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Computing Religion: A New Tool in the Multilevel Analysis of Religion

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Abstract
The computational approach has become an invaluable tool in many fields that are directly relevant to research in religious phenomena. Yet the use of computational tools is almost absent in the study of religion. Given that religion is a cluster of interrelated phenomena and that research concerning these phenomena should strive for multilevel analysis, this article argues that the computational approach offers new methodological and theoretical opportunities to the study of religion. We argue that the computational approach offers 1.) An intermediary step between any theoretical construct and its targeted empirical space and 2.) a new kind of data which allows the researcher to observe abstract constructs, estimate likely outcomes, and optimize empirical designs. Because sophisticated multilevel research is a collaborative project we also seek to introduce to scholars of religion some general computational issues, and finally applications that model behavior in religious contexts.

Keywords
modeling religion, computer simulations, method, simulation data, multilevel analysis

I. Introduction

Religion is without a doubt a highly complex phenomenon. Indeed it is probably not so much a phenomenon as much as a cluster of interrelated phenomena that blend seamlessly into other cultural domains (Boyer 2001). Like all cultural behaviors, it is impacted and implicated in all levels of human organismal

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function and its various aptitudes—at the biochemical, information-organizational, neurological, psychological, and sociological level, to name the most prominent (Deacon 2003).

Scholars of religion expose themselves to serious deficiencies when they underestimate the complexity of the systems impacted and implicated by such behaviors. Multilevel analysis of religion must take into account both bottom-up and top-down feedback systems that mutually enable and constrain functioning at proximal and distal locations. Any approach to the study of religion identifies a limited problem space of necessity, but always also at the expense of artificially cutting itself off from other influential systems. The result is inevitably a degree of overreach in what any individual approach can say. An explanation that purports to explain religion without qualifications is therefore naïve. The computational approach offers excellent tools for multilevel analysis in general and as methodological pluralists in the study of religion, we want to advance an argument for the utility of the computational approach in the study of religion.

During the last thirty years there has been an explosion in both use and development of the computational approach. This approach has given the scientific community a number of modeling possibilities that are hitherto unprecedented (Maki and Thompson 2005). The study of religion, however, seems to have been somewhat reluctant towards using these possibilities. Up until now we are only aware of a small handful of studies being either based on or integrating the computational approach in probing phenomena that are directly related to religion. While we do not think all studies can or should in principle be carried out by means of the computational approach, we think it is unfortunate that the approach is not more widespread. At the same time we acknowledge that its popularity is as much dependent on proficient modelers as on acceptance and understanding from scholars of religion.

This article will argue that it makes good sense to incorporate the computational approach into the methodological toolbox of the study of religion. The argument will focus especially on the mediating role of computer models and the status of computationally generated data. To increase understanding of the computational approach, the article will furthermore introduce readers to some of the general methodological issues. Finally the article will review several applications of the computational approach to the study of religion.

II. From Theoretical Space to Empirical Space and Back Again

On an abstract level research consists of constructing a set of empirically motivated concepts that map onto a set of raw data. However, we often want to move beyond the mere description and categorizing of a data set and explain it in terms of some underlying mechanism. We then build a theory linking the set of concepts with general constructs that can account for a certain relation between the concepts. To make sure that our 'theoretical space' maps onto real world phenomena we explore or test consequences of it on 'empirical space.' The possible outcomes of the testing can then be used to rebuild or extend the theoretical space. This continuous loop of research can be empowered and extended considerably by the mediating role of computational models and simulations (Winsberg 2001).

Before we proceed let us make clear what we mean with a set of concepts that at times will be used more or less interchangeably, namely, computer model, computer simulation, computer modeling, and the computational approach. A computer model is an abstract object, as is any scientific model, but it is instantiated in an operational form by means of algorithms and code. It has the purpose of aiding our understanding of a given system via scientific methodology. A computer simulation introduces temporal dynamics into a computer model, so the modeled system can be investigated as it evolves during some measurement of time. Computer modeling is the application of computer models and simulations to analyze a given target domain in order to explore and predict what might happen with various actions given the validity of the computer model and simulation's assumptions and simplifications. The computational approach then, is scientific research that primarily utilizes and dependent on computer modeling in understanding and explaining a given target domain. Notice that this is a very broad definition of the computational approach that primarily targets the use of research tools and principles from computer science to guide and implement a scientific research. The definition does however exclude the use of word processing programs, image manipulation programs, as well as several uses of both qualitative and quantitative analysis programs as members of the computational approach. The average user of these programs never has to transform scientific models into algorithms, write simulations in code, let alone interpret program output as predictions that map onto a target domain. Finally, some research areas have a somewhat different, more theoretical, application of the concept 'computational' that focus on the rule-based or information processing properties of their subject matter, such as computational linguistics or computational neuroscience. In actual scientific praxis however these areas also fall within the computational approach as we define it.

What then is the nature of data generated by simulating behaviors? While we have portrayed simulation as an instrument of great value to scholars in the study of religion, any answer to that question depends on what this instrument is used for, why a given researcher has turned to modeling in the first place, and what, if any, data the researcher has prior to the modeling exercise. On the most abstract level, simulation is a useful theory-testing device. Translating theoretical constructs into simulations can decide whether a theory is viable as it is currently formulated. More provocatively, and assuming a model is possible based on the theoretical construct it instantiates, the model can offer *forecasting* data. Just as weather modeling offers forecasts of likely outcomes of complex atmospheric variables, so modeling human behavior is similarly complex but susceptible to forecasting. All such models can point the skilled user in directions for more profitable empirical research. It cannot offer predictions in the manner of the hard natural sciences, but it can constrain the design, nature, and scope of empirical investigations that test theory validity.

