organism's coupling to its external environment is fundamental to that organism's cognition and behaviour (Brooks 1991). In that case, neuroscience studies of this sort might very well be accused of generating and recording 'artificial' neural data, producing datasets that differ fundamentally from the real behaviour of such neurons. How then do neuroscientists apply such data to the behaviour of real rats, and in turn to humans and other higher mammals?

In fact, research of this type proceeds on the assumption that such isolation of these cortical slices from normal cognitive activity actually increases the experimental validity of the study. By removing the neurons from their natural environment, the effects of external stimuli can be eliminated, meaning that the experimenters have total control over the stimulus provided to those neurons. In addition, the chemical and electrical responses of each neuron to those precise stimuli can be measured precisely, and the influence of experimenter error can be minimised.

With respect to the artificiality introduced into the study by using such means, neuroscience as a whole appears to have reached a consensus. Though removing these cortical slices from the rat is likely to fundamentally change the behaviour of those neurons as compared to their normal activation patterns, the individual behaviour of each neuron can be measured with much greater precision in this way; thus, the cortical slicing procedure can be viewed as Artificial^1, as the individual neurons are behaving precisely as they should, despite the overall change in the behaviour of that cortical slice when isolated from its natural context. Given the (perhaps tacit) agreement that these methods are Artificial^1 in nature, the data from such studies can be agreed to consist of 'real' neuroscience data.

3.6.5 Artificial Data and the 'Backstory'

The two examples above drawn from empirical science demonstrate that even commonplace tools from relatively orthodox fields are nevertheless theory-dependent in their application, and further that such dependence is not necessarily immediately obvious or straightforward. The tacit assumptions underlying the use of TMS and rat studies in neuroscience are not formalised, but they do provide a working hypothesis which allows for the use of data derived from these methods as 'real' empirical data. The lack of a conclusive framework showing the validity of these techniques does not exclude them from use in the research community.

This is of course welcome news for the strong Alife community, given that a tangible and formal definition of what constitutes a living system is quite far from being completed. However, strong Alife also lacks this tacit 'backstory' that is evident in the described empirical methods; without this backstory those methods may fall afoul of the Artificial^1/Artificial^2 distinction. With this in mind, how might the Alife community describe a similar backstory which underwrites this research methodology as a valid method for producing new empirical datasets?

The examples of TMS and rat neuroscience offer one possibility. In each of those cases, the investigative procedure begins with an uncontroversial example of the class of system under investigation (i.e., in the case of TMS, a human brain). This system is then prepared in some way in order to become more amenable to a particular brand of investigation; rat neuroscientists, by slicing and treating the cortical tissue, allow themselves much greater access to the functioning of individual neurons. In order to justify these modifications to the original system, these preparatory procedures must be seen as neutral in that they will not distort the resulting data to such a degree that the data becomes worthless. Indeed, in both TMS and rat neuroscience, the research community might argue that these preparatory procedures actually reduce some fairly significant limitations placed upon them by other empirical methodologies.

At first blush such a theoretical framework seems reasonable for Alife. After all, other forms of 'artificial life' such as clones or recombinant bacteria begin with such an uncontroversial living system and 'prepares' it while still producing a result universally accepted to be another living system. However, this does fall substantially short of one of the central goals of strong artificial life, as these systems certainly produce augmented datasets regarding the living systems involved, but they do not generate entirely novel datasets. While recombinant bacteria and mutated Drosophila may illuminate elements of those particular species that we may have been unable to uncover otherwise, the investigation of 'life-as-it-could-be' remains untouched by these efforts.

In addition to these shortcomings, the preparatory procedures involved in a standard Alife simulation are quite far removed from those we see in standard biology (or the neuroscience examples discussed earlier). These simulated systems exist entirely in the digital realm, completely removed from the biological substrate of living systems; though many of these simulated systems may be based upon the form or behaviour of natural living systems, those systems remain separate from their simulated counterparts.

Further, this computer simulation is 'prepared' in this digital substrate through a process of programming to produce this artificial system. Programming is inherently a highly variable process, the practice of which differs enormously from one practitioner to the next, in contrast to the highly standardised procedures of neuroscience and biology. The result of these preparations is to make the system amenable to creating life, rather than simply taking a previously-existing system and making it more amenable to a particular type of empirical observation. While characterising this extensive preparatory process as benign, as in neuroscience and biology, would be immensely appealing to the Alife community, the argument that preparing a computer and somehow creating life upon its digital substrate is a benign preparatory procedure is a difficult one to make.

3.6.6 Silverman and Bullock's Framework: A PSS Hypothesis for Life

Thus, while we have seen that even orthodox empirical science can be considered strongly theory-dependent, the gap between natural living systems and Alife systems remains intimidatingly wide. From this perspective, characterising Alife as a useful window onto 'life-as-it-could-be' is far from easy; in fact, Alife appears dangerously close to being a quintessentially Artificial^2 enterprise.

Newell and Simon's seminal paper regarding the Physical Symbol System Hypothesis offers a possible answer to this dilemma (Newell and Simon 1976). Faced with a similar separation between the real system of interest (the intelligence displayed by the human brain) and their own attempt to replicate it digitally, the PSS Hypothesis offered a means of justifying their field. By establishing a framework under which their computers offer the 'necessary and sufficient means' for intelligent action, Newell and Simon also establish that any computer is only a short (albeit immensely complicated) step away from becoming an example of real, Artificial^1 intelligence.

The PSS Hypothesis also escapes from a potential theoretical conundrum by avoiding discussion of any perceived similarities between the behaviour of AI systems and natural intelligence. Instead Newell and Simon attempt to provide a base-level equivalence between computation and intelligence, arguing that the fundamental symbol-processing abilities displayed by natural intelligence are replicable in any symbol-processing system of sufficient capability. This neatly avoids the shaky ground of equating AI systems to human brains by instead equating intelligence to a form of computation; in this context, the idea that computers can produce a form of intelligence follows naturally.

With this in mind, we return to Langton's concept of the information ecology (1992). If we accept the premise that living systems have this ecology of information as their basis, then can we also argue that information-processing machines may also lead to the development of living systems? Following Newell and Simon's lead, Silverman and Bullock (2004) offer a PSS Hypothesis for life:

1. An information ecology provides the necessary and sufficient conditions for life.
2. A suitably-programmed computer is an example of an information ecology. (Silverman and Bullock 2004, p. 5)

Thus, assuming that the computer in question was appropriately programmed to take advantage of this property, then an Alife simulation could be regarded as a true living system, rather than an Artificial^2 imitation of life. As in Newell and Simon, the computer becomes a system that is a sort of blank slate, needing only the appropriate programming to become a repository for digital life.

This PSS Hypothesis handily removes the gap between the living systems which provide the inspiration for Alife and the systems produced by an Alife simulation. Given that computers inherently provide an information ecology, an Alife simulation can harness that property to create a living system within that computer. Strong Alife then becomes a means for producing entirely new datasets derived from genuine digital lifeforms rather than simply a method for creating behaviours that are reminiscent of natural life.

3.6.7 The Importance of Backstory for the Modeller

As discussed in earlier sections about examples of the theoretical backstory in empirical disciplines, the presence of such a backstory allows the experimenter to justify the usefulness of serious alterations to the system under study. In the case of rat neuroscience and TMS research, their back-stories allow them to describe the changes and preparations they make to their subjects as necessary means for data collection.

In the case of Alife, such a claim is difficult to make, as noted previously, given that the simulation is creating data rather than collecting it from a pre-existing source as is the case in our empirical examples. The PSS Hypothesis for Life avoids this difficulty by stating that any given computer hardware substrate forms the necessary raw material for life; in a sense, our simulation is merely activating this potential to create an information ecology, and then collecting data from the result. Thus, we may say that our programming of the simulation has prepared this digital substrate for empirical data-collection in a manner similar to that of empirical studies.

Of course, such a backstory is significant in scope, and could invite further criticism. However, such a statement is difficult to refute, given the unsophisticated nature of our current definitions for biological life, and a lack of agreement on whether life may exist in other substrates. Either way, the importance for the modeller is that such a simulation takes on a different character. The focus of such a theoretical justification is on implementing a model which produces some empirical data collection that may bear on our overall understanding of life, not on simply tweaking an interesting computational system to probe the results. The PSS Hypothesis for Life gives us some basis on which to state that this view of Alife models has some theoretical validity.

3.6.8 Where to Go from Here

Now that we have produced a theoretical backstory which underwrites Alife research as a means for generating new empirical data points, what is missing? The PSS Hypothesis for Life allows us to pursue simulations of this type as a means for understanding life as a new form of biology, investigating the properties and behaviours of entirely novel organisms. One can imagine how such endeavours could provide interesting insight for those interested in the broader questions of what makes something alive.

However, none of this allows us to provide any direct relevance in our results in Alife to the biological sciences. The biologist who views our bird migration model, justified as an information ecology under the PSS Hypothesis for Life, as interesting, but irrelevant to the concerns of the empirical ornithologist. Indeed, if our simulation is producing merely a bird-like manifestation of digital life, then we have no basis on which to state that what we see in our results can tell us anything about real birds, completely removed from the virtual information ecology we have implemented.

This issue becomes the focus of the next chapter, the final chapter of Part I. How might we apply Alife modelling techniques and agent-based models to the broader canvas of biological science? An in-depth discussion of methodological and theoretical issues related to modelling in population biology will provide us with the context necessary to begin to answer this question. The concerns of the strong Alife modeller as depicted in this chapter differ in several important respects to those of a modeller with a weak Alife orientation, and those concerns focus largely on creating a relationship to external empirical data rather than creating their own empirical data as the PSS Hypothesis for Life describes.

3.7 Summary and Conclusions

ALife by its very nature is a field which depends upon the use and acceptance of artificially-generated data to investigate aspects of living systems. While some members of this research community have posited that artificial systems can be alive in a manner identical to biological life, there are numerous philosophical and methodological concerns inherent in such a viewpoint.

The comparison with artificial intelligence laid out in this chapter illustrates some of the particular methodological difficulties apparent in ALife. ALife seeks to replicate properties of life which are heavily dependent on the biological substrate, in contrast with AI, which seeks to emulate higher-level properties of living organisms which seem more easily replicable outside of the biological realm.

AI does not entirely escape the problem of artificiality in its data and methods however, nor for that matter does conventional empirical science. Some disciplines are able to make use of a great deal of artificial data by tying it to a theoretical 'backstory' of a sort. ALife up to now has lacked this backstory, while AI has Newell and Simon's PSS Hypothesis (Newell and Simon 1976) as one example of such a theoretical endeavour.

Silverman and Bullock (2004) used Newell and Simon's account as an inspiration for a PSS Hypothesis for life, a framework which could be used to underwrite strong ALife as a form of empirical endeavour. By accepting that life is a form of information ecology which does not depend exclusively on a biological substrate, a researcher signing up to this backstory may argue for the use of strong ALife data as a form of empirical data. Initially such an idea is appealing; after all, the strong ALife proponent seeks to create forms of 'life-as-it-could-be' in a digital space, and this variant of the PSS Hypothesis describes such instances of digital life as a natural consequence of life itself being an information ecology.

However, this framework does not account for the more pragmatic methodological concerns which affect modelling endeavours of this type, and in fact modelling in general. Constructing a computational model requires a great deal more than a useful theoretical justification to function appropriately and provide useful data. As one example, accepting ALife simulations as a form of empirical enquiry does not simplify the task of relating that data to similar data derived from entirely natural systems. As exciting as the prospect of digital life may be, creating self-contained digital ecosystems which are unrelatable to natural ecosystems seems of limited utility for the biologist. Such issues, examined in the context of mathematical models in population biology in the following chapter, will provide greater insight into these crucial elements of our growing theoretical framework for simulation research. This framework can then be expanded to bear on our upcoming discussion of simulation for the social sciences in the second overall section of this text.

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Part II
Modelling Social Systems

The advent of Alife lead to a period of great excitement, as the power and flexibility of simulation suggested whole new ways to study the processes of biology. So too with social simulation, a relatively recent development in the social sciences in which simulation methods – most commonly agent-based models – are used to model social systems and their behaviours. The prospect of using simulation to model the emergence of population-level effects from individual social interactions at the agent level.

In Part II we will investigate social simulation as a methodology, uncovering both the strengths and weaknesses of this approach for revealing the processes underlying human society and its evolution. We will examine the complex relationships between social simulations, real-world population data, and social theory. We will also expand the methodological analysis begun in Part I and discover how the modelling frameworks we studied may be applied to social simulation, and how they compare to similar frameworks developed by social modellers and theorists themselves.

In order to examine these frameworks and their potential utility for social simulation, we will take inspiration from the early days of the field. The beginning of social simulation is frequently credited to Thomas Schelling and his residential segregation model, an elegantly simple investigation of how even minor preferences amongst individuals for living near to others similar to themselves can lead to residential segregation emerging at the population level. We will use Schelling's model to compare the methodological frameworks uncovered through Parts I and II, and use the insights gained to propose a way forward for social simulation as a whole.

Chapter 5
Modelling for the Social Sciences

Eric Silverman and John Bryden

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

E. Silverman, *Methodological Investigations in Agent-Based Modelling*,
Methodos Series 13, https://doi.org/10.1007/978-3-319-72408-9_5

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 Luhman'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 easer, 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 Kluver 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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Chapter 6
Analysis: Frameworks and Theories for Social Simulation

6.1 Overview

The previous chapter focused upon the current methodologies and theoretical implications of agent-based modelling in the social sciences. While many within this growing field accept that agent-based models provide a potentially powerful new method for examining social behaviours and structures, a great debate still continues over the best methods for utilising the strengths of this methodology.

As seen in Part I, such debates are not unique to social simulation. Indeed, artificial life and more conventional forms of biological modelling have faced similar challenges over the past few decades. With this in mind, this chapter begins by placing artificial life within the various theoretical frameworks discussed thus far in Chaps. 3, 4 and 5. In this way the limitations of each framework can be illuminated.

Social science simulation using agent-based models shares a number of constraints and methodological difficulties with biological modelling using the same methodology. Thus, having placed artificial life and biological models within a theoretical framework, social simulation will be subjected to a similar analysis. Finding the most appropriate framework for social simulation will lay the groundwork for Chap. 7, in which one of the more prominent exemplars of social simulation will be subjected to theoretical and methodological analysis. Chapter 7 lays the foundation for the conclusions of Part II, in which our analysis of Schelling's residential segregation model will provide a means to demonstrate the most important elements of a useful modelling framework for the social sciences.

E. Silverman, *Methodological Investigations in Agent-Based Modelling*,
Methodos Series 13, https://doi.org/10.1007/978-3-319-72408-9_6

6.2 Frameworks and ALife: Strong ALife

6.2.1 Strong ALife and the Lack of 'Real' Data

As noted by critics of artificial life, social simulation and related methodologies, computational simulations suffer from a perceived lack of 'real' data, or data derived from experimental observation. Part of this inherent difficulty stems from the need for abstraction in many such models; for example, connectionist models of cognitive processes embrace the idea of 'distributed representation' and their potential role in cognition, while generally avoiding integrating those models into larger, more complex neural structures as seen in the brain (Rumelhart and McClelland 1986).

Strong ALife simulations suffer even more strongly from this shortcoming. Ray's Tierra provides an enticing look at a 'digital ecology' composed of evolving computer programmes competing for memory space (Ray 1996), but those creatures are purely artificial constructions. While the parasites and hyper-parasites which eventually evolve in Tierra's world may provide an analogue to real-life parasitic behaviour, the specialised nature of their virtual world is such that analyses of Tierra would be very difficult to apply to the natural world. Ray might argue that his open-ended evolutionary system, which lacks the standard fitness function of many genetic algorithms and instead provides selection only through life and death, evokes real-world interactions in evolving systems. Does the difficulty of verifying such claims confine analyses of Tierra to the realm of mathematical curiosity?

6.2.2 Artificial[1] vs Artificial[2]: Avoiding the Distinction

As noted in Silverman and Bullock's description of differing varieties of artificiality in science (Silverman and Bullock 2004), providing a distinction between man-made instances of natural systems and man-made facsimiles of natural systems is important to understanding the goals of a simulation. In the case of strong ALife, researchers aim to produce models that embody Artificial[1], or a man-made instance of something natural; these models claim to create digital life, rather than simply resemble biological life. In this case, the strong ALife researcher falls into the role of a sort of digital ecologist, studying the behaviour and function of real, albeit digital, organisms. Of course, such claims seem remarkable, but in the absence of a complete and verifiable definition of life such claims are difficult to refute.

6.2.3 Information Ecologies: The Importance of Back-stories

The inclination of the strong ALife researcher to study 'real' digital organisms points to the importance of formulating a theoretical backstory for any given simulation model. As per Silverman and Bullock's PSS Hypothesis for Life, presuming that:

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 the strong ALife researcher may claim, under such a framework, that their simulation represents an information ecology, and thus is a digital instantiation of a biological system. Whether or not the low-level functions of that system match those of real-life, carbon-based biological systems is immaterial; the only criterion is the presence of an ecology of information in which genetic material competes for representation, and under this criterion the position stated here is justifiable.

