A General Agent-Based Model of Social Learning

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Preface

This report describes a general agent-based model (ABM) for studying the ways in which micro-level social influence gives rise to population-level dynamics at the macro-level, as well as the dynamics that can result from the general ABM for different classes of generic behaviors. ABMs consist of interacting “agents,” which in our case are individuals. This report also describes how we tailored the general ABM to model a specific behavior—breast cancer screening—using a nationally representative survey we designed specifically to inform the structure and parameterization of the breast cancer screening ABM. Finally, the report describes other potential ways in which the general ABM might be tailored in the future.

The research in this report is the result of work conducted in two projects funded by the National Institutes of Health (NIH). The first, Health Outcomes, Risk Perceptions, and Preventive Behavior on Social Networks, sponsored by the National Cancer Institute (NCI), assessed how people evaluate the relative risks of engaging or not engaging in preventive health behavior using information gathered from their social networks. In that project, we developed a general ABM for social learning; and, using breast cancer screening and seasonal influenza vaccination as examples, we developed two tailored ABMs. We designed and conducted two surveys specifically to inform and parameterize these tailored ABMs. While breast cancer ABM and influenza ABM are described in other publications, this report is the first to document the general ABM. In the second project, Building an Inter-Disciplinary Network on Culture and HIV Risk, sponsored by the National Institute on Minority Health and Health Disparities, we explored used the general ABM to explore key types of dynamics that social learning processes can exhibit for generic classes of behaviors and developed concepts for how our general ABM could be further tailored to model different types of behaviors in future work.

We are currently developing and refining tailored ABMs of breast cancer screening decisions, influenza vaccination, and tax evasion under three ongoing projects sponsored by the National Cancer Institute, the National Institute of Allergy and Infectious Diseases, and the National Science Foundation, respectively.

The report is intended primarily for researchers concerned with social networks, information flows, and decision making, including but not limited to those working in fields related to health, policy, social science, and psychology.

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Summary

When engaging in behaviors that may entail risks or outcomes that are unknown or uncertain, individuals often look beyond their own experiences to consider the experiences of others in their immediate social networks. This is social influence at the micro-scale, and it can bring about change in the greater social web in such a way that local social networks may have profound effects on behaviors at the population level. This report describes a general agent-based model (ABM) for studying the ways in which micro-level social influence gives rise to population-level dynamics at the macro-level. ABMs consist of interacting “agents,” which in our case are individuals. These individuals are connected to each other through a social network and can share information about behaviors and experiences with others to whom they are connected. In turn, individuals’ behaviors can be influenced by information they receive from other agents in their social networks. The general ABM we developed can be used on its own to examine how social networks influence generic classes of behaviors—that is, groups of behaviors that share certain characteristics (e.g., behaviors for which outcomes are always self-reinforcing)—or it can be tailored in conjunction with surveys to examine specific behaviors. This report discusses results from the general ABM and describes the two ways in which we used a national survey to tailor the general ABM in the past, and the additional possibilities for how we might tailor the model in the future.

We examined the following different classes of behaviors the ABM could produce. We evaluated cases in which individuals were engaging in one of two mutually exclusive behaviors $A$ and $\bar{A}$ (such as vaccinating or not vaccinating):

1. The outcomes of both $A$ and $\bar{A}$ suggest that $A$ is the better behavior; for example, $A$ could represent the adoption of a new, superior technology. We find that if memory, information transmission, and the effect of learning about network outcomes are relatively large, most individuals in the network will end up engaging in behavior $A$. If these parameters are small, most individuals will revert to a default behavioral state.

2. The outcomes of behavior $A$ suggest that behavior $A$ is a good choice and outcomes from $\bar{A}$ suggest that $\bar{A}$ is a good choice, as would be the case with membership in one of two equally attractive groups (e.g., becoming a fan of different sports teams). This type of social learning mechanism can lead to distinct clusters of behavior in the population if there are few long-range connections between individuals and if initial conditions include large, relatively homogeneous clusters of individuals engaging in behavior $A$ or $\bar{A}$. Small clusters and large numbers of long-range social network connections can destabilize initial clusters.

3. The outcome of behavior $A$ suggests that behavior $\bar{A}$ is the better choice and the outcome of behavior $\bar{A}$ suggests that $A$ is the better choice, as may be the case with two unsatisfying cable service providers. This results in dynamics in which
individuals alternate between behaviors $A$ and $\bar{A}$. If individuals are highly connected, they may switch from one behavior to another in groups. If they are not, they may switch as individuals.

4. Behavior $A$ results in many positive outcomes that reinforce behavior $A$, but occasionally lead to very bad side effects that suggest behavior $\bar{A}$ is better—that is, behavior $A$ leads to some outcomes with positive influence and other outcomes with negative influence. An example of this would be a medication that is generally helpful, but has a rare and severe side effect. In this case, behavior $A$ will initially spread rapidly in a population, but may temporarily decrease in frequency, or may no longer occur entirely as individuals begin to experience adverse outcomes.

Additionally, we note that while our general ABM can produce dynamics reminiscent of those that might result from many different types of behaviors, the general ABM will need to be tailored when it is used to model any particular behavior. We discuss how we created a tailored ABM of breast cancer screening behavior in past work. We also describe other ways we might tailor the general ABM in the future. These include an extension to examine cases in which anecdotal information from the social network is sometimes transmitted as information about a behavior only, is sometimes transmitted as information about an outcome only, and is sometimes transmitted as a behavior-outcome pair. In addition, we describe two extensions of the model that could be used to explore the role of culture in social learning. For the first extension, we describe how individuals in different cultures might have different preferences and beliefs for how much information individuals should share with others about their own behaviors and outcomes. For the second extension, we detail a belief hierarchy that describes how individuals in different groups or cultures might have different models of causality related to behavior. For example, the groups might have different beliefs about disease causality, which act as different lenses through which they interpret information they learn about in their social networks.
The authors would like to thank David Kennedy, Ryan Brown, Raffaele Vardavas, Christopher Marcum, Sebastian Linnemayr, and Sarah MacCarthy for their insights and many helpful discussions. We are also grateful for the comments and close reading of the document by our reviewers. Any omissions or oversights are the authors’ responsibility alone.

