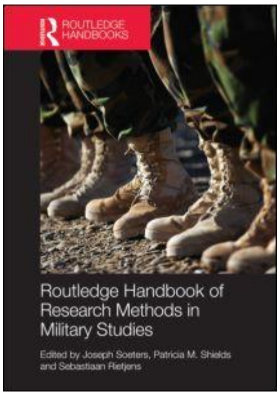

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Computational Modeling to Study Conflicts and Terrorism

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COMPUTATIONAL MODELING TO STUDY CONFLICTS AND TERRORISM[1]

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J. M. Epstein (2002) "Modeling civil violence: An agent-based computational approach," *Proceedings of the National Academy of Sciences of the United States of America 99*(Suppl 3): 7243–7250.

Epstein provides two general computational models of civil violence. The first examines a government attempting to suppress a decentralized rebellion and the second investigates government efforts to quash communal violence between rival ethnic groups.

Model I or the rebellion vs. state model involves two broad categories of actors: the state vs. the population or what Epstein terms the *Cops* vs. *Agents*. Like other computational models, each category of actor includes a heterogeneous mix of types. Members of the population (Agents) vary according to their (H) hardship and (L) legitimacy. H is a parameter to capture social and economic grievances. L is the perception of legitimacy of the government. While one could argue about the distribution of types in society (how many people are highly aggrieved, what proportion feel the government is not legitimate), computational models make this assumption clear and allow the analyst to shift this distribution and show the implications for the growth of phenomena, such as rebellion or intercommunal violence. Additionally, Epstein builds in local rationality (a limited bounded form) that is missing in many other formal or verbal models of similar processes. Epstein makes clear that the ideas are general and not meant to predict any single case and that the parameters are not direct measurements of actual grievance or legitimacy. Epstein provides a table showing the different experiments he undertakes and the values for key parameters that he seeds the model with.

One of the most important findings from computational models is an outcome that *emerges* from the interaction of agents. One critique of these models is that properly programmed, the model can tell the analysts anything they want to know. When results are counterintuitive or macro outcomes emerge from micro decision rules that are non-obvious, the model provides microfoundations that

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are unlikely to be unearthed using other methods. Epstein finds deceptive behavior by Agents that were active rebels to hide from the Cops and parade around as normal citizens (something we know occurs). Epstein also finds important tipping points outlined in game models, such as work by Kuran (1991), that occur when parameters move beyond a particular threshold.

In the second model, members of two ethnic groups can choose to target each other. L is still a parameter in the model, but it refers to the belief that the other side has a right to exist. Cops are also included and attempt to reduce ethnic killings. Stylized facts that emerge from the model include: when legitimacy is high, Cops are completely unnecessary. Reductions in L lead to episodes of ethnic cleansing even when force levels are high. Variance in genocide episodes increase as force levels do suggesting that increasing guardianship will work in some cases and not others.

Both models highlight the strengths and weaknesses of this modeling approach. The models are general enough to make predictions about a wide array of phenomena, such as ethnic cleanings, genocide, rebellion, and the emergence of public preferences. To be useful for predicting specific cases of interest for policymakers and the military, initial modeling parameters should be seeded with values consistent with the local context. The equilibria that develop can then be tested using dyadic events data (see for example Findley et al. 2010). Utilizing a lattice with actual GIS information consistent with the context of interest can also help match the model to reality. One danger though is to build such a complex model that it becomes *too real*. In short, with too many parameters (Miller and Page 2007), it is unclear which one is influencing the equilibria in the observed way. Models must strike a balance between being specific and thus actionable and yet parsimonious and as a consequence tractable.

Introduction

A randomized experiment is the gold standard for establishing causality in the sciences. If researchers want to understand how a change in an actor's behavior can be attributed to a stimulus, random assignment to the treatment and control group is an absolute prerequisite (see Chapter 20). While this premise is mostly accepted across the social sciences, it is challenging to implement such a design when studying many applications involving military conflict, such as the dynamics of insurgency, counterinsurgency, and terrorism.