To use our central example, if we construct a bird migration model in Alife fashion using individual interacting agents, we may wish to demonstrate that we are in fact performing some form of empirical data collection, rather than simply investigating an interesting mathematical system. So, we claim in this case that are simulated birds do in fact demonstrate an information ecology; perhaps our agents evolve and reproduce, this producing a dynamic of information amongst the agent population. If we follow Langton, and are willing to class ourselves in the strong Alife camp, then signing up to the PSS Hypothesis for Life may be a good course of action for us to take. In that case, our bird model becomes a true information ecology, and thus presents an opportunity for empirical data-collection in this virtual population of birds.

6.3 Frameworks and ALife: Weak ALife

6.3.1 *Artificial^1 vs. Artificial^2: Embracing the Distinction*

In contrast to strong ALife, weak ALife faces some initially more daunting theoretical prospects. This seems somewhat paradoxical; after all, the strong ALife researcher seeks to equate digital organisms with natural organisms, whereas the weak ALife researcher seeks only the replication of certain properties of natural life. However, while the strong ALife researcher may justify their investigations into a digital ecology by signing up to an appropriate theoretical backstory, however far-fetched, proving the relation between a natural system under investigation and a computational model based on that system is a more difficult problem and requires more in-depth justifications.

Returning to our central example, recall our researcher who wishes to model the flocking behaviour of migrating birds. While a great deal of experimental data exists upon which one can base such a computational study, the researcher must choose which elements of that data provide a useful background for the simulation and which do not. Data about bird migration varies greatly across different species and climates, and the researcher must identify the most salient forms of collected data to use as a basis for the model. These choices will in turn inform the construction of the model, and the related points of theory regarding migration that must be incorporated into that model.

As Chalmers suggests (Chalmers 1999), these abstractions reveal the inherent theory-dependence of artificial life as an enterprise; the researcher's choice of abstractions may conform to their specific theoretical biases. In order to make these choices effectively, and to draw a strong correlation between the digital system and the natural system, one must find a framework which embraces the inherently artificial nature of such simulations and uses the advantages of the digital medium effectively to draw useful experimental conclusions.

6.3.2 Integration of Real Data: Case Studies

6.3.3 Backstory: Allowing the Artificial

The integration of a suitable theoretical backstory into weak ALife research seems a more difficult task than for strong ALife. As Bryan Keeley describes, weak ALife can only hope to be functionally related to natural life, producing behaviours that are analogous to those displayed in biology (Keeley 1997). However, establishing a clear relationship to a natural system is not always straightforward, particularly when the artificial system under consideration bears less resemblance to the fundamental make-up of the natural world.

For some researchers and theorists, these artificial worlds present a tantalising opportunity to examine characteristic evolutionary behaviours in a simplified environment, one amenable to study; given that natural evolution is far more difficult to observe than an abstracted evolutionary algorithm, this naturally seems an attractive prospect for those who wish to observe evolution in action. Ray (1994, 1996) goes so far as to assert that digital forms of evolution can produce the same diversity of forms that we observe as a result of natural evolution (though perhaps given his statements regarding Tierra as a whole, this position is, for him, milder than most).

Unfortunately for Ray, while Tierra does display an impressive variety of self-reproducing digital entities that display unexpected behaviour, the simulation tends to get caught in an eventual evolutionary cycle in which certain forms repeat. This contrasts strongly with real-world evolutionary behaviour, in which the general level of complexity in evolving populations tends to continue to increase over time. Similarly, Avida and other simulation environments developed by the ALife community suffer the same problem, preventing the community from replicating the sort of staggering diversity seen in nature (Adami and Brown 1994). Bearing this in mind, can the researcher be certain that these artificial evolutionary systems are truly functionally related to natural evolutionary systems? Given that the overall processes of evolution are still under constant debate and revision, and the innate difficulty of providing appropriate selection pressures in an artificial environment, how much do these systems coincide on a 'given level of abstraction' (Keeley 1997).

In cases such as this, one must be careful in defining a theoretical backstory linking the natural system to the artificial. A clear statement of the mechanisms at work in the simulation and how they relate to similar theorised mechanisms in natural evolution seems most helpful; given that there is no fundamental metric to determine just how abstracted a given model is when compared to reality, a clear statement of assumptions made and potential confounds in the simulation (i.e., difficulties in fitness functions and similar issues) could be helpful in attempting to link the simulation results to empirical results.

In the case of our bird example, such a backstory would need to include information about the assumptions made when constructing our simulation. We would have to describe the real-world instances of bird behaviour that we are trying to replicate, and how these real-world instances have influenced our implementation of the model. Where simplifications have been made, i.e. by simplifying the structure of the agents to facilitate computability and simplicity of analysis, we would need to note this fact and mention how these simplifications may change the character of the behaviour observed in the simulation. In the ideal situation, someone reading a paper describing our bird model should be made aware of the shortcomings of the simulation, where it attempts to reproduce real-world bird behaviour and physiology, and where it makes abstractions for the purposes of making the simulation tractable.

6.4 The Legacy of Levins

6.4.1 The 3 Types: A Useful Hierarchy?

As discussed at length in Chap. 4, the Levinsian framework for modelling in population biology appears generally useful for ALife modelling endeavours. After all, Levins seemed intent upon creating a pragmatic framework for constructing biological models, and since ALife often falls within that remit his ideas remain relevant. However, the extended framework developed from Levins in Chap. 4 seems perhaps more useful within the context of artificial life.

With Braitenberg's Law in mind, the concept of a tractability ceiling placed on ALife seems appropriate, if vexing. With ALife systems spanning an enormous variety of biological phenomena, often incorporating versions of vast and complex biological mechanisms such as evolution, the question of analysis becomes of paramount importance. While we may comfortably classify ALife models within Levins' three types with relatively little difficulty, we remain uncertain how analysable those models will prove to be with only that classification in mind.

6.4.2 Constraints of the Fourth Factor

Indeed, the fourth Levinsian factor appears to place some serious limitations upon ALife systems. As noted in Chap. 3, such systems frequently fall into the Type 3 category, oriented as they are toward producing broad-stroke investigations of generalised populations. Applying those results toward real populations becomes increasingly problematic as tractability concerns become important; without reasonable analysis of the data produced by these simulations, the researcher will have great difficulty applying that data to any understanding of a natural biological system. In essence, even with carefully-designed simulation models, this tractability ceiling prevents highly complex simulations from being productive of great insight.

Thus, our Alife-type bird migration model may run into difficulties if we incorporate too many real-world complexities. If we use agents with neural network controllers, for example, then such networks are very difficult to analyse (recall Beer 2003a,b). As modellers we must judge whether the use of such components in the simulation is justified given the increase of complexity and analytical difficulty. The more we incorporate added elements in an attempt to capture real-world complexity, the more we approach the tractability ceiling.

Even assuming that our model manages to balance Levins' three types appropriately while maintaining a reasonable level of tractability, significant problems still remain. With Braitenberg's Law in mind, agent-based models in general suffer a greater disconnect between invention and analysis than other modelling methodologies, leading to a greater chance of producing impenetrably opaque simulations.

If we then apply agent-based methodologies to the field of social science, in which there are already significant difficulties in constructing models based upon strongly empirical social data, then these problems become increasingly acute. Bearing in mind these discussions of theoretical frameworks in relation to ALife and agent-based models in general, we shall examine how these same frameworks impact upon the agent-based social simulations detailed in the previous chapter.

6.5 Frameworks and Social Science

6.5.1 Artificial^1 vs. Artificial^2: A Useful Distinction?

ALife research focuses on living systems and their governing processes, and as such relies upon definitions and theories of life as a basis for enquiry. Life being difficult to define empirically, strong ALife can, as illustrated earlier, attempt to demonstrate a digital instantiation of life itself when life is defined appropriately within the context of that research. However, when expanding beyond processes relating to simple organisms and populations and attempting to model social structures and processes, additional layers of complexity come into focus. Epstein (1999) provides a comparison to the famous 'Boids' model of flocking behaviour:

> Generating collective behaviour that to the naked eye "looks like flocking" can be extremely valuable, but it is a radically different enterprise from generating, say, a specific distribution of wealth with parameters close to those observed in society. Crude qualitative caricature is a perfectly reasonable goal. But if that is one's goal, the fact must be stated explicitly.... This will avert needless resistance from other fields where "normal science" proceeds under established standards patently not met by cartoon "boid" flocks, however stimulating and pedagogically valuable these may be. (p. 52–53)

In essence, Epstein presents a position reminiscent of our earlier discussion of Braitenberg: imitation of a system with a model, as in mimicking the behaviour of flocking birds, is far simpler than creating a model system which can generate that behaviour. Further, such models can confuse the research landscape, perhaps claiming to produce more insight than they are fundamentally capable of providing. In such cases a model which seeks this sort of qualitative similarity is not constructed in such a way as to allow any insight into the root causes of that complex behaviour. Epstein implies later in his discussion that in the case of social science, which involves interacting layers of actors in a society, this problem becomes more acute for the computational modeller.

In such a context, any argument for 'strong social-science simulation' seems difficult to justify; in order to accept that a given social model is a digital instantiation of a social system, one would have to accept that the agents have sufficient complexity to interact with one another, generate a social structure, and react and respond to that structure in an appropriately non-trivial manner. There is a significant danger, as noted by Epstein, of a model of a complex social system falling within the realm of a 'crude qualitative caricature.' Social science then may be said to lie within the domain of Artificial^2: something made to resemble something else.

Fortunately, our examination of Luhmann has revealed the problematic nature of building an Artificial^1 social simulation. With our search for a fundamental social theory relying upon developing a new means for hypothesis-testing and social explanation, creating instantiations of 'digital society' is rather less than useful. Thus, while remaining within the domain of Artificial^2 may seem initially limiting, in fact the social simulator is likely to find it of far greater utility than the alternative.

6.5.2 Levins: Still Useful for Social Scientists?

As demonstrated earlier in this chapter, Levins' framework for modelling in population biology is remarkably applicable to today's more modern computational methodologies. Our updated Levinsian framework developed in Chap. 4 and its consideration of tractability presents an account of a concern common to most varieties of computational models: efficient utilisation of computing resources relies on a relatively tractable and analysable problem. However, when considering the application of such a framework to social simulation, some differing concerns come to light.

As Gilbert and Tierna note (Gilbert and Terna 2000), emergent phenomena in social science reflects a certain additional complexity in comparison to the natural sciences:

> In the physical world, macro-level phenomena, built up from the behaviour of micro-level components, generally themselves affect the components. . . . The same is true in the social world, where an institution such as government self-evidently affects the lives of individuals. The complication in the social world is that individuals can recognise, reason about and react to the institutions that their actions have created. Understanding this feature of human society, variously known as second-order emergence Gilbert (1995), reflexivity Woolgar (1988) and the double hermeneutic, is an area where computational modelling shows promise. (p. 5)

Thus, Gilbert and Tierna contend that agent-based models can capture this emergent phenomena more vividly than other methodologies which, while providing potentially strong and useful predictions of a macro-level system's behaviour, do not provide an explanation of that behaviour in terms of its component parts. Epstein (1999) takes this statement further, arguing that in certain contexts, successful mathematical models may be 'devoid of explanatory power despite [their] descriptive accuracy' (p. 51). Epstein goes on, however, to acknowledge the difficulties inherent in creating an artificial society with sufficient 'generative power, proposing the use of evolutionary methods to find the rule-sets most amenable to complex emergent behaviour in a given simulation.

Levins' framework, which depends upon tractability as a key concern for the modeller, may at first blush seem insufficient to deal with the methodological complexities inherent in the simulation of social structures. After all, the researcher is dealing with multiple interacting layers of complexity, with some of these emergent behaviours relying upon not just reactions to a changing environment, as in an artificial life simulation, but a cognitive reaction to that environment, which can then influence both that agent and others within that artificial society. With such high-level abstractions taking place in these simulations, how might one quantify the realism, generality and precision of a social model?

To clarify, imagine that we have designed and implemented an agent-based model of our migrating bird population. Each agent is capable of moving through a simulated spatial environment, reproducing, and thus evolving through simulated generations. Now, in an effort to capture the social effects at play within a bird colony upon arrival at its destination, we allow each agent to communicate and exchange information with its compatriots. In order to capture this we suddenly need to add all sorts of new elements to our implementation: a means of encoding commuication between individuals, means for choosing the method and frequency of those communications, and deciding how these interactions will affect the agent, its communication partners, and the surrounding environment. How can we capture such effects? How might we model the birds' communications, and how they affect the simulation as a whole? Already we have introduced a number of new factors into the model for which there is little hard empirical information to guide our implementation of these factors. If we cannot identify the level of realism of these new components of the simulation, how is it possible to clarify the position of our new model amongst Levins' four dimensions of model-building?

In essence, without a solid set of criteria identifying the realism of simulated social behaviours and cognition, one becomes reliant on qualitative judgements to decide the validity of a social simulation; in other words, the researcher must determine that the behaviour of that artificial society sufficiently resembles the behaviour of a real society to call it a successful result. Perhaps then social simulations begin skewed away from realism, and further toward generality and precision than other simulation varieties. With realism so difficult to define in a social context, and with the necessary abstractions for social simulation so wide-ranging, the researcher seems best served by striving to provide examples of possible mechanisms for an emergent social behaviour based upon a very general picture of agent-based interactions and communications. Definitive statements regarding which of these mechanisms are responsible for a given social phenomenon may be impossible, but the model could provide a means for illuminating the possible role of some mechanisms in the formation and behaviour of social structures (this being one of Epstein's suggested roles for simulation in 'generative social science').

6.5.3 Cederman's 3 Types: Restating the Problem

If Levins' framework is insufficient to capture some of the methodological complexities particular to modelling for the social sciences, perhaps this framework could be usefully informed by Cederman's own framework of C1, C2 and C3 political models (see Table 5.1). With some examination of this framework, we may be able to draw useful parallels between these three types and those described by Levins.

Cederman's C1 models focus on modelling the behavioural aspects of social systems, or the emergence of general characteristics of certain social systems in a computational context. He cites Axelrod's Complexity of Cooperation as a major foray into this type of modelling, as well as Schelling's residential segregation model (Cederman 2001). This type of model seems related to Levins' L3 models, which sacrifice precision for realism and generality; Cederman's C1 models do not attempt to link with empirical data, but instead seek to demonstrate the emergence and development of behavioural phenomena in a generalised or idealised context.

Cederman's C2 models aim to explain the emergence of configurations in a model due to properties of the agents within the simulation (Cederman 2001). Examples of this methodology include Lustick's Agent-Based Argument Repertoire Model (Lustick 2002, 2006), which provides agents with a complex set of opinions which they may communicate with other agents. The opinions of agents within the simulation can alter through these communications, leading to the apparent generation of social structures within the agent population.

In this case, the comparison with Levins is more difficult; while the agents themselves are designed to be more complex within a C2 model, can this necessarily be pinned down as an increase in either precision or realism? The closest analogue appears to be Levins' L2 models, which eschew realism in favour of generality and precision. While a C2 Cederman model or an L2 Levins model is not concerned with comparison to empirical data, these models do seek to provide a useful framework for describing complex social behaviours in an idealised context, similar to those population biology models alluded to by Levins. In either discipline, the modellers hope to illuminate some of the contributing factors that produce the modelled behaviour, and perhaps stray closer to a useful description of the real-life instantiation of that behaviour than may be expected initially from such an abstracted model.

Cederman's C3 models are the most ambitious in that they attempt to model the emergence of both agent behaviours and their interaction networks (Cederman 2001). He specifically cites ALife as a field which may provide illuminating insights in that regard, given that ALife is concerned with such complex emergent behaviours and structures. As discussed earlier, however, Cederman's categories have no hard borders between them, particularly in the case of C3 models; Cederman himself admits that C1 and C3 can easily overlap. As a consequence, identifying where the C3 models lie amongst a given crop of social science simulations is not always such a simple task, though the C3 categorisation does provide useful context in which to examine how the goals of different varieties of models can affect their construction and implementation.

Once again, though, the comparison with Levins is difficult; allowing for such emergent behaviours as described by Cederman in the C3 categorisation does not correlate directly with Levins' three categorisations. Perhaps the closest analogue here is once again Levins' L3 models, given the focus on emergence of both agent-level and societal-level behaviours; in neither case is the modeller overly concerned with a direct relation to empirical data. Instead the modeller hopes to provide a cogent explanation for the emergence of social behaviours by allowing agents to interact and change due to pressures within the model, rather than due to complex constraints placed upon that model.

6.5.4 Building the Framework: Unifying Principles for Biology and Social Science Models

We have clearly run into a difficulty in comparing Levins and Cederman's respective modelling frameworks. Levins reserves the L1 category for those models which seek a direct relationship to empirical data, leaving generality behind in favour of realism and precision. However, Cederman's 3 types leave out this distinction, instead providing what appear to be two variations on Levins' more general L3 models. Both Cederman's C1 and C3 models appear to leave precision behind, seeking instead to describe social phenomena in an idealised context; C1 models focus purely on the emergence of social structures, while C3 models focus on the emergence of both societal and individual structures and behaviours.