Simulation data also have a *proxy* quality. Through the proxy the researcher can observe abstract processes and structures that in most other cases can only be inferred from behavior. Importantly, the proxy is more than just a mere illustration or theoretical invention; it is a real empirical phenomenon, generated by the complex interactions of assumptions, modeled data and computational architecture. Initially the modeling endeavor implies, even embraces, simplification and explication, in other words reduction, but the proxy is reconstructive. It reassembles the bits and pieces into a new configuration that removes noise and *re*presents core principles of the phenomena under investigation. Regarding the multilevel analysis, we might take a high level phenomenon, such as religious concept acquisition, generated by some low level mechanisms, for instance neuronal dynamics. We can then try to infer an intermediate level of principles that account for both levels and their interaction (c.f., O'Reilly and Munakata 2000). It is exactly this intermediate level that simulation data allows you to observe and perturb in a proxy format, that is, as a stand in for the actual but often elusive principles that our scientific constructs refer to. In other words, the proxy offers a computationally based empirical investigation of how such principles organize processes that connect phenomena on multiple levels.

We believe that the mediating role of the computational approach is important to the methodological and theoretical development of the study of religion. It opens new possibilities in the continuous loop between theoretical space and empirical space in terms of both top-down and bottom-up perspectives. A new kind of data on religion, simulation data, can be used to optimize empirical designs and observe processes that are only indirectly accessible in empirical space. Given the fact that well-designed empirical studies can be costly and often lead to dead-ends or unanticipated difficulties in implementation, we suggest that all researchers avail themselves of the data computer modeling provides. In its absence, the risk of false starts, invalid experimental designs, unproductive questions, or unsubstantiated field site selection for the research program only grows. Today many areas of research are highly dependent on the benefits of computational approach and it seems imprudent to exclude the study of religion from this development.

III. Assumptions, Simplifications, and Predictions

Especially three features of the computational approach are considered prime virtues: Explicit assumptions, precise simplification, and real world predictions.

Assumptions are specified properties, either theoretically or motivated by ad hoc computational reasons that are built into the computer model. Whereas most theories and experimental designs contain tacit assumptions which bias their structure, the assumptions of a computer model have to be explicitly written in code. This feature guarantees a high degree of transparency in computer modeling and makes it easy to change and explore different ideas. In understanding a computational model it is of utmost importance to pay attention to these assumptions. Any sound simulation report typically states such assumptions in the introductory part of an article. If for instance the model in question is a connectionist network there will be a range of general assumptions belonging to that branch of computational psychology typically summarized in a couple of sentences such as: "... using neurobiologically plausible mechanisms (e.g. the spread of activity among simple processing units along weighted connections) in order to identify the principles that are most relevant to behaviour" (Miller and Cohen 2001: 182). General assumptions are usually supported by the specific branch of computational psychology, but their status can be debatable within the area. Specific assumptions belonging primarily to the model in question are on the other hand chosen for the implementation of the specific system and should be scrutinized thoroughly. Typical examples from our own modeling of such specific assumptions might be the distribution of religiously salient objects in an artificial environment or the ratio of instrumental to ritual actions that the computer simulation processes.

Closely connected to assumptions is the inherent simplification of modeled processes because assumptions often serve the function of simplifying the modeled system. There is a long standing critique of simplification as exercised by the computational approach, especially in the social sciences and the humanities.[1] However, we believe that the critique is often generated by a

[1] This critique is often encountered at conferences, but very little seems to be published on the subject. It is primarily computer modelers that tend to incorporate it into methodological sections of their own publications (e.g. Nielbo forthcoming; O'Reilly and Munakata 2000; McClelland 2009).

misunderstanding of the computational approach's scope. In building a computer model one tries to account for a body of empirical data and get insight into the principles that structure the data or one tries to explore consequences of theoretically motivated principles. A successful computer model does not prove anything and neither does an unsuccessful one (McClelland 2009). It illustrates possible interpretations and helps us organize and explore consequences of ideas, but it does so in a precise and transparent form. Precise simplification should therefore be considered an aid of understanding and a good model should strive for simplicity. A blueprint which encompasses every detail and aspect of the represented system ceases to be a blueprint or, as noted by James L. McClelland and Jorge L. Borges, a geographic map in a 1:1 scale would be useless as a map (McClelland 2009). In a computer simulation, the construct of religion can for instance be made operable by simplifying it to priors that some agents have, which make them more susceptible to counter-intuitive beliefs, or ritual can be modeled as action sequences which, compared to instrumental sequences, lack causal linking. Just as the majority of scholars of religion that undertake empirical research do not claim to explain 'religion in its entirety,' the modeler does not claim that these operational simplifications cover all the possible extensions of the modeled construct. In comparison with conceptual simplifications, the advantage of computational simplifications is their preciseness as well as the possibility of making an estimation of their effect. Again, as with assumptions, it is important to notice the precise simplifications, because their effects are essential to understanding the model.

