Agent-Based Modeling for Archaeologists: Part 1 of 3

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ABSTRACT

Formal models of past human societies informed by archaeological research have a high potential for shaping some of the most topical current debates. Agent-based models, which emphasize how actions by individuals combine to produce global patterns, provide a convenient framework for developing quantitative models of historical social processes. However, being derived from computer science, the method remains largely specialized in archaeology. In this paper and the associated tutorial, we provide a jargon-free introduction to the technique, its potential and limits as well as its diverse applications in archaeology and beyond. We discuss the epistemological rationale of using computational modeling and simulation, classify types of models, and give an overview of the main concepts behind agent-based modeling.

Keywords: agent-based modelling, simulation, complex systems, complexity science, computational modelling, NetLogo

Modelos cuantitativos robustos de sociedades humanas en el pasado tienen el potencial de informar los temas de debate actual, particularmente modelos informados por estudios de arqueología. Modelos basados en sistemas multiagente proveen un marco práctico para explorar modelos cuantitativos de sociedades en el pasado. Aun así, al ser un método de informática no es aún bien establecido entre la mayoría de arqueólogos. En este artículo y el tutorial que lo acompaña, proveemos una introducción a estos métodos, libres de jerga técnica, su potencial y sus límites, y también las diversas aplicaciones en arqueología. Además, discutimos la epistemología de utilizar modelos computacionales y de simulación, clasificamos los tipos de modelos, y proveemos un resumen de los conceptos principales de los modelos multiagente.

Palabras clave: modelos basados en agentes, simulación, sistemas complejos, modelos computacionales, NetLogo

Archaeology is uniquely positioned to use modern technology to understand the long trajectory of human history. The time-depth of archaeological inquiry allows researchers to investigate long-term and large-scale trends in human behavior, such as the evolution of social hierarchy (Crabtree et al. 2017), the changes in subsistence strategies (Powers and Lehmann 2014), or the resilience of human groups in the face of natural disasters (d'Alpoim Guedes et al. 2016). Just as material culture studies greatly benefited from the introduction of formal statistical tools, many current conceptual models— often grouped under the umbrella term of "theory building"—would benefit from a systematic and formal approach of computational modeling (d'Alpoim Guedes et al. 2016; Lake 2014).

One class of computational models that has been used increasingly in archaeology over the past two decades is agent-based modeling. Researchers studying archaeological systems worldwide have adopted this formal modeling technique to approach their research questions (e.g., Cegielski and Rogers 2016; Kohler 2012; Linde and Romanowska 2018; Madella et al. 2014; Perry et al. 2016; Rogers and Cegielski 2017; Romanowska 2015; Wurzer et al. 2015). Archaeologists use agent-based modeling to understand archaeological patterns across a range of temporal and spatial settings (e.g., Angourakis et al. 2014; Balbo et al. 2014; Morrison and Allen 2017; Perrault and Brantingham 2011; Premo 2015; Wren et al. 2014).

Our own experiences with simulation reflect this topical diversity, as we have used simulation to explore the development of the wine industry during the Bronze to Iron Age transition in Littoral France (Crabtree 2016), exchange practices and the development of hierarchy in the US Southwest (Crabtree 2015; Crabtree et al. 2017), Pleistocene hominin dispersals (Romanowska et al. 2017), and the formation of archaeological landscapes in Australia (Davies et al. 2016). Although the scenarios are simulated, the implications for research are real. For example, Lake (2014) discusses how formal reaction-diffusion models and long-term evolutionary models have already helped to move research forward on different aspects of human origins studies, noting that agent-based models have the potential to address many other areas of inquiry.

In this series of articles and in the accompanying tutorials we walk the reader through the process of building an agent-based

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simulation using an example of a model used to understand toolkit richness (Brantingham 2003). Lithics are commonly used to develop hypotheses about the behavior of their makers, but the causal relationship between any particular foraging strategy and the composition of lithic assemblages remains unclear. Using this example, we show how Brantingham's model enables researchers to use archaeological data (patterns in lithic assemblages) to identify behavior of people in the past (foraging strategies).

