Agent-Based Modeling in Political Decision Making

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Summary and Keywords

Political systems involve citizens, voters, politicians, parties, legislatures, and governments. These political actors interact with each other and dynamically alter their strategies according to the results of their interactions. A major challenge in political science is to understand the dynamic interactions between political actors and extrapolate from the process of individual political decision making to collective outcomes. Agent-based modeling (ABM) offers a means to comprehend and theorize the nonlinear, recursive, and interactive political process. It views political systems as complex, self-organizing, self-reproducing, and adaptive systems consisting of large numbers of heterogeneous agents that follow a set of rules governing their interactions. It allows the specification of agent properties and rules governing agent interactions in a simulation to observe how micro-level processes generate macro-level phenomena. It forces researchers to make assumptions surrounding a theory explicit, facilitates the discovery of extensions and boundary conditions of the modeled theory through what-if computational experiments, and helps researchers understand dynamic processes in the real-world. ABM models have been built to address critical questions in political decision making, including why voter turnouts remain high, how party coalitions form, how voters' knowledge and emotion affect election outcomes, and how political attitudes change through a campaign. These models illustrate the use of ABM in explicating assumptions and rules of theoretical frameworks, simulating repeated execution of these rules, and revealing emergent patterns and their boundary conditions. While ABM has limitations in external validity and robustness, it provides political scientists a bottom-up approach to study a complex system by clearly defining the behavior of various actors and generate theoretical insights on political phenomena.

Keywords: agent-based modeling, political decision making, political psychology, political behavior, computer simulation

Introduction

Political systems involve citizens, voters, politicians, parties, legislatures, and governments. These political actors interact with each other and dynamically alter their strategies according to the results of their interactions. A major challenge in political science is to extrapolate from the process of individual political decision making to collective outcomes such as voter turnout and election results. Complexity science offers a means to comprehend and theorize the nonlinear, recursive, and interactive political processes. It views political systems as complex, self-organizing, self-reproducing, and adaptive systems consisting of large numbers of heterogeneous agents that follow a set of rules governing their interactions (Pierson, 2000). These agents produce higher-level emergent phenomena that cannot be simply explained by mere aggregation of individual behavior (Bonabeau, 2002). For example, each voter tries to support politicians with policies that best match his or her personal policy preferences. Meanwhile, politicians take positions and offer packages that aim to win maximum support from voters (within certain constraints). Therefore, what voters choose at an earlier time of the election process affects the choices of politicians and voters at a later time. This dynamic and continual interaction between voters and politicians leads to complex political phenomena.

Agent-based modeling (ABM) is a methodology that allows the specification of properties of agents and rules governing their interactions in a simulation to observe how such micro-specifications can generate the macro-level phenomenon of interest (Goldstone & Janssen, 2005; Heckbert, Baynes, & Reeson, 2010; Salgado & Gilbert, 2013). ABM assumes that complex collective patterns can emerge from the repeated execution of individual behaviors once lower-level individual properties and rules are specified in a simulation (Chalmers, 2006). For example, the classic ABM work of Schelling (1971) showed via a checker-board-like grid how racial segregation could still occur even when residents are generally tolerant toward people of a different race. In the grids in Figure 1, red cells refer to residents of race A, blue cells refer to residents of race B, and white cells refer to empty sites. At the beginning of the simulation (t = 0), residents of race A and race B are randomly distributed in the grid (Figure 1A). Given a rule that residents will keep changing their location to seek out minimally sufficient number of neighbors of the same race, racial segregation is seen to eventually emerge even when residents only need 30% of their neighbors to be of the same race (Figures 1B through 1D).

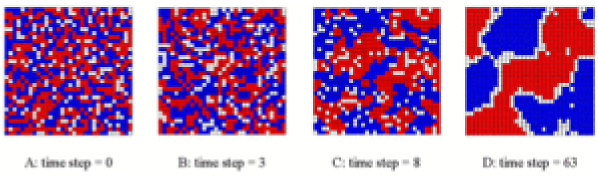

Figure 1. Evolution of segregation.

Image generated from Schelling's Model of Segregation (McCown, 2018).

In political science, researchers have adopted ABM for theory development, testing, and refinement (Johnson, 1999; Marchi & Page, 2014). This article starts with key characteristics of ABM, followed by an outline of how ABM works in political science and how ABM has been used to address critical questions in political decision making.

Key Characteristics of ABM

In the following, key aspects of ABM are highlighted in the context of political decision making. Readers are advised to explore readings provided at the end of the article for steps and techniques in creating and running an ABM.

Agents, Environment, and Time

Three key components of ABM are agents, environment, and time. Agents are entities in the model that have attributes, states, and rules that affect how individual agents interact with other agents and the environment. In the context of the study of political decision making, agents can be parties or voters and are usually heterogeneous. For example, Sobkowicz (2016) built a model to reflect the typical communication strategies political parties use (such as focusing on messages that are emotional or informational) and showed how the introduction of a newcomer party differentially reduces support for initial dominant parties. Voter agents in the model were heterogenous in attributes and states: they had different emotions, party preferences, and spatial locations. However, the voter agents all followed the same rules of interaction and exposure. Their emotions and party support changed with interaction with their neighbors and exposure to media messages. In Kollman, Miller, and Page's (1992) model on party competition, parties were heterogeneous because rules were defined differently for each party depending on their party strategy. The rules specified whether parties will search randomly in the issues space, make changes incrementally, or adopt selected features of successful candidates in the process of party competition.

