

Agent-Based Modeling: A Guide for Social Psychologists

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Abstract

Agent-based modeling is a longstanding but under-used method that allows researchers to simulate artificial worlds for hypothesis testing and theory building. Agent-based models (ABMs) offer unprecedented control and statistical power by allowing researchers to precisely specify the behavior of any number of agents and observe their interactions over time. ABMs are especially useful when investigating group behavior or evolutionary processes, and can uniquely reveal non-linear dynamics and *emergence*—the process whereby local interactions aggregate into often-surprising collective phenomena, such as spatial segregation and relational homophily. We review several illustrative ABMs, describe the strengths and limitations of this method, and address two misconceptions about ABMs: reductionism and “you get out what you put in.” We also offer maxims for good and bad ABMs, give practical tips for beginner modelers, and include a list of resources and other models. We conclude with a 7-step guide to creating your own model.

Agent-Based Modeling: A Guide for Social Psychologists

From Detroit to El Paso, New York to Los Angeles, urban environments are divided by race and ethnicity. The pernicious consequences of segregation lead us to infer pernicious causes: people must live in homogenous neighborhoods because they are racist. This explanation for segregation seems plausible, as prejudiced individuals do avoid people of other races—but it assumes that the collective behavior of neighborhoods can be explained similarly to the behavior of individuals. Almost 40 years ago, Thomas Schelling (1971) challenged this assumption, asking whether segregated neighborhoods would form even when individuals had no prejudice, and only wanted a few neighbors similar to themselves.

Schelling placed red and green pennies on a chessboard to represent people in neighborhoods. People were happy—and remained in their square—if they were surrounded by at least 30% of their “color;” if this number dropped below 30%, however, people became unhappy and moved to a new square. Schelling played out this model by moving pennies one-by-one until each person on the board was happy, by which time the board was highly color-segregated. At higher (75%) or lower (15%) thresholds of similarity, segregation was more or less pronounced (see Figure 1 for an illustration of these effects), but the key is that even individuals who embraced high diversity could still end up segregated.

Schelling’s work is an elegant testament to how simple and innocent individual preferences can produce surprising societal outcomes over time. His model also serves as a prototypical—if low-tech—example of the power of agent-based modeling (ABM)¹ in understanding emergent social behavior.

¹ While we use the term “agent-based modeling” in this paper, the terminology around ABM is diverse and potentially confusing. Alternative terms include “multi-agent systems,” “agent-based simulation,” “agent-based computing,” and “individual-based modeling.”

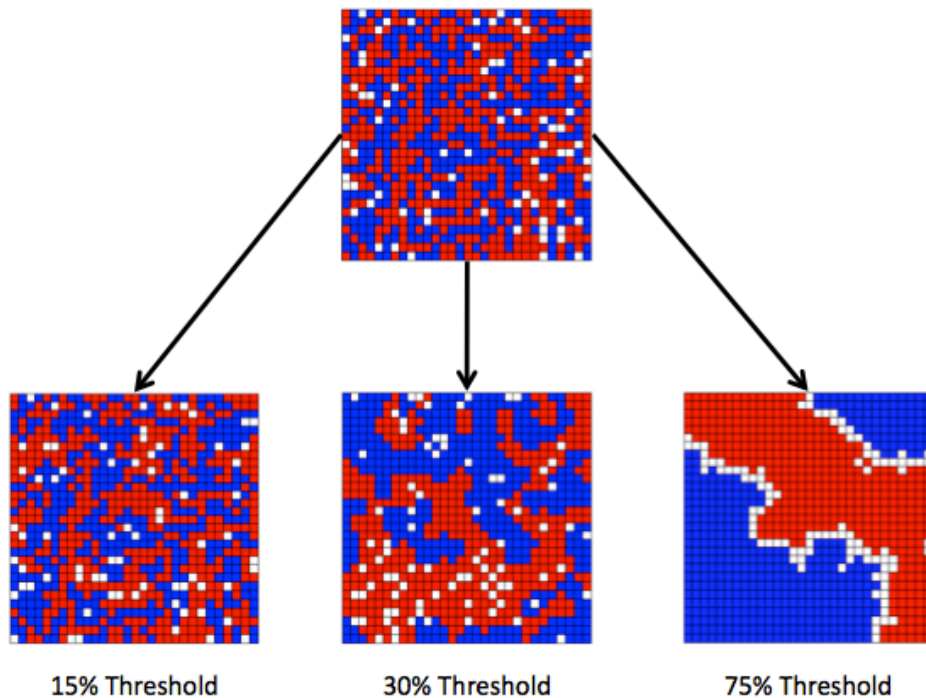


Figure 1. Visualization of Thomas Schelling's (1971) segregation model at its commencement (top panel) and conclusion (bottom panels). When agents have a 15% threshold for similarity (left panel), only minimal segregation occurs. However, 30% (middle panel) and 75% (right panel) thresholds produce striking segregation. Figure retrieved from <http://nifty.stanford.edu/2014/mccown-schelling-model-segregation/>.

Agent-Based Modeling

Agent-based models (ABMs) are computational simulations in which artificial entities interact over time within customized environments. These entities (“agents”) are programmed to represent humans who behave in precisely specified ways. As summarized by Macy and Flache (2009, p. 247), agents are adaptive in that they respond to their environment through learning and

evolution and are autonomous in that they control their own goals, states, and behaviors. They are also intentionally simplified, usually following only one or two basic rules (representing habits, norms, or preferences) throughout the simulation.

The outcomes of ABMs, however, are anything but simple. A well-programmed model offers insight into how local interactions between agents can lead to complex group- and system-level phenomena. Consider how a single bird's tendency to align and remain close (but not too close) to her peers can create a swirling flock that appears to be moving with a collective mind (Reynolds, 1987), or how predator-prey interdependence can explain animal species' resurgence following near extinction (Borschev & Filippov, 2004). ABMs are uniquely equipped to shed light on such phenomena and countless other applications involving interacting individuals.