The content of this report is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health.
## Abbreviations

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
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<tbody>
<tr>
<td>ABM</td>
<td>agent-based model</td>
</tr>
<tr>
<td>NCI</td>
<td>National Cancer Institute</td>
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<td>NIH</td>
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1. Introduction

When engaging in behaviors that may entail risks or outcomes that are unknown or uncertain, individuals often look beyond their own experiences to consider the experiences of others in their immediate social networks. This is social influence at the micro-scale, and it can bring about change in the greater social web in such a way that local social networks may have profound effects on behaviors at the population level. This report describes a general agent-based model (ABM) for studying the ways in which micro-level social influence gives rise to population-level dynamics at the macro-level. ABMs consist of interacting “agents,” which in our case are individuals. These individuals are connected to each other through a social network and can share information about behaviors and experiences with others to whom they are connected. In turn, individuals’ behaviors can be influenced by information they receive from other agents in their social network. The general ABM we developed can be used on its own to examine how social networks influence generic classes of behaviors—that is, groups of behaviors that share certain characteristics (e.g., behaviors for which outcomes are always self-reinforcing)—or it can be tailored in conjunction with surveys to examine specific behaviors.

The first four chapters of this report describe the general ABM, some of its properties, and the dynamics it can display for generic behaviors. In Chapter Five, we will describe how we tailored the general ABM to model a specific behavior—breast cancer screening—using a nationally representative survey to inform the structure and parameterization of the ABM.

We chose this approach of combining ABMs with tailored surveys to model specific behaviors because, when used independently, surveys and ABMs each have their own strengths. ABMs can illuminate the dynamic interactions and feedback loops that complex systems often display. However, these models often rely on behavioral theories or expert judgment to describe behavioral mechanisms and parameters. Because of this, they are sometimes criticized as being “ad hoc” and assumption-laden. Surveys can be used to test and build theory about individual behavior, but they are generally unable to test or explore dynamic interactions and feedback loops. Our approach leverages the strengths of each. That is, the approach allows us to build ABMs that are firmly grounded in an empirical foundation, taking advantage of the benefits of both survey and agent-based modeling approaches.

The general ABM and approach to tailoring it to model a specific behavior that we present in this report were originally developed under two projects funded by the National Institutes of Health (NIH). The first project, *Health Outcomes, Risk Perceptions, and Preventive Behavior on Social Networks*, assessed how people evaluate the relative risks of engaging or not engaging in preventive health behavior using information gathered from their social network. In that project, we developed a general ABM for social learning; and, using breast cancer screening and seasonal influenza vaccination as examples, we developed two tailored ABMs. We designed and
conducted two surveys specifically to inform and parameterize these tailored ABMs. In the second project, *Building an Inter-Disciplinary Network on Culture and HIV Risk*, we used the general ABM to explore key types of dynamics that social learning processes can exhibit for generic classes of behaviors.

**Organization of This Report**

This report is divided into seven chapters. In Chapter Two, we provide greater context to our work by discussing social learning models in general. In Chapter Three, we describe our general ABM. In Chapter Four, we discuss some of the types of population-level dynamics that arise from the general ABM for various classes of generic behaviors subject to social influence. In Chapter Five, we describe how, in past work, we used a survey of women’s breast cancer screening decisions to tailor our general ABM to create breast cancer screening ABM. In Chapter Six, we describe additional ways that we envision tailoring the general ABM in the future. In Chapter Seven, we provide a summary and conclusions.
This chapter presents background on theoretical models of decision making and social learning, as well as background on simulation models of social learning.

Theoretical Models of Decision Making and Social Learning

A great deal of research and work has focused on developing behavioral models of how individuals make decisions in general (Tversky and Kahneman, 1974; Kahneman and Tversky, 1982; Bandura, 1986; Ajzen, 2011) and health behavior decisions specifically (Janz and Becker, 1984; Bandura, 1998). Many of these models describe how individuals’ past experiences and the experiences of those they know may influence individuals’ decisions (and, in turn, their behaviors). While these models differ somewhat in the specific pathways and predictors of behavior that they propose, they share common themes.

Figure 2.1 shows our overall theoretical framework, which draws on this past literature and focuses on social and psychological factors.

*Intention may be influenced by other factors not shown, such as demographic and cultural factors.
Determinants of Intention and Behavior—Individual Level

**Box A** in Figure 2.1 shows individuals’ beliefs about behavior and risk. One key set of decision-making determinants includes an individual’s perceived likelihood of good or bad outcomes that may result from a behavior (Janz and Becker, 1984; Bandura, 1986; Ajzen, 2011) and the level of confidence or uncertainty in his or her knowledge of the outcome’s likelihood. **Box B** shows individuals’ perceived norms: Perceptions about others’ attitudes and behaviors can influence an individual’s decision making. **Box C** in Figure 2.1 shows individuals’ self-efficacy: An individual’s perception of his or her ability to control their own behavior and health outcomes is a key predictor of intention and actual behavioral change (Bandura, 1977). **Box D** shows individuals’ intention. The factors in boxes A through C influence individuals’ intentions to change their own behavior (links 1–3 in Figure 2.1). Intention is also likely influenced by other factors, including demographic and cultural factors (not shown in the figure).

**Behavior:** Intention then influences behavior (link 4). Even when individuals have an intention to change their behavior, self-efficacy can facilitate or inhibit change in behavior (link 5). Beyond social and psychological factors, other factors not shown in Figure 2.1 may act as facilitators or barriers that influence the link between behavioral intention and actual behavior. These include environmental factors that might facilitate or inhibit behavioral change.

**Outcomes:** Outcomes depend on individuals’ behaviors (link 6). They may also depend on other factors (not shown). For example, the outcome of an individual’s vaccination decision (whether the individual becomes infected) will also depend on the vaccination behaviors of others in the population. Outcomes also act as feedback informing future beliefs (link 7).