The environment determines who agents interact with and how they interact. In Fowler and Smirnov (2005), voters directly learned about the satisfaction levels of their neighbors and attempted to mimic their neighbors' behavior. Voters in Bendor, Diermeir, and Ting (2003) on the other hand did not interact with each other directly but stigmergically via the results of the election, much like isolated traders interacting via price signals. The environment in the model contained attributes that recorded the election outcomes. These outcomes were a result of the actions of some agents and subsequently affected the actions of other agents.

The component of time determines the sequence of interactions among the agents. With the ease of computing power in the present day, synchronous (i.e., concurrent) rather than asynchronous (i.e., sequential) updating of states across agents and the entire system is achievable and recommended. Whether the model is run synchronously or asynchronously may affect results; Michor and Nowak's (2002) work showed how even with identical rules, just by switching between synchronous and asynchronous run settings, their model produced different patterns of how cooperators and defectors coexist. The time component also determines the fixed point and temporal granularity to which data are observed or compared with. Most models typically start with a system state that is distributively random and focus on the final results taken from when the outcome of interest has stabilized or when the model has reached equilibrium. The results taken from the model (e.g., voter turnout percentage) when it is at equilibrium are then compared with figures observed in the real world. If they are qualitatively similar, then it can be argued that the model may be one potential explanation of the observed real-world phenomena. On the other hand, models like Sobkowicz's (2016) aim to match their outcomes with real-world data and predict real-world results. Each step in the model is defined according to specific time in the real world. For example, step 950 to step 1180 in Sobkowicz's model are considered as June 10 to October 30 in 2015 for the purpose of comparing simulation results with real electoral outcomes.

Bottom-Up Emergence

ABM allows researchers to observe patterns resulting from interactions of agents (e.g., voters with voters, parties with parties, voters with parties) to understand how the co-evolution of multiple processes such as voter turnout and left–right preference generates emergent phenomena. For instance, Kollman et al.'s (1992) main outcome of interest is the extent to which the winning platforms are able to yield maximum utilities for most voters. This outcome about centrality resulted from the competition between ideological parties and ambitious parties using three different strategies. The model showed how centrality varies with parties' probability of winning each election and their distance from the position of the median voter. Fowler and Smirnov (2005) generated data on turnout rate and right–left vote shares across time and across parameter combinations to reveal how the cost of turnout, information sampling, and the distance between party platforms interact to influence turnout. Bendor et al. (2003) let users of their model observe the dynamic change of voter moves, payoffs, and the averages of individual adjusted propensities and aspirations to understand the relationship between these variables. They show that the starting proportion of voter turnout across all runs is nearly negligible, but turnout increases as agents interact and learn. The model did not show how such learning and interaction could occur in the real world but unveiled how, starting from a low baseline turnout, the rules and processes coded about agent interaction and adaptation can give rise to high levels of turnout seen in the real world.

Observations of collective outcomes in ABM could come from numerical measurement as well as visual patterns (e.g., Schelling, 1978). Figure 2A shows levels of support for two dominant parties at each constituency represented as grid cells (t = 600) in Sobkowicz's (2016) model. Intensity of red color represents amount of support for the dominant Polish party Platforma Obywatelska (PO), while blue represents that of the other party, Prawo I Sprawiedliwość (PIS). From time steps beyond t = 600, a newcomer representing the Kukiz party is introduced to the simulation. Figure 2B shows that, in the same constituencies, the newcomer takes away more support from the PO party than that for the PIS party (t = 850). The model explains the asymmetrical effect on existing dominant parties due to the communication strategies the parties use. Specifically, because PIS focuses more on irrational and mobilizing messages than PO, which focuses more on rational and demobilizing messages, the newcomer party is able to erode the support of rational and demobilizing messages more easily. The model groups individual agents into constituencies for easy visualization and provides insights through visualization across spatially identical grids.

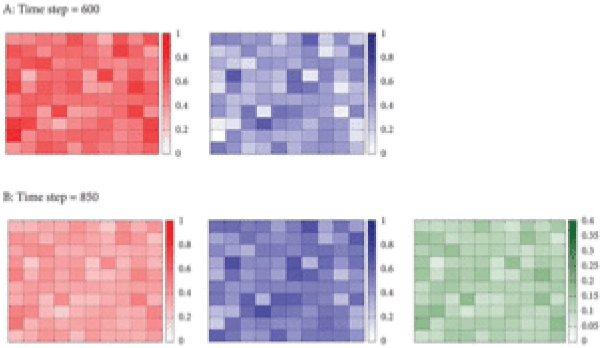

Figure 2. Constituency support for parties. Grid cells represent constituencies. Intensity of red represents support for the party Platforma Obywatelska (PO), intensity of blue represents support for the party Prawo I Sprawiedliwość (PIS), and intensity of green represents support for the party. From Kukiz (Sobkowicz, 2016), Creative Commons License.