Generally speaking there are two interrelated ways of judging a computer model's success. If one is explicitly modeling data an obvious measure of the model's success is its capacity to make a good data fit. This will naturally lead to an interest in exploring new aspects of the data, which eventually produces real world predictions. For a more theoretically oriented model the essential measure of success is real world predictions. In both cases what we are interested in is finding consequences based on the assumption that our model is a valid implementation of a given system Using the extended loop, the real strength of the computational approach is that it enables you to move from an abstract theory to concrete predictions without the need to empirically test every possible prediction of the theory. It cannot be stressed enough that when trying to make sense of the computational approach, one should either look for explicitly stated predictions or consider the real world consequences of the computer generated results. To a certain extent a computer simulation will generate some predictions no matter what, but do they make sense in terms of the simulated system and are they open to empirical falsification? From the modeler's perspective it is always important to consider what kind of predictions one would expect and preferably how they should be tested.

The three prime virtues of the computational approach can all have a downside, which is probably why they all figure prominently in various critiques. In some cases simplification might transform the system to a degree where it is only recognizable to the modeler. This will often be motivated by computational efficiency, which admittedly is extremely important, but at the same time the computer simulation should retain a recognizable structural similarity with the system it is simulating. In other words, a computer model should be constrained by the relevant problem domain. Another related issue is the willingness to interpret any prediction as relevant to the problem domain, and by extension therefore a confirmation of the model's success. However, these issues are not a necessary part of the computational approach. As a critique they are mainly relevant with reference to particular applications. We urge the reader to take into considerations what has already been said about the scope of computer modeling, before criticizing the computational approach for its insistence on assumption, simplification, and predictions.

IV. Applications in the Study of Religion

While artificial intelligence and cognitive modeling scholars have been building computer models of how people acquire beliefs and communicate them to others for at least half a century (Russell and Norvig 1998), most of the early work was focused on individual cognition at the expense of interaction with others- the so called *brain in the vat* approach. A number of developments in computational (e.g., distributed and multiagent systems (Weiss 1999)) and social sciences (e.g., situated cognition (Greeno 1989)) in the 1980s and 1990s led to the development of computational models that could be used to study social phenomenon such as religion (Bainbridge *et al.* 1994; Epstein and Axtel 1996). While computational applications of religion still lack widespread use by scholars of religion, a number of pioneering studies have shown the potential advantage of this approach. These include studies of how socio-cultural and religious beliefs are created (Doran 1998; Hoffman 2002; Upal 2005a; 2005b; Dow 2008), how cultural ideas spread in a population (Bainbridge 1995; 2006; Epstein 2001; Newman, Barabasi, and Watts 2006), studies of ritual behavior (Nielbo and Sørensen forthcoming; Kahn and Whitehouse 2010; Hochberg and Whitehouse 2010), and formation of the social structure of organizations (Prietula, Carley, and Gasser 1998). In the rest of this section we provide more detail of some of the studies that are most relevant to the scholars of religion.

God from the Machine

For the last two decades, the sociologist of religion, William Sims Bainbridge, has persistently argued for the utility of the computer simulation in the social sciences. Several types of computational structures have been applied by him, including artificial neural networks and cellular automata. Whether one agrees with Bainbridge and Stark's (1985) rational choice theory of religion or not, his importance to the field is indisputable.

More than a decade ago Bainbridge introduced the use of artificial neural networks in the study of religion (Bainbridge 1995). Based on the Stark and Bainbridge theory of religion he simulated the emergence of religious beliefs through the interaction of cognizing agents modeled by means of artificial neural networks. Central to this section is Bainbridge's use of computer simulations as deductive proofs of a theory and a method for sweeping through a theory's design space.

Bainbridge's (1995) simulation consisted of twenty-four agents exchanging different rewards that were either produced among themselves (i.e. energy, water, food, and oxygen) or not (i.e. eternal life). Each agent was equipped with a "small artificial mind, capable of learning and making decisions" (Bainbridge 1995: 486). Their mind consisted of one neural network for each type of reward. Through interaction with other agents, each agent's mind learned who could supply a desired reward. At the same time the mind constructed general theories about the social structure of its environment. If the agent chosen for the interaction had a desired reward and at the same time was interested in what could be offered, an exchange took place. Otherwise the exchange failed and a small penalty was given to the disappointed agents. Finally, the agents learned from an exchange by modifying the weights in their mind's memory registers. By means of a rather idiosyncratic use of modulo arithmetic Bainbridge modeled the emergence of supernatural beliefs in the minds of his agents. Since no one could supply the eternal life reward, an agent could never have a satisfactory exchange of that reward. This prompted the agent to construct what Bainbridge calls supernatural numbers, which he maps to supernatural beliefs in the real world (Bainbridge 1995: 490).

By means of this elegant social environment of artificial neural networks Bainbridge managed to explore the Stark and Bainbridge theory and show how two theoretical constructs of the theory (i.e. the subculture evolution model and the psychopathology model) could be modeled by simple computational manipulations. Some agents were in a constant state of credulousness, believing that gods are good exchange partners because the agents never get any evidence to the contrary. More prudential agents on the other hand acquired beliefs through communication with other agents following exchanges

(Bainbridge 1995: 491). Both possibilities represent ways in which religion might emerge and be sustained according to Bainbridge. Following the subculture evolution model: "an intensely interacting group of individuals commit itself to the attainment of rewards some of which are...impossible to obtain" [e.g. eternal life] (Bainbridge 1995: 492). Explanations of how to get such rewards are hard to evaluate and can, as a consequence, produce religious beliefs concerning the rewards, finally resulting in religious congregations. The simulation showed how subculture evolution of religion might emerge through a communicative chain, producing agents that in general have a substantial belief in the existence of several gods (Bainbridge 1995: 493). Contrary to this, religion can originate in the influence of one exceptional individual that, following the psychopathological model, has developed: "supernatural beliefs that will not encounter empirical disconfirmation" (Bainbridge 1995: 492). In the simulation, such messianic religion emerged when special agents influence different groups, resulting in very divergent religious beliefs between the groups (Bainbridge 1995: 493).

