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The Computational Science of Religion

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This article provides a basic overview of the most common methods of computer modelling and simulation that are currently being used to study religion. It focuses on the use (and illustrates the value) of system dynamics models, agent-based models, including game theory and multi-agent artificial intelligence models, and artificial neural networks. General use case examples are provided, and considerations for future research are discussed. We conclude by encouraging scholars interested in religion and related fields to incorporate techniques from the computational science of religion into their collaborative methodological toolkits.

Introduction

The study of religion has been able to leverage methods and theories from a wide range of fields throughout its history. Over the past decade, a growing number of scholars have begun to utilize computer modelling and simulation methodologies, which are ideally suited for studying complex social systems. In fact, some scholars of religion have actually been pioneers in the development of new computational techniques in the social sciences more broadly. In this article, we present a basic overview of three popular forms of computer modelling: system dynamics modelling, agent-based modelling, and artificial neural network modelling. In each case, we introduce the general contours of the modelling approach, explain how it uses data in the study of religion, and provide a brief discussion of its strengths and weaknesses. We conclude with a summary and an assessment of the future of what we here call the computational science of religion (Lane and Shults 2018; 2019).

Keywords: computer modelling, simulation, religion, artificial intelligence, agent-based model, system dynamic model, natural language processing

It is helpful to begin with the distinction between a model and a simulation. In this context we skip over the complex epistemological debates behind this distinction and its relevance for the study of religion, and limit ourselves to a simple description of the general consensus about the difference between them. Simply put, a model is a theory we have about the world. In the social sciences, models have traditionally been presented in narrative formats; that is, the relationships among variables are more or less formally described using some human language (such as English). In some instances, linguistic description is supplemented with visual models – as in the case of the formalization of ritual form theory (Lawson and McCauley 1990; McCauley and Lawson 2002). More rarely in the study of religion, there are some theories that are formalized mathematically, wherein relationships between variables are defined using the formal language of mathematical notation (the most readily available examples of this in the study of religion are found in the subfield of cultural evolution). More recently, some researchers have begun to use computer languages to formalize theories. In an abstract sense, we can think of these computational models as a "retranslation" of a theory. Durkheim's *Les formes élémentaires de la vie religieuse* was originally published in French in 1912, and later translated into English as *The Elementary Forms of Religious Life* by Joseph Ward Swain (Durkheim 1915). In a similar way, computer modelling involves taking theories from the social sciences that have been published in human natural language and "translating" (or implementing) them into computer programming languages such as Java or C++.

When models are implemented in a computer programming language the relationships among variables and their effects on one another must be clearly specified. In some instances, they can be specified in such a way that describes their change *over time*. In other words, computational architectures can specify the time dynamics of a model. This is crucially important in the study of religion, which – as a set of complex and "lived" phenomenon – has a complex web of cognitively rooted causes, effects, feedback loops and generatively emergent features that unfold over time (Lane 2015, 2018). The explicit incorporation of the temporal dimension into the logic of a computer model allows for the execution of the computer code in a simulation. Simply put, then, a simulation is an execution of a computer model. Simulation experiments allow researchers to explore the temporal (and sometimes spatial) dynamics of a model and test hypotheses about changes in religious belief and behaviour under varying conditions.

Insofar as a model is a computational implementation of a theory, its outputs can be considered predictions of the theory. The hypothesized predictions of the theory can then be tested against real world data related to the target of the simulation. This process, which we can call "output validation"

(Lane 2018) is one way of ensuring that the model adequately corresponds to the real world system it intends to simulate. It is also important to ensure that the model has adequate correspondence between its simulated causal mechanisms and the mechanisms in the real-world. We call this "mechanistic validation" (Lane 2018). This allows scholars of religion, who have produced and analysed dozens of complex theories over the decades, to test whether the logic of those theories are able to produce valid and useful predictions when compared to real world data whether it comes, for example, from religious demographic surveys, the historical or ethnographic record, or databases including records of religiosity in human groups throughout history (e.g., Human Relations Area Files 2015; Database of Religious History 2015; Seshat Databank 2017).

It is important to note that many mathematical models, which can also specify changes over time, may be considered simulations as well. This is the case for models that look at continuous time as modelled through differential and difference equations, which can be implemented as system dynamics models. In other cases, mathematical models are more statistical in nature, and either consider the time dimension as an externality or do not model it explicitly. Structural equation models and regressions are examples of the latter. In some cases, artificial neural networks utilized as classifiers fit into this category as well, since they do not usually specify any time dimension in their model. However, we include artificial neural networks in our discussion below because of the role they are likely to play in the future of the computational science of religion, especially in conjunction with more advanced forms of multi-agent AI modelling.