Information Is Transmitted in the Social Network

Links 8, 9, and 10 in Figure 2.1 show how information about an individual’s behavior can be transmitted to their social network. In some cases, those in the social network will generally see just a behavior and not an outcome (**Box G**). For example, when individuals take on large amounts of personal debt, their spending (the behavior) will be more observable than their finances (the outcome). In other cases, combined information about a behavior and outcome is likely to be transmitted together (**Box H**). In prior work, we found that most of the time, when women learn about breast cancer diagnoses of others they know, they are aware both of the screening behaviors and prognoses of the women diagnosed (Nowak and Parker, 2014). Finally, sometimes an outcome is more observable than a behavior; for example, if an individual overeats when alone, the likely resulting overweight and obesity are highly observable, whereas the health behavior is not (**Box I**).

Social Networks Influence Behavioral Factors at the Individual Level

Link 11 in Figure 2.1 shows how coupled social network information about behavior and outcomes can influence others’ beliefs about the behavior. Individuals often use the ease with
which they can recall or imagine certain events, also known as the availability heuristic, to estimate the likelihood of such events (Tversky and Kahneman, 1974; Rotliman and Schwarz, 1998). Therefore, they often will perceive outcomes as more linked to certain behaviors when they can more easily recall instances of that decision-outcome pair, such as those they have observed in their social networks. For example, individuals might be more likely to perceive vaccination as effective when they can recall many instances of others becoming ill with vaccine-preventable disease after not being vaccinated and recall few, if any, instances of others becoming ill with vaccine-preventable disease after being vaccinated. This type of influence is also a key part of the theory of diffusion of innovations, which describes the factors that influence the dynamics of adoption of a new technology (Rogers, 2003). The theory describes how individuals’ willingness to adopt a new technology increases when they observe others benefit from adopting the innovation (Valente, 1996).

Link 12 in Figure 2.1 shows how observing the outcomes of others in the social network can influence norms and lead individuals to emulate others they know. While some definitions of emulation include copying others’ behaviors, we are adopting the definition that uses “imitation” to refer to copying the behaviors of others and “emulation” to refer to trying to achieve the same outcomes that others have (Huang and Charman, 2005; Whiten, McGuigan et al., 2009). For example, an individual might try to emulate the lifestyle of wealthy individuals he or she knows without taking the same path to make money.

Link 13 in Figure 2.1 shows how directly observing the behavior of others in the social network can influence perceived norms about the frequency with which others are engaging in that behavior (Bikhchandani, Hirshleifer, and Welch, 1998). The ability of the social network to affect perceived norms has been extensively studied, both empirically (Christakis and Fowler, 2007, 2008) and using mathematical simulation (Dodds and Watts, 2004). Social contagion models describe how behaviors can spread through a population; as behaviors in a social network become more common, they tend to also be perceived as more common, increasing the likelihood that others will adopt the behavior. Link 14 shows how observing others successfully execute a behavior can increase self-efficacy. Past research has shown this sort of observations as a key influencers of self-efficacy (Cialdini and Goldstein, 2004).

The Architecture of Our General ABM

To more tractably be able to represent the social learning process in a simulation model, we developed an architecture for the general ABM (shown in Figure 2.2) that is a simplified version of the full theoretical framework (shown Figure 2.1). We use this architecture as the basis for our general ABM and for our analysis of survey data to inform the parameterization of tailored ABMs. In the general ABM, we track the “propensity” to engage in a particular behavior, which incorporates beliefs, norms, self-efficacy, and intention, as well as other external factors such as access and barriers. This propensity determines the probability with which the individual makes
a particular decision, and behaves accordingly; then, he or she will experience an outcome as a result of that behavior. The individual’s experience can be relayed to others in the social network. Social network influences are described as “anecdotal information” in Figure 2.2.

Figure 2.2. Architecture for Our General ABM

In each subsequent behavioral decision, after receiving anecdotal information from social networks, individuals’ propensities will be influenced both by experiences they have had in the past and by new anecdotal information they have learned through their social networks. These updated propensities may lead individuals to engage in different behaviors in each new iteration, and these processes of feedback and updated decision making can continue.

Simple Models Can Lead to Important Insights

Our general ABM is greatly simplified compared with the way many processes involving real-world decision making play out. However, simple simulation models can provide fundamental conceptual insights into at least an initial set of plausible options for policymakers. Here, we describe some past simulation models of social learning by way of offering context for our general ABM.

Game theory, as developed by researchers at RAND and beyond, is one area where simple models made clear policy contributions by helping to clarify the range of viable and non-viable policy actions (Wagner, 1958; Schelling 1980). Our models focus on the basic mechanisms for individual and social learning; these models take a different approach to modeling collective behavior than game theoretic models do. Game theory considers individuals as actors who use deductive reasoning—applying general theory to determine their specific actions—and who react to global states and global outcomes. In contrast, in social learning models, individuals use
inductive reasoning—applying multiple observations to reach a general theory/conclusion—to extrapolate from their personal experiences and the behavior and experiences of others they know personally.

Models of vaccination behavior are one area in which game theoretic models and social learning models draw upon very different behavioral mechanisms. Game theoretic models assume that individuals deductively estimate the likelihood of contracting a vaccine-preventable disease based on disease transmission parameters and the proportion of the population that is vaccinated (Bauch and Earn, 2004). In these models, the likelihood that an individual decides to be vaccinated decreases as a greater fraction of the overall population becomes vaccinated because individuals are more likely to be protected from the disease by herd immunity even if they are not vaccinated when others in the population are vaccinated.

However, in prior empirical work, we found that most individuals do not consciously consider the herd immunity effect in influenza vaccination decisions; instead, they report being more likely rather than less likely to vaccinate as vaccination rates increase among those around them (Parker, Vardavas et al., 2013). In prior modeling work, we found that these two different assumptions—that individuals consciously consider herd immunity and are likely to do the opposite of what those around them do or that individuals conform to what others around them do—lead to very different predicted dynamics and levels of vaccination (Bodine-Baron, Nowak et al., 2013).