First, the ability to randomly assign interventions to treatment and control is difficult if not impossible in most cases. Many strategies affecting war and peace are typically not practical or ethical to implement. Second, most experiments need to be replicated to ensure their reliability and validity. Yet, it is impossible to rerun history. Third, we cannot directly observe outcomes that did not occur. What would have happened to the trajectory of the World War II had Hitler been successfully killed by coup plotters? Would the post-Iraq War reconstruction have been more stabilizing had the US and its partners not disbanded the Iraqi Army? Both of these questions are what social scientists term counterfactuals. In short, a counterfactual is an attempt by an analyst to reference a condition where the outcome of an event would have been different had a key causal factor been absent (Fearon 1991). Fourth, even when we use controlled experimentation, we want to know how an individual would have reacted in both a treatment or control condition. Yet, we generally only observe them in one of those states (Holland 1986).

These four fundamental problems with experimentation in military science applications suggest a potentially dismal outlook for research in this area: we can undertake studies in this domain, but we can never approximate the ideal study to make valid causal inference. With recent breakthroughs in field experiments applied in comparative and international politics notwithstanding (Fearon et al. 2009; Findley et al. 2013), we argue that computational modeling is a research methodology that can address some of these problems and lead to the development of sound theory in social and military sciences that informs policy choices by political and military strategists.

In the chapter that follows, we first outline the methodology of computational modeling. We explain how to develop a model, how to use computational modeling to assess counterfactuals, how to integrate with data, and how to interpret the final results. We also identify the strengths and weaknesses of the approach and the appropriate domain and usages of this methodology. In the next section, we provide an application to military science focusing on insurgency and counterinsurgency dynamics. We highlight the ability to model many different kinds of actors in a dynamic, interactive, laboratory-like framework. After discussing a more general use of this technique, we focus on particular social science applications, including prominent models that can inform future applications. Next, we discuss the application to policy and how this theoretical approach can be merged with other more empirical tools. Following this discussion, we identify and compare the various tools analysts use to design and implement models. In the conclusion, we summarize key discussion points, outline some best practices for using computational modeling, discuss the preparation needed to become a modeler and suggest some potentially fruitful avenues for future research.

Modeling war and terrorism dynamics

Schelling's (1960) revolutionary work that applied the tools of game theory to conflict helped develop a more dynamic and strategic study of conflict. There are many benefits of game theory to the study of violent conflict (Bueno De Mesquita 2002). Potentially most important, however, is the general framework for finding the equilibrium strategy of violent actors that depends on the incentives of each actor but also on the *strategy of the opponent*. Game theory helped devise a nuclear deterrence strategy even when no nuclear conflict ever actually occurred (Schelling 1960; Powell 1990). Game theory also captures some of the foundational features of the international system making it a useful tool for understanding conflict that spills across borders and engulfs multiple states (Snidal 1985).

Computational modeling builds on game theory in a number of core ways and even extends some of the benefits of a formalized way to generate theory that overcomes some of the limitations of game theory. Two limitations are of particular note for military and conflict applications. First, game theory assumes rational agents with generally fixed preferences. Computational models allow agents to adapt over the course of the interactions. These actors can be rational, boundedly rational, Bayesian, or endowed with other decision rules that allow them to change, adapt, die, or proliferate (Macy and Willer 2002).[2] In an application to ethnic conflict Epstein (1999: 49) notes:

> Game theory may do an interesting job explaining the decision of one ethnic group to attack another at a certain place or time, but it doesn't explain how the ethnic group arises in the first place or how the ethnic divisions are transmitted across the generations

Second and related, most games have a minimal set of actors to make solving the models tractable. A government against an insurgent group, or a homogeneous population and a government, are two actor pairings likely to be modeled in a game theory approach. As experiences from Vietnam to Afghanistan have demonstrated, insurgent conflicts have many kinds of participants, with a variety of interests that change over time, based on conditions and interactions with other actors. Game-theoretic models are ill-equipped to handle this type of heterogeneity as solving these games becomes increasingly difficult with the inclusion of each additional actor, parameter, and distributions of characteristics.

Case studies and more descriptive approaches can handle this heterogeneity and richness of data. Case studies, like both game theory and computational models, can be a tool for generating theory and subsequent testable hypotheses (Gerring 2004). Especially when dealing with a single case over time, the logic of control allows for an analyst to examine a particular unit that should be nearly identical between periods except for the identified intervention. For example, a question, such as, "Was the rule of law affected in the US after the attacks of September 11th?" can be examined using case methods that should help develop more specific hypotheses about the relationship between these attacks and the implementation of law inside the United States. Like the limitations discussed at the outset, however, case studies also do not allow for a different outcome of the case. In sum, we only examine the effect of the treatment on the actual outcome rather than the effect of non-treatment (or the control condition) on another possible outcome.