Cederman's view can be used to further qualify Levins' original framework however. Levins himself cites L3 models as the most promising, and his preferred

Table 6.1 One possible Levins/Cederman framework

Modified Levinsian framework	
L1	Precision and realism at the expense of generality
L2	Generality and precision at the expense of realism
L3A	Generality and realism at the expense of precision at one level of simulation
L3B	Generality and realism at the expense of precision at multiple levels of simulation

methodology within population biology; similarly, Cederman cites his C3 models as the most promising within political and social science (though interestingly, Cederman's recent work has strayed towards a version of Levins' L1; see Cederman 2006 and the section below). The question then becomes: how can we characterise Cederman's C1 vs. C3 distinction in terms of the Levinsian factors of generality, precision and realism?

One can envision a further subdivision of Levins' L3 into a L3A and L3B: L3A being characterised by a sacrifice of precision in one level of the simulation (i.e., Cederman's C1 which seeks emergent social behaviours), and L3B being characterised by a sacrifice of precision at multiple levels (as in Cederman's C3, which seeks both emergent social behaviours and interaction networks); Table 6.1 provides a summary of this potential framework.

Alternatively, with the incorporation of tractability into the Levinsian framework as a fourth factor as in Chap. 4, this subdivision may be much simpler. Both Levins and Cederman acknowledge these L3 models to be both the most useful and the most challenging; perhaps then Cederman's C1 and C3 may be characterised by differing levels of tractability. In this way we can maintain this modified Levinsian framework as a more fluid continuum, based upon the determining factor of overall tractability, rather than introducing additional sub-categories for special cases of specific methodologies.

6.5.5 Integration of Real Data

Some researchers involved in computational modelling have attempted to sidestep the difficulties of the inherent lack of 'real data' by attempting to integrate experimental data into their simulations. Cederman's 2006 paper on geo-referencing in datasets for studies of civil wars provides a useful example. In this case, Cederman uses data and maps from the Russian Atlas Narodov Mira, an atlas produced by a 1960s Soviet project aiming to chart the distribution of ethnic groups worldwide. The project then seeks to formulate agent-based models using this data to examine the potential causes of ethnic conflict. As Cederman notes, 'there is no substitute for real-world evidence' when attempting to understand the causes of such conflict; however, the ethnographic data in this case is both limited and quite old.

Of course the worldwide ethnographic distribution has likely changed significantly since the publication of this atlas in 1964, and updating the information contained therein is no simple task. The integration of such data into an agent-based computational model seems like a potentially fruitful method for tying the results of that model more closely to political and social reality. However, with the limitations of this dataset and the difficulties inherent in collecting future data of a similar type, is this data integration still useful as a framing mechanism to place this model on more solid empirical ground, or is it an interesting but ultimately misguided enterprise?

A further difficulty with the Atlas Narodov Mira dataset is that the atlas provides a static ethnographic picture. While it is a remarkably detailed look at a particular time in world history and the related distributions of peoples throughout the globe, the lack of similar data in the following decades leaves us with an inability to directly associate the intervening political and social changes with ethnic conflicts that have erupted in the years since the atlas' publication. Some argue that computational modelling in such a circumstance provides a remarkable capacity for hypothesis testing; by basing a relatively realistic model on such a solid footing of experimental and observational data, the researcher can experiment with varying parameters and initial conditions in an attempt to replicate the ethnic conflicts seen since the atlas was produced. However in such a case the same problems return to haunt the researcher: deciding which abstractions to make can be critical, and deciding how to formalise the influence of complex social and political interactions is far from trivial.

6.6 Views from Within Social Simulation

6.6.1 Finding a Direction for Social Simulation

While the last chapter provided an in-depth examination of the current state of social simulation, and an analysis of its ability to explain and interpret real-world social phenomena, we still have relatively little understanding of the perception of the utility of social simulation within the social sciences. A number of prominent social simulators display great enthusiasm for the pursuit, as would be expected, but how do those viewing this growing trend from other parts of the field react?

With this in mind we will examine some views of the general purpose of social simulation, and descriptions of the perceived problems of the methodology, from within the social sciences. We can then incorporate these analyses with our own discussion of the importance of simulation in a fundamental social theory and further expand our growing methodological and theoretical framework for social simulation.

6.6.2 Doran's Perspective on the Methodology of Artificial Societies

Doran in his article for Tools and Techniques for Social Science Simulation provides a coherent examination of the major difficulties facing the artificial society methodology in social simulation (Doran 2000). Doran describes this method as follows:

> The central method of artificial societies is to select an abstract social research issue, and then to create an artificial society within a computer system in which that issue may systematically be explored. Building artificial societies is a matter of designing and implementing agents and inter-agent communication, in a shared environment, and existing agent technology provides a wealth of alternatives in support of this process. (p. 18)

Thus, Doran views social simulation as a means of examining the workings of large-scale, abstract social issues. For Doran simulation provides a way to generate new 'world histories,' allowing the researcher to watch a society grow from a provided set of initial conditions and assumptions.

Of course he notes the significant methodological difficulties inherent in this artificial society approach. He identifies three main problems: searching the space of initial conditions and parameters; describing the results of the simulation in a tractable way; and overcoming problems of instability due to changes in initial conditions. The first and third problems here are highly reminiscent of more general problems common to agent-based modelling as a whole, while the problem of analysis and tractability harkens back to Levins and our initial theoretical explorations of artificial life.

Interestingly, however, Doran posits that the greatest problem facing the social simulator is the largely undefined nature of the computational agent itself. He notes that different uses of agent-based models often incorporate different base properties for the agents within the model, and that despite the simplistic views of what constitutes an agent within social science, there is little overall consensus regarding a definition of agent architectures.

He argues that agents should be defined in computational terms, and thus should be able to emerge from a model in the same way as other more complex phenomena. Of course, this is not the normal course in most agent-based models; in practice such models are designed to include predefined agent structures based upon certain theoretical assumptions. As a consequence, this would not be an easy task for the modeller; constructing a simulation in which agent structures are expected to emerge seems extremely difficult. There would almost certainly need to be some sort of precursors to defined agents to allow such structures to develop, given that the earliest beginnings of our own life and society are so murky to begin with and can provide little clear inspiration. The purpose, however, is sound, as producing simulations that at least approach such possibilities would allow the modeller to step away further from the difficulties produced by theory dependence and pre-defined agent structures.

Doran's view is also interesting in that it meshes with our earlier discussion of Niklas Luhmann and the search for a fundamental social theory. Since in Doran's view, artificial societies aim to examine the general development of human society in an abstract fashion, these societies must be based upon valid assumptions. However, those assumptions are necessarily based upon our own cultural experiences, and thus will be imprinted upon that model in some fashion. A model which eliminates this difficulty, or at least minimises it, would allow for agents to develop in simulation which bear far fewer markings of our own societal preconceptions. For the social scientist looking to develop new social theory, such an approach would be far more fruitful than the heavily theory-dependent alternative.

As discussed in the previous chapter, Doran agrees that artificial societies should strive to develop from the earliest beginnings of societal interaction ('the lowest possible level, even below the level of agent' in Doran's phrasing [p. 24]), and that the mechanisms of society should emerge from that basis. This would avoid producing a simulation constructed around pre-existing assumptions from our own society.

6.6.3 *Axelrod and Tesfatsion's Perspective: The Beginner's Guide to Social Simulation*

Axelrod and Tesfatsion (2005) lay out a brief guide to social scientists hoping to incorporate social simulation into their current work. Given the authors' prominent position in the current social simulation field, this guide provides an illuminating look at those aspects of agent-based modelling perceived to be the most valuable by those within this area of research.

After beginning with a brief introduction to the basic characteristics of agent-based models (including a brief discussion on creating 'histories,' as described by Doran), Axelrod and Tesfatsion lays out a four-part description of the potential goals of simulation models in the social sciences. They describe each of these potential goals in turn:

1. Empirical understanding: 'ABM researchers seek causal explanations grounded in the repeated interactions of agents operating in specified environments.'
2. Normative understanding: 'ABM researchers pursuing this objective are interested in evaluating whether designs proposed for social policies, institutions, or processes will result in socially desirable system performance over time.'
3. Heuristic: 'How can greater insight be attained about the fundamental causal mechanisms in social systems?'
4. Methodological advancement: 'How best to provide ABM researchers with the methods and tools they need to undertake the rigorous study of social systems through controlled computational experiments?' [p. 4–5]

Here we discover yet another framework underwriting agent-based models in social science. However, unlike the work of Levins or Cederman, Axelrod and

Tesfatsion prefer not to discuss specific criteria which may place a given agent-based model within these categories, preferring instead to provide only examples of each research goal.

Interestingly, despite their initial mention of Doran's described 'artificial societies' methodology, and the general goal of generating artificial 'world histories,' the remainder of Axelrod and Tesfatsion's introduction presents a sharp contrast to Doran's ideas. They stress the potential for agent-based models to produce substantive empirical insights related to real-world societies, rather than produce more general insights about the initial formation of societies and social interaction as a whole.

However, given the caveats presented thus far with agent-based social simulation, Axelrod and Tesfatsion's research goals seem at odds with the conclusions we have reached. If we agree, as discussed in the last chapter, that social simulation may lack some critical elements required to provide social explanation, then hoping to use such simulations to design real-world social institutions may produce disastrous results. Similarly, developing empirical understanding and 'causal explanations' would be equally problematic, particularly as any non-reductive aspects of the society under investigation would be difficult to identify.

Even if we disagree with the alleged difficulties in social explanation for social simulation, Doran's views have illuminated a further difficulty for Axelrod and Tesfatsion's suggested approaches. Without a clear definition of what constitutes an 'agent' in an empirical or normative simulation, the level of correspondence between these agents and human social actors is too ill-defined. What cognitive capacities would agents require to provide that degree of understanding? Surely Schelling-esque simplicity is not going to be the best course for all possible investigations using simulated societies?

6.7 Summary and Conclusions

Thus far we have seen a great variety of proposed theoretical frameworks for the use of agent-based models. Artificial life provided a useful starting point, given its relationship to the long-standing use of mathematical models in various biological disciplines. Comparing the methodological difficulties of artificial life with mathematical models in biology allows us to develop a greater understanding of the problems most particular to agent-based models.

However, applying the resulting methodological discussions to agent-based models in social science is not so straightforward. As discussed in Chap. 5, social scientists must cope with some unique difficulties: social structures are not clearly hierarchical in nature; empirical studies of social phenomena are frequently problematic due to the interacting complexities of individual and collective behaviour; and social explanation may suffer from difficulties similar to those faced by researchers in mental phenomena, as some social phenomena may be similarly irreducible to straightforward low-level behaviour.

Obviously all of these points impact the social simulator and make the job of model-building significantly more difficult. However, as seen during this analysis, these difficulties shift in emphasis depending on the purpose of the model (as we might expect from previous discussion regarding the Levins and Cederman frameworks). Taking an external, Luhmannian perspective, and incorporating Doran's related views, social simulation may be able to provide a unique window into certain aspects of social theory that are otherwise inaccessible through standard empirical means.

This methodology brings us back to the artificial world problem of Chap. 4. If we accept that 'growing' artificial societies from a level even below that of agents is a promising means for investigating potential fundamental social theories, we must likewise accept that these artificial societies may be quite difficult to relate to real-world societies. Given the gaps in our understanding in social science, ranging from unanswered questions in individual behaviour through to questions of high-level social organisation, can such artificial societies bring us any closer to the desired fundamental social theory?

The next chapter will bring us closer to answering this critical question. By examining one of the most prominent exemplars of social simulation, Schelling's residential segregation model, we will be able to illuminate this concern in greater detail. Schelling's model is the very definition of abstraction – and yet it is credited with producing some important insights into the social problem it is based upon. By determining how Schelling's model surpassed its abstract limitations, we can develop a framework which may underwrite future models in social simulation of a similar character.

This analysis of Schelling marks a conclusion of sorts to the arguments and frameworks discussed thus far in Parts I and II. Having discussed modelling frameworks in Alife and biology, and having brought those together with new elements from simulation in the social sciences, Schelling's model will provide a means to demonstrate the importance of these theoretical, methodological, and pragmatic frameworks for the modeller who wishes to push social science forward through simulation. As we shall see, Schelling's simple model was not nearly so simple in its widespread influence and overall importance. The elements which contributed to this success can be seen via its relationships to the frameworks discussed thus far.

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Chapter 7
Schelling's Model: A Success for Simplicity

7.1 Overview

In the previous chapter the numerous methodological and theoretical frameworks elucidated thus far were analysed as a whole in an attempt to develop a useful synthesis for the social science modeller. Bringing together elements from population biology, artificial life, and social science itself, we examined the multiple dimensions that must be addressed in a successful social simulation model.

In this chapter we will examine one particular example of such a successful model: Schelling's residential segregation model. After describing the context in which this model was developed, we will analyse this relatively simple model under the constraints of each of the theoretical frameworks described thus far. Despite the abstractions inherent in Schelling's construction, the model achieved a remarkable measure of recognition both inside and outside the social science community; our analysis will discuss how this 'chequerboard model' found such acceptance.

Using Schelling as a case study, we can further develop our fledgling modelling framework for the social sciences. In the quest to underwrite social simulation as a more rigorous form of social-scientific exploration, Schelling will provide a valuable examination of the issues facing modellers as this methodology grows in relevance throughout social science. After discussing the issues brought forward by this analysis, which brings together the frameworks and methodological proposals discussed thus far, we will move on to the last chapter of Part II and present a synthesis.

E. Silverman, *Methodological Investigations in Agent-Based Modelling*, Methodos Series 13, https://doi.org/10.1007/978-3-319-72408-9_7

7.2 The Problem of Residential Segregation

7.2.1 Residential Segregation as a Social Phenomenon

7.2.1.1 The Importance of the Problem

One of the most puzzling aspects of the sociological study of residential segregation is the sizeable gap between the individual residential preferences of the majority of the population and the resultant neighbourhood structure. The General Social Survey of major US metropolitan areas asked black respondents whether they preferred to live in all-black, all-white, or half-black/half-white areas; 55.3% of those surveyed stated a preference for half-black/half-white neighbourhoods (Davis and Smith 1999). However, census data reveals that very small percentages of black individuals in major US metropolitan areas actually live in half-black/half-white neighbourhoods; the 1990 census indicates that for most major cities, less than 5% of black residents live in such mixed areas.

7.2.2 Theories Regarding Residential Segregation

The phenomenon of residential segregation is a complex one, involving interacting contributing factors at various levels of societal structure. A definitive statement of why residential segregation occurs still troubles researchers; the problem varies so widely across cultures, societies and ethnic groups that the specific factors at play are still elusive.

Freeman's summary of residential segregation of African-Americans in major American metropolitan areas (Freeman 2000) provides one example of the difficulties facing social scientists in this area. As Freeman notes, African-Americans seem particularly prone to residential segregation; other minority populations tend to 'spatially assimilate' after a period of residential segregation, integrating with the majority population as educational and financial disparities decrease (Massey et al. 1985). African-American populations, however, do not display significant spatial assimilation, despite the decrease in socio-economic disparities evident from the available data; some posit that this may be due to unseen bias in local housing authorities, cultural cohesion keeping African-Americans in established minority communities, or decreased access to public services in low-income areas, but none of these possibilities can fully account for these unusual tendencies in the data.

7.3 The Chequerboard Model: Individual Motives in Segregation

7.3.1 The Rules and Justifications of the Model

Schelling's 'chequerboard model' sought to make a singular point, as illustrated by the simplistic construction of the model. He argued that if the racial make-up of a given area was critical to an individual's choice of housing, then even populations of individuals tolerant to mixed-race environments would end up segregating into single-race neighbourhoods (Schelling 1978). Schelling hoped to illustrate that large-scale factors such as socio-economic or educational disparities between ethnic populations could not explain the generally puzzling phenomenon of residential segregation; indeed, without a greater insight into the preferences and thought processes of individuals within a given population (their 'micromotives'), some critical aspects of this social problem may elude the researcher.

Schelling illustrated this idea using a model constructed in a simple fashion, using a type of cellular automaton model (initially constructed using a physical chequerboard, hence the model's nickname). He describes a world composed of square cells, filled with agents of one of two types. Each agent interacts only with its eight direct neighbouring cells, and there are no higher-level structures incorporated into the model. The agents are given a tolerance threshold: if the number of adjacent agents of its own type is less than that threshold, the agent will move to a nearby location on the grid where its tolerance requirements are fulfilled. Thus, the model incorporates a very simple rule set which allows each agent to display a singular micromotive which is taken to represent that agent's level of racial tolerance. Schelling hoped to demonstrate the powerful influence of this simple micromotive on the resulting racial structure of the neighbourhood inhabited by the agents.