**Simple ABMs of Social Learning Can Produce Complex Emergent Patterns of Behavior**

Prior ABMs (Granovetter, 1978; Hegselmann and Krause, 2002; Schelling, 2006) have shown how even very simple agents can exhibit complex emergent patterns of behaviors. For example, Franz and Matthews (2010) showed that cultural traditions with adaptive behaviors (behaviors that increase the chance of survival and success), neutral behaviors (those that neither increase nor decrease the chance of survival and success), and maladaptive behaviors (those that decrease the chance of survival and success) all could emerge from models in which agents had even a mild tendency to mimic the behavior of a single randomly observed alter (social network neighbor). The agents in that model did not learn anything about outcomes nor did they have any bias toward the behavior most common in the group (i.e., no peer pressure or conformity bias). Despite the simplicity of these agents, simple social learning interacted with simple reinforcement learning curves and the network structure to produce behavior that was durable over time, typical of the entire social group, and could be adaptive, maladaptive, or adaptively neutral.

The simplicity of ABMs, however, can derive important and unexpected insights. For example, work by Nunn and colleagues (Nunn, Thrall et al., 2009) showed how many cognitive biases for social influence had little effect on the final population-level distribution of behaviors. One such bias that did not affect population-level behavior was bias by which individuals preferentially copy the behavior of other “prestigious” individuals. An example of a behavior
that directly benefits individuals beyond any social benefit would be individuals using different methods to relieve pain in which one pain relief method is more effective than others. Therefore, while these cognitive biases are much researched, and while there may be important heuristics by which individuals arrive at adaptive behaviors (Boyd and Richerson, 1985; Henrich and Boyd, 2001; Henrich and Gil-White, 2001; Boyd and Richerson, 2005), they may be less important to the equilibrium state of a population when some learned behaviors carry greater extrinsic benefits than do others.

On the other hand, ABMs that model behaviors whose value is defined solely by social norms (such as style of dress) appear to confirm that cognitive biases can play an important role to the final distribution of behaviors and structuring of social groups (Wildman and Sosis, 2011). Empirical confirmation of this phenomenon is demonstrated in the finding that a bias to adopt a trait of the majority of one’s social contacts (e.g., conformity bias, peer pressure, social reinforcement) fundamentally alters the transmission of behaviors on experimental networks (Centola, 2010). Because people display conformity bias, behaviors can propagate better in highly clustered networks than in “small world” networks in which there is actually a shorter average path between all individuals (Centola, 2010).

Our General ABM Builds on Prior ABMs of Social Learning

Agents are simulated individuals who obey decision rules that define their learning mechanisms. Agents in ABMs usually are not completely deterministic, and they exhibit some random variation in their behaviors just as real people exhibit a seemingly random (or at least idiosyncratic) aspect to their behavior, given our limited abilities to quantify actual behavioral inputs and outputs.

In what follows we demonstrate several conceptual insights about how local social network influence occurring at the micro-scale can influence the dynamics of how behavior and outcomes evolve in the population-level social network. In addition, the general ABM we have developed lays a foundation one could build on to model many specific policy situations by suitably parameterizing our models based on empirical findings. This task of parameterizing an ABM to then use it for more focused prediction tasks is a wholly different and additional use of ABMs from the attempt to gain high-level conceptual insights.

Most prior ABM work on social learning has modeled two distinct learning processes: (1) an individual learning process in which individuals learn from their own positive and negative experiences and are more likely to repeat behaviors that led to positive outcomes and are less likely to repeat behaviors that led to negative outcomes; and (2) a social learning process in which individuals observe the behaviors of others and are more likely to copy the behaviors they observe most frequently in others (regardless of whether the outcomes are beneficial or not). Note that this means that these prior simulation models focused on links 13 and 14 in Figure 2.1, and did not include information transmission in links 11 and 12 in Figure 2.1.
Some of this prior work has emphasized social learning more than individual learning in order to understand how social influence propagates. This is in part because many prior ABMs have focused on testing scenarios for the initial bio-cultural evolution of social learning in other animals. In most other species, social learning capabilities appear limited to attention being drawn to the behavior itself rather than to the outcome (Franz and Matthews, 2010), although chimpanzees, the nearest evolutionary relatives to humans, appear to have some abilities to mimic the outcomes of observed actions (Nagell, Olguin, and Tomasello, 1993).

In early social learning work that modeled both social and individual-level learning, agents were often either individual learners or social learners (Rogers, 2003). However, more recent models have allowed individual agents to use both social learning and individual learning processes (Nunn, Thrall et al., 2009; Franz and Matthews, 2010). Our model follows the more recent literature that incorporates both individual and social learning components within each agent; this more realistically captures how human learning takes place and conforms better to the sort of mixed social/individual learning strategies that are known to produce more adaptive behaviors in prior ABM work (Laland and Kendal, 2003).

In addition, unlike prior social learning ABMs, our general ABM conceptualizes social learning as a process by which observers attend to the coupled behaviors and outcomes of the behaviors of their social connections, rather than attending to the behaviors themselves. Therefore, in our general ABM, agents react to both the positive or negative experiences from their own behaviors and to the positive and negative experiences they observe in their social connections to update their probability of subsequently engaging in the behavior. As such, these models conform to long-established knowledge of the basic mechanisms for trial and error reinforcement learning (Bandura and Walters, 1977).

We made this assumption, in part, to render the individual learning and social learning mechanisms more parallel computationally, but this assumption also matches an often hypothesized mode of influence for health behaviors or criminal behaviors (Conger, 1976). It is by this means, for example, that the deterrent effects of swift and certain punishment of criminal acts by law enforcement are thought to operate (Akers, 1990). The public punishment in fact spreads knowledge of the crime more widely than if the criminal were never caught. Thus, if individuals attended only to the behaviors (crime) themselves, such punishments would increase the criminal act in question, but observers of course also attend to the punishment (i.e., the outcome of the act).