Bainbridge's own view of the computational approach is that it can be used as a deductive proof. Based on assumptions from the Stark and Bainbridge theory he can derive theorems in accordance with the theory through an explicit mathematical procedure. We believe that this is a too modest and somewhat restrictive view of the computational approach. Since computer simulations generate data, they are more than engines of formal deduction. Interesting predictions can be made on the basis of Bainbridge's simulation, for instance that the implemented subculture evolution model tends to generate polytheistic-like congregations in contrast to the more monotheistic-like output of the psychopathology model. One might criticize several of the assumptions of the simulation, such as the use of a mentalistic and economic model of religion, but it is important to notice that Bainbridge is very explicit about those. He does not claim that the simulation is a complete model of religion, but instead that given certain assumptions we can explore aspects of religion following from these assumptions.

There are especially three methodological issues that we believe are important in Bainbridge's article. First, he rightfully points out that with unlimited time and computational power he could create a realistic or ecologically valid simulation of interacting humans, but that such is unnecessary for exploring theories. The computer simulation stipulates certain features of the system under scrutiny and by relying on explicit assumptions and mathematical manipulations it can model the system in a satisfactory way (Bainbridge 1995: 487). Second, Bainbridge's underlying methodological motivation for writing the article is the somewhat problematic ignorance of neural networks among his fellow researchers. And finally, with his use of several neural networks he foresaw the possibilities of combining computational sociology and psychology.[2]

A decade after his 1995 article, Bainbridge published *God from the Machine* (2006). The purpose of this book was, in his words, to underscore the point that "[I]t is time for computer simulation to be applied to the scientific study of religion" (2006: 1). To display the wide range of issues that can be tackled productively with the aid of computational simulations, Bainbridge modeled various dynamics in the field of the sociology of religion such as segregation effects, recruitment, cooperation, and cultural dissemination patterns. His approach is largely similar to the earlier article, using in our parlance cellular automata systems to model social learning or cognition. Amusingly, he dubs the small world of his experiments *Cyburg*. While many of his targets are worth further investigation, the experiments on cooperation dynamics are the most relevant to this article.

No investigations of the evolution of religion can afford to forego its role in facilitating in-group cooperation and out-group demonization (Bulbulia 2007). The difficulty of extending cooperation beyond the upper limits of human intimacy is fundamental to why religion evolved and came to dominate human cultural activities. Based on encephalization measures up and down the evolutionary branch of mammalian life, Robin Dunbar has quite convincingly argued that a direct correlation between brain size and social group size exists (1998, 2005). In the case of *homo sapiens* the upper limit of the human ability to retain direct knowledge of conspecifics is approximately 150. Yet clearly humans exceed this cognitive limit when they engage in cooperative behavior beyond kinship and reciprocity-based altruism. How is this achieved?

In the case of Bainbridge (and Rodney Stark since Bainbridge draws from their 1987 collaborative work, *A Theory of Religion*), his hypothesis centers on the control of religious specialists in the dispensation of supernatural rewards (1987: 98). He notes that game theoretic constructs are radically altered if an additional type of agency is introduced into the exchange system, namely a supernatural being that possesses goods that are highly desirable and at the same time solely at the discretion of that being. To test this claim, he modeled a version of *Cyburg* to run variations of iterated cooperation tournaments in which all contestants followed one of seven cooperation algorithms (1987: 104-107). In the next set of runs, Bainbridge expands the behavioral repertoire of his agents by adding further permutations to their operant algorithms—what social scientists call reputation management features, ability to reject cooperative opportunities, and faith-based compensators for coopera-

[2] For a more recent example see social connectionism (Van Overwalle 2007).

tion, mainly the promise of eternal life. The result of the later runs was that golden-rule-like versions of cooperative strategies tended to succeed better than the alternatives, and this success could be further enhanced by supernatural incentives.

Knowledge-rich Agent-based Social Simulation

Upal (2005a; 2005b; 2007a; 2008) has argued that traditional agent-based social simulation systems assume representations that are too impoverished to result in the emergence of richly interconnected shared beliefs we call religious ideologies. Traditional agent-based social simulation systems are designed based on the keep-it-as-simple-as-possible principle. The idea is that if complex social patterns can emerge from a simulation employing agents with simple decision making and agent-interaction rules and extremely limited memory (e.g., 1 or 2 bits) then it is easy to compute the causal links between the micro-level cognitive processes and macro-level social patterns. The problem is that what makes religious beliefs interesting and religious is the very fact that they are richly connected with other religious and non-religious beliefs. Such richly connected beliefs cannot emerge from a society of agent whose memory capacity is limited to one-bit (Doran 1998; Epstein 2001). A reformulation of traditional agent-based social simulation approaches is needed to allow us to model complex cultural phenomena such as the formation and propagation of religious beliefs (Sun 2008; Upal and Sun 2006). In order to have complex shared beliefs emerge at the societal level, individual agents need to be able to represent such beliefs and be able to acquire and modify them. To design predictive computational models we need to design agents that can models cognitive processes of information comprehension, information integration/belief revision, and communication.