7.3.2 Results of the Model: Looking to the Individual

The results of Schelling's model were surprising to social scientists at the time. The model showed that, for a wide range of tolerance thresholds, these initially integrated neighbourhoods of tolerant agents would 'tip' toward one group or another, leading the outnumbered group to leave and resulting in segregation (Schelling 1971). Given that residential segregation was widespread in American cities prior to the civil rights movement, even the rising tolerance following the additional rights granted to African-Americans was not sufficient to provoke a significant decrease in residential segregation, even by 1990 (Sander 1998).

Schelling's model demonstrates that a mere improvement in individual preferences and a lack of housing discrimination (as outlawed by the Civil Rights Act of 1968) are not sufficient to eliminate residential segregation. In fact, largely tolerant 'microbehaviours' can still result in such problems, as long as social factors such as race remain a consideration in housing choice.

7.3.3 *Problems of the Model: A Lack of Social Structure*

Since Schelling's original model formulation and the resultant interest of the social science community, many researchers have since attempted to update the model with more sophisticated computational techniques and a greater number of influential social factors within the model. While Schelling's model was accepted as a remarkable illustration of a simple principle regarding the large-scale effects of individual housing preferences, some modellers sought to create a more 'realistic' Schelling-type model which could incorporate socio-economic factors as well (Sander et al. 2000; Clark 1991; Epstein and Axtell 1996). Given the accepted complexity of residential segregation as a social problem, and the new insight into the effects of individual preference illuminated by Schelling, models incorporating Schelling-style 'micromotives' and large-scale social factors were seen as a potential method for examining the interactions between these two levels of social structure, something that was very much lacking in Schelling's original formulation.

7.4 Emergence by Any Other Name: Micromotives and Macrobehaviour

7.4.1 *Schelling's Justifications: A Valid View of Social Behaviour?*

Interestingly, despite the general simplicity of Schelling's model and the lack of a larger social context for the agents in the model, his discussion of micromotives quickly gathered momentum among social scientists. His contention that certain non-obvious conclusions regarding social behaviour may follow from studies that do not depend upon empirical observation was influential, leading other modellers to seek patterns of interaction in generalised social systems [other tipping models here].

In addition, Schelling's description of critical thresholds that lead to these 'tipping' phenomenon led to an influx of sociological models exploring this possibility in relation to numerous large-scale social phenomena. Within political science, Laitin used tipping models to examine the critical points at which populations choose one language over another, as in the case of Ghana (Laitin 1994), and in the growing acceptance of the Kazakh native tongue over Russian in Kazakhstan (Laitin 1998). In general, then, Schelling's justifications for his residential segregation model have been widely adapted throughout the social sciences; this simple method for examining critical points in societal interaction seems to have generated a great deal of related research in the years following his book's publication.

Perhaps more importantly for the larger social science community, Schelling's model also sparked additional interest in empirical studies over the years as social scientists wished to confirm his claims. The most prominent example of this model feeding back new ideas into the empirical domain was W.A.V. Clark's study (Clark 1991). Clark used the most recent demographic surveys available at the time to examine elements of local racial preference in residential segregation in real communities; while the character of the results did differ from Schelling, the influence of local racial preferences was strong, confirming Schelling's most important claim. This sort of empirical validation only lends further credence to Schelling's methodology and its success.

7.4.2 Limiting the Domain: The Acceptance of Schelling's Result

While Schelling's model did not incorporate any semblance of large-scale social structure in its simple grid-world, this lack of detail may have contributed to the general acceptance of his model amongst the social-science community. While his work did provide a significant influence on later modelling work in the field and some empirical work, as noted above, his initial forays into the residential segregation problem were very limited in scope (Schelling 1971).

Schelling aimed to illuminate the role of individual behaviours in producing counter-intuitive results in large-scale social systems, and his simple residential tipping model produced just such a counter-intuitive result by demonstrating the inability of individual tolerance for racial mixing to eliminate segregation. In this way the initial chequerboard model provided a theoretical backdrop for the larger thesis of his later book-length examination Micro-Motives and Macro-behaviour (Schelling 1978). Rather than producing one large, complex model which illustrated the importance of these individual preferences in the behaviours of social systems, he produced a number of small-scale, simple models which illustrated the same point in a more easily digestable and analysable way. Perhaps then the lack of complexity on display was what made his models so influential; providing such a basic backdrop made replication and expansion of his result straightforward for the research community.

7.4.3 Taylor's Sites of Sociality: One View of the Acceptance of Models

Computational modelling, as described earlier, is inherently a theory-dependent exercise. Modellers seek to simplify reality in order to examine specific behaviours within the system of interest, and those simplifications and abstractions often betray a theoretical bias. In addition to this difficulty, Taylor describes the concept of 'sites of sociality' within modelling communities (Taylor 2000). In Taylor's view, these sites correspond to points at which social considerations within a scientific discipline begin to define parameters of a model, rather than considerations brought about by the subject matter of the model itself.

Thus, if a certain evolutionary theory has become dominant within a specific domain of population biology, for example, a model which ignores the conceits of that theory may not find acceptance among the community. Schelling's modelling work served to add to current social theory in evidence at that time, but did not seek to overturn the dominant ideas of the field; perhaps, in Taylor's view, this was a powerful method for gaining widespread acceptance in the social science community.

7.4.4 The Significance of Taylor: Communicability and Impact

Taylor's description of sites of sociality within modelling communities brings an important point to bear. Even if a model is constructed in such a way that the modeller can justify its relevance to the broader empirical community, that community may be operating under a different understanding of what is important to display in a simulation, or the importance of simulations as a whole.

Once again, we may use Vickerstaff and Di Paolo's model as an example (Vickerstaff and Di Paolo 2005). Their model was accepted and communicated in a very popular experimental biology journal, despite being entirely computational in nature. The editors of the journal still accepted the paper despite its lack of hard empirical data; the model's relative simplicity kept it from being too alien a concept for the biological readership, and the data it presented was novel and relevant despite its origins. The ability to comprehend the model in a more substantive way is vital to its acceptance; if the model had been too complex and difficult to replicate, the results would have been less impactful and interesting for the target audience.

Also like Schelling, the nature of the model makes it very palatable to the experimental biology readership in a different manner: the model was adding to the discourse on a particular topic in biology, rather than attempting to make major alterations to the field. If an Alife researcher submitted a paper to an experimental journal that proclaimed an end to conventional insect biology as we know it, for example, then the editors are unlikely to be receptive. As with Schelling, this paper served to illuminate a new idea regarding an issue relevant to the community it addressed; the paper did not ignore the pre-existing conceits of the community, and the data it produced was of value to the theories established in that community by decades of difficult data collection and analysis.

Thus, Schelling and Vickerstaff and Di Paolo both show the importance of communicability in a model which seeks to engage the wider research community. Schelling had great impact due to the ease of communicating his model results, and the ease with which members of the social science community could replicate and engage with those results; similarly, Vickerstaff and Di Paolo achieved success by crafting a model which demonstrated relevant new ideas that could be communicated well to the biological community despite the differing methods of data collection. Moving forward, we will see how the simplicity of a model can not only assist communicability and impact for a given model, but also its tractability and ability to produce useful, analysable results.

7.5 Fitting Schelling to the Modelling Frameworks

7.5.1 Schelling and Silverman-Bullock: Backstory

Under Silverman and Bullock's framework (Silverman and Bullock 2004), Schelling's model succeeds due to the integration of a useful theoretical 'backstory' for the model. Schelling represents the chequerboard model as an example of one particular micromotive leading to one particular macrobehaviour, in this case residential segregation. In the context of this backstory, Schelling is able to present his model as a suitable example of the impact of these micromotives on one particularly thorny social problem.

By restricting his inquiry to this singular dimension, the model becomes more palatable to social scientists, as the significant abstractions made within the model facilitate the portrayal of this aspect of the phenomenon in question. This serves to emphasize Schelling's original theoretical formulation by stripping away additional social factors from the model, rather than allowing multiple interacting social behaviours to dilute the evidence of a much greater role for individual preference in residential segregation.

7.5.2 Schelling and Levins-Silverman: Tractability

Under our clarified Levinsian framework from Chap. 4 (see Table 4.1), in which tractability forms the fourth critical dimension of a model alongside generality, realism and precision, Schelling's model appears to fall into the L2 categorisation. The model sacrifices realism for generality and precision, producing an idealised system which attempts to illustrate the phenomenon of residential segregation in a broader context.

Meanwhile, tractability remains high due to the simplistic rules of the simulation as well as the general ease of analysis of the model's results; for many social scientists, a simple visual examination of the resultant segregated neighbourhoods from a run of the simulation proves Schelling's point fairly clearly. More in-depth examinations are also possible, as seen in Zhang's assessment of the overall space of Schelling-type models (Zhang 2004); such assessments are rarely possible with more complex models, which involve much more numerous and complex parameters.

7.5.3 Schelling and Cederman: Avoiding Complexity

In Cederman's framework (Cederman 2001, see Table 5.1), Schelling's model is a C1 simulation, as it attempts to explain the emergence of a particular configuration by examining the traits of agents within the simulation. In this way the model avoids the thorny methodological difficulties inherent to C3 models, as well as the more complex (and hence potentially more intractable) agent properties of C2 models. While C3 models are perhaps more useful to the social science modeller, due to the possibility of producing agents that determine their own interactions within the simulation environment, constraints such as those imposed by Schelling help to maintain tractability. This tractability does however come at the expense of increased self-organisation within the model.

7.6 Lessons from Schelling

7.6.1 Frameworks: Varying in Usefulness

Having tied Schelling's work into each of our previously-discussed modelling frameworks, a certain trend becomes apparent in the placement of Schelling's model within each theoretical construction. The simplicity of Schelling's model places it toward the extreme ends of each framework: it has an easily-defined theoretical backstory; lies well within the range of tractability under Silverman and Bullock; and falls firmly within the C1 category described by Cederman.

While Cederman's categorisation may help us to understand the aims and goals of a Schelling-type model, such ideas are already apparent due to the theoretical backstory underlying the model (which in turn places the model in good stead according our modified Levinsian framework). The pragmatic considerations of the model itself, as in whether it is amenable to analysis, are more important in driving our declaration of Schelling as a useful model. After all, a very ambitious and completely incomprehensible model could quite easily fall into Cederman's C3 category; however, its impenetrable nature would be exposed to much greater criticism under the more pragmatic views of Levins and our revision of Levins presented in Chap. 4.

7.6.2 Tractability: A Useful Constraint

As described earlier, Schelling's model benefits in several ways from its notably simple construction. Referring back to our revised Levinsian framework, the general concern of tractability is mollified by the model's inherent simplicity. Given that the model can produce a visual demonstration of a segregation phenomenon, the job of the analyst is made much easier; the qualitative resemblance of that result to an overview of a segregated, real-world neigbourhood already lends credence to the results implied by Schelling's model.

Perhaps more interestingly, the abstract nature of the model also makes further analysis less enticing for those seeking harder statistics. While the model does represent agents moving in space in reaction to stimuli, they do so as abstract units during time and space intervals that bear no set relation to real-world time and space. Fundamentally, the model seeks only to demonstrate the effects of these agents' micromotives, and the effects of those micromotives on the question of interest; in that sense an in-depth analysis of the speed of segregation through the model's space and similar measures, while interesting, are not necessary for Schelling to illustrate the importance of individual motives in residential segregation. As will become evident in the following section, Schelling's ideas regarding modelling methodology drove him to construct his model in this way to maintain both tractability and transparency.

7.6.3 Backstory: Providing a Basis

Silverman and Bullock's concept of the importance of a theoretical 'backstory' for any modelling enterprise (Silverman and Bullock 2004) seems supported by the success of Schelling's work. His approach to modelling social micromotives derived from a theoretical backstory which takes in several important points:

1) Within a given research discipline, there are non-obvious analytical truths which may be discovered by means which do not include standard empirical observation (specifically mathematical or computational modelling in this case).

In the case of Schelling's residential segregation model, the non-obvious result of the interaction of his tolerant agents is that even high tolerance levels still lead to segregation; one should note in this case that Schelling's result was not only non-obvious in the context of the model, but was also non-obvious to those who studied the segregation phenomenon empirically.

2) The search for general models of phenomena can lead to the important discovery of general patterns of behaviour which then become evident in examples across disciplines.

Schelling uses 'critical mass' models as an example (tipping models being a subclass of these), arguing that they have proven to be useful in 'epidemiology, fashion, survival and extinction of species, language systems, racial integration, jay-walking, panic behaviour, and political movements' (Schelling 1978, p. 89). The explosion of interest in tipping models following Schelling's success with residential segregation indicates that such inter-disciplinary usefulness may indeed be a crucial element to the success of his model.

3) Modellers should seek to demonstrate phenomena in a simple, transparent way. As he states, a model 'can be a precise and economical statement of a set of relationships that are sufficient to produce the phenomena in question, or, a model can be an actual biological, mechanical, or social system that embodies the relationships in an especially transparent way, producing the phenomena as an obvious consequence of these relationships' (Schelling 1978, p. 87).

Schelling's own models conform to this ideal, utilising very simple agents governed by very simple rules to illustrate the importance of individual behaviours in social systems. Zhang's analysis of Schelling-type models using recent advances in statistical mechanics shows one of the benefits of this transparency in a modelling project (Zhang 2004).

7.6.4 *Artificiality: When it Matters*

The importance of artificiality within a simulation methodology as espoused by Silverman and Bullock (2004) is especially crucial to an evaluation of Schelling-type models. Schelling himself posits that models can illuminate important patterns in a system of interest without requiring recourse to empirical observation (Schelling 1978); in this fashion his work suggests Silverman and Bullock's Artificial^1 and Artificial^2 distinction as a sensible path for models to take. However, he further clarifies this idea by proposing that such models must remain transparent and easily analysable, displaying a clear interaction which leads to the appropriate results in the system of interest; an overly-complex Artificial^1 model, in his view, cannot provide that clear link between the forces at play within the model and the resultant interesting behaviour.

Further, Schelling's two-part definition of models goes on to describe the potential for using an actual biological or social system in a limited context to illustrate similar points (Schelling 1978); this statement implies that Artificial^2 models, which would be a man-made incidence of these natural behaviours, may be able to provide that simplicity and transparency that empirical observation of such complex systems cannot provide. In one sense, then, Schelling appears to dismiss the question of artificiality in preference to the modellers motivations: in order to display the effect of micromotives or emergent behaviour, the model must display a clear relationship between the resultant behaviour and the contributing factors alleged to create that behaviour, and whether that model then embodies Artificial[1] or Artificial[2] is not necessarily of any consequence.

7.6.5 The Practical Advantages of Simplicity

Schelling also demonstrates the practical usefulness of creating a simple model of a phenomenon. So far we have seen how this simplicity allows us to avoid some of the methodological pitfalls that can trouble those who choose to utilise agent-based models, and likewise it is easy to demonstrate how this same property can help the modeller in more pragmatic ways.

Firstly, such simplicity not only allows for higher tractability, but also much simpler implementation. In the case of Schelling's model, numerous implementations of the model exist in a large variety of programming languages. Writing the code for such a simulation is almost trivial compared to more complex simulations; indeed, some pre-packaged simulation codebases such as RePast (designed for the social scientist) can be utilised to produce a Schelling-type model in only a few lines. Beyond simply the time savings of these ease of implementation, the simple construction of Schelling's model vastly reduces the amount of time spent tweaking a simulation's parameters. In more complex simulations, such as an evolutionary model, parameters such as mutation rates can have unexpected impacts on the simulation results, and finding appropriate values for those parameters can be time-consuming.

Secondly, starting from such a simple base allows for much greater extendability. With the Schelling model being so easily implemented in code, extending some elements of that model becomes very easy for the researcher. For example, alterations in the number of agent types, the complexity of the agents themselves, or the set of rules governing the agents are easy to create. In addition, the simple nature of the initial model means it is also easy to change one aspect of the model and see clearly the results of that change; in a more complex formulation, changing one element of the simulation may produce unexpected changes, and complex elements in other areas of the simulation could be affected in ways that produce unanticipated results.

Finally, the modeller benefits from potentially a much larger impact of the simulation when it is simple to implement. For example, we saw previously how Zhang was able to probe the properties of the entire space of Schelling-type models (Zhang 2004). If Schelling's model were too complex, this would be an impossible task. Instead, due to its simplicity, dozens of interested researchers could implement Schelling's model for themselves with little effort, see the results for themselves, and then modify the model or introduce new ideas almost immediately. Such ease of replication and modification almost certainly helped Schelling to reach such a high level of impact from his initial model; the simplicity of the model essentially lowers the barrier of entry for interested parties to join the discussion.

7.7 Schelling vs Doran and Axelrod

7.7.1 Doran's View: Supportive of Schelling?

Doran's views of agent-based models in social science (Doran 2000) proposes that such models can provide a means to generate new 'world histories,' or artificial explorations of versions of human society that may have come into being given different circumstances. While Schelling's model could be construed as an 'artificial society' of the simplest order, the model is oriented less toward reaching grand conclusions about the structure of society as a whole and more toward a demonstration of the low-level factors in a society which may produce one particular phenomenon.