In summary, ABM provides a means to understand complex phenomena (e.g., voter turnout, electoral win) as a form of emergence that is generated from underlying evolutionary and self-organizational processes (Bedau, 1997).

Theory Development

Existing literature has emphasized aptly that ABM as a simulation method (a) forces researchers to make assumptions surrounding a theory explicit, (b) facilitates the discovery of extensions and boundary conditions of the modeled theory through what-if computational experiments, and (c) helps researchers understand dynamic processes in the real-world phenomenon modeled (Borrill & Testfatsion, 2011; Burton & Obel, 2011; Davis, Eisenhardt, & Bingham, 2007; Hughes, Clegg, Robinson, & Crowder, 2012).

The work of Kollman et al. (1992) is a good example of how ABM and theory development can work together to inform each other. The authors stated several theoretical assumptions of classic spatial models and described clearly how they relaxed certain assumptions to derive new extensions of the spatial models. They also made explicit the auxiliary assumptions in their model, such as having only two types of parties and seven possible positions on each issue. The explicitness of their assumptions allows for future replication of their model by other researchers and contributes to a more precise understanding of the factors behind the results. This step also clarifies what may have been implicitly assumed in verbal theories of Downs (1957). Furthermore, they showed that the same rules underlying the convergence also generates a strong advantage for incumbent parties. These findings strengthened the case for classic spatial models while pointing to new hypotheses testable with empirical data.

Likewise in elucidating theoretical assumptions, Clough (2007B) showed limits to Duverger's prediction of the party system when interactions between voters in their social environment are modeled and incomplete information and voter heterogeneity are considered. In deriving new theoretical insights, Bendor et al. (2003) used ABM to reveal that high voter turnout could be a result of the voter's regret. In showing how simple theories explain evolution of collective party preference across time, Sobkowicz (2016) showed how a cusp catastrophe model of attitude formation led to fluctuating and evolving voters' collective candidate preference with real-world parallels. All these works generate theoretical insights about collective level patterns from simple micro-level rules.

Internal Validity, Robustness, and External Validity

Validity is generally concerned with whether the model is well designed and operates as intended (internal validity), and whether the model matches reality well (ecological validity). This issue has been discussed at length, and most researchers recognize that ABM has high levels of internal validity and theoretical precision but suffers from low ecological validity (e.g., Adner et al., 2009; Burton & Obel, 2011; Davis et al., 2007; Hales, Rouchier, & Edmonds, 2003).

ABM has high internal validity because its data are fully generated by explicitly coded rules that are computationally executed by agents with individual tractability. The phenomenon observed is fully attributable to the code and the computational environment. In addition, to assess whether the code matches the intended theory, a process of verification (Gilbert, 2008; Sargent, 1988) can be performed with a two-person code walkthrough (North & Macal, 2007), to make sure the literal word-based verbal theory is interpreted correctly when converted to computational codes.

Yet, given the computational nature of the data, there can be questions with regard to robustness of the findings, such as replication by other researchers or modelers, and whether the emergent patterns are observable across a sufficiently wide range of conditions to be reasonably expected in most situations. Except for the purposes of investigating black swan events, results and properties observed under a narrow set of conditions would be deemed less applicable to the real world than that observed across a wide range of conditions and relaxed assumptions. Fundamentally, these are important concerns to ensure the adherence of ABM to basic epistemological principles.

For the former concern on replication, protocol for the proper documentation for the purpose of communication have been proposed by Grimm et al. (2010). The Overview, Design concepts, and Details (ODD) protocol requires the modeler to state the key decisions in building the model, such as the purpose of the model, the agents with their attributes and states, and the initial conditions at the start of the simulation. The aim is for readers of the protocol to be able to comprehend with clarity important aspects of the model and have sufficient details about the model from which they can build a similar one. Such replication by the larger scientific community is exemplified in the technique of "docking" (Burton, 2003; Wilensky & Rand, 2007), that is, to implement as closely as possible a known model using a different modeling paradigm. The logic is that if the findings between the original and replicated model are similar, there can be greater confidence with regard to the relationship observed between the micro-theory model, the assumptions coded, and the patterns that emerged.

For the latter concern on obtaining similar findings across a wide range of conditions, the modeler can assess the robustness by (a) running the simulation numerous times to obtain a distribution of generated data for further analysis, (b) conducting a sensitivity analysis by running the model across a wider range and finer-grain of parameter values, or (c) relaxing or modifing auxiliary assumptions to rule out.

The problems with lower ecological and external validity stem from the abstract and controlled nature of ABM. In most cases, ABM involves partial explanation (Grüne-Yanoff & Weirich, 2010) because it explains the appearance of a phenomenon in the real world via a simulated system that is highly controlled. Even when matching steps in the model to real-life events such as in Sobkowicz (2016), the simplicity of the model makes it unrealistic to include many factors that could influence the results in real life. On the other hand, ABM models that provide fuller explanations simulate a whole society by taking into account a myriad of factors with calibrated parameter inputs. Dean et al.'s (2000) work, which modeled the terrain, weather, and major historical decisions of the Anasazi civilization to explain its fall, is a prime example of full explanation because of the high fidelity of their model. Nevertheless, many researchers tend to keep their models simple because even though they are highly idealized, they offer powerful and counterintuitive insights (Epstein, 2006).