Perhaps because of their ability to simulate large-scale dynamics with bottom-up processes, ABMs are popular in economics (e.g. Tesfatsion & Judd, 2006), sociology (Bruch & Atwell, 2015; Macy & Willer, 2002), political science (Cederman, 2005; Johnson, 1999), and some applied sciences (e.g. artificial intelligence; Beer, 1995; Gasser, Braganza, & Herman, 1987; Wooldridge, 2003). In psychology, however, ABMs continue to exist at the field's margins (see Goldstone & Janssen, 2005; Smith & Conrey, 2007), perhaps because psychologists view them as difficult to implement and see their results as only reflecting the assumptions of their programmers ("you get out what you put in").

This paper aims to address these concerns and to pique social psychologists' interest in ABMs. We provide examples of classic and recent ABMs that illuminate social behavior, compare modeling to other methods in social psychology, and give concrete advice to social psychologists wishing to implement their own ABMs. Although there are ABMs that simulate non-social events (e.g. weather patterns or artificial intelligence), we focus on models of social

processes. We hope to provide an in-depth but accessible introduction to ABM for social psychologists.

Social Psychological Questions Addressed by ABMs

Schelling (1971)'s model of segregation addresses one of social psychology's core questions: Why do individuals segregate based on race? ABMs also address other important questions: What is the basis of group formation? What is the best strategy for maintaining cooperation? Why do couples pair off in terms of attractiveness? These questions are well-suited to ABM because they involve individual behaviors interacting to produce surprising collective phenomena.

What is the Basis of Group Formation?

Social identity is the dominant framework for understanding why people split into “us” versus “them:” people with similar race, religion or culture form groups, which then square off against each other (Tajfel, 1982). However, these social identities can only emerge once people separate into groups. This logic creates a regress in which groups require identity but identity requires groups. To escape this chicken-egg dilemma, Gray and colleagues (2014) examined whether groups could form in a completely homogeneous population without any identities. The authors programmed agents with only two simple characteristics: reciprocity (the tendency to cooperate with those who have previously cooperated with you) and transitivity (the tendency to share your network's social preferences)—each of which was a well-established social tendency (Holland & Leinhardt, 1971; Levine, 1998). The model's results revealed robust group formation even though agents had no sense of “us” or “them,” suggesting that groups can form even without identity (see Figure 2).

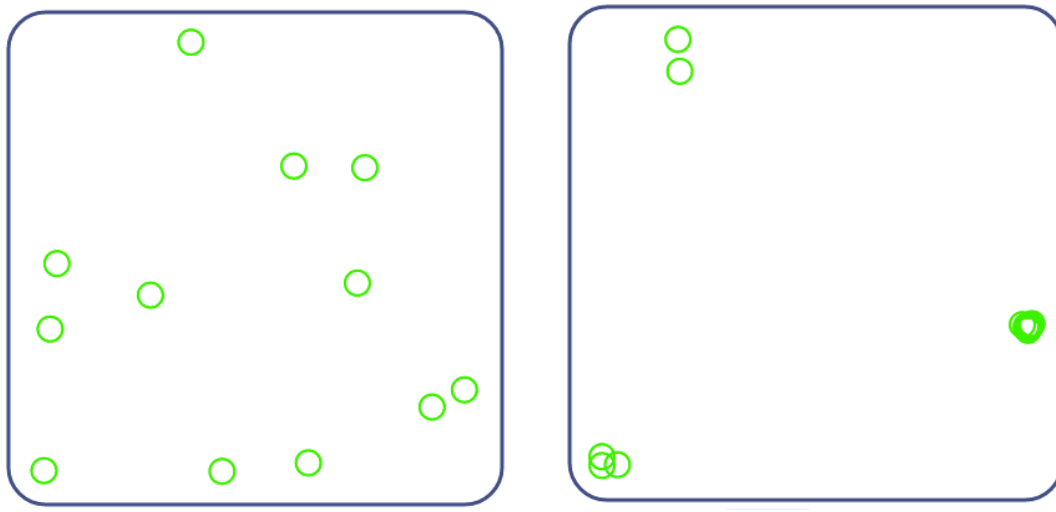


Figure 2. Visualization of Gray and colleagues’ (2014) model displayed at round 1 (left panel) and round 300 (right panel). Figure retrieved from online simulation at <http://www.mpmlab.org/groups/>.

What is the Best Strategy for Maintaining Cooperation?

Real-world questions of cooperation are captured by the “prisoner’s dilemma,” in which two people each have the choice to cooperate or defect. The *group* payoff is maximized when both people cooperate, but each player is made better off *individually* by defecting—capturing the essential tension of social dilemmas. Political scientist Robert Axelrod asked people to program agents with different strategies for repeated prisoner dilemma games (e.g., always cooperate, always defect, copy your partner’s past behavior), and then paired these agents with each other in a round-robin design (Axelrod, 1980; Axelrod & Hamilton, 1981). As long as the agents engaged in repeated interactions, the winner was a very simple agent—“tit-for-tat”—which began with cooperation, and then copied its partner’s previous decision. Axelrod’s ABM

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was important because it revealed a simple route for the emergence of cooperation, even in complex societies.

More recently, Bear and Rand (2016) developed an ABM to explore the psychological basis of cooperation. Agents played either one-shot or repeated prisoner's dilemmas. They could engage in two different kinds of cognition: a low-cost generalized intuitive response, or a higher-cost calculated response that could tailor its choice to whether the game was one-shot or repeated. The results showed that—given a high likelihood of repeated interaction—the best strategy was to intuitively cooperate and deliberately defect when the game was one-shot. This ABM therefore offered an evolutionary explanation for why people sometimes cooperate when they can get away with defection.