This is the first in a series of three articles and tutorials on agent-based modeling. A recent survey (Davies and Romanowska 2018) showed that the majority of archaeological modelers had to depend on self-teaching and peer support to acquire skills necessary to build their simulations. Although other agent-based modeling tutorials exist (e.g., Grimm and Railsback 2011) this series is unique in that it presents a case study of an archaeological system. We have also kept it largely jargon free with the intention of presenting the method to researchers with no previous experience in computational modeling.

In Part 1, we discuss the definition and function of agent-based models and introduce some key concepts in simulation. In the associated tutorial, we show how to build a simple hypothesis-testing agent-based model using a user-friendly, open-source, cross-platform simulation framework—NetLogo (Wilensky 1999)—and provide an outline of programming concepts. Part 2 (Davies et al. 2019) builds on this tutorial and incorporates realistic geographic information systems dataplanes to move the model from abstract to more realistic. Finally, in Part 3 (Crabtree et al. 2019), we demonstrate how agent-based models can be used for outreach to explain archaeological patterns to the public, whereas the associated tutorial will focus on analyzing the results.

WHY MODEL? AND IF SO, HOW TO MODEL?

Simulation has been hailed as the third leg of the scientific tripod: a qualitatively new scientific method falling between theoretical and empirical research (Axelrod 2006; Epstein 2006; Hartmann 1996; Kohler 2012). For example, Axelrod says:

> Simulation is a third way of doing science. Like deduction, it starts with a set of explicit assumptions. But unlike deduction, it does not prove theorems. Instead, a simulation generates data that can be analyzed inductively. Unlike typical induction, however, the simulated data comes from a *rigorously specified set of rules* rather than direct measurement of the real world [Axelrod 2006:95, emphasis added].

In fact, as Whitley (2016) points out, archaeologists commonly engage in what can be called "an analogue simulation." For instance, flintknapping experiments aimed at replicating past techniques or reenactments of medieval battles do not differ from computer simulation in the normative sense. Both start with a model—that is, a set of basic assumptions (e.g., knapping was performed using hands)—and are validated by comparing the simulation results (e.g., the shape and dimensions of a knapped stone tool) with the available data (e.g., archaeological artifacts).

Simulation is an established scientific tool, widely used across the natural and social sciences, as well as outside of academia, where it is commonly applied in industry, economics, and policy making (e.g., Abergel et al. 2014; Chattoe-Brown 2013; Davidsson and Verhagen 2013; Farmer and Foley 2009; Hammond 2015; Hartmann 1996; Mitchell 2009; Pyka and Werker 2009). Although there are many different types of simulation techniques, they share a number of characteristics.

At the core of every simulation is a model—a simplified representation of a real-world system, composed of entities and the relationships between them. In the philosophy of science, a model is defined simply as a set of assumptions (Godfrey-Smith 2003). Some models can be built using observations derived from experiments or from systems that can be directly studied. For example, a model of a preindustrial village may assume that people who lived in a single household were in some way related because of what we know from the observations of modern human groups and their family-forming behaviors. In other cases, the dependencies or the importance of different types of entities and processes are theorized about (known as "conceptual modeling"). If we were interested in how different degrees of social cohesion may lead over time to different habitation patterns, a conceptual model of social interaction would form the basis of the simulation.

Similar to a model, simulation is an artificially constructed and simplified representation of a real-world system with all relationships formally defined (known as "ontology"), but with the additional dimension of time (Hofman et al. 2011; Smith 2000). Therefore, simulation investigates changes occurring in a system over time and space as a result of external (exogenous) factors or the internal dynamics of the system.

The rapid rise of simulation since the 1960s came hand-in-hand with the recognition that many (if not most) real-world systems are complex; that is, governed by nonlinear processes, which escape more traditional, reductionist scientific methods focused on detailed description of system elements. Instead, it was the interaction between these elements that explained the system (Ladyman et al. 2013). For example, Schelling (1971) showed how a complex pattern (racially segregated neighborhoods) may emerge from relatively small sets of simple rules (slight incline of urban dwellers toward settling down among people similar to them), often defying expectations or common sense ("intolerance"—that is, having a low tolerance for neighbors of a different type—actually decreases segregation; see Chattoe-Brown 2013 for discussion).