Upal and colleagues designed one such multiagent society called CCI (Communicating, Comprehending, and Integrating agents) and embedded it into a multiagent version of Russell and Norvig's (1995) Wumpus World Domain (MWW). MWW is an NxN board game with a number of wumpuses and treasures that are randomly placed in various cells. Wumpuses emit stench and treasures glitter. Stench and glitter can be sensed in the horizontal and vertical neighbors of the cell containing a wumpus or a treasure.

Once the world is created, its configuration remains unchanged i.e., the wumpuses and treasures remain where they are throughout the duration of the game. MWW is inhabited by a number of agents randomly placed in various cells at the start of the simulation. The MWW agents have a causal model of their environment. They know that stench is caused by the presence of a wumpus in a neighboring cell while glitter is caused by the presence of treasure in a neighboring cell. Agents sense their environment and explain each stimulus they observe. While causes (such as wumpuses and treasures) explain themselves, effects (such as stench and glitter) do not. The occurrence of effects can only be explained by the occurrence of causes that could have produced the observed effects, e.g., glitter can be explained by the presence of a treasure in a neighboring cell while stench can be explained by the presence of a wumpus in a neighboring cell. An observed effect, however, could have been caused by many unobserved causes.

Agents store their world model-observations and past explanations-in their memory. In each simulation round, an agent has to decide whether to take an action or to stay pat. Possible actions include the physical action to move to a vertically or horizontally adjacent cell, or the communication actions of understanding a message sent to it by another agent or sending a message to another agent present nearby to request information that the current agent does not have. The MWW agents are goal directed agents that aim to visit all treasure cells on the board while avoiding wumpuses. Agents create a plan to visit all treasure cells they know about. The plan must not include any cells that contain wumpuses in them. Unlike Bainbridge's agents CCI-MWW agents are not programmed to favor beliefs in phantom agents. They are also capable of having inter-connected beliefs: beliefs about the presence of a wumpus in a cell is connected to the belief in stench in the neighboring cells. Even so our experiments with a version of the society where we disabled communication revealed that patterns of false beliefs emergent in such a society have a particular structure to them; agents are more likely to have false beliefs about wumpuses than about treasures (Upal 2007). The reason appears to be that while hypotheses about the presence and absence of wumpus are harder to confirm and disconfirm for the agents than the hypotheses about the presence and absence of treasures. This is because agents seek the cells where they believe treasures lie but avoid cells where they believe wumpuses live. This is exactly what Stark and Bainbridge (1987) argued, hypothesis which are harder to confirm and disconfirm are more likely to be believed by believers. Furthermore, subsequent experiments (Upal and Sama 2007) have shown that even when agents are allowed to communicate with other agents, this pattern continues to hold i.e., communication between agent does not eliminate the advantages that harder-to-confirm beliefs enjoy.

Hybrid Models

Recently Nielbo and Sørensen employed a combined methodology using both behavioral experiments and artificial neural networks. They did this to test and explore their theory concerning prediction error during observation of so-called non-functional actions, such as ritualized behavior (Nielbo and Sørensen 2011 forthcoming). Non-functional action,[3] that is, an action characterized by be lack of necessary and direct causal relations between the different sub-actions and the action sequence goal, is an action category that encompass cultural rituals, displays, non-instrumental or ritualized behaviors (Nielbo and Sørensen 2011; Boyer and Liénard 2006). In functional or instrumental action, on the other hand, there exists a necessary and direct causal relation between the different actions that the action sequence consists of and its end state in terms of a goal.

By means of the event segmentation paradigm, according to which participants segment action sequences into units typically by means of a response button (Newtson and Enquist 1976; Wilder 1978; Hanson and Hirst 1989; Zacks 2004), Nielbo and Sørensen showed that human participants segment non-functional action sequences in a more fine-grained manner than the functional counterpart. To support their theory Nielbo and Sørensen decided to simulate these experimental results in terms of a continuous measure of prediction error and test the influence of abstract goal information in artificial neural networks.

To replicate the experimental result with a more exact measure of prediction error than button presses, Nielbo and Sørensen used the artificial neural network environment *Emergent*,[4] to train forty simple recurrent networks.[5] The networks were trained on two sets of sequential patterns that represented functional and non-functional actions respectively. The networks' task was, when presented with one sub-action of an action pattern, to predict the following sub-action. Statistical analysis showed that the networks found it much harder to predict the structure of non-functional than functional actions (i.e. they had significantly higher prediction error in the non-functional condition). For the study of religion this result is interesting because there are several theories stating that ritualized behavior is highly attention demanding and saturates humans' cognitive resources (Boyer and Liénard 2006; Zor, Keren, Hermesh, Szechtman, Mort and Eliam 2009; Zacks and Sargent 2010). The

[3] 'Non-functional' is only meant in proximal terms, that is, in terms of how the action works. In an ultimate explanatory model proximally non-functional action sequences might serve a range of functions. Several theories claim that action sequences containing ritualized behavior have social functions (Bulbulia 2004; Alcorta and Sosis 2005).

[4] For more information on the neural modeling system *Emergent* see (Aisa 2008).

[5] A type of artificial neural networks that has successfully been applied to the study of cognition in a number of sequential domains, such as language and action processing (Botvinick and Plaut 2004; Reynolds, Zacks and Braver 2007, Elman 2009).

increase in prediction error during non-functional actions might be an explanation for exactly those phenomena.