Do Couples Seek out Similarly Attractive Partners?

Members of a romantic couple tend to be similarly attractive, but it is not immediately clear why. Although some believed that people intentionally search for their attractiveness “match” (Huston, 1973; White, 1980), Kalick and Hamilton (1986) used an ABM to test whether matching could occur even if all people preferred maximally attractive partners. Heterosexual male and female agents were assigned an attractiveness score from 1 to 10, and were repeatedly paired up. Pairs asked each other on “dates” and if both agreed, they left the pool, otherwise they were paired up with new agents. Kalick and Hamilton ran two variations of the model: one in which people wanted maximally attractive partners (motivated for supermodels) and another where people wanted similarly attractive partners (motivated for matching). In the “motivated for matching” condition, agents’ attractiveness was *very* highly correlated ($r = .85$) with their partners’—significantly higher than what actually occurs in real life. In contrast, agents who were “motivated for supermodels” had their attractiveness moderately correlated ($r = .5$) with

their partners’—nearly the same correlation as in real life (Critelli & Waid, 1980). This moderate matching occurred because when everyone preferred the prettiest people, the prettiest ended up together first, and the less pretty were left to pair up afterwards. As with many ABMs, people’s individual preferences (for attractive partners) led to unexpected collective patterns (attractiveness matching).

Emergence

Agents in the previous examples were not programmed to segregate, to form social groups, to maintain stable cooperation, or to find partners of a similar attractiveness. Instead, these group phenomena arose via *emergence*—when the aggregation of small-scale *individual* behavior yields qualitatively different *collective* behavior. Emergence lies at the heart of almost any complex phenomenon, from traffic jams, to the wetness of water, to the neural basis of consciousness (Bassett & Gazzaniga, 2011; Tononi, Sporns, & Edelman, 1994). For example, while no individual neuron is conscious, their collective interactions yield human consciousness. Likewise, Schelling’s model revealed that segregation could arise from the innocent decisions of relatively egalitarian individuals.

Historically, the impact of ABMs has been proportional to the amount of emergence they reveal—the apparent disconnect between individual and collective behavior. For example, the models from the previous section feature large-scale phenomena that are difficult to predict from individuals’ behavior. Importantly, in explaining complex group-level phenomena with simple individual-level rules (see Smaldino, 2014), good ABMs typically reduce complexity—leading to these two complementary maxims for research with ABM:

Maxim for Good ABMs: Reduce complexity by revealing how higher-level phenomena emerge from the repeated interaction of simple rules.

Maxim for Bad ABMs: Introduce complexity by taking a simple phenomenon and inventing complicated rules to explain it.

These maxims serve as useful criteria in evaluating whether ABMs add to or detract from a paper. The very best ABMs are explainable in plain prose and should reveal the emergence of complex or surprising phenomena using simple principles. Conversely, bad ABMs take a straightforward, intuitive phenomenon and complicate it with unjustified assumptions and abstruse mathematics. These maxims also help to address two traditional criticisms of ABMs.

Reductionism

ABMs are often seen to be reductionist, destroying the specialness of psychological processes by explaining them with simple agent behaviors. For example, claims of reductionism have been leveled against research linking love to hormones—if hormones are involved in love, is love “just” hormones? But fears of reductionism ignore the possibility of emergence, and the fact that all phenomena are embedded in a chain of lower and higher level events. Even if love can be “reduced” to hormones, there is still an undeniably powerful *feeling* of love, a higher-level emergent experience that motivates people to write sonnets and run through the airport at the last minute. Emergence also provides a defense against claims of reductionism in ABMs. Even if reciprocity and transitivity are sufficient conditions for group genesis (Gray et al., 2014), groups themselves prompt powerful feelings of solidarity and important behaviors—from war to religious movements—which cannot be reduced to these lower-level processes.

You Get Out What You Put In

Critics of ABM have also claimed that the results of ABMs are closely tied to researchers' decisions in setting their models' parameters. In some sense, this is a strength of ABMs: unlike in the laboratory or the field, the behavior of agents can be isolated and specified with precision—which forces researchers to explicitly formulate their theories. ABM-derived hypotheses are therefore decidedly falsifiable, with no ambiguity about what a model should predict. Of course, this level of experimenter control has the potential to make the final outcome seem obvious—but again, this criticism holds primarily with models that fail to show emergence. In Schelling (1971) there is nothing obvious about a slight preference for similarity causing rampant segregation, and in Gray and colleagues (2014), there is nothing obvious about two simple rules of interaction—reciprocity and transitivity—leading to stable grouping within homogenous populations.

Comparing ABM to other Methods

In addition to the theoretical framework of emergence, ABMs offer several methodological advantages that complement other methods. In comparison to laboratory experiments, field studies, or archival investigations (including “big data” analysis), ABMs offer a unique combination of experimental control and massive scale, along with the ability to capture nonlinearities and underlying mechanisms. However, like any tool in a social psychologist's toolbox, ABMs come with limitations, of which external validity is most notable. This drawback is mitigated by supplementing ABMs with other tools—such as laboratory or field experiments—in multi-method investigations. Table 1 shows a comparison of the relative advantages and disadvantages of ABMs compared to other methods.