Statistical modeling has proliferated in the study of civil violence and terrorism over the past 15 years. Statistical models have tremendous advantages in that they allow the inclusion of a large number of cases and established techniques to control for alternative explanations. In large statistical studies, there is scope for many different values of independent and dependent variables. Unfortunately, however, most statistical models rely on observational data for which the data generating process produces systematic and difficult-to-solve biases. To draw on the experimental analogy introduced at the outset, most observational studies are effectively broken experiments where analysts are trying to use statistical fixes to approximate the theoretical experiment. While many statistical approaches are possible, instrumental variables and matching to name a few, they all typically have a number of limitations that prevent strong counterfactual and causal analysis.

We thus turn to computational modeling as a way to address some of these limitations. Clearly computational modeling does not fully solve all limitations in other studies. Instead, it provides a different way of addressing the problem that may illuminate poor conclusions from other approaches. Early computational approaches modeled structural relations using primarily differential and difference equations (see discussion in Cioffi-Revilla and Rouleau 2010). In the last two decades there has been a turn to computational models that are less structural and more generative; most models now capture *bottom-up* processes in which large numbers of interacting agents produce various emergent outcomes (Epstein and Axtell 1996; Axelrod 1997; Epstein 1999; Miller and Page 2007). We now turn to a discussion of how agent-based, computational models (ABM) are typically set up and executed.

The methodology of computational modeling

Computational modeling is a generic name for a wide variety of modeling practices. Social scientists typically use agent-based, computational models (Gilbert 2008)—also referred to as complex adaptive systems models (Miller and Page 2007) a deeper field of study from which Agent Based Modeling (ABM) originated—that share a number of features. In particular, nearly all models specify several basic components: the agents or actors, the environment, and the overall model or mapping to some real-world phenomenon. Furthermore, most models are executed in a similar way: through a variety of controlled, computational experiments. A chapter of this length does not permit an adequate explanation of all parts of an ABM. We will briefly discuss some of the tradeoffs, but refer interested readers to much lengthier treatments of ABM elsewhere (see for example Holland 1998; de Marchi 2005; Miller and Page 2007; North and Macal 2007; Gilbert 2008).

Agents

A first crucial step in any ABM is to specify the agents. At its simplest, agents are the decision-making components in some complex system (North and Macal 2007). The agents can represent any sort of decision-maker the researcher decides. An agent could be an individual militant, a militant organization, a state fighting against a militant, a citizen affected by a militant, or many others. Agents could be specified at different levels as well. In one model, an agent could be an individual and in another model the agent could be some aggregation of individuals. Both could occur in the same model as well.

Of course, some representations may be more sensible than others and the researcher needs to be cautious about how complicated the agents are. Existing agent-based models of insurgency and terrorism have specified agents in most of the ways discussed (see for example Axelrod 1997; Bennett 2008; Cederman 1997; Cederman 2002; Findley 2008; Findley and Young 2006). A hallmark of agent-based models is that collections of agents have heterogeneous attributes (Page 2007). That is, rather than only assuming that agents hold one or two types, as in many game-theoretic models, agents can each take on different values from some distribution. In the Epstein (2002) model discussed previously, for example, agents take on a full range of hardship and legitimacy levels drawn from a uniform distribution.

Environment

Agents are situated in some environment, which they affect and are affected by. The environment refers to the virtual world within which agents are situated and interact (Gilbert 2008). Modelers face a number of decisions about the appropriate environmental setup. Some environments are abstract and agents are simply matched with each other for various types of interactions. Other environments are more complex with some explicit spatial landscape on which agents interact.

In models where there is no explicit spatial representation, agents typically interact in some hypothetical space similar to game-theoretic models in which agents are simply matched without saying how or where. Thus, agents could interact on the basis of some random matching specification (as in works such as Riolo et al. 2001). Alternatively, the non-spatial setup could be modeled according to a network, for example a small-world network (Watts 1999), in which other actors may exist in neighborhoods but not necessarily being overlaid onto a grid or GIS landscape. And some applications to the realm of insurgency and violence have coupled random matching with network structures (for example Bhavnani et al. 2009).