In the real world we find that information concerning abstract goals of non-functional actions is supplied by the socio-cultural context. Although salvation does not follow directly from the actions involved in the Christian Eucharist, people performing the ritualistic behavior are told by their peers that such and such is the reason why the abstract goal can be obtained. To investigate if abstract goal information decreases prediction error during non-functional actions twenty new neural networks were trained by Nielbo and Sørensen. These networks were given abstract information relating to every single action in both sets. Such information is comparable to telling the networks that a particular action has a specific, although not necessarily apparent, goal. The performance of the networks with abstract information was compared to those from the previous simulation. The results showed that information concerning an action, independent of its type, lowered prediction error. However, abstract information seems to be particularly efficient at modulating prediction error in non-functional actions. Interestingly though, the significant difference between non-functional and functional actions remain, that is, independent of abstract information non-functional action elicits a high prediction error signal. Again, this is interesting to the study of religion because on the one hand prediction error can explain why ritualized behavior is attention demanding and on the other hand it can explain the need for reducing the instability caused by prediction error through means of ritual exegesis.

Nielbo and Sørensen predicted that high prediction error during non-functional actions results in a fragmented and incoherent representation of non-functional actions. Furthermore, they predicted that abstract information raises the general threshold for environmental updating (i.e. the need to attend to perceptual information). And finally, that in social-cultural context where non-functional actions are considered relevant, such as religious domains, there will be a pressure on transmitting abstract information that can reduce prediction error (Nielbo and Sørensen forthcoming).

Several explicit assumptions were made in these simulations, first and foremost that non-functional actions are less frequently experienced than functional actions. This assumption was not tested empirically, but justified in terms of an organism's need for performing functional actions to survive and reproduce. Another assumption, which might seem problematic, was the algorithm used to train the neural networks. This algorithm is not very biologically plausible, but the authors claimed that it, on a computational level, simulated the brains mechanism for error-based learning.

To increase the simulations realism or ecological validity as it is called in the experimental literature, Nielbo is presently employing a new kind of data set to train similar recurrent networks. This data set is based on actual human movement transformed into code by a motion capture system. Motion capture technology makes it possible to describe postures, or series of postures in the case of action sequences, in a three dimensional coordinate system. If the reproduction succeeds, the networks can then be claimed to process information that shares considerably similarity to human perceptual information.

One especially interesting methodological question is implied by this study, namely, what is the status of output generated by the computational approach? In trying to mirror the original behavioral study, both in terms of design and analysis, the simulations can be thought of as artificial experiments. In that sense the simulation results constitute a kind of data set. Even though the simulation data is not directly based on human participants, the simulations were capable of reproducing the results of human participants. As mentioned earlier in the article, we do not claim that the simulation data are identical to experimental or field-based data, but this simulation illustrates why output generated by the computational approach is data in its own right. A great advantage of such combined methodology is that an experimental study can be continued in a cheap and efficient manner by proxy, because artificial neural networks, as opposed to biological, can be saved on a hard disk. New questions might arise following an experimental study, but initiating a new experiment might be too demanding and the relevant predictions not lucid enough. Here the computational approach offers excellent tools for reassessing the original experimental study.

In 2007, Braxton modeled between-group competition based on the presence of religious costly signaling, an extension of Bainbridge's 2005 small-world model. The simulation platform Braxton used was the *Netlogo*, a multi-agent platform developed at MIT (under the name of *Starlogo*) and currently being developed for a wide variety of applications at Northwestern University. Four groups competed within a single landscape of finite but renewable resources. Many of the resources were capable of being utilized by individuals, but some could only be extracted through cooperation. The resources were vital to the well-being of the population because the capacity of the group to sustain itself (starvation constraint) and replicate itself (reproduction constraint) depended directly on their access to resources. Collect enough resources and membership survives and may even reproduce. Fail to collect enough resources, reproduction declines and starvation among the weak and vulnerable sets in. Each tribal group possessed emblems of their religiosity that they could display. But such emblems were acquired and required resources to display. Once they were acquired, however, their display to others within the in-group meant that no intimate knowledge of this potential partner was required. In other words, religious signaling performed a cognitive work-around for the problem of cooperation and anonymity. In all cases where religious signaling was present and widespread, cooperation increased and the more zealous religious groups outcompeted the less zealous. Of particular significance in the research on this model was the fact that the success or failure of groups with zealous religious signaling was high sensitive to variations in the costs associated with religious displays. There were clearly optima of costs relative to the net wealth of a group. Exceed certain costs, and the drain on the resources of the group exceeds the benefits of the cooperation it guarantees. Lower the costs of signaling and cheaters proliferate, faking commitment because it costs them so little and then acquiring undue share of resources for themselves and their offspring. This kind of simulation offers interesting possibilities of finding empirical predictions for optimal costs associated with religious commitment signaling systems.

Many problems in social cognition are studied in what Dan Sperber first called "an epidemiological approach to cultural distributions" (1996). Braxton sought to model the distribution of ritual forms proposed by McCauley and Lawson in their book *Bringing Ritual to Mind* (2002). McCauley and Lawson propose that the distribution of rituals follows a predictable pattern based on the considerations of human memory, emotional arousal, and the nature of the ritual action undertaken. They predict a bimodal distribution of rituals concentrated around two attractor basins toward which all ritual systems will gravitate. One the one hand, they predict a clustering of high frequency, low arousal ritual forms that cost very little to stage but can have lasting effects on the solidification of religious teachings, especially doctrinal content. On the other hand, they also predict a second clustering of low frequency, high arousal forms that are extravagantly costly and flood human sensory systems. This latter clustering is especially associated, they predict with one-off supernatural interventions of a divine agency as in many wedding ceremonies or in prominent funerals such as that associated with Princess Dianna. The proposal depends on a natural cognitive fit between the form of the ritual and the kind of supernatural intervention envisioned. Low frequency, high arousal rituals are inherently useful in impacting memories systems of participants and observers, persuading that a supernatural being is acting in the display. High frequency, low arousal rituals are likewise inherently useful in stabilizing semantic memory through dramatizations of human mediation of divine power. A ritual system that optimizes these dynamics is far more likely to achieve widespread distributions in the minds of adherent to some cultural complex than its rivals.