Table 1. Comparing ABMs to Other Methods

	<u>Field studies</u>	<u>Lab experiment</u>	<u>Archival studies</u>	<u>ABMs</u>
Control and Realism	Low Control; High Realism	Medium Control; Medium Realism	Low Control; Medium Realism	High Control; Low Realism
Scale	Medium to High Scale	Low to Medium Scale	High Scale	High Scale
Nonlinear Dynamics	Medium Visibility	Low Visibility	Medium Visibility	High Visibility
Mechanism	Medium Clarity	High Clarity	Low Clarity	High Clarity

Control and Realism

In psychology, maximum control is often ascribed to experimental lab paradigms featuring random assignment, but even experiments have their limits. Participants may respond differently to experimental manipulations based on their cultural background (Hong et al., 2003) their religious upbringing (Shariff, Willard, Anderson, & Norenzayan, 2016), or even their transient mood (Forgas, 1995). Despite the flexibility of experiments, they are also limited by questions of ethics and feasibility—there is only so much that participants can do (or be asked to do) in the lab. In contrast, ABMs offer exceptional control: agents in computational models can be instructed to perform almost any initial behaviors, and will follow their instructions with complete uniformity. This control also remains high over indefinitely large samples and infinitely long simulations.

The tradeoff to ABMs' high control is a low degree of external validity. For example, the agents in Schelling's model moved neighborhoods without incurring the financial or social costs inherent in relocation. Kalick and Hamilton's date choice model similarly assumed that individuals who accept dates permanently leave the dating pool, which seldom occurs in real life. Because of these shortcomings, ABMs are most effective when used in conjunction with laboratory or field experiments, which can use human subjects to validate an ABM's parameters

(as in Luhmann & Rajaram, 2015) or its causal pathways (see Bear & Rand, 2016; Kalick & Hamilton, 1986).

Scale

One clear advantage of ABMs over other methods is statistical power. Obtaining sufficient N can prove difficult, as researchers struggle against a subject pool deadline or limited funding for participants. Even in field studies, researchers may obtain large sample sizes but these samples may be incomplete or feature troublesome attrition. In ABMs, sample size is simply a parameter specified in the model. ABMs can also operate over any amount of time and sample at any rate. Of course, large N , long-term and high sampling-rate ABMs may take longer to run, but this typically means extras days and not years (and computing superclusters can substantially reduce this time). The critical point is that by analyzing large samples over an extended time, ABMs can reveal large-scale societal emergence (e.g. segregation and homophily), which is often impossible to observe with more traditional paradigms (and even with “big data” analyses; Lewis, 2015).

Nonlinear dynamics

Most social psychology paradigms often only assess the behavior of one group at one specific time-point, but social processes unfold dynamically across time and individuals. Consider conformity: people generally follow behaviors more as they become more common (Asch, 1956; Boyd & Richerson, 1985; Henrich & McElreath, 2003), except for non-conformists who follow the behavior less (Efferson, Lalive, Richerson, McElreath, & Lubell, 2008). As a result, conformity follows an oscillating pattern of increases, decreases, and stability, which is difficult to fully capture with static experiments (Jarman, Nowak, Borkowski, Serfass, Wong, & Vallacher, 2015). The spread of social attitudes (Nowak, Szamrej, & Latane, 1990) and

stereotypes (Kashima et al., 2000) and the process of group formation (Halberstadt et al., 2016; Jackson, Halberstadt, Jong, & Feldman, 2015) also follow non-linear patterns. In fact, there are few social phenomena that behave truly linearly over time, given the dynamic nature of social-cultural interactions and the unpredictable impacts of initial conditions (Vallacher & Nowak, 1999). ABMs are an ideal method for modeling these non-linear processes, as they can include millions of time-points and multiple runs (Abbott, 1988).

Mechanism

With their high controllability, ABMs are often able to isolate and directly manipulate the discrete psychological processes underlying complex social phenomena. Of course, psychological mechanisms can take many forms, and can exist on many levels of analysis. ABMs are best suited to study how manifestations of individual (or dyadic) behavior influence larger scale group-level phenomena, such as when a slight individual desire for similarity catalyzes neighborhood segregation (Schelling, 1971). One question is whether the mechanism provided by ABM is the same in real life: just because a mechanism sufficiently generates some outcome does not mean this mechanism necessarily or always generates the outcome. However, revealing even likely mechanisms is valuable for both basic research and policy decisions.

Building an ABM

After being inspired by ABM's rich history and unique methodology, readers might want to try their hand at model-building. While training in ABMs is absent from most PhD programs in social psychology, many articles have linked ABMs to specific research questions (e.g., Axelrod, 1997; Carley, 2002; Schelling, 1971) with others providing more detailed, technical guides (e.g., Smith & Collins, 2009; Smith & Conrey, 2007). An edited volume by Tesfatsion and Judd (2006) includes chapters on ABM's history and its applications in economics, as well

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as an introductory appendix with extensive practical tips for newcomers. Gilbert and Troitzsch (2005) provide a broader overview of ABM in the social sciences. Epstein (2008) includes a discussion of ABM's benefits over other methodologies, and Nowak (2004) gives an in-depth overview of emergence in ABM and the utility of simple models for simulating complex processes. Journal issues focusing on ABMs have included *American Behavioral Scientist* (Vol 42, August 1999); *Science* (Vol 284, April 1999); and the *Proceedings of the National Academy of Sciences* (Vol. 99, Supplement 3, 2002). Finally, websites like “OpenABM” (www.openabm.org) and “Agent-Based Models” (www.agent-based-models.com) provide courses, videos, and code libraries of previous models from which researchers can adapt code.

Aspiring ABMers must develop some level of computer programming. Python, MATLAB, R, and C have often been previously used to program ABMs. However, there are also more accessible tools available for those who do not have time to master a traditional programming language. The software package *Netlogo* (<http://ccl.northwestern.edu/netlogo/>; Tisue & Wilensky, 2004) is free and relatively simple, and provides the code and explanation behind several of the models in this paper, such as the predator-prey model, the flocking model, and Schelling’s segregation model. Netlogo also comes with an extensive manual for researchers to learn the programming language as well as practical tips for building an ABM. Other tools that offer ABM training include *Swarm* (Minar, Burkhart, Langton, & Askenazi, 1996), which requires some programming ability (C or Java) but comes with a tutorial and example code to get new users started, and *FLAME* (Flexible Large-Scale Agent Modeling Environment) which is a more accessible computational environment, since models are specified in XML. *Cellular Automaton Explorer* offers a manageable interface to program simple ABMs and is particularly

well-suited for demonstration purposes (see, for example, a popular Wolfram demonstration: <http://demonstrations.wolfram.com/CellularAutomatonExplorer/>).