Given that there will almost always be skeptics of ABM who believe that results are artificial and precoded even when shown otherwise (Jackson, Rand, Lewis, Norton, & Gray, 2017), a number of studies have used empirical data to validate ABM models. Fernández-Gracia, Suchecki, Ramasco, San Miguel, and Eguíluz (2014) created a noisy voter model where voters are probabilistically influenced by their own residential location, their work location, and a random neighbor's political opinion. They used data from the 2000 U.S. Census and Bureau of Labor Statistics to calibrate their model. Electoral results for each county in year 2000 were used as initial conditions, and simulation results were compared with electoral results in year 2004, 2008, and 2012. The simulation results were relatively consistent with those in the real-life elections and showed that vote-share spatial correlation decays logarithmically with distance. Kononovicius (2017) built a model to show that a multistate herding model can reproduce patterns of vote share distribution of local polling stations across Lithuania without modeling complex psychological process. After showing that rank-size distributions and probability density functions of vote share across polling stations in Lithuania's 1992, 2008, and 2012 elections follow a beta distribution, Kononvicius's model produced similar distribution specifically for the 1992 election. Fieldhouse, Lessard-Phillips, and Edmonds (2016) built a complex realistic model and used the 1992 British Household Population Survey to calibrate its initial conditions.

They then replicated earlier social influence mediated models of voter turnout but found that the oft-cited effect of social influence is not as large as that often seen in other non-empirically grounded ABM models. These aforementioned studies used free online archive data with geographical and longitudinal information for model validation.

In addition, empirical results from lab studies may also be used to validate ABM. For example, Meffert and Gschwend (2008) developed a simulation model where agents use sophisticated and heuristic decision strategies to cast votes for four parties in a political system with proportional representation, minimum vote threshold, and coalition government. They then recruited over 200 participants to play a voting game in the same political system and used their observation of similar use of decision strategies in humans to validate their model. Blais, Eriksen, and Rheault (2014) conducted a lab study of strategic voting in proportional representation systems and showed that voters are likely to vote sincerely without strategic coordination when electoral history is not available. When electoral history is available, strategic coordination occurred on parties that performed the best in previous elections. Such lab findings can provide external validity to ABM models that produce similar results.

Bounded Rationality

To approximate the real world, many modeler/theoreticians simulate the idea of human heuristics and satisficing tendencies in agents. In their models, no single agent, be it voters or parties, can know the full state of the world at any point in time. Agents have to rely on incomplete information and use heuristics to make decisions that may not be considered perfectly rational if full information is available. This aspect of incomplete information is as much enshrined in the ideas of the behavioral school (Simon, 1957) as it is as in game theoretic approaches to voting behaviors (Cox, 1997). Modeling incomplete information and bounded rationality reveals theoretical limits and alternative predictions that would not be obtained via the assumptions of full information.

Bounded rationality is a key feature of the agents of multiple models that were covered earlier in this article. For instance, Clough’s (2007A) model has voters estimate parties’ likelihood of winning by sampling information from neighbors in their social network. The model was compared to a revised version where agents know the true distribution of political support at all times. The comparison revealed how much information is needed for coordination among voters to fulfill Duverger’s (1954) prediction. In Kollman et al.’s (1992) model, parties do not know the calculated utilities and policy preferences of the voters. They obtain information through “opinion polls” and respond according to an approximation of the true preferences of the voter population. At each time step, the parties sample the issue space and assess whether it yields better opinion poll outcomes. The positional sampling occurs either as random, incremental, or mutating, depending on whether the parties search strategy is random adaptive, climbing adaptive, or genetic adaptive. Other voter turnout models such as Bendor et al.’s (2003) operationalized bounded rationality as voters’ resistance to change their aspiration levels. It is notable that, in all of these models, their outcomes are much more realistic than those in which agents have access to full information.

Differentiating ABM From Other Methodologies

Prior to applying ABM in research, it is important to understand how ABM differs from other methodological options. Works by Taber and Timpone (1996), Johnson (1999), and Cioffi-Revilla (2017) have provided detailed discussions of various simulation methodologies. In the following, ABM is contrasted with some commonly employed mathematical and computational modeling methods in political science.

Formal theory, or formal modeling, is characterized by the use of formal logic and search for proofs and analytical solutions based on underlying axioms and assumptions. It emphasizes precision and clarity, translating verbal nonformal theory into abstract symbols. As formal models are often highly idealized, their theoretical implications are relevant to a wide range of contexts. Formal theory is similar to ABM in that its process of model building often leads to the discovery of hidden assumptions of verbal nonformal theories. However, formal theory is inherently deductive, while ABM is generative (Epstein, 2006). ABM helps researchers to generate questions and insights from simulation runs and allows for theoretical uncertainty by simulating multiple competing hypotheses.