In policy applications, a complete model would incorporate social learning based on observations of behaviors, outcomes, and coupled behavior-outcome pairs (G, H, and I from Figure 2.1). Although people are capable of incorporating outcome information, prior research shows they do not always attend to outcome information, and often simply mimic behaviors of others. For example, when humans learn to use tools, they exhibit strong tendencies for “over-imitation,” whereby they copy arbitrary forms of behaviors clearly unlinked to any difference in outcome (Whiten, McGuigan et al., 2009; McGuigan, Makinson, and Whiten, 2011). Although
this finding was first demonstrated in children, McGuigan, Makinson, and Whiten (2011) showed adult observers exhibited the tendency even more strongly than did 5-year-old observers. Children in these experiments tended to explain their own copying of actions they recognize are outcome-irrelevant by saying they figured the adult observer had some purpose for doing it (Kenward, Karlsson, and Persson, 2011), while adults explained their own behavior by saying they assumed part of the purpose of the experiment was to copy the observer precisely (McGuigan, Makinson, and Whiten, 2011). To add further nuance to these findings, in experiments where children could choose to copy and seek out information from adults who were providing information children knew to be either true or false, children as young as 3 years old preferentially copied adults who had demonstrated themselves to be accurate informants (Koenig and Harris, 2005).

Therefore, evidence exists for social learning both by copying behaviors themselves irrespective of outcome and by attending to outcomes. How these social learning tendencies play out for health behaviors may have much to do with the time lag for the realization of outcomes; some outcomes from some health behaviors are nearly instant, while other outcomes may not become apparent for decades. One health behavior that can quickly produce outcomes over both short and long time scales is sun exposure; an individual may tan or experience a sunburn within a few hours of sun exposure. In contrast, the effects of sun exposure on the risk of skin cancer can take years or decades to materialize. Thus, social learning of whether or not to limit sun exposure may be more influenced by individual and social network experience with tanning and sun exposure than by individual and social network experience with skin cancer. Of course, when an individual develops skin cancer, he or she may relay both the outcome (skin cancer) and the behavior (sun exposure over prior years and decades) to others in his or her social network. Therefore, a long gap between behavior and outcome does not necessarily mean that information about the behavior and outcome will be uncoupled as social network information. The effects of diet, exercise, and long-term health effects of alcohol consumption (as opposed to the short-term, immediate effects of inebriation) may all lie somewhere in the middle in terms of observers’ ability to integrate outcome information, as these behaviors all produce observable outcomes that are delayed by months or years from the original onset of a given behavioral habit.

The differences in whether behaviors, outcomes, or both are socially learned are important not only for policy interventions directed at individuals but also for predicting the emergent dynamics of the system. For example, Bentley, Earls et al. (2011) argued that behavioral copying causes the rise and fall of largely equivalent consumer products (e.g., models of computers or cars) to display population-level dynamics predicted by random copying. Such dynamics produce repetitively shaped curves for rise and fall in popularity, but without ability to predict \textit{a priori} that particular products will become popular (Bentley, Earls et al., 2011).

We will return to this discussion of cases in which information about only behaviors or only outcomes is transmitted through the social network in Chapter Six, where we discuss potential ways to tailor our general ABM.
3. Our General ABM

In this chapter, we describe how we mathematically implement our general ABM, which is based on the architecture in Chapter Two, Figure 2.2. Specifically, we detail how we model the many outcomes that can result from each individual’s behavior, the way information about the behavior and outcomes is transmitted through the social network, the way in which an individual’s own past experiences and the experiences he or she learns about through the social network inform the propensity for future behaviors, and the way that we model the relationship between the propensity to engage in a behavior and the actual behavior itself. We will also describe how the simulation iterates through these processes; these iterations represent how a behavioral decision an individual repeatedly makes influences and is influenced by the behavior of others (as shown in Chapter Two, Figure 2.2).

Every Behavior Has Many Possible Outcomes

Figure 3.1 illustrates how different outcomes may result from a behavior using the example of vaccination. This case includes six different possible outcomes following vaccination or non-vaccination. A vaccinated individual can ($E_1$) become ill but not experience any side effects of vaccination, ($E_2$) neither become ill nor experience side effects of vaccination, ($E_3$) both become ill and experience a side effect of vaccination, or ($E_4$) not become ill but experience a side effect of the vaccine. Each of these outcomes occurs with some probability, and the sum of these probabilities, given the behavior to vaccinate, will be one.

A person who is not vaccinated may ($E_5$) become ill or ($E_6$) not become ill. Similar to the case where the individual is vaccinated, the probabilities of outcomes five and six occurring, given that the individual was not vaccinated, will sum to one. Note that we consider not becoming ill following vaccination and after not vaccinating to be two separate outcomes. This is because the individual likely interprets these two outcomes very differently. For example, not becoming ill following vaccination may be seen as evidence of the vaccine’s efficacy, while not becoming ill following non-vaccination may be viewed as evidence that the vaccine is unnecessary. Similarly, we consider becoming ill following vaccination and following non-vaccination to be different outcomes.
In general, the parameters that determine the probabilities of different outcomes, given individuals’ behaviors, will come from the literature rather from a survey, as the processes are largely biological. For example, in a model of influenza vaccination, the probability of getting the flu given vaccination and non-vaccination will be driven by an empirically based disease transmission model. In contrast, the effects of past behaviors and outcomes on future behaviors will be based on results from a survey, as these processes are largely psychological.

**Experiences Are Transmitted Through the Social Network**

Next, we model how experiences are transmitted through the social network. As shown in Figure 3.2, each time an individual has an experience (defined as a coupled behavior/outcome pair), he or she will (with some probability) relay the experience to others in the social network in the form of anecdotal information.
Figure 3.3 shows how we model the transmission of anecdotal information in the simulation model. We assume that the number of people informed about a particular experience will depend on the experience itself. For example, if an experience is mundane or embarrassing, few people may be informed. If an experience is sensational, many people in the social network may be informed. In this case, the person illustrated by the black node at the center of the graph has two experiences, colored orange and teal (representing an initial individual’s experience), where the teal experience is more sensational. Four neighboring individuals in the network—so-called alters—are informed about the teal experience, while two are informed about the orange experience. Subsequently, each individual who is informed about the teal experience informs two others about the black node’s experience, and each individual who learns firsthand of the orange experience informs one other individual about the black node’s orange experience.
As a practical matter, in our breast cancer work, we did not model the effect of secondhand and thirdhand accounts, because it is difficult to gather information about secondhand or more distant accounts in a survey (Nowak and Parker, 2014).