In models with an explicit spatial component, the landscape can be artificial or it can be based on real-world data. Artificial landscapes include representations such as a square grid or a torus where there are no artificial edges (see for example Findley and Young 2006, 2007; Bennett 2008). Although artificial, some implementations also populate the landscape with attributes intended to represent actual terrain (Cioffi-Revilla and Rouleau 2010). Real-world representations include the use of geographic information on factors such as state boundaries, ethnicity, population, or other factors (see for example Girardin and Cederman 2007; Findley et al. 2013).

The agents and environment represent part of the simplification of some realistic phenomenon into a model. In practice, researchers create models in a variety of ways. The question of just how abstract a model should be is not an easy one to answer. Modelers must decide how many agents to include, how many characteristics to ascribe to each agent, how many rules should govern the interactions of agents, how realistic the environment should be, and many more. While some prominent modelers have leaned towards simpler representations (Miller and Page 2007), others are in favor of more complex possibilities (Girardin and Cederman 2007). An alternative is to specify a model's complexity based on the research or policy question at hand (Lustick and Miodownik 2009) with an eye towards one's ability to analyze the model in some tractable way (de Marchi 2005).

Outcomes

Modelers are typically interested in some aggregate outcome. For the topic of this volume, the occurrence and intensity of violence are two frequent outcomes of interest. Popular turnout or participation is another common dynamic or outcome. These outcomes are typically captured in the form of emergent properties (Holland 1995, 1998). The idea of an emergent property has been much debated, but the essence, even if somewhat trite, is that some outcome is more than the sum of its parts. The division is related to the distinction between a complex system and a complicated system. In the former there are dependencies among the various elements of the system that are key to the behavior of that system. In the latter, the various elements maintain a greater degree of independence and therefore dynamics of such systems are easier to reduce (Miller and Page 2007).

Once a model's agents and environment are fully specified, the model is executed as a computer simulation composed of a set of experiments. In each of the computational experiments, a high degree of control can be achieved by holding constant all of the parameters except one. The researcher thus begins by varying a single parameter across reasonable values of its parameter space. After varying one parameter, the researcher then varies a different parameter holding all else constant, including the parameter previously varied. Once all relevant parameters have been varied, then two or more parameters are often varied together to explore the implications of covariance in sets of parameters. In all contexts, the researcher tracks the dynamics and aggregate outcomes (emergent properties) to learn whether there are systematic relationships. Nonlinear relationships are not common, especially as different sets of parameters interact with each other in various ways. Not unlike a carefully controlled experiment in the lab or real-world, this approach allows one to vary key parameters in a way that enables a better understanding of each part of the overall system.

Social science applications

In the international relations literature, early computational models captured interstate war, peace, and system structure. Modeling of violence has since become more common, in the study of insurgency, civil war, and ethnic conflicts. In most cases, these three categories overlap extensively. There are not many computational models of terrorism, which is likely an area ripe for future research.

In these social science applications to violence, researchers set up their models described above: political violence is modeled as the outcome of a complex set of interactions among a set of actors ranging from government leaders to ordinary citizens. The set of actors is typically heterogeneous in motivations for violence and capability to carry out such violence. Other models of strategic interaction largely miss the diversity and resulting emergent dynamics.

Computational models of violence have followed several paths. One distinction is between highly abstract models capturing cooperation and conflict. These models are intended to be applicable, to some extent, to a wide variety of animal and insects species. Prominent examples examining how cooperation and conflict evolved appear in journals such as *Nature* and *Science* including Nowak and Sigmund (1998) and Riolo, Cohen, and Axelrod (2001). Of course much of this literature had its origin in Axelrod's (1984) well-known *Evolution of Cooperation*.

Axelrod followed up with a collection of essays specifically applied to conflict and cooperation within the realm of international relations. About this time, a whole series of works, primarily by Cederman, followed and computationally modeled the dynamics of the international system. These works included models of the development of the international system (Cederman 1997; Cederman 2002), the spread of democracy and the democratic peace (Cederman 2001; Cederman and Gleditsch 2004), and the dynamics of wars (Cederman 2003). While some attention continues to be devoted to interstate wars, much of the literature has now shifted to the dynamics of ethnic and insurgent wars.