Statistical modeling aims to derive theory from real-world observations. Be it a focus on general linear models and unsupervised machine learning or a focus on empirical experiments and big data, its main goal is to generate inference and prediction. To find the most predictive model, statistical modeling often treats a real-world process as a black box. In contrast, ABM aims to specify the mechanism inside the black box and allows researchers to simulate the conditions and boundaries of the mechanism. Although ABM can only offer a simplified explanation, it extends from statistical modeling’s investigation of what-is and what-was to the investigation of what-if (Borrill & Tesfatsion, 2011).

Computational simulation modeling can be described as the representation of some real-world system in algorithmic form and analysis of system behavior through computer-based experiments (Taber & Timpone, 1996). Variable-oriented modeling, such as system dynamics, simulates the changes between variables and considers the system as a whole rather than its constituent elements. For instance, instead of modeling individual voting, the models vote share distribution with respect to other variables such as campaign spending. Focusing on modeling feedback and feedforward relationships and dependencies between variables, system dynamics models define the rates of change between the variables as differential/integral equations to simulate system changes over time. Discrete-event simulation models how events affect the system state and attributes. They describe entity and system states and specify the sequence and conditions for primary and conditional events. Since queues in voting stations could affect the motivation to vote and eventual turnout, such models, sometimes known as queuing models, could also contribute to the understanding of different voting system designs (Allen, 2011; Cioffi-Revilla, 2017). Expert system is a type of simulation that aims to model domain experts' decision-making process using a set of if-then inference rules. Taber (1992) developed an expert system with rules of U.S. foreign policymaking in Asia and generated output that matched actual policy decisions in historical cases. Such systems provide a high level of descriptive realism because their rules specify every step of the decision-making process. However, they are difficult to build because expert knowledge is not easily accessible and is hard to modify when the knowledge base contains hundreds of rules.

ABM focuses on the simulation of the interactions of constituent entities to uncover emergent patterns at the collective level. It is a type of objected-oriented modeling because the rules simulated are encapsulated within the constituent entities. Another type of object-oriented modeling is multiagent systems. They come from the tradition of artificial intelligence. While similar to ABM in that agents are autonomous and interacting, multiagent systems seek to create generic models possessing numerous parameters for calibration with real-world data. Their agents are modeled in a sophisticated manner with detailed rules and reasoning capabilities and often incorporate cognitive science–informed architectures such as Belief-Desire-Intention (BDI; Wooldridge, 2003), State-Operator-And-Result (SOAR; Laird, Newell, & Rosenbloom, 1987), and CLARION (Sun, 2001).

Agent-Based Modeling in Political Science

ABM has been applied in multiple research areas in political science. Seminal work by Axelrod (1986; Axelrod & Hamilton, 1981) showed the emergence of cooperation in the absence of central coordination and inspired the field of evolutionary game theory simulation in political science. Axelrod started with the goal of promoting cooperation between parties in international conflicts. He organized a tournament where scholars from various disciplines, including economics, psychology, sociology, political science, and mathematics, submitted strategies to compete in a game of iterated prisoner's dilemma. Axelrod found that the tit-for-tat strategy, where a game player always mimics another player's previous move, emerged as a consistent winner (Axelrod, 2012). In further ABM simulations where successful strategies are allowed to displace unsuccessful ones, the tit-for-tat strategy was shown to be collectively stable—in that it is difficult for a small group of players holding non-tit-for-tat strategies to convert the rest to use their non-tit-for-tat strategies, while it is easy for those holding the tit-for-tat strategy to convert others into adopting tit-for-tat strategy. Evolutionarily, it shows why tit-for-tat is the dominant strategy in social and political interactions and why people tend to start with cooperation and choose to default only after a transgression has taken place between two parties.

In the classic voter model (e.g., Cox & Griffeath, 1986) and most of its extensions (e.g., Castellano, Vilone, & Vespignani, 2003; Martínez, Balankin, Chávez, Trejo, & Reyes, 2015), voters are represented as nodes placed on a network and assigned one of two "party preferences" from which they will cast their votes. Such binary party preferences are similar to the polarities of mini-magnets in the Ising model commonly studied in statistical mechanics (see Brush, 1967). At each iteration, every node is influenced by a randomly selected neighboring node and adopts the neighbor's party preference. As a result of such interaction, party preferences spread throughout the network and cluster among spatially distributed locale. The validity of such highly simplified assumptions of voting behavior has found support in the context of U.S. presidential elections (Fernández-Gracia et al., 2014) and the compulsory voting election of Brazil (Bernardes, Stauffer, & Kertész, 2002).

The work of Kollman and colleagues (1992) answered the question of how competing parties position themselves when they are uncertain about the positions of voters. Their work conceptualized parties and voters as holding preferred positions on a series of issues based on the classic spatial model (Downs, 1957; Enelow & Hinich, 1984; McKelvey, 1976; Plott, 1967). Unlike analytical models of that time, their model assumed parties will learn over repeated polls about the median position of voters and hence adjust party positions. Two distinct types of parties were considered—the ambitious and the ideological. To obtain the largest number of votes, the ambitious party tries to adjust its position on a set of issues, while the ideological party tries to minimize the distance between its winning positions and its ideal positions across all issues. As each election is preceded by a substantial campaign period where a discrete number of polls are conducted, each party can adopt one of three competition strategies based on knowledge they derive from the polls, namely, (a) a random adaptive strategy where parties randomly select positions in the issue space and adopt those that receive the highest vote in a poll, (b) a climbing adaptive strategy where parties make slight changes on their positions for some issues and adopt the new positions if they prove to be better, or (c) a genetic adaptive strategy where parties identify a subset of positions and select the better-performing half of the subset for random alteration to derive a new platform. The two types of parties and three types of competition strategies result in six factorial combinations of party types and competition strategies. Simulation results revealed a variety of postulates, such as a strong advantage for the incumbent party and the convergence to central regions of the issue space over time regardless of party type (Kollman et al., 1992).

