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Agent-Based Models

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The collection of methodological tools often called *system science methods* are rapidly gaining attention as useful in community-based research for their unique ability to capture ecological and contextual effects in a holistic way. Agent-based models are a specific variety of system science methods, which also include network analysis and system dynamics models (Neal, 2015). These models are designed to simulate the behaviors of agents (e.g., people) as they interact with one another in particular settings. Although they may be used in many ways, their most general purpose is to develop an understanding of how individual behaviors and features of the context can give rise to macroscopic social phenomena. In this chapter, we illustrate this through two extended examples. First, in introducing agent-based models, we describe how Schelling (1969) used an early version of agent-based modeling to understand how individuals' preferences to live nearby similar others (i.e., an individual behavior) and the diversity of a residential neighborhood (i.e., a contextual feature) give rise to patterns of residential segregation (i.e., a macroscopic social phenomenon). Second, in the case study, we describe how Neal and Neal (2014) examined how individuals' preferences to interact with similar and nearby others (i.e., individual behaviors) and the segregation of a residential neighborhood (i.e., a contextual feature) gives rise to sense of community (i.e., a macroscopic social phenomenon), and we adapt this model to explore how community public spaces (i.e., another contextual feature) may moderate this process. Interactive versions of several models discussed in this chapter are available on a companion Web site at http://www.msu.edu/~zpneal/communityabm.

Agent-based models have several features that make them especially useful for community-based research. First, they simultaneously incorporate individual behaviors, the contextual influence of other individuals in the setting, and the contextual influence of other setting characteristics like roads or parks. Thus, these models provide community-based researchers with a single analytic tool that takes a holistic perspective toward what communities are and how they work. Second, as a simulation method, agent-based models allow community-based researchers to study processes that might be impossible or unethical to investigate in real communities and, by simulating what-if scenarios, to anticipate otherwise unanticipated consequences of interventions. Thus, they can be a tool for ensuring that community-based research and community-based interventions are conducted and implemented in responsible ways. Third, as a highly interactive and iterative analytic strategy, agent-based models readily lend themselves to participatory research that seeks to engage community members, but they can also help community-based researchers clarify their thinking about what to do in communities before entering the field. Thus, these models can be a tool for ensuring that community-based work incorporates community members' perspectives while still being respectful of their time.

This chapter has several overarching goals. In the next section we introduce the basic features of agent-based models in a nontechnical way, focusing on the approach's epistemology, assumptions, and basic steps, using Schelling's (1969) simple model of residential segregation as an example. We then explore how agent-based models can be particularly useful for community-based research, focusing on a few key challenges that community-based researchers often encounter and considering the solutions that agent-based models offer. In the case study, we put these ideas into practice, describing the use of an agent-based model to evaluate the use of community public spaces as a potential intervention for cultivating sense of community. Finally, we offer some suggestions for getting started using agent-based models in community-based research.

INTRODUCTION TO AGENT-BASED MODELS

Agent-based models are embedded in an epistemological perspective known as methodological individualism, which views macrolevel social phenomena as arising or emerging from the microlevel interactions of individual agents (Agassi, 1960; Hodgson, 2007; Udehn, 2002). Methodological individualists contend that a complete understanding of a macrolevel social phenomenon requires explaining it in terms of the actions of the individual agents who caused it. This is a kind of reductionist epistemology, but one that innocently asks, if social phenomena are not caused by the actions and interactions of people and their environments, where else could we possibly look for an explanation? Accordingly, the goal of many agent-based models is to understand what microlevel interaction(s) could generate a given macrolevel social phenomenon, or what Epstein (1999) called the generativist's question. To answer this question, Epstein proposed that researchers conduct what he called the generativist's experiment: "Situate an initial population of autonomous heterogeneous agents in a relevant spatial environment; allow them to interact according to simple local rules, and thereby generate—or 'grow'—the macroscopic regularity from the bottom up" (p. 42).