In the following major sections of the article, we describe three of the most promising approaches in the computational science of religion: system dynamics models, agent-based models, and artificial neural networks.

System dynamics models

A system dynamics model (SDM) uses mathematical formulation to simulate the changes in and between variables in a system over time. The primary aim of an SDM is to model the change in a "currency" as it moves through "stocks" over time. A currency may be something relatively simple such as water flowing through a plumbing system, but it can also be more complex such as the flow of attitudes in a person's mind or the flow of persons in a social system. In the study of religion, for example, researchers have developed models of the flow of people attending a specific religious ritual (e.g., Kaše *et al.* 2018) or adhering to a particular religious tradition (Shults *et al.* 2018), the flow of supernatural beliefs within religious cognition (Lane and Shults 2019; Shults *et al.* 2017), and the flow of individuals through complex transitions involving religion such as the Neolithic revolution, the Axial Age or secular modernity (Shults and Wildman 2018; Shults, Wildman *et al.* 2018; Wildman *et al.* 2020).

Changes in the SDM's currency are modelled as movements of the currency from one stock to another. *Stocks* are places where a currency can gather in a simulation. For example, a SDM of religious conversion in a population could see someone move from a stock representing a population of Muslims to another stock representing Atheists. The rate at which the currency moves from one stock to another is defined in its flow. *Flows* are pathways that allow the currency to go from one stock to another at a defined rate. This rate can be set as a static value throughout the course of a simulation or varied in response to other changes in the model (which can be used to formalize feedback loops). Often, flows are defined or changed in relation to the value of a variable within the model. *Variables* are entities that take on different abstracted values in the model and help calculate and govern the rates (and changes) in the model over time. For example, if the number of conversions in a model is dependent on the current level freedom within that society, then the flow described from the Muslim to the Atheist "stock" would be defined as a rate that utilizes some measure of freedom in its calculation. The applications of this method are widely varied and have been used to predict things from electricity flows on national level power grids to the spread of disease in a population.[1] Within the study of religion, these types of model are also common within the literature on cultural evolution, which often uses the "s-curve" of epidemiological models of the spread of ideas or adoption of innovations as models for cultural change.

Like all other methodologies, the system dynamics approach to modelling human social systems has its strengths and weaknesses. The primary strength of SDMs is that their formalizations can be reduced to a set of differential and difference equations. As such, even very complex SDMs with many variables can be run on standard computers. This makes them relatively accessible to researchers within academic departments without easy access to specialised computer systems (such as those required for some agent-based models and machine learning discussed below).

When it comes to studying and explaining complex social systems (such as religions) the primary weakness of an SDM has to do with the assumption of homogeneity: all of the entities or units of the "currency" in an SDM are considered to be identical in all respects. For example, all of the "people" who

1. For an example of a disease spreading model that you can run in the cloud, see https://cloud.anylogic.com/model/d465d1f5-f1fc-464f-857a-d5517edc2355?mode=SETTINGS.

flow toward (or away from) participation in the "stock" of religious ritual are homogenous. This limitation means that one cannot take into account the differences among individuals, which is problematic since countless psychological studies have demonstrated that humans vary on just about every measurable trait. Even in cases where the variations are not "normally" distributed, it is clear that human individuals are heterogeneous. These variations are often "significantly" different in both the statistical and epistemological meaning of the term. In fact, if it weren't for variations between individuals, the statistical basis for the field of psychology would lose its foundation entirely. When it comes to the study of human beings and social systems, this is a serious weakness of SDMs. Nevertheless, this modelling approach has a clear heuristic and pedagogical value that should not be dismissed. Even if they are not able to capture critical aspects of human cognition, SDMs may be useful as a way of formalizing relationships and for creating interpretive models of religious dynamics (Lane 2019). This is the case even when the models are not able to accurately capture critical aspects of human cognition that would preclude their ability to be appropriately validated against real-world data.

Agent-based models

Agent-based models (ABMs) employ an entirely different paradigm of modelling and simulation than SDMs, but these approaches can often be complementary. For example, researchers in the cognitive science of religion have utilized both types of models in combination to illuminate the underlying dynamics of religious cognition in relation to terror management and hazard precaution theory (Shults *et al.* 2017) and to cultural attraction (Kaše *et al.* 2018).