A number of works have modeled the role of identity and ethnicity in civil wars. These various works have captured: the construction of ethnic identities (Lustick 2000), the scale of ethnic violence (Bhavnani and Backer 2000), the diffusion of ethnic norms (Bhavnani 2006), ethnic polarization (Bhavnani and Miodownik 2009), ethnicity and nationalism (Cederman and Girardin 2005), and rumor diffusion in ethnic conflicts (Bhavnani et al. 2009). This work took seriously the importance of capturing subnational dynamics of ethnicity while the rest of the field was fixated on national level empirical measures such as ethnic fractionalization (Fearon and Laitin 2003). Indeed, much better empirical work on ethnicity followed this rigorous modeling (Cederman et al. 2010).

A closely related literature uses computational models of civil violence, but with less emphasis on ethnicity and identity. In this set of models, scholars have examined the role of commitment to insurgency that could be a function of identity or other factors (Findley and Young 2006, 2007), emotional attributes of agents including anger and fear (Bennett 2008), heterogeneous contextual factors such as hardship and legitimacy (Epstein 2002; more on Epstein below), government structure and dynamics (Cioffi-Revilla and Rouleau 2010), systemic factors of an insurgent ecology (Bohorquez et al. 2009), and actor-specific dynamics such as the emergence of social movements and the occurrence of splintering (Findley 2008; Findley and Rudloff 2011).

Models of terrorism have received considerably less attention than have models of insurgency and ethnic conflict dynamics. With few exceptions (Leweling and Nissen 2007), this area is almost unexplored. And yet there is reason to believe that models of terrorism could be very fruitful. For one, militants that utilize terrorism are often organized in networks, something that agent-based models can capture well. Moreover, terrorists vary dramatically in their group size, motivations, constraints, and so forth. The heterogeneity afforded by computational models could directly capture these characteristics.

Policy applicability

Over the past decade, computational modeling has been implemented in diverse arenas ranging from military needs (Keller-McNulty et al. 2006; Pew and Mavor 1998) to academic applications (Macy and Skvoretz 1998; Cederman 2003; Findley and Young 2007). In this section, we discuss the costs and benefits of using this methodology as well as other practical issues that need to be taken into account before scaling up the use of computational models. We also discuss the challenges of integrating real-world data with simulated assumptions and data in an agent-based model.

In a review of the difficulty of merging academic quantitative research with the policy community, Mack (2002) argues that there are many barriers to communication between the groups. Some that relate to computational models and demonstrating their utility to the policy community and military include: different ways of communicating, the notion of probabilistic theory, and debates in academia.

First, as Mack (2002) notes, many quantitative scholars speak a different language and do not attempt to translate their results to busy policymakers. Computational modeling can be at least as complicated and theorists in this tradition should strive for communicating their results in as non-technical and non-jargon-filled ways as possible.

Second, computational modeling produces empirical predictions that are probabilistic. Single cases that counter the equilibrium of a model do not destroy the entire enterprise. Policymakers, however, often think of cases that refute a claim as deadly to the claim. If COIN doesn't work in Iraq, then this approach is often thought as a failure across other cases. Computational models are often more general and should apply to numerous cases. If users want a more tailored model to a particular case, then it can be seeded with relevant parameters, data from the case, and other factors that will increase fit. If the model still does not accurately predict a particular outcome, this does not destroy the model. Academics working in this tradition generally prefer models that predict better than other models and that predict better than a random guess. Perfectly determined outcomes are not the goal using this methodology.

Third, academics and modelers do not always agree about the best way to do research and how it will be used by policymakers. They also have major theoretical divisions. Policymakers wanting a single piece of advice about the best course of action can be easily frustrated by trying to sort through the academic arguments and deciding which is more powerful (Mack 2002).

There are major debates about the best ways to use computational modeling. Without outlining all the dimensions, there is at least one major division worth noting. Modelers struggle with whether to be complex and more realistic or parsimonious. A recent computational model by Cioffi-Revilla and Rouleau (2010), for example, makes an entire simulated society with different structures and processes. Other models include just a few parameters and have a small number of actor types, although their values on parameters vary according to some predetermined distribution (e.g. Epstein 1999, see textbox). Each decision has costs. More complex simulations can accurately apply to particular cases, but they lose their generalizability. Another important cost of complex models is that the so-called parameter space becomes prohibitively large. De Marchi 2005 discusses just how quickly the parameter space can get too large to adequately analyze fully.