A key feature of agent-based models is their flexibility: They can be used to explore nearly any macrolevel social phenomenon and nearly any kind of microlevel interactions, including those between two agents, or between an agent and its environment, or between different parts of an environment. For the sake of concreteness, we illustrate the basic principles of agent-based models in this section by using Schelling's (1969) model of segregation. Schelling (1969) was interested in understanding the macrolevel social phenomenon of residential segregation. He recognized that many mechanisms might explain the existence of residential segregation, including top-down institutional forces such as mortgage redlining and restrictive covenants, but was specifically interested in whether segregation would still emerge in the absence of these forces. If institutional forces do not impose segregation, is it likely to emerge anyway?

Basic Principles

Agent-based models begin with a population of autonomous, heterogeneous agents. The agents are the entities that act, interact, and react in the simulated world. In Schelling's model and in many other community-based models, the agents are people, but the agents could also be households, organizations, animals, and so on. These agents are assumed to be autonomous; that is, they act on their own and are not fully controlled by external forces. Importantly, the assumption that agents are autonomous does not imply that they have unrestricted autonomy; agents' actions may be heavily constrained by their environment or heavily influenced by other agents. In Schelling's model, people have autonomy to live where they wish, but their decisions are constrained by the availability of space and by the demographic characteristics of their neighbors. Agents are also assumed to be heterogeneous; that is, they are not interchangeable but differ from one another on any number of characteristics. In Schelling's model, people differ from one another in two ways: demographically (some are type A people, and some are type B people) and spatially (each person has his or her own residential location in the simulated world).

The population of agents is situated in a relevant spatial environment. In many agent-based models, the environment takes the form of a grid, where each square represents a location in the environment and may have its own unique characteristics. In Schelling's model, the environment is very simple: Each square represents a parcel of land where a person may choose to move and reside if it is unoccupied. In other models of a community, squares may represent parcels of land that differ in value or desirability, or some squares may represent residential opportunities while other squares represent parks or roads.

Once a simulated world of agents in an environment is created, the agents are allowed to interact according to simple, local rules. This closely mirrors Barker's (1968) behavior setting theory, which contends that people are essentially rule-following creatures who take cues about how to act from their setting. This component of agent-based models has three key features. First, the rules that agents follow are simple: People are not like computers that consider all possible actions and select the optimal one, but rather they follow heuristics and rules of thumb. In Schelling's model, people follow a single, simple rule when selecting a place to live: Find a place where at least X% of my neighbors are similar to me. The exact value of X can be adjusted by the researcher, thereby modifying the behavioral rule. Second, the rules that agents follow are local: People are not omniscient, but rather they selectively attend to the most salient features of their environment. In Schelling's model, when people consider whether a potential residential location meets their criteria, they consider only their immediate neighbors, not those living miles away. Finally, the agents are allowed to interact: The macrolevel social phenomena that emerge in the simulated world are strictly endogenous, arising purely from the agents' interactions with each other and their environment. In Schelling's model, people keep moving around according to their single behavioral rule, without any outside intervention, until they are all satisfied with their neighborhoods.

Perhaps the cardinal principle of agent-based models is simplicity. As Box and Draper (1987) explained, "all models are wrong, but some are useful" (p. 424). The goal is not to simulate reality in its full complexity and obtain the "right" model, which would be impossible, but rather to identify the minimal set of features necessary to "grow" the macrolevel social phenomenon of interest and thus be useful for understanding it. In Schelling's case, he showed that it was possible to observe the emergence of residential segregation in a world populated by two types of people both following the same plausible, simple rule. Although perhaps not realistic, he thus demonstrated that the emergence of segregation does not require top-down institutional forces, complex combinations of multiple demographic characteristics, a preexisting history of segregation, and so on. Perhaps even more noteworthy, he demonstrated that residential segregation would emerge even when the rule guiding peoples' neighborhood preferences was relatively weak (i.e., when the researcher makes X, the variable that controls the behavioral rule, small). For example, even when people are willing to be a minority in their own neighborhoods and merely want at least one third of their neighbors to be similar, fairly extreme segregation still develops. Here, the model is "wrong" because it omits many features of reality, including, for example, the role of streets (Grannis, 1998), school choice (Saporito, 2003), or mortgage foreclosure (Rugh & Massey, 2010). Nonetheless, it is still "useful" because it highlights how even subtle, innocuous preferences can make segregation nearly inevitable. It is also useful as a first step in a modeling cycle, which in subsequent iterations may incorporate some of these more complex phenomena.