ABMs model the interactions among different entities (or agents) in an environment, as well as the agents' effects on one another and their environment. While the ABM approach (in its many variations) is widespread across scientific disciplines, its use in the study of religion was more constrained until relatively recently. It has gained momentum rapidly as scholars in the relevant fields increasingly emphasize the explanatory power of these approaches (Braxton *et al.* 2012) and their capacity to create models with better correspondence between the model and the real world system (Lane 2013), not only in the case of the correspondence between the models output and some real world target ("output correspondence," discussed above), but also in the mechanistic correspondance (described above), as the mechanisms of change in any social group or institution are based on complex interactions between and within individuals and their cultural and physical environments.

"Agents" in an ABMs can be people (Gore *et al.* 2018), religious or cultural groups (Nowak and Sigmund 1993), firms and organizations (Axtell 2016), or even structures such as buildings (Axtell *et al.* 2002). In addition, agents can also be placed in relationship to one another in social networks; this enables the simulation of the way in which humans actually communicate within constrained networks (e.g., Arnaboldi *et al.* 2015; Czachesz 2014; Dávid-Barrett and Dunbar 2012; Lane 2018). Although the popularity of ABMs in the study of religion has grown rapidly only recently, the pioneering work in the computational science of religion goes back to the turn of the 21st century (see especially Bainbridge 1995, 2006; Upal 2005a, 2005b; and Iannaccone and Makowsky 2007). In recent years, several grants have produced a variety of ABMs of religious phenomena, often utilizing the idea of multi-agent artificial intelligence (Lane 2021, 2013); these are discussed in more detail below more below.

By helping us understand the conditions under which – and mechanisms by which – macro-level patterns at the population level emerge from micro-level behaviours and interactions at the individual level, ABMs can also be more useful for policy planning and analysis. Such models are increasingly being used by policy professionals in a variety of fields (Ahrweiler 2017; Gilbert *et al.* 2018). Insofar as the cognitive science of religion and related disciplines are able to provide new information about the mechanisms that can facilitate religious radicalization and extremism, for example, computational models informed by this research might contribute to predicting and preventing such phenomena (Lane 2017a; Shults, Gore *et al.* 2018).

ABMs have generally been used to study religion from one of two perspectives, focusing either on their "ultimate" or their "proximate" explanations. The ultimate perspective typically involves attending to evolutionary principles that help make sense of observations about religion in the ethnographic and historical record. For example, researchers have employed evolutionary models to understand how specific traits such as norms (Roos *et al.* 2015), cultural beliefs (Henrich and Boyd 1998; Kameda and Nakanishi 2002), beliefs in types of gods (Lane 2017b), or groups (Whitehouse *et al.* 2017) evolve over time. The proximate perspective, on the other hand, focuses on the more immediate mechanisms that generate and regulate the dynamics of religious systems. Examples of this sort of approach include ABMs of the theory of divergent modes of religiosity presented by Whitehouse *et al.* (2012) and Lane (2018; McCorkle and Lane 2012) and the model of cultural attraction presented by Kaše *et al.* (2018).

This distinction between ultimate and proximate explanations represents an over-simplified version of a broader framework outlined by Tinbergen (1963). Tinbergen attempted to articulate modes of explanation along two dimensions (ultimate-proximate and static-dynamic), which led to 4 different sorts of questions. Scholars in the scientific study of religion, including the computational science of religion, have for the most part focused on proximate static mechanisms (i.e., the cognitive capabilities that facilitate religion in the present) or ultimate dynamic phylogenies (i.e., the evolution of changes over multiple generations). The other two options within Tinbergen's grid have been largely neglected. For notable exceptions, see the analyses of proximate-dynamic mechanisms in Rybanska *et al.* (2018) and of ultimate-static mechanisms in Slone and Van Slyke (2015). With reference to the two most common perspectives mentioned above, two types of ABM approaches have become particularly influential in the study of religion: game theory and multi-agent AI.

Game theory models implement the rules of different economic games, such as the prisoner's dilemma (Fudenberg and Tirole 1991; Gintis and Schecter 2016; Mitchell and Taylor 2018), which form the basis for agent interactions within an ABM. In many of the most influential models, the games result in "payoffs" that are associated with a specific trait. After playing the game according to the rules, those agents with the lowest total payoffs are removed from the model and replaced with those who have the highest total payoffs – and then the game is played again. In this way, the model introduces an evolutionary dynamic to the game; in fact, such models are often called "evolutionary games." These sorts of models have been particularly influential in the study of cultural evolution (e.g., Axelrod and Hamilton 1981; Lane 2017b) and group selection (e.g., Whitehouse *et al.* 2017).

