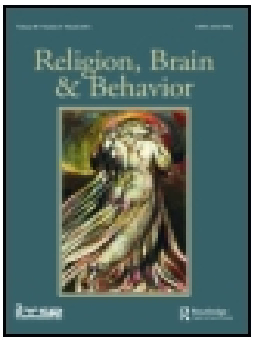


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# Can we predict religious extremism?

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# Can we predict religious extremism?

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**ABSTRACT**
Given events such as 11 September, the 2013 Boston Bombing, and the 2015 Paris attacks it is becoming increasingly apparent that religious extremism has great potential to negatively impact our daily lives. Predicting religious extremism could – in principle – allow us to respond to, mediate, or eliminate threats more efficiently. It is argued here that predicting religious extremism is possible but religious systems are complex dynamic systems and should be addressed as such. To address religious systems in a way that could provide useful predictions, one should use multi-agent artificial intelligence models that are validated using empirical studies of human cognition to define rules for the agents and historical and contemporary data sources (ex. "big-data" and historical databases) to calibrate and parameterize simulations. Ultimately, I conclude that near-term prediction is possible if one incorporates social and biological environments as well as inter- and intra-agent cognitive mechanisms, but long term predictions would be unreliable. Key to this approach is the admission that cognitive mechanisms play crucial roles in the generation and transmission of culture as well as the recognition that social and biological environments provide input to these mechanisms but neither social or biological environmental input is sufficient by itself.

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Religion; cognitive science; complex systems; informatics; predictive analytics; modeling and simulation

## Motivation for the problem

Groups such as ISIS have justified acts of terrorism as a form of religious warfare. This extreme form of religiosity represents a significant threat to safety and stability. The ability to predict extremism could help prevent loss and manage responses to acts of terrorism. Although the approach outlined below could be generalized to predict other human social systems, I posit that the knowledge required to appropriately describe the necessary and sufficient variables to predict religious extremism requires that specialists from religious studies work with computational modelers.

## Restating the problem

There are two ways to formulate the problem:

- *Strong formulation*: can religious systems be predicted at time points $t{:}t_n$, where n is unbounded?
- *Weak formulation*: can religious systems be predicted at time points $t{:}t_n$, where n is bounded?

In order to provide an answer, I will discuss how to formulate the relevant variables and their interactions within a paradigm that could potentially predict a religious group's actions within a

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specific range of possible outcomes by incorporating intra-agent, agent–environment, and inter-agent interactions.

## Predicting socio-cognitive systems

Given the assumption that typically developed human minds are instantiated with similar cognitive facilities, we can assume that all agents can execute the same set of rules. These rules can be described using research on human cognitive facilities. However, the input to a mechanism in one agent may be premised on the output of some mechanism in another agent. Furthermore, this mechanism may be premised upon the output of another mechanism, which is internal to an agent (depicted in Figure 1).[1] However, although one cannot control for every externality, the output of a cognitive mechanism can be bounded within a certain interval, as described in the empirical literature on human cognition. Although this does not eliminate stochasticity in the system, it does allow for a mathematical formalization of complex interactions.

Modeling environmental interactions would not include every environmental parameter. Rather, it should include only the necessary and sufficient variables required to define the conditions relevant to predicting a religious group. Studies addressing environmental aspects such as the ratio of in-group to out-group members (Hoverd, Bulbulia, Partow, & Sibley, 2015) or the presence of potential hazards (Liénard & Lawson, 2008; Mort, Fux, & Lawson, 2015) demonstrate that environments affect religiosity. This also demonstrates that dynamics of religious systems are susceptible to initial conditions. Conditions can include, for example, the number of in-group or out-group members, available from demographers such as Pew Research Center or the World Religion Database (2016). Additionally, resource scarcity data can be drawn from pre-existing sources such as the World Bank dataset (The World Bank, 2016), which has an API that can be leveraged to incorporate their data directly into models of religious behavior. For many countries, census data are available. Given the importance of environmental variables in the manipulation of religiosity, any system aimed at predicting religious extremism must also address agent–environment interactions. As an agent uses resources in their environment, the environment is impacted by the loss or transformation of those resources. As such, there is a secondary feedback loop between the agents and their environment (Figure 2).[2]

Furthermore, data for parameterizing social interactions can be drawn from currently available online sources. Data concerning the structure of social interactions can be approximated (or drawn directly) from online social networks such as Twitter, which has 310 million active users, most of them outside of the US (Twitter, 2016), or Facebook, which has 1.65 billion users each