The Modeling Cycle

The development of an agent-based model proceeds through a modeling cycle (Railsback & Grimm, 2011). As with most research projects, the first step involves clearly articulating the research question, which often takes the form: How does the researcher's macrolevel phenomenon of interest emerge from microlevel interactions? For Schelling, the goal was to understand how residential segregation emerges. Second, the researcher identifies the kind of agent(s) involved and the characteristics they have, the characteristics of the agents' environment, and the rule(s) that govern how the agents interact with each other and their environment. Schelling's model involved people with a single binary demographic characteristic, in a grid where squares represent possible residences, where people select residences by aiming to satisfy a preference for neighborhood demographic composition. The clearer, simpler, and more concrete the research question and model characteristics, the easier the third step: implementing the initial model using software. Once implemented, the model is checked for errors, run multiple times with experimental manipulations of features of the model, and the results examined to determine which interaction rules yield the macro-level phenomenon of interest. The goal of Schelling's analysis was to determine what percentage of similar neighbors (i.e., the value of X) people must prefer before segregation emerges; as noted earlier, the value is surprisingly low. At each stage in the modeling cycle, the researcher may refine or expand the model, incorporating additional elements (e.g., a new interaction rule or a new agent), making the process truly cyclical and iterative.

Just as agent-based model development proceeds through a cycle, running an agent-based model can also be viewed as involving a series of steps. Running a model usually begins with an initialization step, in which the simulated world (i.e., the agents and their environment) is created. This is followed by an interaction step, in which each agent takes a turn following one or more rules. In Schelling's model, during the initialization step, equal numbers of type A and type B people are each placed on random squares in the grid. During the interaction step, each person takes a turn counting the percentage of his or her neighbors that are similar. If this percentage exceeds the person's preference, the person is happy and stays, but if the percentage falls short of the person's preference, the person is unhappy and moves to a new location (i.e., an unoccupied square elsewhere in the grid). The interaction step can be repeated, allowing people to continually move and reevaluate their neighborhoods, until all people are happy with their location or until it becomes clear that universal satisfaction is impossible. At each step, the researcher can observe the current level of segregation and watch changes in the neighborhood's spatial patterns dynamically shift.

Software

There are a large number of specialty software programs designed for developing and running agent-based models. However, NetLogo (Wilensky, 1999) is particularly useful for a number of reasons. It is free to download (https://ccl.northwestern.edu/netlogo/) and use, and, as a Java-based program, will run on both PC and Macintosh computers. It is also accompanied by a tutorial, extensive documentation, and a library of example agent-based models to facilitate learning. Finally, it features a graphic interface that allows researchers to view and interact with models as they are running. An interactive version of Schelling's (1969) segregation model implemented in NetLogo (adapted from Wilensky, 1997) is available online. It helps illustrate the NetLogo interface and many of the features of Schelling's model discussed in this section. First, it includes an adjustable slider that allows the user to set the total population of the simulated world, which is created in the initialization step when the "1. Setup" button is pressed. Second, it includes an adjustable slider that allows the user to set the people's level of preference for similar neighbors, which people aim to satisfy in the interaction step when the "2. Go" button is pressed. Finally, it includes a graphic display of the simulated world and a line graph of the world's level of segregation over time, allowing the user to watch residential segregation emerge as agents move around seeking to satisfy their preferences.