This shift in research focus from the "detail" to the "whole," coupled with rapidly increasing computer power available to researchers, led to the development of complexity science. The core idea behind complexity science is the observation that simple interactions of multiple entities may lead to surprising global patterns and that this connection could not be easily deduced from studying each of the system's elements in isolation. This process, known as "emergence," is often summarized by the emblematic motto: the whole is greater than the sum of its parts (Mitchell 2009:13). The emergent properties of complex systems mean that simulation is the primary tool for studying them.

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DIFFERENT TYPES OF MODELS

Hartmann (1996) recognized five main applications of simulation techniques used across different scientific disciplines: (1) simulations as a technique used to investigate the detailed dynamics of a system; (2) simulations as a heuristic tool for developing hypotheses, models, and theories; (3) simulations as a substitute for an experiment when performing it is unfeasible or not practical; (4) simulations as a tool for experimentalists used to support empirical experiments; and (5) simulations as a pedagogical tool allowing students and wider audiences to gain understanding of a process. Four of them are directly applicable in the context of traditional archaeological inquiry, whereas application (4) has been shown to be a valuable tool in archaeologically inspired anthropological research (Mesoudi and O'Brien 2008).

Simulation as a Technique

Many scientific disciplines can study systems by directly observing them; for example, microbiologists may observe an organism as it undergoes a change, and sociologists can ask a sample of the population to share their thoughts. However, in many cases, the actual dynamics of the system cannot be observed because the process takes too long (e.g., macroevolution of a species), the scale is too small (e.g., quantum physics), or the system does not exist anymore (e.g., past societies). In those cases, simulation is the appropriate research tool.

Simulation is a formal computational tool that reveals causal relationships between system entities and the evolution that the system undergoes. Equally, it allows the researchers to investigate the impact of specific events, such as a particular initial state or rare events, on the evolution of the system (known as "historical contingency" or "hysteresis"). Finally, exploratory models (Premo 2010), built on the minimum set of assumptions (known as "null models" or models from "first principles"), enable researchers to test their beliefs about the system's dynamics and the relative importance of different factors influencing it. We will see the value of this particular methodology in the archaeological example explored in the tutorial.

Simulation as a Theory-Building Tool

Simulation is commonly used as a tool for hypothesis development. Di Paolo and colleagues (2000) call simulation an "opaque thought experiment" because it represents a computer-based theoretical exercise in examining what-if scenarios (known as "subjunctive models"; David et al. 2013). The advantage of using a computer tool is that it can explore more complex, multiscalar and multivariate scenarios than can ever be reliably entertained in one's brain. In addition, as numerous examples have shown (e.g., Reynolds 1987; Resnick 1997; Schelling 1971), even simple models can unfold into surprising and counterintuitive patterns. As already mentioned, this phenomenon is known as "emergence" (Epstein 2006). The counterintuitive nature of such conclusions means that, by definition, they would be unlikely to be proposed as a result of conceptual modeling "in one's head." Another important function of modeling is that it allows researchers to produce archaeologically testable predictions out of existing conceptual hypotheses, articulated in natural language. Premo describes the role of simulation as a "virtual lab" for "eliminat[ing] the plausible scenarios that are unlikely to have occurred, given observed characteristics of empirical data" (2006:108). As a result, instead of producing new theoretical models, which do not surpass the already existing ones, formal methods such as simulation build an increasingly strong framework based on "knowledge that over time is cumulative at both a theoretical and empirical level" (Neiman 1995:30).

Simulation as a Substitute for an Experiment

Simulation can replace an experiment in situations when practical constraints or ethical issues come into play (for example, if the investigated social process takes decades to evolve or if the experiment would subject the experimental population to hardship). Creating an artificial society and pestering it with climatic fluctuations, social upheavals, or natural disasters is a way of approaching such topical subjects as long-term social change, resilience, evolution, and impact of innovation without referring to modern and historical analogues and anecdotal evidence, or needing extensive Institutional Review Board/Ethics Committee oversight.