To augment these resources, we provide a 7-step conceptual ABM algorithm, with each step illustrated by Schelling's (1971) segregation model and Gray and colleagues' (2014) grouping model. For more examples of the seven steps, we also provide a substantial (though not exhaustive) supplemental table with 35 additional ABMs on social-psychology topics ranging from the dynamics of online chatting to decisions about expressing pain. This collection offers insight into how other researchers have translated their research question into simulations.

Some of these steps do not apply to all models or all research questions, and so researchers should feel free to adapt them to their own needs. Nevertheless, the steps provide a useful guide for exploring social processes and for creating simulated worlds with the potential for collective emergence.

- 1. What are your world's dimensions?** Is your world flat or multidimensional? Schelling's segregation model is 2D—like land—but group formation models are often multi-dimensional to represent complex social spheres (although these models often still involve 2D visualizations to present data). In choosing the dimensionality, researchers must consider if the actions of one agent necessarily constrain the behavior of other agents—the more mutual constraints, the lower the degrees of freedom and the lower the dimensionality (e.g., if I move across town from you, I not only move further from you, but also your neighbor). Note that dimensions only apply to models where interactions between agents are governed by space. In network models, for example, there are no dimensions.

Application of Step 1. In Schelling’s model, agents were paired in a two-dimensional space (as illustrated in Figure 1), while in Gray and colleagues’ grouping model, agents interacted in a multidimensional space where one agent’s position did not impede other agents’ movement.

2. **How do agents meet?** Behavior in ABMs is usually divided into rounds, and on each round, some number of agents interact with each other. One question is how to select which agents interact. Do they interact only with their neighbors, or can they be paired up with any other agent in the simulation? These choices stem in part from the dimensionality (see Step 1), but there are other choices within each of these sets. In some models, agents can avoid interactions entirely—perhaps because they are “unpopular”—while in others, agents can interact with more than one agent. In the latter case, what rules will govern interaction order? And will agents prioritize some interaction partners over others? Will interactions be governed randomly or according to a rule (or a bit of both)? The answers to these questions (along with your world’s dimensionality) will determine the network you choose for your model. Three popular networks are displayed in Figure 3.

Application of Step 2. Since Schelling’s segregation model focused on neighborhood dynamics, he programmed agents to only interact with their next-door neighbors. In contrast, Gray and colleagues’ agents could interact with any other agent in the model, though they were more likely to interact with “friends” than with “enemies”—and they only interacted with one partner per round.

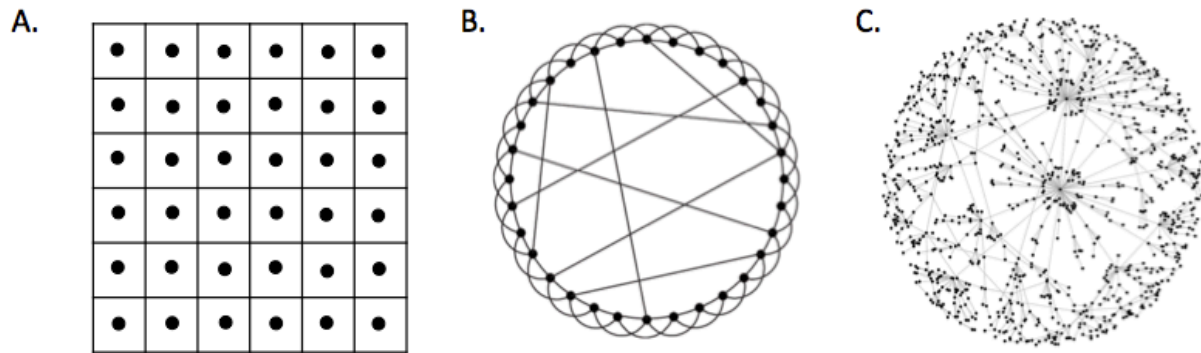


Figure 3. In the lattice network (A), agents only interact with their neighbors (applicable to residential models). In the small-world network (B), cross-network connections compliment neighboring connections, so that any two agents are connected by only a few degrees of separation (applicable to almost any social network). In the scale-free network (C), densely connected agents are more likely to generate new connections compared to sparsely connected agents (applicable to the internet and citation networks).

3. How do agents behave? When agents meet, what do they do? Do they ask other agents on dates (Kalick & Hamilton, 1986)? Do they share food (Jahanbazi et al., 2014)? In many social science ABMs, agents repeatedly play economic games, which allows for experimenters to mathematically approximate real social behavior (Perc & Szolnoski, 2010). For example, prisoner's dilemmas can represent people's decisions to either act selfishly or cooperatively. In any ABM, researchers should ensure that agents' behavior approximates the type of social behavior of interest, which often involves programming in a degree of randomness for variability.

Application of Step 3. In Schelling's model, agents decided whether to stay in their neighborhood or to move to another vacant space on the grid. Gray and colleagues' agents played a prisoner's dilemma game.

4. **What is the payoff?** Payoffs correspond to what agents get out of an interaction, and can represent money, happiness, or social bonds. In some ABMs there is no payoff system, but in many ABMs that feature interactive decision-making, payoffs are determined by considering an agent's decisions and those of that agent's partner(s). In a prisoner's dilemma, for example, an agent's decision to cooperate yields a different payoff depending on whether their partner chooses to also cooperate or to defect.