APPLYING AGENT-BASED MODELS IN COMMUNITY-BASED RESEARCH

Although they have not yet been used extensively in community-based research, agent-based models offer a promising approach to addressing many of the challenges that emerge from conducting community-based research and can act as an important complement to data collected directly from community members. First, they can be used to guide community-based research and data collection without wasting researchers' or community members' time and resources. Second, they allow researchers to explore questions that would be impossible to examine in community settings. Third, they can help researchers anticipate the consequences of planned community interventions or efforts toward social change. Fourth, the cycle used to develop agent-based models provides many natural points to seek community input during model building and assessment, facilitating participatory inquiry.

Guiding Community-Based Research

Large-scale community studies and interventions can be challenging to plan and implement because there are often a bewildering array of individual and ecological characteristics that might be measured and examined. Agent-based models can be used as a first step, to inform the development of research questions and identify the most crucial data to collect, which can save researchers' and community members' time by helping them avoid unnecessary data collection and refine the scope of work to be done. Consider the case of developing a community-based intervention to reduce the spread of HIV/AIDS. A community-based researcher might consider measuring the prevalence of many different sexual behaviors within a population, including condom use, testing for HIV, frequency of sexual encounters, and duration of sexual relationships. However, each of these is costly for researchers to measure, requires invasive inquiry for community members, and is time consuming for all parties. A preliminary agent-based model might help the researcher ask, what do I really need to measure? An interactive AIDS model available online (adapted from Wilenski, 1997) simulates HIV/AIDS transmission in a community driven by these behaviors and can be used to see that testing frequency has a much greater impact on a community's rate of infection than other behaviors. This model-derived insight might provide a guide for data collection that not only makes the study more feasible for the researcher but also less burdensome for the community members.

Asking Unaskable Questions

Communities are real places, and community members are real people. These are the key reasons that community-based research is so important, but they also impose some substantial limitations on what community-based researchers can do. Many potential research questions or experimental manipulations would be unethical, impossible, or difficult to study in community settings. A study of how HIV/AIDS spreads in a particular community might benefit from exploring the impact of eliminating residents' access to condoms. It would surely be unethical to do this in a real community, but the AIDS model mentioned earlier provides the researcher a way of asking this otherwise unaskable question by simply instructing the agents (i.e., simulated community residents) to never use condoms and watching what happens as a result. In other cases, an experimental manipulation may not be unethical, but it may simply be impossible. In the mid-1990s, Hoffer (2006) ethnographically studied the local heroin market in Denver, Colorado. Examining the impact of police busts on the market would have been impossible for a variety of reasons, including the inability to experimentally control the timing and intensity of the busts and the inability to remain in the field after having done so. Instead, Hoffer, Bobashev, and Morris (2009) used the ethnographic findings to develop an agent-based model of the heroin market, within which they were able to simulate the effects of police busts. Finally, there are many cases where the data needed are ethical and possible, but not feasible, to collect. Social network data are a prime example because accurate network analysis requires high levels of participation and has a low tolerance for missing data (see Chapter 21), which severely limits the feasibility of collecting this type of data in (large) community settings. Rather than collect social network data from real community members, which can be very costly and time consuming, agent-based models can be used to simulate the dynamic formation of social networks among community members as they interact with one another according to certain rules (see Chapter 22). The resulting, simulated networks can give researchers a sense for the kind of network structures they might expect to find in real communities. We discuss an example of this type of model in the next section.

Perhaps one of the most pressing but unaskable questions in community-based research is the causal question. Community-based researchers are often relegated to the territory of association, left to conclude that X is associated with Y, but unable to push the epistemological envelope and conclude that X causes Y. However, the earlier AIDS, segregation, and social network examples highlight that agent-based models also allow community-based researchers to ask causal questions. Because the researcher has complete control over the simulated behaviors of the agents, and of the simulated environment in which they interact, agent-based models make it possible to conduct true (not merely quasi- or natural) experiments in simulated communities (Devine, Wright, & Joyner, 1994). Thus, whereas a field study may ultimately conclude that a community's lack of access to condoms is associated with higher rates of HIV infection in the community, an agent-based model may allow researchers to much more usefully conclude that, at least within the simulated community, lack of access causes higher rates of infection.