This process can be exemplified by comparing middle-range theory to simulation (Binford 1982; Kosso 1991; Premo 2007; Raab and Goodyear 1984). Ethnoarchaeologists study modern human groups because their behaviors and relationships can be directly observed. The material record generated by a modern group can then be compared with the archaeological record. If the two resemble each other, it is concluded that it is likely that these archaeological remains have been generated by processes similar to the ones driving the modern human group.

Similarly, an agent-based modeler constructs an artificial society governed by a strictly defined set of behavioral rules, making processes and causal relationships directly observable. The consequences of the simulated processes are then compared to the patterns in archaeological data. The aim of both types of research is to understand the dynamics of an accessible and, therefore, well-understood system well enough to be able to infer whether similar processes might have taken place in the past.

While modern scientists have critiqued the use of ethnoarchaeology (Fahlander 2004), cautioning that modern hunter-gatherers are not archaeological groups frozen in an early development stage (Kelly 2013), most archaeologists use ethnographic analogy explicitly or not. This is mostly done with appropriate caution, as researchers understand that all societies are dynamic and changing (Martelle Hayter 1994) and realize the limitations of their models. Agent-based modelers, who are usually archaeologists themselves, do the same.

Simulation as a Pedagogical Tool

Simulation can be used as an education tool. For example, Resnick (1997) used StarLogo (an early version of NetLogo) to explore the nonintuitive phenomena of emergence, decentralization feedback, self-organization, and criticality among high school students. Similarly, the interactive visualizations (known as "explorable explanations") of Hart and Case (2015) guide the participants through the process of simulating social phenomena, such as segregation, thus elucidating the real-life societal consequences of seemingly innocuous individual decisions. Because of

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its game-like properties, agent-based models are engaging and fun for specialists and non-specialists alike. They can, therefore, be an easy and cost-effective way to represent complex relationships and ideas and to let members of the general public, stakeholders, or students gain deep understanding of complex concepts by performing their own experiments. For example, van Havre (2018) has built a model of an archaeological landscape that archaeology students can use to explore how successful different sampling strategies will be in finding archaeology depending on the original distribution of artifacts. Part 3 will further explore these themes.

AGENT-BASED MODELING (ABM)

Agent-based modeling (ABM) is considered a "bottom up" simulation approach because it comprises heterogeneous individuals whose actions and interactions (both with each other and with the environment) lead to emergent population-level patterns. This method is often contrasted with Equation-based modeling (EBM), or the "top down" approach, where the individual actors are treated in aggregation as a homogenous population, whose characteristics are defined by a set of variables and whose interactions are described in equations (Macal and North 2010; Railsback and Grimm 2011).

In agent-based models, agent behavior is described in a set of rules (algorithms; Grimm et al. 2005; Ahrweiler and Gilbert 2005) and often modeled using probabilities (i.e., stochastically). Thus, ABM allows the researcher to model individual-driven mechanisms—such as cognitive processes, cultural transmission, and communication—and to introduce heterogeneity in the population, be it genetic/cultural diversity or even simple age and sex differences. As a result, the method enables a crossover between two levels of analysis: an individual perspective, which is very much at the heart of archaeological interest, and the global or population-level patterns representing the consequences of aggregated individual actions, which can be compared to the archaeological record. ABM provides a platform that facilitates the integration of the spatial environment as one of the primary model entities considerably (O'Sullivan and Perry 2013; see also Part 2 in the series), and the ability to construct models out of familiar entities (people, groups, households, etc.) rather than in the non-natural language of equations makes agent-based models easier to consult with and to communicate to the archaeological (and public) audience (see also Part 3 in this series). Finally, the explicit focus on individuals and agency is a particularly important feature for archaeologists, who for decades have been concerned with the lack of "the individual" in the focus of archaeological practice. For example, Gamble and Porr argue that "the individual needs to be seen as the center of causality in order to understand why change and variation occur. It is individuals that make decisions and deal with choices" (2005:7). Computational modeling, and ABM in particular, holds great potential for addressing this issue as it provides a formal environment for testing the relationships between individual decisions, aggregated actions, and the consequences of these actions that are represented by the archaeological record.