Application of Step 4. Schelling's agents received no payoff, since there was no interactive decision-making. Gray and colleagues' agents, however, received a payoff that depended on their prisoner's dilemma decisions.

5. **How do agents change?** Agents can change in a number of ways throughout the simulation. In many economic models, agents "remember" the way their counterpart treated them and adjust their behavior in future rounds. In evolutionary models, each round will end with some agents dying (often if they have received a low payoff) or reproducing (often if they have received a high payoff). In mating models, agents can pair up (or break up). In models where agents form groups, agents can become closer to some agents and move further from others.

Application of Step 5. Both Schelling's and Gray and colleagues' agents changed via movement, moving to a randomly selected grid space (Schelling) or closer to those who treated them nicely (i.e., their friends; Gray and colleagues).

- 6. How long does your world last?** As mentioned earlier, one of the major advantages of ABMs is their scale. Researchers can collect data for any specified amount of time, meaning that an ABM investigation will almost never be underpowered. However, researchers should set a theoretically meaningful length to their model. In some cases, models should run until they have reached some form of equilibrium. In other cases, models should run for a length that approximates some phenomenon of interest (e.g. Luhmann & Rajaram's, 2015, model of collective memory), but still allows the researcher to conduct analyses with adequate reliability. In either case, decisions are limited only by (practically unlimited) computer storage space and CPU speed.

Application of Step 6. Both Schelling's and Gray and colleagues' models ran until a point of equilibrium. In Schelling's model, this equilibrium was the point at which agents were no longer moving across neighborhoods. For Gray and colleagues, equilibrium represented the point at which agents had all formed groups or group formation was impossible.

- 7. What do you want to learn from your world?** At the end of the day, ABM is a theory-testing and development paradigm (Smith & Conrey, 2007) with independent and dependent variables. In the case of ABMs, independent variables (or "parameters") are customized by the experimenter, while dependent variables are measured throughout the model or at the model's conclusion. If experimental hypotheses are confirmed, researchers should consider adding other independent variables into the model as moderators. Using new variables or situations to test the generalizability of a phenomenon is often called a "robustness analysis," and it can reveal surprising new effects or non-linearities.

Application of Step 7. Schelling's central parameter was agents' desired similarity, while his dependent measures were agents' positions at the conclusion of the simulation. His finding was that a relatively low rate of similarity seeking (~30%) could produce relatively homophilous agent distributions at the conclusion of the simulation.

In Gray and colleagues' model of "us and them," the central parameters were agents' tendency to show reciprocity and transitivity, and the central dependent variable was group clustering. Varying parameters and measuring clustering revealed how reciprocity and transitivity could produce stable grouping. Gray and colleagues also examined a moderating role for "trust"—the baseline tendency for cooperation or defection.

Conclusion

ABM is not a new technique, but its promise and power are often overlooked by social psychologists. We believe that there are two assumptions that have hindered their increased use. The first is that ABMs are difficult to learn or understand. However, good ABMs should be easy to conceptually understand, and the resources discussed above should make their implementation easier. The second assumption is that ABMs fail to generate new knowledge. As we suggest, good ABMs harness the power of emergence, in which higher-level phenomena derive from the simple behavior of agents. As with any method, ABM is imperfect, but it does offer social psychologists a powerful way to implement precise hypotheses and to explore emergence. Not only can researchers build whole worlds to examine social processes, they also can sample from these worlds over thousands of generations to yield unprecedented insight into collective behavior. Whether studying relationships, stereotypes, culture, attitudes, emotions, religion, or the self, social psychologists should consider adding ABM to their methodological toolbox.

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Supplemental Table for Jackson et al., 2016

Table 1. A Summary of Agent-Based Models with Relevance to Social Psychology							
Model reference	What are the world's dimensions?	How do agents meet?	How do agents act?	What is the payoff?	How do agents change?	How long does the world exist?	What do we learn from the world?
Atkipis, 2011	Two-dimensional lattice	Agents interact with other agents in their grid space	Agents play public goods game Agents enter and leave groups	Resource payoff depending on group donations	Agents can leave and enter groups Agents can gain and lose resources	50,000 runs	Cooperators perform better when they can leave defecting groups
Atkipis et al., 2016	Dyadic network	Model contains two individuals, who repeatedly interact	Agents transfer resources (herding stock)	Resource payoff (stock) depending on response to stock requests	Agents' stock size can change Agents can die	Average of 10,000 rounds	Dyads that transfer wealth based on need are more successful than dyads that transfer wealth based on accounts-keeping
Andrighetto et al., 2012	Isolated tetrad networks	Model contains groups of four individuals, who repeatedly interact	Agents play public goods game Agents punish or communicate with other agents	Resource payoff depending on group donations and punishments	Agents can gain or lose resources Agents can remember group cooperation norms Agents can update strategies	30 runs	Communicating norms boosts a group's cooperation to a greater extent than material punishment
Axelrod, 1980	Multiple dyadic networks	Cooperation strategies are paired with all other strategies in a round-robin format	Agents play prisoner's dilemma	Resource payoff depending on each agent's cooperation decision	No change	200 moves per game	Assuming Axelrod's parameters, the most effective cooperation strategy is to cooperate on the first move and then copy one's partner on all future moves
Axelrod, 1997	Two-dimensional grid	Agents interact with their neighbors	Agents compare their features with their neighbor's features	No payoff	Agents can change their features	81,000 runs	Given interaction based on shared features, agents will converge towards features with their neighbors, but diverge globally