Anticipating Unanticipated Consequences

Community-based researchers often address complex problems, which makes it difficult to predict both how the problem will evolve over time and how different efforts to solve the problem might shift that evolution. Agent-based models provide one approach to anticipating the potential consequences of taking (or not taking) action in a community. This frequently takes the form of simulating a series of what-if scenarios in an agent-based model. For example, a community-based researcher might develop a model designed to simulate the formation of social networks among a community's stakeholders, which by itself may be useful for understanding stakeholder engagement. However, the researcher might subsequently use this model to explore the potential consequences of hosting monthly stakeholder meetings (e.g., what if I simulate all of the stakeholders interacting once per month?) or of an unanticipated community change (e.g., what if I simulate one of the stakeholders suddenly leaving the community?). By probing these what-if scenarios, community-based researchers can develop interventions and community change agendas with greater caution and confidence.

When paired with relatively fast and inexpensive computing resources (most agent-based models run quite fast on even modest personal computers), the range of what-if scenarios that can be examined is virtually unlimited. In practice, the examination of intended and unintended consequences in agent-based models often takes the form of a "parameter sweep." The researcher identifies one or more variables of particular interest (e.g., HIV testing frequency, intensity of residential preferences, likelihood of a stakeholder leaving) and conducts a simulation at each possible level of the variable(s), observing the outcome in each case. In this way, community-based researchers can examine all possible combinations of variable values, including those combinations that occur in real communities, as well as those that could plausibly occur but for which no real-world examples are available to study, to anticipate the outcomes that might be expected in both real and possible communities.

Engaging Community Members

Although nearly all community-based researchers see the value of engaging community members in their research, it is not always clear how or when this engagement should occur. The modeling cycle, through which agent-based models are developed, provides multiple ways and multiple opportunities for this type of engagement. During the model conceptualization phase, input from community members can illuminate which microlevel and macrolevel phenomena are valuable to investigate, while further community input during model design can define the kinds of agents and interaction rules that should be included to ensure the model accurately mirrors the setting. At the evaluation stage, engaged community members can interpret the results of the model alongside the researcher, providing feedback on whether outcomes make sense in the context of their experiences and identifying areas that need further development. Engagement can also foster a sense of community ownership of the model and increase the likelihood that participants will use the final model after the completion of the initial research project.

Often called participatory agent-based modeling, or PABM, these steps can help ensure that the model includes all appropriate phenomena and can bolster the models' validity. Moreover, unlike attracting community members' participation in more traditional forms of research, because agent-based models often look like "computer games" and community engagement often takes the form of "playing with" the model, participation can be easier to obtain. PABM remains somewhat rare, but the literature still contains several useful examples. Community members have used participatory modeling processes as tools for addressing issues such as resource allocation and land usage (Castella, Trung, & Boissau, 2005; Naivinit, Le Page, Trébuil, & Gajaseni, 2010). Castella et al. (2005) implemented PABM to understand changes in land usage over time among farmers in Vietnam. They collected data to inform model design by engaging community members in role-playing games and individual interviews to understand the kinds of simple rules that govern their land use decisions. Community members were ultimately able to employ the model as a tool for making decisions about how to move forward with sustainable practices that met the needs of all stakeholders involved in the local agriculture system. Naivinit et al. (2010) similarly used a role-playing game and follow-up interviews to build a participatory model of rice production and labor migration in Thailand. Participants then used the resulting model to understand and take collective action around issues related to labor migration. Although PABM remains relatively unexplored in community-based research, the ease of engaging participants in the modeling cycle and the benefits that emerge from its use make it a very promising approach to research.