To explore these claims, Braxton built a landscape made of human minds in *Netlogo.* (Braxton *in press*). These minds came equipped with memory registers and finite, but renewable life resources. The memory registers came with only one qualification, a working memory limit of 7 units, a value derived from the so-called chunking behavior studied by psychologists (Bourtchouladze 2003). Moving about this landscape was a range of rituals with costs correlated impact. The cheapest rituals had the least impact and the most expensive rituals had the greatest impact. At either end of the range of ritual forms, a ritual pushed the limits of human memory constraints: at the lowest end, quick and dirty rituals (imagine Christians' tendency unconsciously to cross themselves for various reasons) and at the highest end, extreme rituals that overload human systems with massive sensory pageantry but no better memory impact than slightly less costly ritual displays. Finally, a slight boost was given to those rituals that conformed to the pattern that cheap rituals underscore human agency directed at a god and expensive rituals dramatize transformative, divine actions on humans.

In this model, rituals wandered randomly competing for the attention of minds that made up their world. They petitioned minds to watch a performance and if the mind in question possessed adequate resources, it consented to the display. If a ritual form achieved adequate performance levels, then it gave birth to a copy of itself. If it did not, then it died. The model ran through 2000 iterations and the distribution of ritual forms was tabulated. The model predicts an optimal distribution of ritual forms of 12 to 1. That is to say, a monolithic religious culture achieves optimal replication if it encourages 12 low-arousal rituals for every 1 high-arousal ritual, all other factors being equal. The model is formal working with memory constraints and resource availability. It models a simplified world of one culture, with a range of rituals evenly distributed across the populations. These simplifications are crucial, as we have argued repeatedly, because they allow us to isolate one variable, in this case memory mechanisms, and explore its bottlenecking properties for acquiring and retaining information from ritual displays. Likewise, it generates simulation data and predictions on the basis of this data. One can test for frequency distributions of ritual forms in the wild to see if they track with the model's prediction. Of course, as a simplification, the model excludes considerations that are likely to be highly relevant to any ritual system in the wild. For example, religious groups rarely exist by themselves and in the absence of direct competition.

In 2009, Braxton undertook the modeling of the formation of radicalized religious groups whose characteristics make them primary candidates for religiously motivated violence (hereafter RMV). For this modeling exercise, a cultural landscape was constructed that displayed randomly distributed cultural tokens. 50% of these tokens were modulated to display slightly positive attitudes toward the world's host culture and 50% were modulated to display equally valenced negative assessments of the dominant culture. A small number of the tokens were religious in nature—both positively and negatively oriented. To qualify as a specifically religious token, a cultural element simply evokes the supposition of a causal supernatural agent. In this world, human agents were randomly distributed throughout. By contrast, supernatural agents were relatively rare but persistent and appeared as embedded elements of a subset of cultural information. Human agents possessed slight seeding values of positive and negative attitudes toward the dominant culture. These attitudes were minimal (values of plus and minus 1 in a range of attitudes that ran 500 units in total (plus or minus 250). The agents were equipped with a standard percept range and a Bayesian decision-making algorithm. The relative distance of any given cultural token to the agent weighted its impact (greater distance meant weaker impact computed as vectors). The sum of the values of the cultural tokens within their percept range was calculated to result in a report of the state of the culture within the agent's percept range. The agent was then asked to judge the percept report using a Bayesian decision rule. The rule biased the decision-making process so that the more intense the attitude of the agent, the more likely it was to accept confirmatory reports and the less likely it was to embrace reports that violated its basic attitude. The degree of bias was directly tied to its degree of commitment to a positive or negative attitude toward the dominant culture. This process was probabilistic in the truest sense of the word since sometimes agents had to accept the disconfirming evidence based on the roll of a die (a random number generator). The chances of the die toss requiring cognitive reframing changed incrementally based on the strength of the agent's attitudes.

A second constraint was imposed on the agents called a "Wealth and Education Index" (hereafter WEI). Agents were randomly assigned a WEI reflecting their educational attainment and wealth within the world's culture. Following studies of RMV (Krueger 2008), this feature reflects the best available statistics on persons engaged in ideologically motivated (aka religious) violence. The model assumes no differences between religiously motivated violence and violence motivated by other, intense ideological commitments other than the simple assumption of a postulated supernatural agent. In essence, the lower the level of education and wealth, the less likely is an alienated person to embrace ideologies that undertake violence to impact the society. Such patterns have been empirically established for both secular and religious violence among radical cells. (Krueger 2008)

A final dynamic was added to the behavioral repertoire of the agents. If their commitments to positive or negative attitudes toward the dominant culture crossed a specific threshold, they began to scan their percept range for other agents with similar attitudes. If some were detected, the agent then began to approach the potential comrade, again judging which to approach using weighted vector analysis. In this way, coalitional structures emerged.