With this in mind, Doran's further concerns about the undefined role of agents in social simulation also seem of particular import. Doran argues that agents in social simulation should be defined on a computational basis to allow those agents to develop emergent behaviour in the same way as other aspects of the simulation. Schelling's model incorporates agents in a most abstract way; each individual in the model makes only a single decision at any given time-step, based on only a single rule. Given this simplicity, could we argue that these agents are sufficiently advanced to bring us a greater understanding of the residential segregation problem? If not, how might Doran's view inform a more rigorous version of Schelling's original vision?

While Schelling's model is indeed oriented toward a specific social problem in an intensely simplified form, in a sense he is providing a minimal 'artificial society' as Doran describes this methodology. Schelling is able to create alternate 'world histories' for the limited two-dimensional space inhabited by his simple agents; he can quite easily run and re-run his simulation with different tolerance values for the agents, and examine the resulting patterns of settlement following each change. For example, he could determine the result of populating a world with completely tolerant agents, completely intolerant agents, and all variations in between.

With regard to Doran's concerns regarding the roles of agents in social simulation, Schelling's model suffers more under scrutiny. Despite the simplicity of the model itself, the agents are built to a pre-defined role: each agent is assumed to be searching for a place to settle, with its preference for a destination hinging upon the appearance of its neighbours. This presumes that individuals in a society would prefer to remain settled, rather than move continuously, and that all individuals will display a primary preference based upon the characteristics of its neighbours; both of these assumptions have been placed into the model by Schelling's own conceptual model, rather than having those agent properties emerge from the simulation itself.

One could imagine constructing a Luhmannian scenario in which agents are given only the most base properties: perhaps a means of communication, an ability to form preferences based on interactions, and the ability to react to its neighbours. Might these agents, based upon interactions with neighbours of different characteristics, form preferences independent of the experimenter's expectations? If so, then these preferences would emerge from the simulation along with the resultant agent configurations in the simulated world, making the agents more independent of the experimenter's biases, though of course never entirely independent of bias. Such a set-up would certainly alleviate Doran's concerns about pre-defined agents and theoretical biases, but whether the results would be more or less useful to the community than Schelling's original is still debatable.

7.7.2 Schelling vs Axelrod: Heuristic Modelling

Robert Axelrod and Leigh Tesfatsion's introduction to agent-based modelling for social scientists, discussed in the previous chapter, describes four main goals of social simulation models: empirical understanding, normative understanding, heuristics, and methodological advancement (Axelrod and Tesfatsion 2005). Schelling's model seems to fall most readily into the heuristic category, seeking as it does a fundamental insight into the mechanisms underlying the phenomenon of residential segregation.

Axelrod's view, unlike Doran's, stops short of examining specific methodological difficulties in social simulation modelling. Instead, he develops these four general classifications of model types, placing agent-based modelling into a framework oriented more toward empirical study. Given that three of Axelrod's four categories are directly concerned with empirical uses of agent-based models, this framework offers little guidance as to the appropriate use of models like Schelling's.

Of course, as indicated by the discussion of Axelrod's categorisations in the previous chapter, our analysis thus far has indicated a number of theoretical difficulties with this empirical approach to social simulation. With this in mind the fact that Schelling lies outside the prominent focus of Axelrod's approach is not particularly surprising. Along with Doran, Luhmann, and Silverman and Bryden (Silverman and Bryden 2007), Schelling's model is more appropriate in the context of a more general and abstracted modelling perspective, one which seeks general understanding of social phenomena rather than data relating to specific aspects of society.

7.8 Schelling and Social Simulation: General Criticisms

7.8.1 Lack of 'Real' Data

While Schelling thus far has held up well under the scrutiny of several major theoretical frameworks regarding simulation models, there are still concerns levelled generally at social simulation which must be addressed. The first, and potentially the most troublesome, is the lack of 'real' data attributed to models within social science, and the resultant disconnection between these simulations and empirical social science.

Schelling quite clearly falls afoul of this methodological sticking point. There is no aspect of the chequerboard model which is based upon empirical data: the chequerboard itself is designed arbitrarily, with no real-world context or comparison; the agents are given a tolerance threshold by the experimenter, not one based upon any empirical study; and there is no representation of the nuances of human residential areas, such as buildings, other residents, or other interacting social factors that may effect the residential segregation phenomenon. In other words, Schelling's model is very much an abstraction with no real basis in empirical social science.

However, given the context of Schelling's work, the abstraction is entirely justifiable. Had Schelling proposed to understand residential segregation in one particular circumstance, then produced such an abstract model, then he would have been reaching for conclusions far beyond the scope of the model itself. His question instead was much more broad: can we illustrate the effect of individual 'micromotives' on an otherwise difficult-to-explain social phenomena? His model answers this question without the need for specific ties to empirical data-sets, and indeed 'real' data would most likely dilute the strength of his result in this context.

7.8.2 Difficulties of Social Theory

Revisiting Kluver and Stoica once more, we recall their assertion that social theory does not benefit from being easily divisible into interacting hierarchical structures as in other fields, such as biology (Klüver et al. 2003). Given that a social system will encompass potentially millions of individuals, each interacting on multiple levels, while higher-level social structures impose differing varieties of social order, the end behaviour of a society through all of these factors can be exceedingly complex. This inherent difficulty in social science makes the prospect of empirically-based simulation seem ever more distant.

However, Schelling once more illuminates the benefits of a more abstract approach to examining social systems. Schelling's model suffers little from the problem of interacting social structures, as the model itself involves only a set of agents interacting in a single space: there are no social structures; no imposed social order in the system; and only a single type of interaction between agents. The model thus escapes this difficulty by quite simply eliminating any social structures; without these multiple interacting structures to confound analysis, the model's result remains clear.

7.8.3 Schelling and the Luhmannian Perspective

With the abstraction and simplicity of Schelling's model allowing it to escape from the methodological traps common to most social simulation endeavours, we are left with an interesting perspective on our earlier proposed method for developing fundamental social theory. Similar to Schelling's tipping model, the Luhmannian modelling perspective would construct an agent-based model bearing as few assumptions as possible, allowing the resultant configurations of agents and model properties to emerge of their own accord.

In essence, Schelling's model takes the Luhmannian approach and boils it down to an exploration of a single aspect of human society. While Luhmann asks what drives humanity to develop social order (Luhmann 1995), Schelling restricts his domain to only residential segregation, asking whether individual motives can drive agents to separate themselves from one another. While Luhmann condenses the whole of human interaction down to social developments linked to an iterated process based on our 'expectation-expectations,' Schelling similarly condenses the puzzling behaviour of human segregation down to a series of simple individual decision-making steps.

Schelling's success, then, gives the Luhmannian approach a further emphasis. While the investigation of the overall origins and development of the human social order is certainly a much more complex endeavour than that of investigating a single social phenomenon a la Schelling, this residential segregation model provides an insight into the benefits of the process. Schelling wrote of the importance of demonstrating the relationships between model properties transparently (Schelling 1978), and with a Luhmannian model the same approach is necessary.

7.8.4 Ramifications for Social Simulation and Theory

Having established the importance of Schelling's perspective, and the links between his modelling paradigm and our proposed means for developing fundamental social theory, a further re-evaluation of Schelling's impact on social simulation is required. We have seen the import of this model's simplicity and transparency, and even how its inherent abstraction enables the model to draw intriguing conclusions within the larger context of general social theory. Does this imply that the empirically-based approach of Cederman, Axelrod and others is a scientific dead-end?

Perhaps not: certainly as the field of geographic information systems (GIS) continues to advance, and real-time data collection within social science becomes more wide-spread and rigorous, then the introduction of real and current data into social simulation becomes an interesting possibility. This after all is a central criticism of social simulation of this type: real data is hard to come by, and that data which is available is often limited in scope or out of date. When this obstacle disappears, then simulations more closely linked to data produced by real human society becomes more viable.

However, the other fundamental concerns related to social simulation still remain. Doran's concerns regarding the lack of definition of the roles of agents in social simulation (Doran 2000) remain important, and as integration with real data becomes vital to a simulation that concern becomes ever more central. The question of how to develop cognitive agents with an appropriate set of constraints and assumptions to produce parsimonious results is not one that will be answered quickly.

Similarly, the inherent abstraction of social processes and structures necessary in a computer simulation could be problematic in a simulation designed to produce empirically-relevant results. Axelrod and Tesfatsion (2005) proposes social simulations that may inform public policy (his 'normative understanding' category of social simulations), and while this is an enticing prospect, we have already seen the troubling pitfalls the researcher can encounter in this approach (see Chaps. 4 and 5).

This reinforces the importance of Schelling's model as deconstructed in the preceding analysis. While initially appearing simplistic, the theoretical implications of Schelling's work are rather more complex. The importance of this model in social science despite its simplicity, complete abstraction, and lack of empirical data shows the potential of social simulation to stimulate social theory-building. Schelling's model stimulated the field to view the importance of individual 'micromotives' in a new fashion; a more sweeping model portraying the emergence of a social order in a similar way could have an equally stimulating effect on social theory.

7.9 The Final Hurdle: Social Explanation

7.9.1 Schelling's Model and the Explanation Problem

As described in Chap. 5, there is some debate over the explanatory power of computer simulation within the social sciences. While the predominant idea within such endeavours is that of emergence, or the development of higher-level organisation in a system given interacting lower-level components, some theorists argue that social systems do not produce higher-level organisation in this way (Sawyer 2002, 2003, 2004).

Sawyer's development of the idea of non-reductive individualism, in which certain properties of a society cannot be reduced to the actions of individual actors in that society, does pose a fundamental problem for agent-based modellers. If agent-based models proceed on the assumption that individual-level interactions can produce the higher-level functions of a social order purely through those interactions, then such models may be missing a vital piece of the explanatory puzzle within social science. In this respect individual-based models need a theoretical underpinning in which emergence is a valid means for the development of high-level social structures.

Schelling's model focuses entirely on the actions of individual agents, and the impact of their individual residential preferences on the racial make-up of a given neighbourhood. In this sense the model does seek to demonstrate the emergence of a higher-level configuration from the actions of individuals, which according to this view of social explanation is problematic.

However, Macy and Miller's take on this social explanation problem (Macy and Willer 2002) would allow for Schelling-type models, as the model focuses purely on a situation for which there is no central coordination of the behaviour in question. The agents in Schelling's chequerboard world do act individually, but the results he sought were not a higher-level social organisation or function, but instead merely a particular configuration of those individuals at the end of a simulation run. Even in Sawyer's less forgiving view, Schelling's simulation does not strive to explain a larger-scale structure that might be dubbed irreducible.

7.9.2 Implications for Luhmannian Social Explanation

Our earlier discussions of Niklas Luhmann's ideas regarding the development of the human social order presented a means for applying these ideas to agent-based models designed to examine the fundamentals of society. By applying Luhmannian ideas of extremely basic social interactions that lead to the formation of a higher social structure, a modeller may be able to remove the theoretical assumptions often grafted into a model through the design of restrictive constraints on agents within that model.

However, our examinations of the difficulty of social explanation remain problematic for a Luhmannian approach. If certain high-level aspects of human society depend on functions which are irreducible to the properties of individuals within that society, then even the most cleverly-designed agent-based model would be unable to provide a complete explanation for the functioning of society. This places a fundamental limit on the explanatory power of the Luhmannian approach, barring us explaining the social order in its entirety.

Perhaps Sawyer's comparisons with non-reductive materialism within the philosophy of mind may provide a solution (Sawyer 2004). As he notes, 'the science of mind is autonomous from the science of neurons,' alluding to the disconnect between psychology and neuroscience (Sawyer 2002). Indeed, within the study of mind there are conscious and unconscious phenomena which are irreducible in any straightforward way to the functioning of the underlying neurons; after all, psychologists still struggle to explain how neuronal firings lead to the subjective experience of individual consciousness.

However, very few psychologists still adhere to the concept of dualism: the idea that conscious experience is a separate entity from the physical brain itself. Sawyer clearly does not, as is evident from his discussion of non-reductive materialism. In that case, while we may not be able to draw a direct relation between conscious phenomena and brain activity, the relation nonetheless exists; neurons are the cause of conscious phenomena, merely in a way we cannot understand straightforwardly.

In the same sense, individuals will be the fundamental cause of large-scale social phenomena, whether those phenomena display clearly evident relationships or not. If we accept that a sufficiently advanced and appropriately constructed computer may be able to achieve consciousness, then surely a similarly advanced social simulation could allow sophisticated structures to emerge as well? In either case, the functioning of those individual units would be very difficult to relate to the emerging high-level phenomena but developing artificial (and hence de-constructable) models of both these processes could provide a unique insight.

Thus, Sawyer may very well be correct, and understanding the relation between high-level social structures or institutions to individuals in society may be difficult, or even impossible. But this is not to say that individuals, even in a model, could not produce such phenomena; nor that study of such models would not produce any insight. The Luhmannian modelling perspective aims to discover the roots of human society, and if those individual roots produce irreducibly complex behaviour, those models have surely functioned quite well indeed.

7.10 Summary and Conclusions

In this chapter we have examined one particular example of social simulation, Schelling's chequerboard model, in light of the various theoretical concerns raised thus far. Schelling's model was a marked success in the social sciences, producing an endless stream of related works as the idea of social phenomena emerging from the actions of individuals grew in the social sciences as it did in artificial life.

The simplicity and transparency of the model allowed it to have a stronger impact than many more complex models. Along with being easily reproducible, Schelling's results were restricted to a very specific question: can individual housing preferences drive the mysterious process of residential segregation? The answer, demonstrated by the starkly-separated patterns of white and black squares so prominent in the literature, appeared to be yes.

This approach, while falling within the remit of the theoretical frameworks laid out by other social simulators, also provides an insight into new paths for producing social theory. While the use of social simulations for empirical study is enticing, and potentially both useful and lucrative, the methodological and theoretical difficulties involved in such an approach are many and complex. In contrast, a simple model with few inherent assumptions can offer a more basic and general description of the origin of various social phenomena.

Schelling's model also provides a view into the potential benefits of the proposed Luhmannian modelling approach for the social sciences. Like Luhmann, Schelling's model took very basic interactions as a basis for producing more complex social behaviour; Luhmann takes a very similar approach, but on a much larger canvas. In this respect Schelling shows that the Luhmannian approach could allow social theorists to develop ideas regarding the social order that may have large ramifications for social science as a whole.

Of course, the problem of social explanation still looms as large for Luhmann as it does for Cederman or Axelrod. The debate over emergent phenomena in social science is unlikely to subside, and as such the results of such simulations may always be disputed on some level. However, even if we accept that some aspects of a Luhmannian simulation may not provide complete explanatory power, the results could still be revolutionary for social theory.

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Chapter 8
Conclusions

8.1 Overview

The previous chapter focused on demonstrating our developed modelling frameworks in the context of one particular case study: Schelling's well-known residential segregation model (Schelling 1978). Despite this model's inherent simplicity, the results were seen as significant within social science. Our analysis of the methodological and theoretical underpinnings of Schelling's model provided some insight into how his simple model of societal micromotives became so influential.

However, Schelling need not be the only example of a successful computational modelling endeavour. While Schelling does fare well when viewed in the context of a number of different modelling frameworks, there are other examples of computational research which can provide useful results through varying means.

By revisiting our central bird-migration example, and viewing each of our developed modelling frameworks from the first two sections of this text in the light of our analysis of Schelling, we can put together a more comprehensive set of ideas regarding the limitations of computational modelling. The effect of such ideas on substantive modelling works are also important to discuss; with these methodological frameworks in place, research utilising computational modelling will necessarily need to adapt to these restrictions.

8.2 Lessons from Alife: Backstory and Empiricism

8.2.1 Backstory in Alife

Our analysis of Alife in Chap. 3 focused first on the distinction between two proposed varieties of artificiality: Artificial[1], a man-made example of something

E. Silverman, *Methodological Investigations in Agent-Based Modelling*, Methodos Series 13, https://doi.org/10.1007/978-3-319-72408-9_8

natural; and Artificial^2, something made to resemble something else. This distinction proved most important in the contrast between strong Alife and weak Alife: strong Alife seeks to create systems that are Artificial^1 in nature, while weak Alife seeks only Artificial^2 systems.

Along with the drive to create digital examples of life, members of the Alife community have sought to use their simulations as a means for providing new empirical data points useful for studying life. Such an empirical goal is far from trivial, and requires a cohesive theoretical backstory to provide a basis for allowing that data to be used as such. As described in Sect. 3.6, our PSS Hypothesis for Life provides one example of such a perspective: if one accepts that life is an information ecology, then a suitably-programmed computer can also instantiate such a system.

However, a backstory of this nature requires additional philosophical baggage. While a researcher may utilise this PSS Hypothesis to justify investigations into a digital living system, that system still exists only in a virtual form. The researcher becomes a digital ecologist, studying the output of the simulation for its own sake.

8.2.2 Schelling's Avoidance of the Issue

Our analysis of Schelling provides a means for escaping these philosophical conundrums. Rather than proposing a model which is an Artificial^1 instantiation of human society in order to explore residential segregation, he produces a simple model which only illustrates an example of his concept of micromotives and their effect upon society (Schelling 1978).