CASE STUDY

Community-based researchers and activists often find themselves at the crossroads of conflicting goals in their work. A prime example is the twin goals of promoting community diversity and sense of community. An extensive literature around the dialectic of spatial integration and social cohesion has emerged, suggesting that as communities become more diverse and integrated, they experience declines in cohesion and sense of community (e.g., Portes & Vickstrom, 2011; Putnam, 2007;

Townley, Kloos, Green, & Franco, 2011). Neal and Neal (2014) sought to understand why this dialectic exists, or stated in terms of the generativist's question: What microlevel behaviors lead to the macrolevel social phenomena of integration and cohesion having a negative relationship?

To answer this question, they used an agent-based model to conduct a generativist experiment. Their model begins with a population of people who differ on a single unspecified demographic characteristic (Schelling, 1969), in a neighborhood with a specific level of spatial segregation. Some of their simulated neighborhoods were highly segregated, with people living only near demographically similar others, while other simulated neighborhoods were highly integrated, with people living among demographically mixed others. In the interaction step of the model, each person had the opportunity to form a relationship with each other person in the setting. The probability of a relationship forming between two people depended on two factors: (a) the tendency to have friends who are demographically similar (i.e., homophily) and (b) the tendency to have friends who live nearby (i.e., proximity). After a social network was formed in the simulated neighborhood, Neal and Neal computed the level of cohesion, which they operationalized as the average density of each person's personal social network (i.e., the clustering coefficient).

They simulated a large number of communities using range of possible values for segregation, homophily, and proximity (i.e., a three-parameter sweep), each time recording the level of cohesion observed in the community. This analysis showed that whenever social networks form through tendencies toward both homophily and proximity, there is a negative relationship between the community's level of integration and its level of cohesion. The more residentially integrated communities had less social cohesion, while the less integrated communities had more cohesion. Thus, answering the generativist's question, they found that the tendencies of homophily and proximity that are commonly observed in social network formation are sufficient to generate or "grow" the integration-cohesion dialectic. Interestingly, their parameter sweep also highlighted that a reversal in the tendency toward homophily (i.e., if people preferred dissimilar friends) or proximity (i.e., if people preferred friends who live far away) would eliminate the dialectic and make simultaneously integrated and cohesive communities possible. However, although reversing the tendency toward homophily or proximity is possible in an agent-based model, where the simulated people follow the researcher's instructions, it is likely not possible in reality and thus likely not a potential avenue for a community-based intervention.

Neal and Neal's (2014) study illustrates the use of an agent-based model to understand how a community phenomenon is generated by individual behaviors. Here, we build on their model to test a possible intervention to simultaneously cultivate community integration and cohesion and overcome the dialectic that they and others have observed. Specifically, we add to their model to explore a series of what-if scenarios that involve the construction of one or more community public spaces, like parks or community centers. We hypothesized that community public spaces can bring people together, including people who might not otherwise interact, and serve as a site for the formation of community relationships (Neal, 2013; Orum & Neal, 2009). These public space-based relationships may enhance community social cohesion, even in integrated neighborhoods where the community social network might otherwise be fragmented. However, parks and community centers are costly to build, and interventions are often accompanied by unanticipated consequences. Thus, a preliminary test of the intervention's hypothesized effect using an agent-based model offers a useful first step.

Our refined agent-based model includes several features not present in Neal and Neal's (2014) original model. First, we allow the simulated community to contain community public spaces, where each person in the community uses his or her nearest community public space. Second, in addition to the probability of a relationship between two people depending on homophily and proximity, we add one more: the tendency to have friends who use the same community public space. Finally, we allow minor adjustments in the location of the community spaces, including whether the spaces should be spread out or located near each other, and whether the spaces should be located randomly, in mostly integrated areas of the community, or in mostly segregated areas of the community. An interactive version of this model is available online.