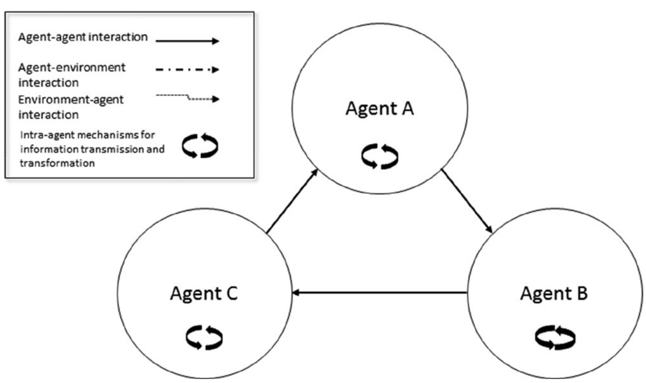


**Figure 1.** Inter- and intra-agent interactions.

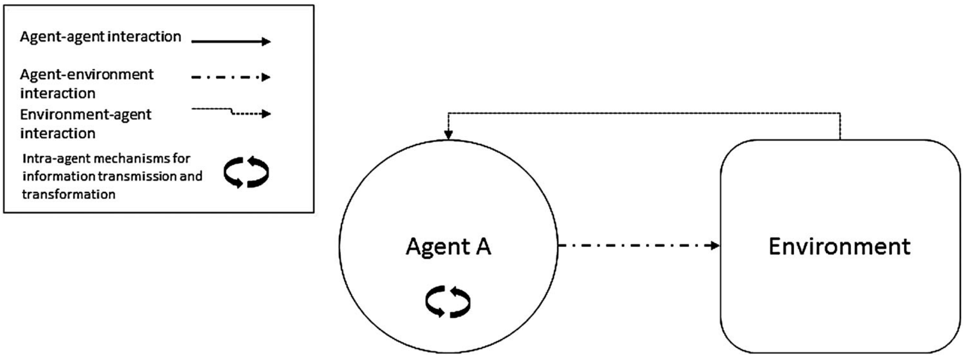


**Figure 2.** Agent–environment interactions.

month, 84.2% of whom are outside of the US and Canada (Facebook, 2016); this helps overcome the sample biases noted in psychology (Henrich, Heine, & Norenzayan, 2010). These online social networks have been shown to mimic real-world network structures with acceptable accuracy for use in computer models (Arnaboldi, Passarella, Conti, & Dunbar, 2015). Additionally, emails or phone records could be used (Pentland, 2014).

Combined, the proposed approach incorporates intra-agent, inter-agent, and agent–environment interactions, which results in a complex stochastic system with embedded feedback loops (depicted in Figure 3) to predict extremism.

## *Solving the problem*

The formulation of interactions above accepts that religious systems (1) are susceptible to initial conditions, (2) are stochastic, (3) include many simple but interacting rules, and (4) produce output that seems to persist with local predictability, but perturbations can evoke radical changes in the system.

We can conceive of agents in religious systems as a type of complex automata. Automata are entities that change states and act in accordance with a set of rules – in this case, rules are defined by cognitive facilities. For religious agents, it is important to keep in mind the complexity of these rules, which are bounded by constraints and proclivities. Some functions of the agent's cognitive

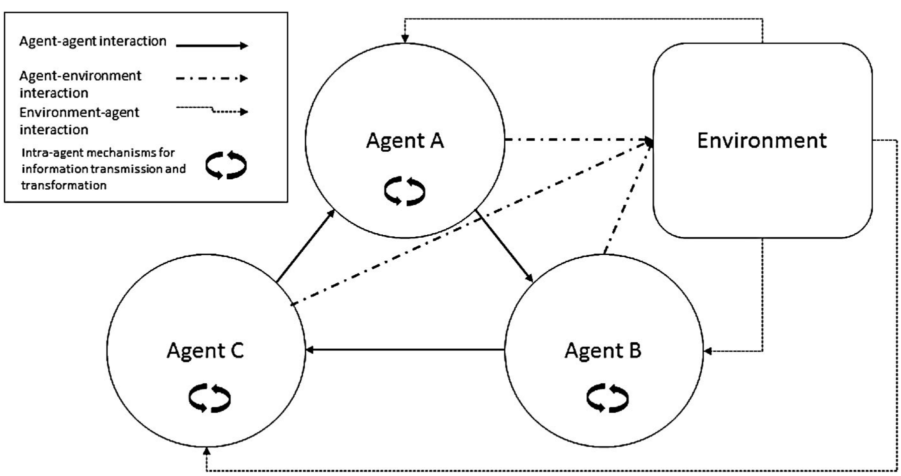


**Figure 3.** Inter- and intra-agent–environment interactions.

**Table 1.** Complexity classes.

| Class | Mathematical Definition | Effect of Perturbations | Description for Religious System |
|---|---|---|---|
| *Class I* | Exhibit fixed, homogeneous, static state patterns | Changes die out, system returns to stasis | Religion never changes |
| *Class II* | Exhibit periodic changes or oscillations | Changes may persist, but will remain localized | Religion periodically goes from one state to another |
| *Class III* | Exhibit chaotic, aperiodic, "random" pattern | Changes may lead to infinite regions of randomness | Religion shows no discernable structure |
| *Class IV* | Exhibit complex, local structure that is susceptible to random permutations | Changes may be irregular and are largely localized through specific structures | Religion shows local predictability but changes over time |