In our framework, we empirically estimate the number of people who are informed for each experience type. Figure 3.4 provides an example where individuals illustrated by black nodes have a particular experience. They then inform other individuals (illustrated by red nodes) in the social network about that experience. The question we seek to answer empirically is the number of red nodes (or arrows) per black node. In this example, two individuals are informed about the experience per individual with the experience.

Empirically, in the survey, we ask respondents to report about key experiences they have learned of firsthand. For example, we may ask how many people the respondent knows that were diagnosed with breast cancer in the previous year. We then divide the rate of learning firsthand about the experience with the population-level rate of the experience, usually from the literature. For example, if 10 percent of women report learning firsthand of at least one breast cancer diagnosis in the previous year, and women who learn about breast cancer diagnosis learn about them from two alters on average, and approximately 0.1 percent of women are diagnosed with breast cancer each year, we conclude that 0.1*2/0.001 = 200 women on average are told firsthand when another woman is diagnosed with breast cancer. The formula for this expression is:

\[ \text{# women informed per diagnosis} = \left( \frac{\text{percentage of women who learn about any diagnoses firsthand}}{\text{percentage of women in the population who are diagnosed each year}} \right) \times \left( \frac{\text{average # of alters they learn from}}{\text{average # of alters}} \right) \]

**Individuals, Propensity, and Behaviors**

At this point, we will skip ahead and describe how we define and model an individual’s propensity to engage in a certain behavior (Figure 3.5), which will allow us to then go back and describe how this propensity is affected by the individual’s experiences and anecdotal
Figure 3.5. An Individual’s Propensity Determines the Likelihood of Future Behaviors

For each individual $i$, we define the probability $\omega^i_n$ that individual $i$ will engage in behavior $A$ in iteration $n$ as:

$$\omega^i_n = \logit^{-1}(s^i_n) = \frac{\exp(s^i_n)}{1 + \exp(s^i_n)},$$

where $s^i_n$ is the individual’s propensity at iteration $n$. We define a propensity because it is more convenient mathematically in the simulation to track a propensity whose value is unbounded (it can take on values from $-\infty$ to $\infty$) and then later rescale it to a probability, which must take on values only between 0 and 1. Note that the $i$ here is the index for an individual, not an exponent. Figure 3.6 graphically shows the relationship between the probability of engaging in behavior $A$ (given by $\omega$) and the propensity $S$. When the propensity is very negative, the probability of behavior $A$ is near zero, and when the propensity is very large and positive, the probability of behavior $A$ is near one. This formulation for updating an individual’s probability of behavior $A$ differs from many prior ABMs, which often keep a weighted tally of the times a particular choice and strategy pay off, which is normalized to a probability (Vardavas, Breban, and Blower, 2007). While this has the advantage of being a simple and intuitive mechanism, estimating parameters governing how different payoffs are weighted and how the probability is normalized from empirical data is not straightforward. In contrast, the construction we use allows us to easily estimate many of our parameters empirically using logistic regression.
Iterative Changes in an Individual’s Propensity

Next, we describe how each individual’s propensity changes from iteration to iteration with the simulation (Figure 3.7).

First, we need to define several model parameters and variables. We assume that every experience $j$ has an associated weight $\Delta_j$, which describes how learning about someone having experience $j$ affects an individual’s behavioral propensity in the future. We will describe these weights in more detail later in this section. We define $m_{j,n}$ to be the number of times individual $i$ had experience $j$ or learned about an alter having experience $j$ during iteration $n$. There is no constraint on the sum of the experience weights $\Delta_j$ over all experiences $j$—for example, they do not need to sum to 1. We assume that the propensity of individual $i$ at iteration $n+1$, $(S_{n+1}^i)$ is given by Equation 3.1:

$$S_{n+1}^i = \sum_j m_{j,n} \Delta_j + \nu(S_n^i - D^i) + D^i.$$  Eqn 3.1
The change in propensity that results from individual $i$ learning about alters who have had outcomes $j$ is given by the term $\sum_j m_{ij,n} \Delta_j$, so that the change in propensity corresponding to each outcome is equal to the weight of that experience multiplied by the number of times the individual had or learned about that experience in iteration $n$.

To illustrate how relative experience weights can affect such a model, consider the hypothetical example of how an individual who is learning inductively might update his or her propensity to take a bet in which the possible outcomes are a loss of $10 or a win of $100, as depicted in Figure 3.8. In this case, there are two possible outcomes, so $j$ can take on values 1 or 2, with corresponding weights $\Delta_1$ (loss) and $\Delta_2$ (win). For a risk-neutral, rational individual to have no preference about whether or not to take the bet, he or she would need to learn about ten losses for every one win. Therefore, the weight of a loss would be equal to $-1/10$ times the weight of a win, or $-10\Delta_1 = \Delta_2$, as shown in Figure 3.8. In other words, if this individual heard about others losing $10 in a lottery ten times as often as he or she heard about individuals winning $100, the propensity to play the lottery would be zero, and he or she would be as likely to play as not to play. A risk-averse individual might weigh losses more heavily than gains, so that $-10\Delta_1 > \Delta_2$.

**Figure 3.8. The Meaning of Relative Experience Weights for the Question: Should You Play the Lottery? (Risk-Neutral, Rational Individual)**

There are several important features of our general ABM that are worth noting here. First, the modeling framework treats social experience as equivalent to individual experience. In reality, individuals probably weigh their own experiences more than the experiences of others, but this assumption simplifies our initial analysis and exploration of the dynamics that result from this simulation model. Future extensions could address this differential weighting.