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Bear & Rand, 2016	Multidimensional	Agents are repeatedly paired in quasi-random dyadic interactions	Agents play prisoner's dilemma (both one-shot and repeated interaction variants) Agents choose a contribution strategy for each game	Resource payoff depending on each agent's cooperation decision	Agents can gain and lose resources Agents can update strategies	10 simulation runs, each lasting 10^7 generations	Intuitive cooperation is a functional strategy, depending on environmental reciprocity and assortment. Deliberation undermines cooperation with strangers
Bosse et al., 2009	Fully connected triadic network	Model contains a group of three agents, who repeatedly interact	Agents communicate an emotional state	No payoff	Agents can change their emotional state	Variable	Emotions can spiral upward and downward
Brown et al., 2015	Multidimensional	Dyads are randomly paired	Agents decide whether to play prisoner's dilemma Agents play prisoner's dilemma	Resource payoff depending on agents' cooperation decision and infection status	Agents can adjust openness to interactions with distant agents Agents can move to a new position in the network	100,000 runs for each value of infection probability	Groups spontaneously form based on local vs. global cooperative networks under high threat when infection levels are high
Bruner, 2015	Multidimensional	Randomly assembled 10-player groups interact	Agents play stag hunt	Resource payoff dependent on each agent's cooperation decision	Agents can change their contribution strategy Agents can mutate in their traits and tolerance for diversity	1,000 runs	Cooperation can emerge if social traits are fixed. When individuals can change their traits, cooperation comes at a steep cost to diversity
Čače et al., 2007	Two-dimensional grid	Agents interact with their neighbors	Agents communicate with their neighbors	Resource payoff based on agents' food consumption	Agents can move around the grid Agents can increase energy Agents can die Agents can reproduce	5,000 runs	Communication is beneficial for reproduction and resource accrual in agents where parents invest in their offspring
Campenni & Shino, 2014	Multidimensional	Agents choose	Agents play adapted	Resource payoff based	Agents can update their	1,000 runs for each of 100	When cooperative agents can select

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		partners based on memory from previous interactions	prisoner's dilemma	on each agent's cooperation decision	memory Agents can reproduce with mutation	simulations	their interaction partners, they outperform selfish free-riding agents
Danielson, 2002	Multidimensional	Agents are systematically paired in dyadic networks until they have interacted with all other agents	Sequentially play 8 economic games	Resource payoff based on each agent's cooperation decisions	Agents can mutate Agents can reproduce In some models, agents remember previous interactions	Variable	Reciprocity is necessary but not sufficient for optimal cooperation. Competition among reciprocal cooperators shows three emergent organizations: racing to the moral high ground, unstable cycles of preferences change, and hierarchies resulting from exploiting fellow cooperators
De et al., 2015	Two-dimensional grid	Dyads are paired semi-randomly with their neighbors	Agents play prisoner's dilemma	Resource payoff based on each agent's cooperation decision	Agents can remember past encounters Agents can move to other spaces in the grid	30,000+ iterations	Mobility moderates the success of ethnocentric behavior. In high mobility conditions, individual-entitative cooperation strategies outweigh group-entitative cooperation strategies
Epstein et al., 2008	Two-dimensional grid	Agents randomly interact with a local agent (if one is near)	Agents make a decision as to whether to flee, run, or ignore contact with an infected or fearful partner	No payoff	Agents can become sick and recover Agents can become afraid	Variable; model ends when no more agents are infected	Behavioral responses to disease can shape the evolution of that disease, and its spread
Glanville & Bienenstock, 2009	Multidimensional	Dyads are randomly paired	Agents play prisoner's dilemma	Resource payoff based on each	Agents can remember past encounters.	Average of 1,000 iterations	Social networks enable the spread of indirect

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				agent's cooperation decision			reciprocity. In the absence of direct reciprocity and punishment, agents who cooperate in earlier iterations reap the benefits later, whereas uncooperative agents are punished
Gray et al., 2014	Multidimensional	Dyads are semi-randomly paired based on proximity	Agents decide whether to interact with a partner Given an interaction, agents play prisoner's dilemma	Resource payoff based on each agent's cooperation decision	Agents can move closer to other agents	Continued until all agents had formed groups or group formation was impossible	Reciprocity and transitivity can lead to stable group formation amongst homogenous agents
Hadzibegano vic, Lima, & Stauffer, 2012	Two-dimensional small-world network	Dyads are semi-randomly paired based on proximity	Agents play prisoner's dilemma Agents adapt their strategy based on their partner's tag color	Resource payoff based on each agent's cooperation decision	Agents can reproduce sexually and asexually Agents can die	3 x 10 ⁶ time steps	Altruistic acts in non-repeated interactions can emerge as a natural consequence of heritable traits such as visual tags
Hammond & Axelrod, 2006	Two-dimensional grid	Dyads are paired semi-randomly with their neighbors	Agents play prisoner's dilemma	Resource payoff based on each agent's cooperation decision	Agents can move around the grid Agents can reproduce Agents can die	10 runs of 2,000 steps	Ethnocentrism is a functional strategy, and allows for greater resource accrual than out-group cooperation
Jahanbazi et al., 2014	Two-dimensional grid	Dyads are semi-randomly paired based on proximity	Agents eat, steal, and share food Agents take revenge on thieves Agents choose mates	Energy payoff from eating food Resource payoff from robbing other agents	Agents can move around the grid Agents can reproduce Agents can die Agents can go to jail and can be released	1,000+	A leader's level of altruism affects downstream levels of population altruism