A version of our bird-migration model could take advantage of simplicity in a similar way. If we constructed a model which presented each bird as only a simple entity in a grid-world, with simple rules which drives the movements of those birds, we may be able to present an example of how singular micromotives could drive birds to shift from one location to another (say by moving according to food distribution or other factors that may contribute to our bird agents' well-being under the given rule set). In such a formulation the question of Artificial^1 versus Artificial^2 is unimportant; the model is obviously Artificial^2 in nature, and no claim is made to be creating real, digital bird equivalents. The model simply seeks to show the impact of Schelling-esque micromotives in bird migration.

However, while avoiding the problem of artificiality can be advantageous to the modeller, the question of relating that model to empirical data still remains. Without claiming that the agents within our bird model are instantiations of digital life, we cannot be said to collect empirical data on those agents. Might we remain in danger of constructing an artificial world which we proceed to study as a separate entity from the real systems of interest?

8.3 The Lure of Artificial Worlds

8.3.1 Levinsian Modelling

Our examination of the more pragmatic concerns of modellers through the lens of population biology provided some additional considerations for the simulation researcher. Levins' (1966) developed a framework in which three dimensions of generality, realism and precision, important to any given model of a natural system, must be balanced effectively to produce a useful model. He posits that a modeller can focus on two of these modelling dimensions at a time, but only at the expense of the third; this leads him to describe three possible varieties of models, which we denoted L1, L2 and L3 (see Table 4.1).

As noted in Chap. 4, however, applying this framework to certain computational models can be difficult. If our bird migration model uses a highly-simplified set of evolving agents to represent birds, and places those agents in a simplified world with abstracted environmental elements to affect those agents, how might we characterise that model under Levins' framework? Certainly precision cannot apply, as there is no attempt in this formulation to match these agents with any particular real-world species. Nor does realism seem to apply, as the highly-abstracted nature of the model divorces it from the natural systems it seeks to model. Can the model be referred to as simply general in character, or even then is the model seeking insights which may end up generalising in a different fashion than in other varieties of models?

8.3.2 Levins and Artificial Worlds

This difficulty leads us to the question alluded to in the previous section: do we risk becoming mired in the study of artificial worlds for their own sake? Certainly our proposed simulation above would suffer from a lack of available empirical data to use in the model. For example, by using evolving agents to represent the birds we can model the progression of this abstracted species over time, but empirically-collected data following a species through its evolution is not available to provide guidance for this aspect of the model. The modeller can proclaim a serious advantage in being able to model something which is impossible to study empirically through only a relatively modest investment of programming time and processing time, but likewise, the lack of relevance to biology becomes ever more acute (once again, see Webb 2009 for a discussion of this issue in relation to Beer's CTRNN model).

In a certain way, however, this lack of empirical relevance is an attractive feature for the simulation researcher. Replacing the complexities of the real world with simplified abstractions in a wholly artificial world not only makes model construction potentially easier, but even avoids the practical difficulties often associated with traditional empirical methods. As a consequence, our bird model need not be tied down by Levins' pragmatic modelling concerns, and balancing his three dimensions of model-building suddenly appears much easier.

Of course, as discussed in Chap. 4, such artificial worlds create further methodological difficulties of their own. While such a model may appear to avoid Levins' concerns and thus produce more complete models of phenomena, confining that model to an artificial world creates a strong separation from the empirical data that can inform other varieties of models. The modeller is thus in danger of studying the model as a separate entity from the systems on which it is based.

Schelling avoids this difficulty by positioning his model as a means to illustrate the importance of micromotives in social behaviour (Schelling 1971, 1978). While his model does relate to a real system, and it does take place in a highly idealised artificial world, within this context the model does not need a strong relationship to empirical data. Schelling instead strives for transparency maximising tractability by creating an abstract, easily computable model. The question of relating the model to the real system thus becomes simplified: can the model illustrate the potential for individual micromotives to exert a great influence on a society? The answer, for most social scientists, appears to be yes, despite the model's artificiality and simplicity.

8.4 Modelling in Alife: Thoughts and Conclusions

8.4.1 Lessons from Schelling

As seen in the analysis above, there are a multitude of considerations relevant to the ALife modeller. From crafting a suitable theoretical backstory to avoiding the difficulties of artificial worlds, methodological problems are hard to avoid completely. Schelling provides some insight into how to approach these issues. The simplicity of the model allows for a coherent theoretical backstory, focusing only on the possible effects of micro-motives on the larger system. Meanwhile, the model's transparency maintains tractability, though this brings with it a high level of artificiality in the model.

As we see with Schelling, however, this artificiality is not necessarily the problem. The larger concern is the intent with which the model is constructed. A strong ALife practitioner who seeks to create digital life needs to demonstrate Artificial^1, and in this case he would presumably require a much higher degree of complexity than in Schelling's model; even with the PSS Hypothesis for Life as a backstory, a grid-world of simplistic homogeneous agents could hardly be said to compose an information ecology.

8.4.2 *The Power of Simplicity*

The circumstance of being driven away from simplicity toward complexity in this search for Artificial[1] also creates a much more difficult pragmatic situation for the modeller. As noted in Chap. 7, simple models like Schelling permit the modeller to spend far more time theorising than tweaking. For our bird researcher, a situation in which a few simple lines of encode provide the agent's behaviour is preferable to one in which each agent contains complex neural network elements, for example. In the first case, the researcher can write the code and run the simulation quickly, then take the necessary time to examine results, run alternative versions of the simulation, and so forth. In the second case, the researcher could spend far more time tweaking the individual parameters of the agent structures: what sort of sensors might each agent have? How do the neural networks control movement and receive input from the environment? How many neurons are there, and what type are they? The questions become many and varied for the researcher using complex agents, and each day spent tweaking those agent parameters is one less day spent pondering the results of the simulation.

As seen above, Schelling's model provides one example of a means to avoid these pragmatic issues. His model is of such simplicity that writing a version of his simulation takes only a few lines of code compared to more complex simulations. However, clearly other types of models can maintain similar simplicity; Beer, for example, touts his CTRNN-based agents as displaying 'minimally-cognitive behaviour' (Beer 2003a,b). Of course, Beer's analysis of that minimally-cognitive behaviour is extremely detailed and time-consuming, and may indicate that such analysis is impractical for agents of that type even of such relative simplicity. Nonetheless, Beer does demonstrate that relatively simple and analysable neural models are not outside the realm of possibility.

8.4.3 *The Scope of Models*

With all of these points in mind, we see that Schelling-type models are hardly the only permissible variety under these frameworks; in fact, a large number of models may display appropriate theoretical back-stories while remaining tractable. Schelling does, however, illuminate the central concerns tied to these modelling frameworks: the importance of theoretical backstory, artificiality, tractability and simplicity, and the scope of the model.

The final element, scope, is an important one to note. Schelling succeeds not only by having a cogent backstory, using its artificiality appropriately, and remaining tractable, but also by limiting its approach: the model aims only to illustrate the importance of micro-motives in a social system, not produce empirical data. In the same way, if our bird migration researcher chose to model the movements of the birds from place to place simply for the purpose of realistic mimicry of their travels, as in Reynolds' flocking boids (Reynolds 1987), he could do so with little theoretical baggage. If he then chose to declare these mimicked movements as instances of real flocking, or as producing relevant empirical data, suddenly far more justification is required.

8.5 The Difficulties of Social Simulation

8.5.1 Social Simulation and the Backstory

While our earlier analysis of ALife provided some valuable insight into the limitations of agent-based modelling techniques, particularly in contrast to traditional mathematical models, these refined frameworks developed in those chapters do not translate simply to social simulation approaches. Within a field such as social science, the philosophical considerations we addressed in those frameworks grow even more troublesome. Imagine that we have created our bird migration model, and the in-depth construction of our programmed agents allows those agents to begin to communicate and even form social structures of a sort. If our stated goal is to use this model to investigate properties of human societies by providing a new, digital source of empirical data, we must not only accept the PSS Hypothesis (presuming that only living things may create a true society), but also related points. The researcher must be prepared to accept that these digital beings, alive but unrelated in a conventional sense to natural life, can create a real societal structure.

In addition, this societal structure will be further removed from real, natural societies by its dependence on a form of 'life-as-it-could-be.' In that case, even if we accept that this virtual community of birds can create a society of their own through their interactions, how might we be able to relate that behaviour to the development of real-world societies? If we accept Sawyer's concerns regarding the non-reductive individualist character of human society (Sawyer 2002, 2003, 2004), are we not placing ourselves even further from a possible social explanation by basing theories upon this digital instantiation of society? Perhaps the non-reductive characteristics of our digital society differ completely from those displayed in human society. Once again, we would be stuck studying the simulation for its own sake.

8.5.2 Social Simulation and Theory-Dependence

As discussed in Chap. 3, the field of ALife may be considered fundamentally theory-dependent: the structure and function of a given simulation is directly connected to the theoretical assumptions made to create that model. The framework discussed in that chapter chose to deal with this issue by noting the inherent theory-dependence of empirical science, and presenting ideas regarding the importance of theoretical back-stories to any empirically-motivated endeavour.

With social simulation, however, an additional layer is added to this theory-dependent aspect of modelling. Not only do the agents and environment of the simulation present problems of theory-dependence, but also the additional aspects of social communication and behaviour that allows the model to address issues relevant to society.

Further, these additional layers of complexity are not easily subdivided into a hierarchy or other framework which may ease the construction of a computational model (Klüver et al. 2003). The interdependencies between individual action and societal effects means that abstract models will lose a great deal of detail in these missing elements, and conversely that highly-detailed models which address these complexities will veer toward intractability. In either case, theory-dependence becomes a greater issue: abstract models will require strong assumptions to remove these non-hierarchical complexities; and complex models will require incorporating ideas regarding the interaction of individuals and society.

8.5.3 Social Simulation and Explanation

Even if one does manage to construct a tractable social simulation with reasonable theoretical justification, as noted by Sawyer (2004), social explanation via social simulation is a difficult prospect. While the potential for agent-based models to demonstrate the emergence of social complexities is a possible benefit to social science, whether or not those models can provide a coherent explanation of social behaviour is unclear.

Sawyer argues that societies, like the human mind, display qualities which are irreducible to simple interactions of individuals within that society; despite our knowledge of neuroscience, the higher-level study of mental phenomena (i.e., psychology) is still required to understand the human mind. Similarly, Sawyer argues that human society displays a non-reductive individualism, in which social explanation cannot be complete without addressing the irreducible effects of higher-level social structures. The variation of the bird migration example given in Sect. 5.9.2 gives one example of this phenomenon.

8.6 Schelling's Approach

8.6.1 Schelling's Methodological and Theoretical Stance

Schelling's modelling approach, as in our analysis of ALife, provides some important insights into addressing the difficulties of social simulation. Once again, Schelling avoids some of the difficulties facing other social simulations by virtue of the residential segregation model's simplicity. As a C1 model in Cederman's framework (see Table 5.1 for a summary), Schelling avoids the methodological difficulties of using complex agent structures (as in C2), or seeking profound emergent behaviours (C3). Likewise, problems of theory-dependence are minimised by using only simple agents with simple rules, with no attempt to address larger social structure. As a consequence, Schelling's methodology remains influential today with researchers who seek simple models of social phenomena (Pancs and Vriend 2007; Benito 2007).

Schelling further strengthens this approach through his own theoretical framework regarding the best use of models. He posits that general models of behaviour can produce general insights, and that within a given discipline some such insights may not be evident from empirically-collected data. This view seems vindicated by the surprising result of his segregation model, the impact of which was immediate and lasting within social science.

8.6.2 Difficulties in Social Explanation

However, while Schelling's model does address a number of concerns relevant to social simulation, the problem of social explanation still presents a difficulty. As noted above, his model takes no interest in the presence or influence of higher levels of social structure; he is concerned only with the actions of individuals. Within the study of residential segregation, his result is likely to be only a partial explanation simply for that reason: housing reform, tax incentives, and other measures designed to influence racial integration in the housing sector are likely to have an impact as well. Schelling of course does not strive for such a complete explanation, as discussed in Chap. 7; however, those who do seek an explanation of residential segregation could try to use Schelling's model as a starting point.

Unfortunately, Sawyer's perspective argues that avoiding these higher-level elements in an agent-based model and hoping for them to emerge may be fruitless as well (Sawyer 2004). Even if one were to add additional capabilities and complexities to Schelling's model, in the hope of allowing for more complex emergent behaviours, an explanation derived from such a model would lack the contributions of higher-level, irreducibly-complex social institutions. As in the birdsong example in Sect. 5.9.2, there is an argument that such elements must be incorporated to produce a complete picture of the development social behaviours. The issue of how to progress from Schelling's initially successful modelling framework to deeper social explanation thus remains a complex one.

At least the social scientist can take solace in the fact that such concerns are not alien to other modelling disciplines, as in Bedau's discussion of 'weak emergence' as a means for avoiding the difficulty of the effect of downward causation in natural systems from higher-order elements (Bedau 1997). Unfortunately, if anything such difficulties are more acute in social simulation than in biologically orientated simulation, as the additional elements of social institutions, mass communication, and other distinctly societal factors add additional layers of unknowns into an already difficult theoretical situation.

8.6.3 Schelling and Theory-Dependence

As noted above, the issue of theory-dependence looms large within social simulation, and even for Schelling's simple and abstract model these problems seem to remain. Schelling's model is constructed as a singular, vitally important assumption: if we presume that individuals choose their preferred housing based on the racial makeup of their neighbourhood, then segregation will result.

Schelling, and likely other theorists, would argue that such an approach is commendable: Schelling was using his model to test a hypothesis, which is an acceptable role for models. By introducing a highly tractable, transparent model to illustrate the potential import of these factors in residential segregation, he was able to present a new perspective on potential individual choices that can lead to such undesirable social outcomes. However, such an approach becomes difficult when the goal is not hypothesis-testing, but the development of new social theory.

8.7 Luhmannian Modelling

8.7.1 Luhmann and Theory-Dependence

Luhmann's influential treatises on the development of social order (Luhmann 1995) provide a perspective which illuminates potential methods to use social simulation to develop social theory. His ideas regarding the low-level basis for human communication, and the subsequent development of social order, seems a natural partner for the agent-based modelling methodology.

This approach demonstrates the fundamental limitation of Schelling's methodology alluded to in the previous section. While the residential segregation model can, and does, provide a useful test of a hypothesis which demonstrates the importance of individual behaviour in human society, the overall import of that factor is unaddressed by such a model, given that it is confined to a singular behavioural assumption related to a singular social problem. We may build a Schelling-type bird migration model which demonstrates the importance of certain individual-based factors in driving migration behaviour, but the deeper question remains open: how do these behaviours arise in the first instance?

For the social scientist, these are questions that must be addressed in order to develop a deeper understanding of the origin and development of human society. While we can imagine innumerable scenarios in which a Schelling-type model may illuminate certain singular aspects of social issues and problems, the simplicity and related theory-dependence of the approach limits our ability to investigate the fundamental beginnings of society and communicative behaviour.

8.7.2 Luhmann and New Social Theory

Luhmannian modelling can address this larger goal of social simulation, clearly a larger goal of the research community (Cederman 2001; Axelrod 1997; Epstein 1999), by removing these elements of theory-dependence. Any model constructed based upon the functioning of human society will incorporate a fundamental theoretical bias, and remove the possibility of investigating the factors that lead our society developing in that way initially.

Doran's perspective regarding the undefined nature of computational agents in social science (Doran 2000) ties in closely with our developed Luhmannian view. Doran argues that social simulations should begin below the level of agent, allowing for the emergence of agent structures that interact without pre-existing theoretical biases affecting those interactions. In both cases, the removal of theory-dependence from the model is paramount to its success in providing insight for the social scientist into the origin of society.

8.7.3 Luhmann and Artificial Worlds

Recalling the earlier discussion of Levins (1966, 1968) and the lure of artificial worlds for the modeller, this Luhmannian approach seems to fall squarely within this realm. After all, a simulated environment, not based upon empirical data, which includes abstracted virtual agents is already quite separated from the traditional modes of empirical study. A simulation in which most elements of existing theory and data are removed to study the fundamentals of society seems even further away from the real world; one could easily imagine such a model producing quite unusual agents with idiosyncratic interactions. Once again we return to the prospect of studying a model for its own sake, removed from the natural world.

Where the Luhmannian approach is unique in this regard is the way in which this separation from the real world is vital to the model. The search for a fundamental social theory requires the removal of pre-existing theory-dependent elements in order to produce models which illuminate the importance of pre-societal communications and interactions. In essence, the Luhmannian approach utilises an artificial world to illuminate factors in the real world that we may miss, simply by virtue of our pre-existing biases derived from forming our models and theories within a society.

8.8 Future Directions for Social Simulation

8.8.1 Luhmannian Modelling as a Way Forward

Clearly the Luhmannian modelling approach displays promise for those in search of new social theory. Without the removal of more theoretical bias from future social simulations, issues of theory-dependence will continue to provide difficulty for the social scientist who hopes to use these methodologies. Likewise, this approach offers a wide scope for developing new ideas regarding the origin of society, something not provided by Schelling-type methods.