Another assumption of the ABM is that social influence depends on the number of observed outcomes rather than the average of alter experiences. This means that, generally speaking, individuals with more social connections (i.e., alters) will be subject to a greater amount of social influence than will individuals with fewer alters. In addition, we assume all alters have the same amount of influence on the individual. In reality some alters (like social network acquaintances) might have less influence than others (like close friends or family members).
Previously, we discussed how the *relative* values of the different weights affect the model dynamics. The *absolute* magnitudes of the experience weights affect how long (the number of iterations) that having or learning about an experience will affect an individual’s propensity. In Equation 3.1, the terms $\nu(S_n - D^i) + D^i$ have the effect of pulling the propensity back toward a default state given by $D^i$. The default propensity is the propensity an individual has for a particular behavior in the absence of personal or social network experiences. In our general ABM, it is usually zero (neutral between behaviors $A$ and $\bar{A}$), but in tailored models, it is typically informed by the empirical results from our survey. We’ll describe this in more detail in Chapter Five. The further the current propensity ($S^i$) is from the default propensity ($D^i$), the longer it will take for the propensity for engaging in behavior $A$ to become close to the default propensity. Figure 3.9 shows a simple example. If an individual starts at the default propensity, and learns about an experience with a large positive weight (shown as the top green arrow), it will take more iterations for the propensity to decay back to the default than if the individual learns about an experience with a more modest experience weight.

**Figure 3.9. The Duration of an Experience’s Effect Depends on the Magnitude of the Experience Weight**

In addition to dictating the duration of an experience’s effect, the sizes of the weights determine how definitively learning about different social network outcomes affects an individual’s future behavior. Figure 3.10 shows a graphical example of this. The horizontal axis, $S$, is the propensity and the vertical axis, $\omega$, is the probability of making decision $A$. If an experience with a positive weight also has a large magnitude, in the absence of other effects, starting from a propensity of zero, learning about this experience will cause an individual’s probability of behavior $A$ to move very close to 1. If an experience has a positive weight but its magnitude is small, an individual who starts from propensity zero and learns about the experience will more likely engage in behavior $A$ than behavior $\bar{A}$, but the probability of engaging in behavior $A$ may not be much greater than 50 percent.
Figure 3.10. Large Experience Weights Drive Behavior More Definitively Than Smaller Experience Weights
4. Results from Our General ABM

This chapter describes some of the various emergent properties we have been able to produce using our general ABM. One of the most important determinants of the dynamics that the model exhibits is whether each behavior, $A$ and $\bar{A}$, tends to lead to experiences that support the same behavior, or whether they lead to experiences that support switching behaviors. While the models described below are fairly stylized and are, for the most part, simpler than models we would develop for a particular problem (Nowak and Parker, 2014), they can begin to realistically capture the essential dynamics for representative classes of behaviors.

We will examine the following classes of models in this chapter:

1. Class 1—unidirectional behaviors: Outcomes of both $A$ and $\bar{A}$ suggest that $A$ was the better behavior.
2. Class 2—confirming behaviors: The outcome of behavior $A$ suggests that behavior $A$ is a good choice, and outcomes from $\bar{A}$ suggest that $\bar{A}$ is a good choice.
3. Class 3—non-confirming behaviors: The outcome of behavior $A$ suggests that behavior $\bar{A}$ is the better choice, and the outcome of behavior $\bar{A}$ suggests that $A$ is the better choice.
4. Class 4—dual-outcome behaviors: Behavior $A$ results in many positive outcomes that reinforce behavior $A$, but occasionally leads to very bad outcomes that suggest behavior $\bar{A}$ is better.

Parameters for Our General ABM

When considering the model dynamics demonstrated by these four classes of models listed, it is first helpful to lay out a few key parameters needed to specify these models (Table 4.1). $S_{\text{init}}$ is the initial value for the propensity for all individuals and $D_i$ is the default propensity for individual $i$ (which we set to be equal for all individuals in the models we present here). Earlier, we described how outcomes are sometimes complex functions of behaviors individuals engage in. For example, when we model infectious disease, an individual’s probability of becoming infected could depend not only on the preventive measures he or she takes, but also on the preventive measures taken by others in the social network and broader population, because herd immunity is an emergent property of the social network. For the discussion in this chapter, we temporarily set aside this complexity and model cases in which the relationships between behaviors and outcomes are very simple. When individuals engage in behavior $A$, outcome $j$ occurs with probability $\pi_j$, and when an individual engages in behavior $\bar{A}$, outcome $j$ occurs with probability $\rho_j$. In these models, we are considering outcomes to really be coupled behavior-outcome pairs (e.g., being diagnosed with breast cancer after being regularly screened would be considered a different outcome from being diagnosed with breast cancer after not being regularly
screened). For that reason, in the models we present here, $\pi_j \neq 0$ only if $\rho_j = 0$ and $\rho_j \neq 0$ only if $\pi_j = 0$. An alternative model would allow individuals to attend to outcomes alone. In that case, $j$ might represent only an outcome, not a coupled behavior-outcome pair. In that case, both $\rho_j$ and $\pi_j$ could be non-zero.

We previously described the experience weights $\Delta_j$. Another important parameter related to the experience $j$ is the fraction of the social network that an individual tells about having that experience, which we call $\eta_j$. We also previously described the memory parameter, $\nu$.

Finally, we also introduce several parameters related to the network structure. All of the models we present here are run on small-world networks (Watts and Strogatz, 1998), which can be described by $N$, the total number of individuals in the network; $k$, the number of social network ties each individual has; and $r$, the rewiring probability, which is the probability that when we construct a network, we will “rewire” a link initially connected to a nearby node to a node that is far away. We choose to use small-world networks because they display the property that they have “neighborhoods,” which are groups of individuals within the network in which almost any two individuals are connected to each other. Most other network structures that can be described with only a few parameters do not have this property. These network neighborhoods allow us to examine how similar we might expect behaviors to be within groups of highly connected individuals in a real-world context. Neighborhoods in a small-world network might represent physical neighborhoods, workplaces, schools, or members of a religious or community organization in a real-world context. We will describe small-world networks in more detail later in this chapter.