Inspired by Kollman et al.'s (1992) work on party competition, a series of models were built to further understand party strategies and formation. For instance, Laver (2005) found that the strategy to incrementally switch the position of the party in the opposite direction if the current position does not yield higher voter support outperforms the strategy of just moving toward the position of the largest party in obtaining voter support. Laver and Schilperoord (2007) modeled party birth and death as a function of voter dissatisfaction and found that the party strategy that best aids party survival also tended to lead to greatest citizen dissatisfaction. Plümper and Martin (2008) showed how voters' inclination to abstain from voting drives party positions further away from the political center, and Schreiber (2014) illustrated how party positions can converge to the median voter position even when parties do not know the full range of the issue space. In short, these models unveil nonlinear dynamics and emergence in the political system where interactions between political actors lead to often surprising collective behavior.

Agent-Based Modeling of Political Decision Making

Why do voter turnouts remain high? What is the basis of party formation? How do the knowledge and emotion of voters affect election outcomes? How do political attitudes change through a campaign? These are core questions in political decision making that are well suited for ABM as they involve complex and counterintuitive phenomena resulting from individual actions and interactions. This section illustrates how ABM has assisted researchers in answering these important questions.

Why Do Voter Turnouts Remain High?

The Downsian paradox (Downs, 1957) posits that because (a) the probability of one's vote affecting an election outcome is extremely small and (b) any expected gain is likely to be smaller than the cost to make one's way to the ballot boxes, rational voters should not turn out to vote. Yet in reality large numbers of seemingly rational voters continue to participate in voting. To explain this paradox, Bendor and colleagues (2003) developed a model based on the concepts of learning and aspiration. They assumed that voters are adaptively rational in that their current probability to vote is linked to the satisfaction they derive from their previous voting. A voting outcome is considered satisfactory when its payoff passes a threshold that is indicated by the voter's aspiration level. Simulation results showed that with a million voters (500,000 Republicans and 500,000 Democrats), the model predicts a 50% turnout rate even when voters start with low vote propensity. The surprising results prompted the authors to take a deeper look at the model and an intuitive reason for this behavior was revealed on hindsight. That is, by the second election, voters have learned that not voting is associated with a payoff that is below the aspiration level. Therefore, they come out to vote. This discovery led the authors to conduct further computational experiments with varied asymmetric costs showing similar qualitative outcomes.

However, Bendor et al.'s (2003) model did not consider mutual influence between voters. Fowler and Smirnov (2005) incorporated this effect in their work by modeling voters to learn from their neighbors. Their model was implemented on a two-dimensional bounded grid representing the network positions of the voters. The neighborhood of a voter contains eight voters surrounding the voter. Interacting with neighbors and being influenced by them represent the bounded rational aspect of voters. The model also includes two parties, each with preferred policy decisions but no access to the "true" position of the median voter. Parties make policy adjustments based on the inferred position of the median voter from the previous election result. Voters hold preferred policy positions and calculate their individual payoffs from each election based on the distance of the elected party's position from their own personal preference and the cost of voting. Their decision to vote depends on their own level of satisfaction from the previous vote and their observation of their neighbors' satisfaction. Simulations with 1,000 runs were conducted to rule out stochastic influences. The authors found that, consistent with empirical results, the model produced high levels of turnouts that oscillate predictably between 35% and 55%. The model also showed that turnout is negatively related to the final margin of victory in an election, positively related to the distance between party platforms, and negatively related to the number of voters with similar preferences. The relationship between the cost of voting and turnout rate is nonlinear with a clear inflection point indicating the presence of a cost threshold beyond which the turnout rate will drastically reduce to zero.

It is important to note that in all of these ABM models, the macro-level findings about voter turnout were not precoded into the models. The results emerged from micro-level interactions of voters and parties and from agents who had limited information about other agents. With a number of simple but reasonable assumptions about a voter's decision-making process, the ABM models help in explaining the Downsian paradox and providing researchers with important insights into the voting process.

What Is the Basis of Party Formation?

Duverger's law (1959) posits that a two-party system will emerge in a single-member plurality system, while a multiparty system will likely emerge under a proportional representation system. Clough (2007A, 2007B) adopted Cox's (1997) model of strategic voting to examine the boundary conditions of Duverger's law. In the simulation, all voters are assigned ideologies represented by positions on a scalar from 0 to 100 for each issue. Parties are also assigned positions on the continuum. Voters calculate the expected utility they receive from each party (should the party win) according to the distance between their position and the party's position. In the first step, voters vote based on their true preference for the parties. After the initial vote, voters learn about their neighbors' votes and develop a mental representation of the distribution of support for each party based on the information they gather about their neighbors' support. Since voters derive information from different neighborhoods, voters in different neighborhoods will perceive different levels of "true" support for the parties. From the distribution of support for different parties in their neighborhood, voters calculate the likelihood of each party winning the election and combine this information with their original positions to derive prospective ratings for the parties. Each voter will vote for the party with the highest prospective rating.