One of the strengths of game theory models is their capacity to leverage the ABM paradigm to simplify the complexity of n-player games, the probabilistic outcomes for which would otherwise be difficult (if not impossible) to solve. For example, the use of game theoretic ABMs to create an evolutionary version of the prisoner's dilemma game has been fruitful in helping to establish the best strategies for the game (see Axelrod and Hamilton 1981; for a more recent analysis of additional strategies see Mathieu and Delahaye 2017). In addition, the outcomes of game theory models can be compared to experimental data drawn from the field of psychology, where scholars have used economic games as experimental paradigms to research many human social phenomena such as cooperation, conflict, and value-based decision making.

However, the game theory modelling approach also has some important weaknesses. Perhaps the main problem with this method are the (often implicit) assumptions that underlie the construction and exploration of such models. For example, game theoretic models typically assume that agents are rational actors and that generations within a population are discrete (i.e., all members of the population reproduce at the same time, and then die off; therefore, they do not overlap with other generations like how a humans' life will typically overlap with that of their parents for several years, if not decades). Neither of these assumptions is compatible with the findings of cognitive science and evolutionary biology. Many evolutionary games make other (again, usually implicit) problematic assumptions; the prisoner's dilemma game, for example, assumes that the phenomenon of cooperation is an anomaly in human life and thus requires special explanation (Worden and Levin 2007). However, in-group cooperation may in fact be an evolved tendency present in a large number of individuals in human populations, a disposition evoked by different mechanisms in different contexts (*cf.* Cosmides and Tooby 1994).

Agents within game theory are usually assumed to be rational, i.e., they always attempt to work within the constraints and utility functions of the game. This assumption is particularly problematic since the notion of rational actors has been widely rejected by cognitive scientists since the 1980s after several key studies demonstrated that humans are not "rational," even when making simple economic decisions (see Tversky and Kahneman 1981; Tversky *et al.* 1990). In addition, evolutionary games often oversimplify or confuse the application of evolutionary principles, sometimes to the point of rendering their rules incompatible with the theories informing the model design. For example, assuming that generations of individuals are discrete is incompatible with basic observations of human reproductive dynamics. It also presupposes that information can be transmitted to subsequent generations via genetic information and without the need for social learning (for an example, see Whitehouse *et al.* 2017). Some recent studies purport to show epigenetic effects on populations after historical traumas such as civil wars (Costa *et al.* 2018), but the target phenomena for models of cultures and religions develop over time and are more complex than game theoretic models allow. Propensities for religiosity may be inherited, but the epigenetic transmission of personal experiences and religious beliefs is implausible (to say the least). The disjunct between the assumptions typically built into the models and the evolutionary theories they are supposed to be implementing is a serious problem for game theory approaches to the study of religion.

The critical difference between ABMs generally (but particularly game theory models) and multi-agent AI models is that the latter attempt to implement cognitively realistic mechanisms within their agents (Lane 2013). This means that the rules governing agent behaviours and interactions—simplified as they are—achieve a higher level of psychological realism. This in turn makes it possible to explain the emergence of group level properties from those agent behaviours and interactions at the individual level (guided, for example, by empirically supported theories of bounded rationality; e.g., Ariely 2010). This approach to agent-based modelling has emerged and grown rapidly over the last decade (see Lane 2013 for a discussion catered to the cognitive science of religion; see Sun and Hélie 2013 for a more general discussion). Compared to earlier ABMs of phenomena such as segregation (Schelling 1971), cooperation (Axelrod and Hamilton 1981), cultural drift (Bainbridge 1984), and cultural evolution (Axelrod 1997), the agents within multi-agent AI models are typically far more cognitively and psychologically realistic.

Another important feature of multi-agent AI that sets it apart from other forms of AI (such as the artificial neural network techniques discussed below) is that the former can incorporate a mixture of machine learning algorithms (such as those commonly found in "big data" approaches to simulate learning processes) *as well as* algorithms designed to mimic evolved cognitive mechanisms (or modules). This modular approach, which is grounded in evolutionary psychology, distinguishes multi-agent AI from the statistical or machine learning approaches commonly used in AI research.