To examine this model, we do not use a true parameter sweep because many possible parameter combinations would be unrealistic from the point of view of a feasible community intervention. For example, building 1,000 parks in a community, or encouraging people to exclusively make friends at community spaces but nowhere else, may enhance cohesion but are not viable intervention strategies. Instead, we examine a series of parameter combinations that match some plausible intervention scenarios. Figure 20.1 illustrates our findings from these what-if scenarios; each line represents a specific scenario and shows the expected relationship between community integration and cohesion. The solid line in both panels represents the baseline case, drawn from Neal and Neal's (2014) original model, in which people tend to form relationships with similar, nearby others and there are no community spaces. The dash-dotted lines indicate the expected relationship between integration and cohesion when one (the left panel) or two (the right panel) community public spaces are built in random, nonadjacent locations and when the impact of sharing a demographic characteristic and of using the same public space on relationship formation are equal. The remaining lines capture scenarios when the impact of sharing a demographic characteristic is slightly more important for relationship formation (dashed line), and when the impact of using the same public space is slightly more important for relationship formation (dotted line).

These results provide a number of insights into the potential consequences of a public space-building intervention designed to cultivate community integration and cohesion. First, in all of the intervention scenarios that we examine using the model (the 6 shown in Fig. 20.1, and 378 more), the same negative relationship between integration and cohesion observed by Neal and Neal (2014) persists ($-0.91 <$ Spearman's $\rho < -0.44$). This suggests that an intervention rooted in building community public spaces is unlikely to eliminate the much-lamented integration-cohesion dialectic. Second, although the dialectic persists in each intervention scenario, many yield increases in community cohesion compared to the baseline. For example, although an intervention that builds two community public spaces is expected to generate the greatest boost in cohesion in a segregated community, integrated communities would also be expected to experience increased cohesion. Thus, although a public space-building intervention cannot undo the dialectic, it may at least be an avenue toward greater social cohesion.

Finally, and perhaps most important for community-based research, these results help us to locate the intervention strategies that might be expected to work best. For example, an intervention that builds a single community public space,

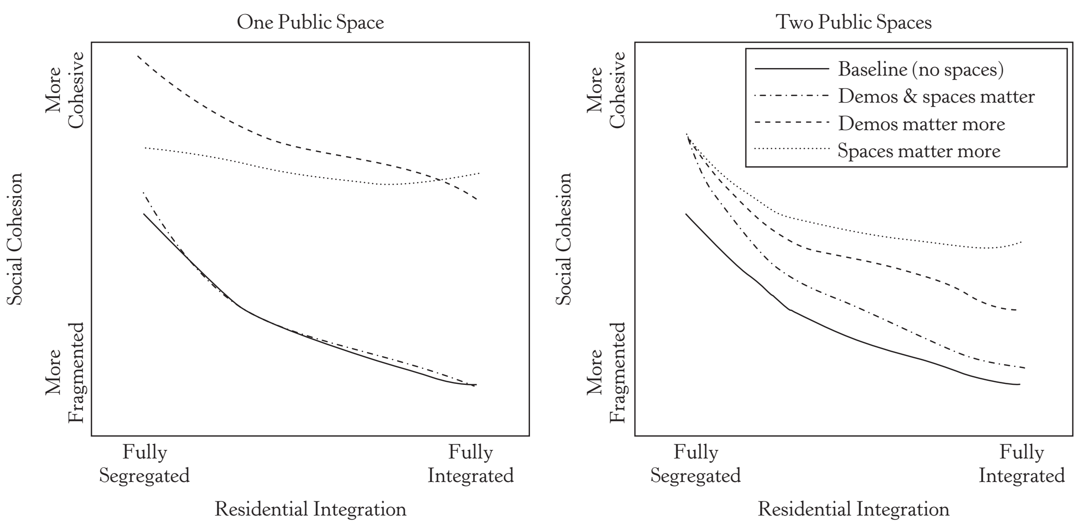

FIGURE 20.1: Results of a simulated public space building intervention.