Often, CRM archaeologists are tasked with finding explanations for the distribution of artifacts in their project area. These explanations are built on established theory, but many CRM projects do not allow for a full-scale analysis of an entire region. Many projects bisect sites, and archaeologists are forced to work within a down-sampled geographic area so that they do not explore beyond the project area. This can hamper their ability to draw meaningful conclusions from these partial datasets. ABM enables the use of partial data to test models and provide predictions. For example, if a researcher wants to understand the distribution of finds along an alluvial plain, writing a simple agent-based model simulating the transportation of artifacts might elucidate the patterns of deposition and could further predict where artifacts would be found. Thus, ABM can serve as a type of "behaviorally driven" predictive modeling that incorporates our knowledge of people's behaviors rather than one-to-one correlations. In doing so, it could counteract the common criticism of predictive models as being a self-fulfilling prophecy (Wheatley 2004).

For example, the members of the Village Ecodynamics Project, despite having a survey coverage of less than 20 percent (Kohler and Varien 2012:18), were able to create an agent-based model that examined the growth of population and the placement of households on the landscape. This model has been successful in testing hypotheses on the lifeways of Ancestral Pueblo people and has aided greatly in our understanding of the prehistory of the area despite the less than complete survey coverage. These themes will be explored further in the tutorial and in Part 2.

THE TUTORIAL

The tutorial based on the model by Brantingam (2003) that accompanies this article has been written with the general archaeological audience in mind. It does not assume any previous knowledge or skill of the reader and has been presented in a very informal and jargon-free style. In our demonstration of agent-based modeling, we will use an existing exploratory-type model framework to approach a new problem and apply it to a specific case study. Tutorial 1 (Supplemental Text 1) will focus on replicating the original model; Tutorial 2 (Supplemental Text in Part 2) will place it in a semirealistic landscape; finally, Tutorial 3 (Supplemental Text 1 in Part 3) will explore how the results can be interpreted and communicated to stakeholders and the general public. In addition, we have prepared a document providing a more extended description of NetLogo structure and features that can be used as a glossary and for further help (Supplemental Text 2).

While simple, the model used in the tutorials is a way to start testing the validity of common archaeological assumptions regarding behavioral strategies presumably employed by people in the past. This model was also chosen because it reflects one of a few instances in which an agent-based model has been subjected to a number of published reevaluations (known as "replications"; Pop 2015; Oestmo et al. 2016). Each of them expands on the base model and leads to new insights, thereby showing how computational modeling facilitates the building up of our understanding in cumulative fashion (later models build upon and improve earlier ones rather than compete with them). For example, Pop (2015) revisited Brantingham's model, arguing that the original model did not fully appreciate the difference between the assemblage of a living forager and an archaeological assemblage, which might have undergone significant changes since the moment of being deposited. Although we acknowledge the

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usefulness of this extension and find his review helpful, our tutorial focuses on Brantingham's original model. A further test of good modeling practice would be applying additions from Pop (2015) and Oestmo and colleagues (2016) to the tutorial presented below, and we encourage students to do just that.

CONCLUSIONS

The benefits of using formal models for theory building and hypothesis testing in an academic environment are manifold. Although conceptual modeling will always have a place in science, building formal models, such as simulations, can enable a deeper understanding of complex processes that incorporate a temporal and spatial dimension. Simulations can also enable researchers to eliminate hypotheses that sound plausible yet do not concur with the archaeological record. Finally, simulations can produce predictions that can be tested on the ground with carefully focused empirical research. Consequently, field-based, lab-based, and computer-based research are not in competition but rather complement each other. We argue that using them together is the best way to bring us closer to understanding the lives of peoples in the past.

Supplemental material

For supplemental material accompanying this article, visit https://doi.org/10.1017/aap.2019.6

Supplemental Text 1. Tutorial 1: The Base Model
Supplemental Text 2. Summary of NetLogo

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Data Availability Statement

No data has been used in preparation of this manuscript. The software used in the tutorial is open access and open source (https://ccl.northwestern.edu/netlogo/).

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