Multi-agent AI also has a number of noteworthy strengths and weaknesses. Because this approach utilizes psychologically realistic mechanisms for the information processing of agents within complex cultural and religious systems, such models can be validated empirically on multiple levels. Most efforts to validate ABMs concentrate on the plausibility of the macro-level output of a simulation, and its correspondence to the model's real-world referent. Multi-agent AI simulations can also test for the plausibility of the micro-level (i.e., proximate) mechanisms underlying the simulation's output, and the extent to which their behaviour reflects our knowledge of the cognitive mechanisms of the human mind as discerned through psychological experimentation (for a more detailed discussion and example see Lane 2018). In addition to these advantages for validation strategies, multi-agent AI approaches are also capable of facilitating multi-paradigm models that incorporate SDMs, artificial neural networks, and other approaches such as topic models, into their underlying architectures. For example, a multi-agent AI model could incorporate an SDM to model cognitive load or affect within an individual and/or an artificial neural network to represent basic associative or recurrent learning tasks.

There are at least two weaknesses associated with the focus on psychological realism and complex agents within the multi-agent AI approach. First, if agents become too complex, researchers can lose "cognitive control" of the model. In other words, so much can be going on in the model that it is simply not possible to understand *why* the model is outputting the data it does. In such a situation, even if the target phenomenon is being replicated *in silico*, the modeler cannot point to the mechanisms driving the output (which is often the main point of modelling). A second challenge is that modelling complex agents requires far greater computational power and far more computer time for running simulation experiments. This is a serious practical challenge because scholars in many departments in the social sciences and humanities do not have access to the appropriate hardware required to run multi-agent AI models with large populations of cognitively complex agents.

Artificial neural network models

Artificial neural networks (ANNs) are probably the least understood computer modelling technique in the study of religion today. The term artificial neural network is often used synonymously with AI and machine learning, despite there being other forms of AI—such as the modular AI, inspired by evolutionary psychology and underlying multi-agent AI discussed above. ANNs are connectionist systems that draw on the biological neurophysiology of human learning. They consist of nodes and links, like a typical social network would. However, the nodes do not represent people. Rather, the nodes represent artificial neurons, which are connected by links, representing artificial synapses. The link weights are set during a training period and each neuron can potentially "connect" with other neurons in the system. As the system is trained, it resets its weights based on observed data so that unobserved data can then be fed into the system in the future to solve a problem such as classification. The size of the number of artificial neurons, how many sets of these neurons there are, and how they re-weight themselves changes based on the kind of network being constructed.

This technique is particularly useful for classification and prediction in data science applications outside of religion. The first published research using this technique in the field of religion was by William Bainbridge (1995), who used systems of neural networks to seek different kind of rewards, including "eternal life." More recently ANNs were employed by Kristoffer Nielbo to study the differences between functional and non-functional action sequences associated with ritual behaviours (Sørensen and Nielbo 2013). They have also been used to study the extent to which different ritual variables critical to the theory of divergent modes of religiosity can predict the form of a ritual as described by ritual competence theory (Lane 2012).

Recently, the use of advanced AI techniques has been used to create "AI gurus," which are AI systems trained on materials coming from specific religious groups (Lane 2021). These AI gurus can be used to study the problem and solution space of religious texts and social learning (i.e., what is the role of social learning in religious belief generation and sustenance, and what problems are there in explaining the dynamic changes of religious beliefs using social learning alone). However, they can also serve a more anthropological agenda by providing a means to interact with different systems that are trained with "expert" knowledge on a subject. While the first of these AI gurus was trained on American Christian sermons, more recent versions have utilized the corpus of material collected by the FBI on Jim Jones, the leader of the People's Temple. Jones infamously led the church to one of the largest mass suicides in history in the 1970s. Jones died during the mass suicide event of his church decades ago, leaving many open questions to researchers. The recreated AI of Jones, based on his beliefs and teachings, can provide a limited – but perhaps useful – lens to further study the beliefs and mind of a rare, but historically important individual. In this way, we can use AI as part of a new horizon in digital ethnography and "virtual anthropology." Such systems raise obvious ethical issues, which can – and should – be discussed within the field (Lane 2021; Shults and Wildman 2019) along with the big-data approaches that are emerging and support the use of artificial neural networks (Lane 2015). Nevertheless, despite their ubiquitous presence in so much of our daily lives today, ANN approaches are relatively rare in the computational science of religion.