Perhaps more importantly, this perspective brings us closer to the larger goals expressed by proponents of social simulation: a means for understanding the detailed workings of human society. From Levins' enthusiasm for L3 models (Levins 1966) to Cederman's for C3 models (Cederman 2001), researchers in various fields continue to seek to explain higher-level behaviour through the interactions of component parts following simple rules. For the social scientist, Luhmann reduces social interaction to its simplest components, giving the community access to a new and potentially stimulating view of the earliest beginnings of human society.

8.8.2 What Luhmann is Missing: Non-reductive Individualism

Despite these promising elements of the Luhmannian approach outlined thus far, the problem of social explanation remains. Sawyer's perspective of non-reductive individualism in social science (Sawyer 2002, 2003, 2004) implies that even an elegant portrayal of the origins of society may not be able to allow for the emergence of complex social structures. Given that some of these structures are irreducible to the actions of component individuals in the society in question, there may be great uncertainty as to whether a given set of Luhmannian rules for a simulation may be able to produce such complexity.

Perhaps, then, our comparison with the study of the human mind is more apt that initially thought. As Sawyer notes, there is both a study of mind and a study of neurons (Sawyer 2004); likewise, such an approach is an option for social simulation. Analogous to the study of neurons, Luhmannian approaches can probe the low-level interactions of individuals in a society through the use of models. Then, analogous to the study of mind and mental phenomena, other models may probe the influence of higher-level organisation upon those low-level agents. A combination of these approaches could provide insight into social science that, as Schelling describes, may be unattainable by other means (Schelling 1978).

For example, Luhmann's discussion of the function of social order (Luhmann 1995) includes an in-depth discussion of the major elements of the modern social institutions which pervade most human societies. This in turn inspired a model in which each of those institutions was modelled very simply, as a monolithic influence on a society of agents, with each institution affecting one element of overall agent behaviour (Fleischmann 2005). Thus, this model attempts to capture the 'science of mind' level of societal interaction, while also incorporating lower-level agent behaviours. Such a model shows great promise, as Sawyer's objections and the difficulties of strong emergence hold much less weight if these downward causation effects can be harnessed appropriately in a model.

8.8.3 Integrating Lessons from ALife Modelling

As our analysis of Schelling shows, the frameworks in the earlier chapters that underwrite certain varieties of ALife models can be brought to bear on social simulations as well. The issue of theory-dependence has proved vital enough to the success of social simulation that the latter chapters of this text aimed to develop a modelling framework which removes that difficulty. Similarly, the pragmatic concerns of generality, realism, precision and tractability will remain important even in a Luhmannian approach which aims to develop social theory; our modified Levinsian framework provides a useful guide to the limiting factors present in all models of natural phenomena.

A larger question in both ALife and social simulation is illustrated neatly by Schelling's model and related theoretical justifications: how does the intent and scope of a model affect its usability, either empirically or theoretically? Schelling shows how a simple model, intended to demonstrate the importance of a singular factor in a singular problem, can have wide-ranging effects on related theory. Despite using agents that followed only a single rule, Schelling's demonstration of the potential impact of individual micro-motives on the segregation problem lead to a great deal of research investigating the impact of such individual factors on all varieties of social problems.

Likewise, our analysis of ALife demonstrated the importance of theoretical backstory in driving the acceptance of a model as a contribution to empirical data within a discipline. Empirical science is full of such back-stories, but they are implicit: the trans-cranial magnetic stimulation researcher believes tacitly that such methods are analogous to producing real lesions in a patient's brain. In contrast, the agent-based modeller deals with artificially-generated data that is not simply produced in a natural source through a different means, but is produced entirely artificially, in a constructed world. For this reason, the theoretical backstory for agent-based models must be explicit, as otherwise a connection between the model and related data from the natural world becomes difficult to establish.

8.8.4 Using the Power of Simplicity

As discussed throughout all three parts of this text, the issue of complexity in models has numerous ramifications. For the researcher, highly complex models are difficult to develop successfully; there are a number of choices to be made at the implementation level. For example, an evolutionary model requires a number of parameters to govern the evolution and reproduction of its agents. How should the agents replicate? Should crossover and sexual reproduction be used? What sort of mutation rates might be necessary, and will test runs of the simulation illuminate the best rate of mutation with which to produce interesting results? Additional complexities such as neural network elements or detailed agent physiologies require even more numerous questions at the implementation level.

Similarly, as discussed in relation to the Levins framework, greater complexity leads to greater difficulties in tractability (in the context used here, a greater difficulty in producing substantive analysis, as well as computability). Levins discussed the possibility of producing models of such complexity that they exceed the cognitive limitations of the scientist studying them (Levins 1968). For the mathematical modeller, a model which captures every possible factor in a migrating bird population could end up consisting of hundreds of linked partial differential equations, a mathematical morass of such complexity that analysis becomes fruitless. For the computational modeller, a model of similar character could produce highly-detailed agents with individual physiologies and complex neural structures that allow for remarkably rich behaviour; yet, such a scenario is a nightmare for the analyst, for whom divining the function and impact of these complex internal structures takes incredible amounts of time even for the simplest neural networks (see Chap. 4 for discussion in relation to Beer's model).

Thus, we must take inspiration from Schelling in this respect. Greater ease in implementation and analysis are two enormous advantages of simpler models. Particularly in the case of social theory, where the potential complexities when studying human society in simulated form are vast, simple and elegant models which illuminate crucial aspects of social systems are the most likely to produce substantive insights.

8.9 Conclusions and Future Directions

8.9.1 Forming a Framework

This text has sought to investigate in-depth both the theoretical and methodological concerns facing researchers who utilise agent-based modelling techniques. By examining these issues, and developing frameworks to understand the limitations of such models, future directions for substantive modelling research can be identified.

Our early analysis of ALife in the beginning of the first section of this text demonstrated the importance of theoretical justification in the model-building process, as well as the potential theoretical pitfalls of artificiality in simulations. Whether it is Newell and Simon's PSS Hypothesis, or Silverman and Bullock's PSS Hypothesis for Life, computational models require a theoretical basis before they can fit into the conventional tapestry of empirical methods. In the case of both of these frameworks, the implied empirical acceptability of models built on such premises comes at the price of philosophical baggage for the modeller to bear. Those who choose not to take such strong philosophical positions, as in weak ALife, find themselves in the situation of facing more difficult theoretical problems despite avoiding philosophical conundrums.

This baggage became increasingly evident during our examination of Levins' modelling framework (Levins 1966). The modeller who seeks to produce useful insights about natural systems must strike a difficult balance between both Levins' proposed three modelling dimensions and the additional aspect of tractability. This fundamentally limits the ability of a researcher to develop models that capture the complexities of natural systems; instead, they are left waiting for techniques that may enhance tractability while still allowing a rough balance of the three Levinsian dimensions.

Initially, our analysis of social simulation in the second section of this text seemed even more problematic than for the ALife community. Social simulations suffer the same methodological and theoretical complexities of ALife simulations, but with the added problem of increased layers of complexity through the addition of social considerations. Even assuming that such problems could be surmounted, the difficulty of providing complete social explanation remained.

However, the introduction of Luhmannian systems sociology introduced another means of utilising simulation in social science. In the case of developing new social theory, creating models that are closer to reality in fact poses a fundamental problem: the issue of theory-dependence prevents the social scientist from producing simulations that avoid biases drawn from our own societal experience. Artificiality thus becomes a desirable trait, bringing the social theorist away from pre-existing theoretical biases in his models. The lure of artificial worlds in this case is thus practical: rather than attempting to avoid the inherent difficulties of modelling illuminated by Levins, and instead losing explanatory capacity, the Luhmannian modeller avoids theory-dependence and gains the ability to generate new elements of social theory.

In essence, the root of the issue comes back to artificiality and intent. A modeller who wishes to create an Artificial^1 instance of life or mind can simply look to the PSS Hypotheses. One who wishes to mimic a natural behaviour as accurately as possible, without claiming any theoretical revelations as a result, can simply declare his work Artificial^2. A weak ALife researcher, or a similar perspective from other disciplines, can apply his Artificial^2 simulation to the examination of a natural system or an element of human society by balancing his model's dimensions within the modified Levins framework, and ensuring both tractability and a reasonable theoretical backstory (as in Schelling and his focus on general insight and transparency in modelling).

For those who wish to apply their models to the development of new social theory, the issue of artificiality becomes more nuanced. The modeller in this case does not seek an Artificial^1 instantiation of a natural phenomenon, nor does he seek an Artificial^2 imitation of something natural. Instead, the modeller seeks to develop a simulation in which pre-existing elements of the natural system are removed, along with pre-existing theoretical positions on that system, in order to develop theories independent of bias.

8.9.2 Messages for the Modeller

Now that we have examined a number of modelling frameworks in detail, analysed and compared each in Chap. 6, and applied them to Schelling in Chap. 7, we have been able to ascertain the most fruitful directions for future models in the social sciences to take. However, on a more general level, the models proposed here will not be the entirety of social simulation. Indeed, a great variety of different types of models will continue to develop in this field, and while Luhmannian modelling may hold great promise for those interested in formulating new social theory and in using simulation by playing to its greatest strengths, this is not to say that other types of models in social science must take a lesser role.

For the social science modeller interested in producing different varieties of models, this argument has brought forth a number of philosophical and methodological frameworks which can provide insight into making those models more relevant to empirical social science. Our discussion of modelling frameworks in Alife illuminated the importance of creating a theoretical backstory; since modelling is inherently a theory-dependent approach, an understanding and elucidation of the theoretical underpinnings of a given model is vital for creating a basis upon which to understand that model. Merely stating that the model is somehow reminiscent of a real-world incidence of some social phenomenon is not enough to create a useful justification.

Our subsequent discussion of modelling in social science saw these frameworks applied to a new area of enquiry, and described the various theoretical problems at issue in the field which have a significant impact for the model-builder. While the idea of a balancing act inherent in creating a model between complexity and analysability is nothing new, bringing the Levins framework into the discussion in social science helps to illuminate more specific pragmatic modelling concerns that are important in computational models. The in-depth discussion of problems of explanation in social science demonstrates how the complexities of modelling human society create additional difficulties for the modeller, adding to the problems of strong emergence in the field of Alife. The modeller interested in social science must take care to understand the limitations of the computational approach, and to avoid incorporating too many elements which may lead to unanalysable complexity. Models offer some new research directions to the social scientist, but also new methodological difficulties; models cannot solve all of these problems and must be deployed appropriately in conjunction with empirical data and useful theoretical background.

Finally, we applied the frameworks discussed in relation to both Alife and social science simulation to one particular example, that being Schelling's residential segregation model. Schelling provides the best means for demonstrating the tensions between model implementation and model design within social science. The model's inherent simplicity limits the conclusions which one can draw from its results; yet, that same complexity allows for greater communicability and impact among the social science community. Replicating and extending Schelling's model is simple in comparison to many computational models, and as a consequence a greater number of the social science community could join in the conversation spurred by the creation and dissemination of the model. In this respect, Schelling's limitation of his model's scope to a simple demonstration of the possible impact of a single individual factor on a complex social problem was a big part of its success; the modeller would do well to remember this point as a reinforcement that models need not encompass every element of a given problem to create intriguing insight and new directions for empiricists and theorists.

8.9.3 The Tension Between Theory-Dependence and Theoretical Backstory

A central element running throughout the three major sections of this text is the discussion of theory-dependence in models. Early on in the Alife discussion this element became important, and the possible theoretical biases on display in a given model become a serious potential difficulty in applying that model to the field in question. The proposed solution to this issue has been the creation of a salient theoretical backstory, one which describes the reasons which make a given model acceptable as contributing in some important way to the discourse of the field to which it is applied. By doing so, the researcher can justify their model and its conclusions as important and not simply relevant only to those interested in mathematical curiosities; as discussed in Chap. 3, the Alife researcher might do so by contending that their model is an instance of an information ecology and thus an instance of empirical data-collection despite its inherently artificial nature.

However, such theoretical backstory can also limit the applicability of a model. Too strong of a theoretical framework, or one which does not hold under closer scrutiny, can result in a model which suffers from greater theory-dependence, rather than less. The tension here then is the delicate balance between providing a theoretical context for a model, and having that model stuck too deeply in theoretical elements that limit its usefulness to the broader field. There is no easy solution to this tension, as these pages have demonstrated. However, the modelling frameworks discussed herein provide guidelines to avoid such pitfalls. A careful examination of the theoretical and pragmatic circumstances surrounding a model can help the modeller to avoid both theoretical pitfalls that may make his model's applicability suspect (as in Webb's discussion of Beer Webb 2009), and to avoid those elements of model construction and implementation that may lead to great difficulties in analysis and the presentation of useful results.

8.9.4 Putting Agent-Based Modelling for the Social Sciences into Practice

Having investigated the use of agent-based models in Alife and social science, we are more aware of the issues facing modellers in these areas and have developed frameworks to help us navigate these complexities. As modellers seeking the most effective application of agent-based models to the social sciences, our work is not yet done, however. General principles for effective modelling are of great value, but within each discipline and sub-discipline of the social sciences there are further complexities to face before we can put these ideas into practice.

Creating individualised modelling frameworks for all the major disciplines of the social sciences is obviously beyond the scope of this text. In order to situate our modelling ideas properly in an individual discipline requires in-depth knowledge of its history, scope and research aims. We would need to analyse the methods of each, determining how agent-based models can enhance researchers' efforts in that field. Finally, in order to be truly convincing to those looking to branch out into agent-based approaches, we would need to present some worked examples that illustrate the potential of these methods to contribute useful knowledge.

In Part III, we will build upon the foundations presented thus far and offer an example of the development of a model-based approach to a social science discipline – in this case demography, the study of populations. Demography is a field with a long history, and close ties to empirical population data. We will present a framework for *model-based demography*, a considered approach to demographic simulation that takes into account the needs of the discipline and its practitioners.

In order to develop a model-based demography, we will start by analysing the methodological development of the field, from its earliest beginnings to the bleeding edge. Demography, given its nature and close ties to real-world data and policy, tends toward the *social simulation* approach to social science modelling. As a consequence, our analysis will focus particularly on the demographic approach to data and how simulation can maintain the field's focus on real-world populations. We will show that demography not only can live up to demographers' expectations in this respect, but it can even enhance their ability to gain new insight about the processes and functions underlying demographic change by helping us to address demography's core epistemological challenges of uncertainty, aggregation and complexity.

We will then examine some worked examples of agent-based modelling, with a particular focus on two modelling projects which will be presented in detail. These two models illustrate how agent-based models can work in tandem with traditional statistical demography to build simulations that closely mirror the behaviour of the real-world populations under study. Finally, we will discuss the status of model-based demography and its potential to contribute to the discipline, and theorise about the implications of this effort at methodological advancement for other areas of social science that are experimenting with a model-based approach.

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Chapter 12
Conclusions

12.1 Model-Based Demography: The Story so Far

As we have seen from the examples presented in Part III thus far, the development of model-based demography is advancing, though still in a relatively early stage. Demography is a field with a lengthy and successful history, and by the nature of the research questions it poses, has always been linked very tightly with concepts of statistics and probability (Courgeau 2012). Far from preventing progress in the field, demography has been influential since its earliest beginnings, proving vital for the study of population change and the implementation of critical social policies relating to its core processes of fertility, mortality and migration.

Perhaps as a consequence of this, the introduction of a new methodology into a field with such an extensive history is one that bears careful consideration. After all, if statistical modelling of population data can still produce figures that journal editors, policy-makers, and research funders find useful and are happy to support, is there any particular need for new methods?

As outlined in Chap. 9, demography has wrestled with this question before, and in each instance has incorporated these new methods and used them to enhance its core strengths. Each of the four methodological paradigms we outlined – period, cohort, event-history and multilevel – developed in response to shortcomings in previous methods that left certain demographic questions out of reach. New methods that addressed these questions thus became part of the demographic toolbox, augmenting the field's capabilities but not replacing the methods that came before.

In that respect, model-based demography answers a similar call. The epistemological challenges posed by the problems of uncertainty, aggregation and complexity lend themselves toward a model-based approach. The application of simulation to demographic problems is not just in pursuit of novelty, but is a means to an end, offering the power to investigate and better understand the complex, multilevel interactions that drive population change. As with cohort, event-history, and multilevel approaches previously, model-based demography will become a key

E. Silverman, *Methodological Investigations in Agent-Based Modelling*,
Methodos Series 13, https://doi.org/10.1007/978-3-319-72408-9_12

tool the demographic toolbox for certain categories of research questions, and the four previous paradigms will continue to be useful for other questions. Indeed, as we have seen in the examples in Chaps. 10 and 11, simulation models and statistical demography can work in combination to answer questions about complex social processes.