Due to limited computational power, Clough (2007A, 2007B) implemented the model in a square toroidal grid of 169 voters. Across various experimental conditions, the party system stabilized after 20 iterations. Clough (2007A) experimented with voter's neighborhood size and found that when voters sample from a small neighborhood, Duverger's prediction of convergence to two parties manifests only about 30% of the time. However, when the neighborhood is large, the percentage of simulation runs that ends with two parties significantly increases from around 75% to almost 100%. In addition, a greater number of parties at the start of the simulation leads to greater difficulty for the model to converge to a two-party end-state. Using the same base model but investigating the impact of neighborhood ideological heterogeneity, Clough (2007B) found that in models where voters mostly sample information from others who have similar ideologies (i.e., homogeneous neighborhoods), Duverger's prediction of a two-party end-state holds only about 50% of the time. This figure only slowly increases to around 100% when the neighborhood size becomes sufficiently large, such that voters can have full information about the preferences of all other voters. These findings highlight that the informational sampling capability of voters is a critical factor in the emergence party systems.

Schreiber's (2014) recent provoking work leveraged on a plausible assumption that parties are coalitions of individual voters who compromise and take a shared position on selected issues. In his model, when two voters agree that they are the closest to each other, they form a coalition and set their ideal point at the mean of their individual ideals. Once formed, the coalition is seen as an entity from which distance to another neighbor is judged. The forming of coalition continues until the coalition has enough votes. The threshold for sufficient number of votes can be set as a certain percentage of the total votes in the model or at the timepoint where a coalition has a majority or plurality. Results showed that Duverger's law is not deterministic but instead probabilistic and relativistic. When the stopping threshold was majority, 71.3% of runs ended with two parties, 25.4% ended with three parties, and 3.1% ended with four parties. When the stopping threshold was plurality, 44.2% of runs ended with two parties, 23.3% ended with three parties, and 20.4% ended with four parties. This work provides another good example of using simple assumptions and rules to highlight the boundary conditions of a classic theory.

How Do Voters' Information Access and Emotion Affect Election Outcomes?

Sobkowicz's (2016) work illustrates how real-world polling and election results can be predicted by a simple yet intuitive simulation model. In his model, opinion formation is based on a simplified and discretized cusp catastrophe model (Flay, 1978; Tesser, 1980) where a voter's opinion for a party depends on two levels of emotions (calm and agitated) and three types of attitudes (pro, neutral, and contrary) toward a party. In addition, a voter will be influenced by a randomly selected neighbor (20% chance) or messages from the media (80% chance). Voters change their opinion only when they are in an emotionally calm state and exposed to contrary views. For example, when a voter who is calm encounters a neighbor with a contrary view, he or she will have a 20% chance of switching to an agitated state. Voters change their emotion based on the emotional state of their neighbors or the messages they receive. For instance, when a voter in an agitated state encounters a calm neighbor or a message that he or she agrees with, the voter will have a 20% chance of switching to a calm state. These changes of emotion are prescribed in two transition matrices.

Sobkowicz's (2016) model was calibrated to predict the outcome of the 2015 Polish presidential election. First, data of polls from January 2015 to June 2015 were used as a guide to stabilize and calibrate the model. The poll results of March 14 and June 10 were compared to the 800th and 950th time step in the model, respectively. Simulation results at these two time points fit the poll results qualitatively well. The model was run until the 1185th time step, which was equivalent to October 25, the date of the presidential election. As proof that the model results were not fabricated, predictions for the subsequent polling results as well as final election results of the three candidates were submitted to arXiv on August 8, 2015 (Sobkowicz, 2015). The predictions were shown to be fairly close to the final election results. This work demonstrates how, again with a few simple rules, ABM can be used to predict the outcome of a complex political process using abstract representations.

How Do Political Attitudes Change Through an Election Campaign?

Kim, Taber, and Lodge (2010) produced a cognitive agent-based model extended from the Adaptive Character of Thought-Rational theory (ACT-R; Anderson et al., 2004). They showed the parallel of the model's dynamics with that of real-world data and compared the viability of two possible theories regarding political attitude formation, namely motivated reasoning and Bayesian learning. They modeled attitude as a function of memory and exposure to candidates' associated concepts, among others. In the Bayesian learning model, new information used by an agent to update beliefs about a candidate is unbiased toward any candidate or prior preference, while in the motivated reasoning model, the agent is preferentially affected by information that is congruent with its existing candidate preference.