Findley et al. (2010) simulate insurgency in the context of India from 1998 to 2008. Using GIS information from India, they build a lattice model that operates in the geographical boundaries of this country to generate predictions about the growth or decline of insurgency. Briefly, they seed the model with a large number of agents that can be insurgents, counterinsurgents, or members of the population that have varying values for key parameters. The agents move through the India-shaped landscape. When the agents meet on the board, they interact and can influence each other. These interactions can lead to moving a member of the population into becoming an insurgent, insurgents being killed, or several other outcomes. After these interactions occur over a fixed time period (100, 1,000 iterations, etc.), the analyst can examine changes in numbers of actors, distributions of key parameters, and a host other factors.

Using dyadic events data, they then test the predictions of the computational model. This research design holds promise for merging complicated theory and large data sets. The initial model can be quite simple, and the results can be tested using the events data. When the two do not match, the analyst can adjust the model. To avoid constraining and fitting the model to predict the data, the model can be taken to other locations and other time periods to test out of sample. The assumptions and parameters then can be informed by real-world values and tested to examine fit and prediction.

Technical needs

Learning to use computational models requires some theoretical training as well as some practical skills. The theoretical background to computational modeling is well developed and many resources exist from which to learn about the methodology. Among the available texts, Epstein and Axtell (1996), Holland (1998), de Marchi (2005), Miller and Page (2007), North and Macal (2007), and Gilbert (2008) are all great sources to get broad exposure to the methodology.

On the practical side of using agent-based models, users need to have some exposure to a computer programming language. Not all agent-based models require a computer, of course (see Schelling's [1971] pioneering work). Most current agent-based models, however, are carried out on a computer and thus require some ability to program the agents, environment, rules, and then graph the outcomes. Programs vary in how much background they provide.

Two toolkits are currently most developed: Repast and Netlogo. Both were developed many years ago and have increased the scope of what they can accomplish while decreasing the barriers to entry. While there is much information readily available for non-programmers, in order to design models to accomplish certain user-specific needs, programming is needed to customize the models. A more recent program, Mason RebeLand, provides a platform specifically for modeling the dynamics of violence.

While these toolkits can be useful for many purposes, they can also be far more complicated than what some social science applications require. Many political science applications are not complicated and require no more than a few hundred lines of code. When political science scholars (and others) are unfamiliar with lower-level programming languages such as Java or C#, many can still use programs such as R or Matlab to program simple models. Many applications using all of these various approaches are available online. Downloading and running others' existing models can be a useful way for beginners to get started.

Some resources provide both a theoretical and practical training. For instance, Kendrick, Mercado, and Amman (2006) develop a number of computational models applied to economics and for each chapter provide the source code for different programs including Excel, Mathematica, GAMS, Access, and Matlab.

Conclusion

Over the past 20 years, computational models have become increasingly common in studies of conflict and violence. Computational models offer some important advantages over other methodological approaches. Perhaps most importantly, they provide a way to approximate a controlled experiment in a context that would otherwise not permit experimental methods. Modelers can develop computational experiments that allow the careful and systematic investigation of a large number of possible explanations. Moreover, whereas such models used to be highly abstract, it is now easier than ever to incorporate real-world assumptions, data, and match against observed outcomes.

The allure of computational models is also a challenge. It is tempting to see computational models as a complete solution to data woes. Unfortunately, computational models are best used to generate and refine theory as opposed to providing empirical tests. For this reason, it is difficult to point to a refined and concrete set of conclusions that has emerged from this research. They have been tremendously useful in generating theory about the connections between micro-level behavior macro-level outcomes in contexts such as insurgency, violence, ethnicity, and beyond.

Although the topics of insurgency and ethnic conflict have received much attention, there is still much room for continued work. Notably, very few models attempt to explain the dynamics of terrorism. It is possible that the explanations for terrorist events follow logics similar to domestic political violence. But we do not know at this stage. Computational models could thus be applied fruitfully in identifying the similarities of differences with other forms of political violence.

Although there are some barriers to entry for computational modeling research and practice, this approach has become more accessible in recent years due to a large number of toolkits, programs, and resources for learning. Computational modeling, we hope, will supplement the already useful tools that social scientists and practitioners are using to understand violence. When used in tandem with these other approaches, we expect that many more useful insights will be possible.

Notes

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2 Some game theoretic models allow for learning among agents (see, for example, Camerer 2003), but this is not the norm.

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