12.2 The Practice of Model-Based Demography

The modelling studies presented in Part III provide detailed examples of the application of simulation modelling methodologies in demographic research. We should note that the studies presented here are far from a comprehensive survey of the whole of model-based demography, though we have tried to present some of the key influences on these studies and acknowledge their critical contribution to the state of the field today. Without the efforts of Axtell et al., Billari et al., and numerous others, the development of model-based demography would not have proceeded so quickly and effectively (Axtell et al. 2002; Billari and Prskawetz 2003; Billari et al. 2007).

The Wedding Ring example in particular serves as a useful illustration of how simple models can add to demographic knowledge. Much like Schelling's residential segregation model (Schelling 1971), the Wedding Ring focuses on a single complex question and seeks to model a possible answer with very little in the way of data or complexity. In both cases, we are not able to offer specific point predictions about the future state of residential segregation or coming trends in partnership formation, but we are able to offer some new conclusions about the social functions underlying those phenomena. With Schelling's model, we can suggest that individual racial preferences may play an unexpectedly large role in the manifestation of residential segregation, and with the Wedding Ring we can propose that social pressure on the unmarried from the married can produce similar partnership formation patterns to those seen in the real world. Most fascinatingly, neither of these models required the incorporation of even a scrap of real-world data.

These modelling approaches thus hew closer to *systems sociology* as opposed to *social simulation* (Silverman and Bryden 2007, to appear). The outcomes of these models help us to understand the social functions underlying a population-level outcome seen in human society, but in neither case are we able to state anything specific regarding a real-world example. This is a marked difference from traditional demography, in which the overwhelming majority of research is applied in nature.

The Wedding Doughnut (Bijak et al. 2013; Silverman et al. 2013a) acknowledges this disconnect and attempts to resolve it, primarily through the integration of statistical demography. The model is extended to increase the influence of spatiality, and fertility and mortality, augmented by statistical demographic projections using real-world data, become key elements of the model's behaviour. The model remains a proof-of-concept more than a focused policy tool, but these extensions demonstrate the capacity for simulation and traditional demography to work in tandem, and in the process harness the strengths – and mollify the weaknesses – of each approach.

The addition of uncertainty quantification in the form of Gaussian process emulators further eases the transition from statistical model to computational. The emulator provides key insight into the impact of simulation parameters, helping the modeller to redress the balance between precision and tractability. In practical terms, we can better understand the model's behaviour and provide more incisive analysis of the results. In pragmatic terms, modellers accustomed to formal mathematical models may feel more comfortable working with computational models that are less of a 'black box'.

12.3 Limitations of the Model-Based Approach

While the development of model-based demography provides new means for generating demographic knowledge, practitioners should remain mindful of the limitations of simulation as set out in Parts I and II. As with any modelling methodology, agent-based methods are best used to answer research questions that would explicitly benefit from modelling individual behaviours and interactions. When modelling problems that are closely related to complex social factors, agent-based models may provide a more suitable platform for explanatory aims.

12.3.1 Demographic Social Simulation

Revisiting the agent-based model of the Anasazi Axtell et al. (2002) provides an example. The model was built using archaeological data, and provides a useful platform for exploring how the Anasazi population eventually declined. However, as pointed out by Janssen et al. (2009), one could argue that the model did not result in a substantial change in the discourse around the Anasazi's decline. The authors' replication shows that, while the model results do closely mirror archaeological data and provide sensible conclusions, the model does not provide much information beyond a comparatively simple model based on the carrying capacity of the Long House Valley itself:

> Within model-based archaeology two approaches can be identified: (1) detailed data-driven simulation models that mimic observed trends like population numbers, (2) stylized models that are informed by empirical data but explore a broader domain of possible social-ecological systems. Which approach is the most appropriate depends on the research question at hand. The fact that the Long House Valley abandonment can not be explained by environmental factors is demonstrated by the original Artificial Anasazi, but it could also be explained by calculating the carrying capacity of the valley. A more comprehensive question like whether exchange networks increase the resilience of settlements in the US south west may need to be addressed by a series of models, including stylized models that simulate various possible landscapes. (Janssen 2009, para. 5.4)

In model-based archaeology, as in social sciences more broadly, the data-driven *social simulation* approach and the abstract, theory-driven *systems sociology* approaches are in evidence. In the case of the Anasazi simulation, one might argue that the model may have been more powerful than was actually demanded by the research question. We might propose as well that the model in this case served a useful role by confirming a result through a more detailed modelling approach, as well as providing a useful example of model-based demography in practice.

The choice of whether to apply an agent-based model to a particular question is not always going to be straightforward, and there is often the chance that a model may be overkill for certain types of research questions. However, as in the case of the Long House Valley model, the model can serve additional purposes beyond testing a hypothesis, by providing a test case for a particular approach, generating new questions that can be examined with a refinement of the model, or by directing future data collection.

12.3.2 Demographic Systems Sociology

The Wedding Ring and Wedding Doughnut provide a useful example of the more abstract side of agent-based demography. These models are more generalised and abstract in their approach, in contrast to the Anasazi model. The Wedding Ring eschews empirical data entirely, building a model focused on testing a particular theory about the influence of social pressure on partnership formation timing (Billari et al. 2007). The approach is more in line with a systems sociology approach, in which we are examining the impact of social factors on a population-level phenomena without reliance on empirical data. The theoretical focus of the model is acknowledged from the outset, and as a consequence the model provides both a useful exploration of theory and an influential proof-of-concept for demographic models with similar research aims.

The Wedding Doughnut (Bijak et al. 2013; Silverman et al. 2013a) takes the foundations of the Wedding Ring and takes them in a more empirical direction. Empirical data is used to generate the initial population and to drive the patterns of mortality and fertility amongst the agents. A simple model of health status is added to illustrate how simple models can still be relevant for the study of social policy. The model does not fully make the leap into social simulation, however, as the authors are not aiming for specific point predictions regarding social care need or UK population change; instead, the model provides an example of the integration of statistical demography and agent-based approaches.

In an empirically-driven discipline like demography, models like these stand out as a more theoretically-driven approach. This can easily lead to misunderstandings, as the results may seem to lack relevance to real-world population change, and too ill-informed by population data to provide demographic insight. However, as noted by Courgeau and Franck (2007), a demography which exists to operate only on successive sets of data using identical methods is not a field which is progressing as a scientific practice. Model-based demography can provide a means to expand the theoretical innovation of demography, as illustrated by the Wedding Ring and subsequent extensions.

In practice, the makers of such models should be mindful of their theoretical backstories, and ensure that the assumptions underlying their construction are clearly delineated from the start. Setting out the aims and purpose of a more abstract model will ensure that the results are properly placed into context by readers, and alleviate potential misunderstandings due to misapprehension of the model's scope and intended impact. This will also help to ensure that comparisons between models and demographic approaches will be made on a *like-for-like* basis. Demographic systems sociology models will not evaluate well when compared against statistical models of a particular population, for example, given that the simulation in that case is not aiming for theoretical relevance in the first place – but if the intended scope of the model is not laid out from the outset, that may not be clear and could lead to a negative evaluation of the methodology by the community.

12.4 The Future of Model-Based Demography

Model-based demography clearly has potential as an approach to certain types of demographic problems, both focused empirical questions and broader, theoretical concerns. However, the unique characteristics of agent-based approaches in particular suggest some particular avenues where this approach would be most fruitful.

The demographic extension of the Linked Lives model discussed in Chap. 11 (Noble et al. 2012; Silverman et al. 2013b) demonstrates the potential of agent-based demographic models for the study of major social policy concerns. Demography has a long history of empirical relevance, and is frequently used by policy-makers to guide their decisions (Xie 2000). The Linked Lives model aims to leverage this strength by combining statistical demographic elements with a detailed model of the supply and demand of social care in an ageing UK society, a problem receiving a great deal of focus in the UK political context at present.

The simulation is built around a simplified version of UK geography, in which individual agents live, form partnerships, migrate, and provide care for loved ones. The original Linked Lives model (Noble et al. 2012) focused on the implementation and demonstration of the model as a useful platform for the examination of the cost of social care; the subsequent demographic extension (Silverman et al. 2013b) incorporated UK census data and demographic projections of mortality and fertility to enhance the realism of the model. This combination produces population dynamics that accurately reflect demographic projections of the UK population.

More importantly, however, the extended model demonstrates how a model of this type can provide unique insights into policy-relevant problems that benefit both from demographic expertise and the modelling of complex interactions facilitated by an agent-based approach. For example, the model illustrates that a policy change that might at first blush seem largely irrelevant to the cost of social care – in this case, increasing the retirement age – has a significant impact. The presence of retired carers actually accounts for a surprisingly large amount of the informal social care being provided in the model, and as a consequence, keeping older potential carers in work longer can backfire when the retirement age is raised too high (Silverman et al. 2013b). This result anticipates the later analysis by Age UK, which highlights the significant cost savings to society provided by these selfless older citizens (Age UK 2016). The use of Gaussian process emulators to confirm the impact of the retirement age parameter further increases our confidence in this result, allowing us to peer deeper into the workings of the model and determine key parameters that may be of particular importance to policy-makers concerned with social care.

While the model remains more of a proof-of-concept, and does not claim to provide specific and solid predictions for the future of UK social care, it does provide a useful exemplar for future excursions into policy-relevant model-based demography. Despite the relative lack of data compared to data-rich microsimulations, the model is able to provide significant insight into the dynamics of social care supply and demand. The incorporation of UK demographic data shows that simulations can be linked closely with population data in a relatively straightforward way. Finally, the use of uncertainty quantification in the form of emulators allows us to more thoroughly explore the simulation's parameter space, and in the process generate scenarios that help us examine possible futures under a wide variety of possible policy shifts.

Thus we may imagine a future for model-based demography in which the approach becomes a trusted tool for the study of empirical questions of population change where social factors are of particular relevance, but also where it flourishes particularly when applied to systems sociological models driven by social theory, and policy-relevant models aimed at the generation and exploration of scenarios. The latter case offers another area of growth for demography, where the implementation of models combining population data and complex agent behaviour allows us to create 'policy sandboxes' where future population trends can be studied under a variety of possible futures. Interacting with models of this type can help policy-makers to spot potential spillover effects of policy changes before real-world implementation, and assist them in the creation of evidence-based policy informed by real-world population data and a scientific approach to the modelling of populations.

12.5 Model-Based Demography as an Exemplar for Social Science Modelling

In Parts I and II, we examined the methodological difficulties inherent in the use of agent-based modelling for the social sciences. By bringing together methodological analyses from Alife, social simulation, population biology, and political science, we established the importance of a theoretical backstory for any given modelling enterprise. These backstories delineate the assumptions on which our models operate, the intended scope of the model, and the level of artificiality we ascribe to the model and its results.

In practice, however, addressing these concerns in detail every time we develop a model seems redundant at best, even a waste of time at worst. The practice of modelling often requires an iterative approach, in which previous simulations are extended in various ways, tested and at times discarded, and as a consequence each instance of the model could approach each of these elements slightly differently, even if the overall research aims stay largely identical.

12.5.1 The Advantages of Developing a Framework

In the case of model-based demography, we are able to alleviate this additional explanatory burden somewhat by developing a widely applicable methodological framework – a paradigm which seeks to justify the general practice of modelling population change in this way from the outset. Under this methodological paradigm, modelling is focused on a classical scientific approach, informed by data and tasked with studying the social factors underlying the processes generating population change. As model-based demographers we seek the integration of demography's greatest strengths – rich population data and a centuries-long history of statistical expertise and innovation – with simulation's ability to surpass some troublesome epistemological limits of demographic knowledge (Courgeau et al. 2017). By extending the concept of the *statistical individual* to the *simulated individual*, we establish model-based demography as a descendant of the methodological tradition of the discipline, and enable a generation of researchers to embrace a new technique without overly troubling themselves with the finer points of Artificial^1 and Artificial^2.

The advantage of this kind of approach is significant. Establishing the theoretical backstory in advance as a methodological addition to the field, or as a sub-field, allows us to approach each new model identifying as 'model-based demography' with a pre-existing knowledge of the likely scope and intent of that model. Where models depart from the core concepts of model-based demography, this can be established when documenting the model by making reference to this paradigm. We are able to spend more time constructing and validating models, confident that our intentions will be understood by the community at large without excessive explanation.

Additional complexities do come into play, however, when we reach the stage of analysing the results of our complex demographic models. If the advantages of model-based demography are to be truly realised, then methods which enable us to understand the impact of model parameters on population-level phenomena should continue to be refined. Uncertainty quantification methods like Gaussian process emulators provide a useful starting point here, and if model-based demographers begin to embrace these techniques then it is likely we will see continued refinements in the future as we begin to adapt them to the particular case of agent-based social simulations.

However, the development of a backstory remains important when working with demographic systems sociological models. Abstract models are simpler in their construction, generally speaking, but are not necessarily simpler in their implications, as we saw with Schelling's residential segregation model (Schelling 1971, 1978). Establishing the scope and artificiality of a model is significant, as simplistic models can easily be misconstrued as making overly ambitious claims otherwise.

12.5.2 Model-Based Social Sciences

The example of model-based demography illustrates the advantages of developing a methodological paradigm as a kind of collective theoretical backstory for an approach to simulation with a specific discipline. The specific case of demography somewhat lends itself to this way of doing things, however; demography boasts a lengthy history and a notable ability to absorb and refine a wide variety of statistical approaches. In that context, establishing another methodological framework to underwrite the use of simulation seems an appropriate way to situate simulation as a tool worthy of the same respect as statistical modelling.

In other areas of social science, however, the range of methodologies in use can be much wider. We see researchers gathering data qualitatively via interviews or surveys, or others analysing texts or artwork, or studying the geographical distribution of people, artefacts and customs. Many of these disparate methods can provide useful knowledge that can be utilised in simulation (Gilbert and Troitzsch 2005), but this does not mean in turn that the simulations will be considered trustworthy or appropriate tools to those same researchers.

In this context we cannot simply write variations of the model-based demography framework as *model-based social science* and expect them to provide an appropriate theoretical backstory for such a broad range of research questions and methods. However, model-based demography does demonstrate a process which can be more transferrable. Model-based demography as a framework addresses core questions that are just as salient elsewhere:

1. What are the key questions asked by our discipline?
2. What is the main unit of analysis in our discipline?
3. What are the main epistemological limits within our discipline?
4. Which of these limits can be addressed in some way using simulation?
5. How can our analyses inform a simulation process?

Model-based demography suggests that simulation efforts in other areas of social science would benefit from a concerted effort to address these core questions, and in the process situate the approach clearly within a disciplinary context. Doing so not only alleviates some of the difficulties outlined above, but it provides a common backstory which also clarifies and communicates the aims of the work to others *outside* the discipline. This in turn allows for easier collaboration between social scientists and simulation practitioners, and eases the time-consuming process of developing a common language in simulation collaborations, which can inhibit progress significantly in new simulation ventures. Collaboration across disciplines also becomes easier, as each member of the collaboration would have a clear statement in hand of the methodological aims and limitations of the work to come.

In a sense, perhaps, we would benefit from developing *modelling manifestos* of sorts. Rather than individual justifications of each model, establishing a united front through which we can embark on journeys into simulation allows us to get on with development and implementation using a common framework. Some models, particularly those of a more abstract, systems-sociological bent, will need to pay more attention to individual statements of scope and purpose, but given the more theory-driven and explanatory nature of such models this is naturally part of such an enterprise anyway. Developing such ‘manifestos’ will certainly spawn its own protracted arguments and divisions, naturally – we are academics, after all. That being said, with the splintering of so many disciplines into sub-disciplines and sub-sub-disciplines, we might benefit from occasional forays into self-reflection on the goals and limitations of our work and how it relates to our colleagues elsewhere in our own disciplines and neighbouring ones as well.

12.6 A Manifesto for Social Science Modelling?

By most measures this volume makes for a rather unwieldy manifesto for social modelling – the word count is excessive; it covers far too many disciplines; and many of the conclusions are highly malleable depending on the reader’s own disciplinary background and research convictions. Fortunately, this volume is not intended to fill that role; specialists within the varied specialisms of social science are far better equipped to handle the task of establishing approaches to modelling in their particular context (see, e.g., Conte et al. 2012).

This volume set out to expose and discuss the challenges faced by simulation modellers, starting from the earliest pioneers in simulation (Schelling, Langton, and the rest) and moving toward the current growing interest in models of human sociality in many different flavours. By bringing together insights drawn from Alife, population biology, social simulation, and demography, we are able to develop a better understanding of the power and the limits of simulation when applied to the social sciences. The development of model-based demography shows us how simulation can be investigated, applied, and refined for a particular social science context.

Ultimately, the further advancement of social modelling will still require significant work, both theoretical and practical. Conversations will need to be started between colleagues who hardly understand one another; conceptual chasms will need to be bridged; and social scientists will need to work with programmers and computer scientists who may have very different views of the world. Hopefully the discussions brought forth in this volume might make those discussions somewhat easier, the bridges a bit shorter and easier to construct, and the gaps in practical and disciplinary knowledge between social scientists and computer scientists less insurmountable. If it facilitates some heated debates over the writing of some modelling manifestos, then so much the better.

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