As the most prominent form of AI currently in use, the strengths of ANNs might seem apparent. While their use for image and speech recognition tasks as well as tasks as diverse as lip reading (Assael *et al.* 2016) and game strategy (Silver *et al.* 2017) now outperform humans, their strengths in the study of religion is largely unexplored. While they could serve as quick categorization tools for new observations in a field (such as a new ritual), it would be an uphill battle to have them accepted when there are already such contentions around the typologies that currently exist. Rather, the strength of ANNs is likely going to be its capacity to help researchers define their problem space, or the components that are important for finding a solution to a problem. Currently, the cognitive science of religion is largely engaged in questions focused on basic research. However, the importance of a cognitive approach to the study of religion cannot be understated in today's world. Researchers in numerous fields, including political science, agree that religion will play an increasingly dominant world in security, politics, and international relations in the coming century (Toft *et al.* 2011). As such, there are very real problems that researchers engaged in the cognitive science of religion can help address. Such problems are vast and complex – as we all know too well. The use of ANNs could help us to untangle vast amounts of data to help us better understand the problems we face, and perhaps even aid in solving them.

There are also weaknesses associated with using ANNs to study religion. For example, neural networks require large amounts of digitized data to train. The study of religion generally has lacked such data, and only recently have efforts been made to collect such data in a way that could be useful for analysis with artificial neural networks (such as the Database for Religious

History). Moreover, like multi-agent AI models, ANNs require higher-end hardware to train, such as graphical processing units (or GPUs) that can be expensive. The greatest theoretical weakness of ANNs today is that they are not well theoretically grounded and have serious issues of interpretability. In other words, while ANNs are demonstrably useful for a variety of tasks, in many cases we are not able to understand how they work (Chakraborty *et al.* 2017; Montavon *et al.* 2018; Voosen 2017). Effectively, this means that they do not always provide a deeper understanding of the data that they are modelling but rather a black-box solution to solving some complex problem for which they can be trained. As such, their potential use in empirical research to help us *explain* religious phenomena remains suspect.

Conclusion

In this article, we have attempted to provide a general overview of the main types of modelling and simulation techniques that have been used to study religion, particularly within the cognitive science of religion. The computational science of religion is still in its infancy but is spreading rapidly across a variety of disciplines as scholars become aware of the illuminative and explanatory power of modelling techniques and simulation tools (Lane and Shults 2019).

As with any interdisciplinary research programme, reaching across the fields of cognitive science and computational modelling to study religion brings both new challenges and new opportunities. Researchers operating within this interdisciplinary space commonly collaborate with philosophers, archaeologists, anthropologists, and psychologists – all of whom utilize other methods that can strengthen the validity of computational models (or point out their flaws). Debates about the underlying causes of religious beliefs and behaviours will likely never be settled. The complex nature of religious systems, coupled with the generative research programs within cognitive science, almost ensure that our answering of one question through reductionist methods will lead to new questions when we contextualize our findings within the "big picture" of religion (i.e., the plethora of empirical findings and theoretical developments across relevant disciplines about the multiple mechanisms shaping religious phenomena).

Computer modelling and simulation, however, provides us with a way of beginning to synthesize this vast array of information and new tools for testing hypotheses about the role of particular mechanisms within these complex social and religious systems. These approaches are not meant to replace other methods in the study of religion, but they do offer a new way of linking insights from a variety of disciplines together and thereby generating new, well-informed, and empirically falsifiable theories.

The outlook for computer modelling and simulation within the study of religion looks optimistic, but there are still some significant hurdles to overcome in the immediate future. One hurdle is intra-disciplinary. Computer modelling is not currently a requirement at any of the major institutes training students in the cognitive science of religion. Indeed, most researchers engaged in the field know little about the methods and tools available for modelling and simulation. However, there are a few research institutes that use these techniques regularly in their work in the field, such as the Center for Mind and Culture in Boston and the NORCE Center for Modeling Social Systems in Kristiansand, Norway.

Another hurdle is inter-disciplinary. As the popularity of modelling and simulation continues to grow in the cognitive science of religion, it will become increasingly important to avoid insulating the discipline from the many other disciplines within which computer modelling is used to study complex social systems. Research centres such as the Max Plank Institute, Santa Fe Institute, and the Virginia Modeling Analysis and Simulation Center have a great deal more experience in modelling and simulation, and the cognitive science of religion would benefit from collaborations with these groups. At the same time, these institutes could benefit from having subject matter experts from the cognitive science of religion on their development teams. Such a collaborative strategy seems more promising than attempting to re-invent the wheel within our own discipline, not only because the latter unnecessarily slows us down but also because the former could help mitigate the intellectual balkanization which slows down everyone interested in the scientific study of complex social systems.

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