architecture could – when applicable – employ Bayesian reasoning, fuzzy logic, or associative learning to govern components of complex decisions, whereas others may use deontic rules, as is the case when reasoning with sacred values (Atran & Ginges, 2012; Berns et al., 2012). One should not assume that all agents are clones; rather, each agent must be able to store information about previous "experiences," which can inform future decisions. Furthermore, interactions can be constrained by dynamic social networks, allowing for realistic interaction dynamics within the environment.[3] Furthermore, by embracing cognitive heuristics and biases (similar to Sperber & Hirschfeld, 2004) and including the use of non-deterministic decision functions – such as Bayesian or fuzzy logic-based decision mechanisms – it allows for agents to act with acceptable ecological validity. In this way, agents are not strict logico-mathematical entities, but complex agents with rich cognitive architectures.

The rules programmed into these agents can come from the theories in the cognitive science of religion, which has already embraced – at least nominally – an information processing approach to the study of religion. Theories such as the ritual competence theory (Lawson & McCauley, 1990; McCauley & Lawson, 2002), divergent modes of religiosity (Whitehouse, 2000, 2004), the Stark & Bainbridge theory of religion (Bainbridge, 2006; Stark & Bainbridge, 1987), and others (e.g., Atran & Ginges, 2012; Boyer, 2001; Sperber & Wilson, 1995; Swann, Jetten, Gómez, Whitehouse, & Bastian, 2012) offer rules to be instantiated in the agents. Careful empirical investigation of these theories in real-world populations can serve as a basis for describing and parameterizing the necessary computational rules.

The approach described above can result in outputs that are bounded, given a set of conditions. Using multiple runs of a stochastic model under a set of conditions can allow for the calculation of probable outputs. However, stochasticity in any model, when the state at time $t_{n+1}$ is at least partially determined by the state at $t_n$ and initial conditions at $t_0$, only allows for useful predictions in proximate time steps. Therefore, indefinite prediction is unreasonable because initial state conditions and perturbations affect local states of the system. Thus, religions appear to be Class IV systems, which are neither fully predictable (ex. class I), nor oscillatory (ex. class II), nor random (ex. class III) (see Table 1).[4]

## Conclusion

If we conceive of religious systems as sets of interacting agents behaving based on rules governed by human cognition, we could predict the system locally within short time intervals using multi-agent artificial intelligence models (Lane, 2013). The only way local and immediate prediction is possible is by accurately defining rules for the system. In the case of religious systems, this is achievable by instantiating agents with psychologically realistic (i.e., empirically valid) cognitive mechanisms (Sun & Hélie, 2013). By doing so, we can produce models that can allow us to "predict" – within some bounds of statistical confidence – what the local states of a religious system will be at time $t_1$ and $t_{1+n}$. However, due to the interactions described above, as n increases, predictive accuracy decreases, eventually reaching a point whereby we could not statistically accept or reject counterfactual hypotheses.

## Notes

1. The complex interactions between agents (i.e., people) and their environment present an Entscheidungsproblem (Turing, 1937). The Entscheidungsproblem is – simply stated – that given a set of computable numbers, a program must know when the computation is finished. The complex inter-agent interactions described above can create situations where it cannot be determined that an agent has sufficient information to stop a calculation. Modeling platforms (e.g., Netlogo; Wilensky, 1999) utilize random action paradigms that choose an agent at random. The agent then performs all necessary calculations before the program chooses a subsequent agent. This is repeated until every agent has performed their actions, providing a practical but artificial solution to the Entscheidungsproblem.
2. Although ideally such feedback systems would be captured within an agent-based framework, environmental systems and their variables could be formalized as system dynamics models, or sets of differential and difference equations, in order to calculate large-scale environmental changes over time more efficiently (see, for example, Meadows, Randers, & Meadows, 2004).
3. Although ideally such a model would leverage geographic information system (GIS) based technology, this would not be required. Simple complex environments have been designed using simple Euclidian planes to model the interactions of agents and environments in the past (see, for example, Axtell et al., 2006; Dean et al., 2006; Epstein & Axtell, 1996; Gumerman, Swedlund, Dean, & Epstein, 2006). Agents would not be set on a grid, as is typical of cellular automata models (see Ilachinski, 2001; Kari, 2005; Wolfram, 1984, 2010).
4. Also see Ilachinski (2001) and Wolfram (1984, 2010).

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