Note: Baseline Scenario: Status Homophily = 1, Proximity = 3, Place Homophily = 0; Demos & Spaces matter scenario: Status Homophily = 1, Proximity = 3, Place Homophily = 1; Demos matter more scenario: Status Homophily = 2, Proximity = 1, Place Homophily = 1; Spaces matter more scenario: Status Homophily = 1, Proximity = 1, Place Homophily = 2. In the scenarios that include public spaces, the spaces were placed in random locations in the community; when two spaces were included, they were separated by at least five grid patches.

in a community where sharing a public space with another person has a slightly greater impact on the probability of forming a relationship than sharing a demographic characteristic with that person (dotted line in the left panel), seems to simultaneously minimize the dialectic and maximize the cohesion-boosting consequences. Reflecting on this finding, it may seem obvious; of course, social cohesion would be high in a community in which all residents use the same public space and for whom that public space is very important. However, it is obvious only in retrospect; note that a one-space intervention is substantially better than a two-space intervention. Although this does not guarantee that building a public space that is important to residents will yield a harmonious community, the finding at least allows us to focus our attention and refine our intervention before entering the field.

CONCLUSION

At first glance, agent-based models may seem to be quite different from more traditional methods used by community-based researchers and to require specialized technical skills in programming. However, in practice the learning curve for newcomers to agent-based modeling is actually quite shallow. Here, we offer a couple of suggestions for getting started. First, download the NetLogo software and complete the accompanying tutorial. This short tutorial takes a few hours to complete, walking the user through many of the software's most important features and the programming language's most important commands. At the end of the tutorial, the user will have written a complete agent-based model from scratch that includes agents interacting with each other and with their environment, which highlights how rapidly a model can be developed. Second, explore the built-in models that are bundled with NetLogo in its Model Library. Each model has a nontechnical description of what it does, as well as annotated programming code to understand how it works. There are a broad range of example models, including models on community-related topics such as urban sprawl, team building and collaboration, wealth distribution, and diffusion of resources through a network.

The tutorial and model library are helpful for getting acquainted with what agent-based models look like, how to interact with them, and what they are capable of. A particularly useful strategy for developing one's own model is to adapt an existing model. For example, the NetLogo model library includes an example model called Virus on a Network that simulates the classic epidemiological susceptible-infected-resistant (SIR) model of disease spread. This model might readily be adapted to investigate the spread of collective action through a community: Community members are "susceptible" to participation, and community change might be realized only after a sufficient number of people are "infected" with participation. However, it may require some minor changes: For example, the original model assumes that all people are susceptible to the virus, but perhaps only some people (i.e., those interested in a community issue) are susceptible to participation. Nonetheless, adapting existing models to new purposes and research questions provides a way to get started using agent-based models in community-based research very quickly.

A final suggestion, whether adapting existing models or building new ones, is to keep it simple. Communities and community-based research are complex, and agent-based models are not intended to capture the full complexity of reality. At each step, consider which aspects of the community are absolutely essential for understanding the core dynamics of the issue and leave everything else out (at first). Starting with a simple (albeit perhaps unrealistic) initial model and adding to it incrementally is more useful than starting with a very complex model that cannot be understood.

As this chapter has highlighted, although agent-based models are not widely used in community-based research currently, they have much to offer. First, they offer a single analytic tool that simultaneously integrates individual and ecological influences and that bridges the explanatory gap between microlevel processes and macrolevel outcomes. Second, they offer some solutions to several different challenges that frequently arise in community-based research, including allowing the researcher to refine research questions before entering the field, to ask unaskable questions, to anticipate unanticipated consequences, and to engage community members. However, agent-based models are not a replacement for other community-based methods, but rather they should be viewed as a useful supplement. Building a useful agent-based model still requires knowledge about the problems that are important to communities, about the microlevel processes that take place in communities, and about the constraints imposed on communities by internal (e.g., norms) and external (e.g., laws) forces. The AIDS model discussed earlier may be useful only in communities where HIV/AIDS is a pressing issue. Likewise, an AIDS model that simulates condom use behaviors may be appropriate only in communities where condoms are available, or one that simulates an abstinence-based intervention may be useful only in communities where local norms view abstinence as an acceptable behavior. However, when paired with at least a preliminary understanding of the research setting, agent-based models offer community-based researchers a powerful complement to other methods.

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