When the model is run, it tracks agents' behaviors on three levels. First, it maintains a running tally of three classes of agents: contents, discontents, and radicals. "Radicals" means here strongly alienated individuals. There are radically contented agents, and these might be candidates for a descriptor like "jingoists" or perhaps "nativists," but because they are so positive toward their host culture they are rarely motivated to engage in RMV. Second, it maintains a second tally of the number of contents, discontents, and radicals who have strong religious convictions based on their exposure to the small number of religious tokens cycling through the cultural system. Third, the model maintains a running tally of coalitional groups. The target of the model is to develop a picture of the conditions and amplitudes of radicalized religious groups. The model does not assume that such radicalized religious groups are inherently violent, only that, all things being equal, they are important candidates for where RMV might arise.

The model projects that in a given population of 1000, 6.37 radicalized groups will form with an average number of members 7.85. These numbers are averages from 50 runs of the model. The variance among outcomes of each model run was minimal. In other words, the model succeeded in producing relatively regular radical coalitions in number that seem realistic to real-world examples of terrorist cells.

The world of this model is utterly abstract and formal. At every instance the distribution of cultural information and agents is randomized. Although the initial conditions of the agents are seeded, this seeding value is kept to a minimum and not designed to push the model in any direction. In fact, the model is set up to favor positively oriented agents slightly at a rate of approximately 60% to 40% (again, the choice of how close to 60% and how close to 40% is decided by a random number generator). Given all these conditions, it appears relatively easy and predictable that any dominant culture can expect these radicalized groups to form, and when religious elements are represented, as is the case in every known culture to date, some of them will be religious radicals.

But the formal nature of the model makes it largely a heuristic tool. To achieve greater empirical utility, Braxton is now involved in translating these dynamics into a modeling environment that reflects real world measures. Currently he is engaged in a study of a specific landscape (the Old City of Jerusalem), taking biometric measures (GSR) of the emotional arousal of subjects and plotting these arousal patterns in space and time GPS technology. The groups being studied are exposed to the same cultural elements in the landscape and vary only in their commitments to one of the three Abrahamic monotheisms. 400 subjects over the course of three years will have their emotional arousal rates mapped into a GIS system creating a small world emotional map of the Old City of Jerusalem. This map can then be imported into the *Netlogo* platform and simulations run using the above-described procedures. Thus, instead of the cultural tokens being randomly distributed, they will be fixed in space as all such cultural information inevitably is. They will carry values based on the emotional reactions they elicit, and they will be clustered and clumped as all built human landscape actually is. This step adds a level of realism to the model. It also pushes the envelope so that specific predictions are possible. In essence, Braxton predicts that RMV is most likely to occur in those locations where two or more religious orientations experience emotional arousal. By comparing this prediction with historical records of RMV events, the researcher can now test the model. Further, if the model passes that kind of test, it can then wager novel predictions about what might happen in the future. This kind of forecasting is, of course, the gold standard in the scientific study of religion. To date, it has been highly elusive.

V. Conclusion

With this article we have tried to supply an introduction to the computational approach and show various possibilities it has to offer the study of religion. The presented material is by no means exhaustive of possible applications of computer modeling to religious phenomena, but reflects our own experience in the field. We have for instance left out the issue of integrating text-based methods with computational tools. We cannot see any reason why our claims should not apply to such methods, but we have not been offered the opportunity to bring the computational approach in that direction yet.

Given that religion is a cluster of interrelated phenomena and research concerning it should strive for multilevel analysis, we have argued for the utility of the computational approach. Both in terms of methodology and theory, the study of religion can benefit from the mediating role of computational space and the type of data that the computer generates (i.e. simulation data). In its function as a mediator the computational approach explores and operationalizes relations and objects from theoretical and empirical space. The approach enables a more qualified understanding of the interaction between theoretical constructs and data in a cheap and efficient way, by extending the continuous loop of scientific research. The computational approach allows the researcher easily to work from fixed features of observed phenomena and then infer what is possible and probable but hidden in the modeled system. This is demonstrated by the somewhat unusual concept of simulation data that offer a proxy through which the researcher can observe abstract processes. More so, simulation data also affords forecasting that can point the researcher to likely outcomes of human behavior given known parameters and thus, refine experimental field designs. Data having such qualities represent invaluable guidelines for research whether the perspective is top-down or bottom-up. Viewed from the top-down, simulation data offer the researcher information for optimizing the process of moving theory into the field or lab. Simulation data can also from a bottom-up perspective guide in theory building by exploring structures that does not conform to expectations or by asking new questions to an empirical data set assuming that the model is a good fit. Examples of both perspectives were given in the preceding section, for instance Bainbridge's use of artificial neural networks as a deductive proof of the Stark and Bainbridge theory or both Braxton's and Nielbo and Sørensen's efforts to use computer simulations as empirical tools. In reality there is a constant interaction between these two perspectives because asking new questions to data inevitably leads to modifications of theoretical space that then generates predictions that can and should be tested on empirical space.

Our motivation for writing this article has primarily been to initiate a dialogue between scholars of religion and computer modelers interested in religious phenomena. On all levels of description we are really talking about the same larger scientific entity. All research involves cyclic sharing of results among theoreticians, computer modelers, and experimentalists. Ideally, a scientific team will include people well suited to various kinds of expertise working in conjunction and in full recognition that each does her or his job better because of the impact of the other domains. The computational approach can in terms of technical demands be quite time consuming which tends to bias the modeler in the direction of their models sometimes at the cost of the system that is modeled. It can therefore be of utmost importance to have both creative input and collaboration with insightful researchers in the study of religion and its adjacent fields.

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