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Johnson, Weidmann, & Cederman, 2011	Two-dimensional grid	Agents interact with neighbors	Agents follow leaders' orders Agents decide which neighbors to attack Agents attack their neighbors Agents ask each other on dates, and decide whether to accept date offers	Resource payoff based on each agent's fighting decision and strength No payoff	Agents can gain and lose resources Agents can increase or decrease their spatial territory Agents leave the dating pool after pairing	200 runs of variable time-steps Continues until all agents are paired	Overconfident agents (provinces) tend to win wars Agents tend to pair with similarly attractive partners even when they desire maximally attractive partners
Kalick & Hamilton, 1986	Multidimensional	Agents are randomly paired	Agents play adapted public goods games Agents punish other group members	Resource payoff depending on group members' cooperation and punishment decisions	Agents can remember who has punished them Agents can reproduce with mutation Agents can die	5 runs of 10,000 generations	Punishment can evolve in models of self-interested agents when punishers do not need to punish every round, free-riding agents can cooperate after punishment, and agents can move between groups
Krasnow et al., 2015	Multidimensional	Agents interact with 10-person groups	Agents encode items in memory Agents reduce the activation of other items in memory	No payoff	Agents' memory is updated	Study 1: 1,000 simulation for each type of group Study 2: 1,000 simulations for each group size Study 3: 1,000 simulations for each network	Collaborative groups perform worse on memory over time, compared to non-collaborative groups, an effect that grows larger in larger groups
Luhmann & Rajaram, 2015	Study 1: Fully connected triadic network Study 2: Multidimensional Study 3: Small-world network	Study 1: Agents interact in 3-person groups Study 2: Dyads are randomly paired in groups of varying size Study 3: Agents semi-randomly paired based on proximity					
Nowak et al., 2015	Two-dimensional small-world network	Dyads are semi-randomly paired based on proximity	Agents choose whether to attack their partner	Strength payoff contingent on the outcome of	Agents can change in their strength Agents can	10 simulations of 50,000 steps	When the environment is unpredictable, honor cultures can evolve in favor of

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				interactions	change in their reputation		rational or dignity cultures
			If attacked, agents can choose whether to give up, fight back, or call the police Agents decide whether to change their attitudes	Reputation payoff contingent on the outcome of interactions No payoff	Agents can die and be replaced Agents can change their attitudes	Continued until there was no longer change in attitudes	Attitude change based on strength, immediacy, and number of sources can result in stable minority attitude clusters within contrasting majorities
Nowak, Szamrej, & Latane, 1990	Two-dimensional grid	Agents interact with neighbors					
Power, 2009	Customized two-dimensional spatial structure	Agents interact with those within their spatial neighborhood	Agents play prisoner's dilemma	Resource payoff depending on each agent's cooperation decision	Agents can remember previous interactions Agents can update their strategy Agents can move within the network	300+ iterations	Mobility is a better predictor of how much agents will cluster based on cooperation style, compared to initial cooperation states
Ren & Kraut, 2014	Multiple multidimensional networks	Agents interact with all those within their network	Agents login to read messages Agents read messages Agents post replies or new messages	No payoff	Agents can update their cost and benefit of sending and reading messages Agents can leave communities	Two 365 "day" simulations for each experimental condition	Personalized moderation of online communities leads to greater participation and commitment compared to community moderation and no moderation
Reynolds, 1987	Two-dimensional grid	Agents interact with all other agents, with weight given to closest others	Agents move towards the other agents Agents match speed and direction of nearby agents Agents	No payoff	Agents move throughout the space	300+ frames	Three simple rules can produce flocking behavior in computer-generated "boids"

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			avoid collision with nearby agents				
Roos et al., 2014	Two-dimensional small-world network	Agents interact semi-randomly based on proximity	Agents play cooperation game Agents decide whether to punish free-riders	Resource payoff depending on each agent's cooperation and punishment decisions	Agents can switch places with other agents in the network Agents can copy their neighbor's strategy	100 simulation runs over 5,000 generations	Under conditions of low mobility and high strength of ties, punishment can be an effective strategy for convincing self-interested agents to cooperate
Roos et al., 2015	Two-dimensional grid	Agents only interact with their neighbors	Study 1: Agents play public goods game Study 2: Agents play coordination game Supplemental materials: Agents play prisoner's dilemma and stag hunt Both studies: Agents decide whether to punish free-riding agents	Resource payoff dependent on each agent's cooperation decision	Agents can update their strategy Agents can reproduce Agents can die	5,000 time-steps per simulation	Ecological threat increases the success of cooperation and coordination
Smaldino et al., 2012	Study 1: Multidimensional Study 2: Two dimensional grid	Study 1: Agents sample all other agents Study 2: Agents sample local neighbors	Agents take stock of their surrounding identities	No payoff	Agents can update their identity	5000+ time steps	Agents cannot individually achieve optimal distinctiveness when they share the same environment, but they can approach optimal distinctiveness when their environments are local and overlapping
Smaldino,	Two-	Agents are	Agents play	Resource/en	Agents' energy	30 simulations per	High

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Schank, & McElreath, 2013	dimensional grid	randomly distributed, and interact with their neighbors	prisoner's dilemma	energy payoff dependent on each agent's cooperation decision	reserve updates Agents can move to unoccupied cells Agents can die Agents can reproduce into unoccupied cells	condition, with $t = 10^7$ per simulation	environmental cost of living threatens cooperation in the short-term but allows for greater cooperation in the long-term
Villatoro et al., 2014	Fully connected tetradic network	Agents interact with their network	Agents detect the salience of norms Agents play public goods game	Resource payoff depending on each agent's cooperation and punishment decisions	Agents can update their strategies	5,000 simulations	Punishment is more effective when coordinated by groups than when expressed by individuals, presumably because it communicates norms
de Williams et al., 2015	Multidimensional	Agents interact semi-randomly based on pre-assigned connectedness scores	Agents forage for food Agents express pain Agents decide whether to help other agents in pain Agents decide whether to exploit other agents in pain	Energy payoff depending on pain state, helping behavior, and exploitative behavior	Agents can gain and lose energy Agents can die and be replaced	100 repeated simulations run for 10,000 iterations	More energy-demanding expressions of pain reduced pain's frequency in successive generations, and increased injury frequency resulted in fewer expressers and altruists. Allowing for exploitation of injured agents greatly reduced expressions of pain

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