They calibrated a population of 100 agents with initial parameter values from the National Annenberg Election Survey (NAES) and started with seven ideological groups across the conservative–liberal spectrum. Each ideological group consisted of a different number of agents, with all agents in each group sharing the same starting distributional mean and standard deviation for the accessibilities and associations for concepts activation. Results were compared with three more waves of data from the NAES survey. Data from the motivated reasoning model better matched responsiveness, persistence, and polarization of political attitudes in the NAES data, while the Bayesian learning model did not show similar persistence and polarization patterns, suggesting that people tend to use a motivated reasoning model in forming their political attitudes. This work makes an important contribution to research on political beliefs and attitudes, as it demonstrates the use of computational modeling to test alternative psychological models regarding electoral behavior.

Discussion

ABM has been applied in political science to study many emergent outcomes such as voter turnout, party emergence, and election outcomes. It is especially useful for studying phenomena where (a) individuals behave according to if-then rules and thresholds; (b) individual behaviors are path dependent and memory based, exhibiting leaning and adaptation characteristics; (c) individuals are heterogeneous and the accumulation of their interaction can generate network effects; and (d) system fluctuations are important because they may generate deviations from regular paths, which are worthwhile to investigate (Bonabeau, 2002). Political scientists may consider using ABM in their research when their research questions meet these conditions.

There are a number of areas where political science can develop further with the use of ABM methodology. First, Lau and Redlawsk (2006) proposed four models of decision making by voters, namely, the rational choice model, the early socialization and cognitive consistency model, the fast and frugal model, and the bounded rationality and intuitive decision-making model. As cognitive miser voters concurrently use various heuristics (Lau & Redlawsk, 2001), models can be built to simulate agents that evaluate candidates or issues with different decision-making heuristics. For example, all four decision-making heuristics can be created as rules encapsulated within an agent. Instead of a homogenous treatment of all issues, a subset of issues could be deemed as more salient and evaluated upon using the fast and frugal heuristics. Meanwhile, a voter would have a higher probability of using the early socialization heuristics when he or she is undecided.

Second, the rapid development of technology and the Internet has also made the landscape of political campaigns more sophisticated, and so new ABM models should be developed and refined to reflect this new political reality. While previous studies have modeled the influence of media messages on voters (e.g., Sobkowicz, 2016), they have not addressed the current widespread personalized targeted ads and fake news on social media. Recent studies have suggested that fake news spreads much more rapidly and can have a much wider impact than true news (Lazer et al., 2018; Vosoughi, Roy, & Aral, 2018). Therefore, possible variations of existing ABM models can be made to incorporate fake news. For example, the model can treat fake news as exogenous noise within the spread of true news. In addition, ABM models can also help to investigate the impact of fake news when they are biased against one party (e.g., to examine how fake news may skew election results in different decision-making models). Models can be built with varying degrees of targeting where voters receive personalized news according to their positions. The impact of targeting can then be measured via evaluating the degree of opinion change and election outcomes. All of these possible extensions address how random or nonrandom errors may aggregate to influence political processes—a major question in research on political decision making (Lau & Redlawsk, 2001).

Existing ABM models in political decision making tend to simplify the interaction among voters by having one agent take the opinion of a randomly selected agent in the neighborhood or take the majority opinion of the surrounding neighbors. However, communication research suggests that interpersonal communication can be far more complicated. For one, communicators do not randomly select their interaction partners. Some communicators may be more inclined to communicate with those with similar opinions, and some may prefer talking to dissimilar others. In addition, during conversations some communicators may speak positively about their own opinion while others may speak of the listener's opinion favorably. After the conversation, speakers may believe more in the opinions that were discussed (i.e., the "saying is believing" effect). These variations in communication styles and acceptance of social influence have been modeled and shown to generate different patterns of opinion diffusion (Chiu & Qiu, 2014; Gao, Qiu, Chiu, & Yang, 2015). Future research may further explore how micro-level communication and cognitive styles may affect macro-level political outcomes.

In conclusion, ABM has been applied in political science to generate theoretical insights on how interaction between heterogeneous political actors such as voters and parties can lead to dynamic and complex political phenomena. A number of models have been developed on issues ranging from voter turnout to party emergence. They illustrate the use of ABM in explicating assumptions and rules of theoretical frameworks, simulating repeated execution of these rules, and revealing emergent patterns and their boundary conditions. While ABM has limitations in external validity and robustness, it provides political scientists a bottom-up approach to study a complex system by clearly defining the behavior of various actors. With the availability of massive records of individual behavior provided by big data (Qiu, Chan, & Chan, 2018), it becomes possible to validate models by empirically testing models against real-world data.

Final Points

The following are a few points to help jump-start an ABM:

1. Do not fear the technique. Download NetLogo (Wilensky, 1999) and explore the models within the library.
2. Start with simple models, following the KISS ("Keep It Simple, Stupid!") recommendation (Axelrod, 1997) and avoid the temptation for high fidelity models, KIDS ("Keep it Descriptive, Stupid!") (Edmonds & Moss, 2004).
3. Use ABM only when you theorize some form of interaction between the agents themselves or with the environment.
4. Start with a very simple theory (Davis et al., 2007).
5. Explore the parameter space to ensure robustness of results and be aware of the assumptions you are making.
6. Remember that a small change to the same model can be deemed a new model itself (e.g., Clough, 2007A, 2007B).

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Further Reading

For quick introduction to ABM and good applications:

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