### Table 4.1. Full Parameter List

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S_{init}$</td>
<td>Initial values for the propensity at iteration $n = 1$</td>
</tr>
<tr>
<td>$D'$</td>
<td>The default propensity for individual $i$</td>
</tr>
<tr>
<td>$\pi_j$</td>
<td>Probability of outcome $j$ given behavior $A$</td>
</tr>
<tr>
<td>$\rho_j$</td>
<td>Probability of outcome $j$ given behavior $\bar{A}$</td>
</tr>
<tr>
<td>$\Delta_j$</td>
<td>Experience weight associated with behavior $j$</td>
</tr>
<tr>
<td>$\eta_j$</td>
<td>Fraction of network ties an individual informs when they have experience $j$</td>
</tr>
<tr>
<td>$\nu$</td>
<td>Memory parameter</td>
</tr>
<tr>
<td>$k$</td>
<td>Number of network ties (neighbors) each individual has</td>
</tr>
<tr>
<td>$N$</td>
<td>Total number of individuals in the network</td>
</tr>
<tr>
<td>$r$</td>
<td>Rewiring probability (for small world networks)</td>
</tr>
</tbody>
</table>
Class 1 Models—Unidirectional Behaviors: All Outcomes Suggest One Choice Is Better Than the Other

The first class of models contains models in which all outcomes (that result either from behavior $A$ or behavior $\bar{A}$) suggest that $A$ is the better choice, meaning that they all have positive weights. We call these model behaviors “unidirectional.” One way to think about these models is that all outcomes “lead” individuals to the same behavior, as shown in Figure 4.1. Results are identical when all experience weights are negative, except that the labels $A$ and $\bar{A}$ will be reversed.

Figure 4.1. In Unidirectional Behaviors, All Outcomes Suggest One Choice Is Better Than the Other

In this class of model, the fraction of individuals engaging in behavior $A$ eventually reaches an equilibrium after many model iterations between two extremes: the default state and the state in which all agents are engaging in behavior $A$. The equilibrium will be near the default state when memory decay is fast (mathematically, this means that the value of the memory parameter, $\nu$, is small), when the experience weights are small, and when few people are informed about outcomes in the social network. Conversely, the equilibrium will be close to the state in which everyone is engaging in behavior $A$ when memory decay is slow, experience weights are large, and many people are informed about outcomes in the social network.

A prototypical behavior that might fall into Class 1 is deciding whether to adopt a new technology that is superior to existing technology, as described by the theory of diffusion of innovations (Rogers, 1995). In this case, adoption of the superior technology is behavior $A$ and non- adoption is behavior $\bar{A}$. For example, consider farmers deciding whether to adopt a new, more-efficient farming technique. Farmers who do adopt the new method will see greater crop yields, an experience which reinforces their behavior ($A$). Those who do not adopt the new technique will see lower crop yields than their neighbors who do adopt the new technology; having this experience will suggest to the non-adopters that adoption is the better behavior. Diffusion of innovation models often have much more richness than the model we describe here; for example, they often incorporate heterogeneity in individuals’ willingness to adopt a new technology, and allow for certain opinion leaders in a network to have greater influence over
behaviors than others (Valente, 1995). Nevertheless, as we show next, even the simple Class 1 model begins to exhibit interesting dynamics relevant to diffusion of innovations.

Figure 4.2 illustrates an example of a Class 1 model with small experience parameters (all values of $\Delta = 0.1$ and other parameters shown in Table 4.2). The figure shows a plot of the fraction of individuals engaging in behaviors $A$ and $\bar{A}$ over time. Note that because these experience parameters are small, the model reaches equilibrium between the default state (defined as 50 percent engaging in behavior $A$ and $\bar{A}$) and all individuals engaging in behavior $A$, but it is much closer to the default state.

![Figure 4.2. Class I Model with Small Experience Parameters](image)

Returning to our example of farmers deciding whether to adopt a more-efficient farming technique, small experience parameters $\Delta$ would correspond to cases in which the new farming technique is only slightly better than the existing technique, resulting in crop yields that are only slightly greater than the yields of farmers using the older technique. As a result, the farmer who adopts the new technology has an experience that only weakly reinforces his behavior, and a farmer who does not adopt the new technology would have an experience that only weakly suggests that the new technology is superior. As shown in Figure 4.2, this could lead to incomplete adoption of the new technology. For the parameters we selected, the equilibrium adoption rate was about 60 percent. Again, the default here was everyone having a 50/50 probability of adoption or non-adoption. This might correspond to a relatively low cost of adopting the new technology. If adopting the new technology were expensive, we could impose a much lower default propensity to adopt the new technology. Alternatively, we could impose different adoption propensities for different groups of individuals, which is often done in the diffusion of innovations literature. That literature describes five groups of adopters, ranging from

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1 In this context, “small” generally means small compared to 1.
early innovators who adopt a technology first to laggards who adopt a technology only after the majority of those they know have adopted it (Valente, 1995). Note that in most simulation models developed to simulate the diffusion of innovations processes, once an individual has adopted a new technology, he or she does not de-adopt. In contrast, in our model, individuals can flip back and forth between behaviors $A$ and $\bar{A}$.

Figure 4.3 shows what happens as we increase the values of all of our experience parameters to $\Delta = 0.5$ (other parameters shown in Table 4.2). As we increase the value of all of the experience parameters to $\Delta = 2$, the equilibrium shifts closer to the “all individuals engage in behavior $A$” state as shown in Figure 4.4 (all parameters other than $\Delta$s are shown in Table 4.2). In terms of diffusion of innovations, this corresponds to an increasing benefit to adopting a new technology compared with the case shown in Figure 4.2, to the point where the new technology is demonstrably and unequivocally superior to a previous technology.

![Figure 4.3. Class 1 Model with Medium Experience Parameters](image)

![Figure 4.4. Class 1 Model with Large Experience Parameters](image)
Table 4.2 shows the parameters we used in our Class 1 model.

Table 4.2. Parameter Values Used in Simulations of Class 1 Models (Figures 4.2–4.4)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
<th>Variable</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( S_{in} )</td>
<td>(-5) (corresponding to 99.3 percent of individuals engaging in behavior ( A ))</td>
<td>( D' )</td>
<td>0</td>
</tr>
<tr>
<td>( \pi_1 )</td>
<td>1</td>
<td>( \pi_2 )</td>
<td>0</td>
</tr>
<tr>
<td>( \rho_1 )</td>
<td>0</td>
<td>( \rho_2 )</td>
<td>1</td>
</tr>
<tr>
<td>( \Delta_1 )</td>
<td>Varies, values shown in figures</td>
<td>( \Delta_2 )</td>
<td>Varies, values shown in figures</td>
</tr>
<tr>
<td>( \eta_1 )</td>
<td>0.02</td>
<td>( \eta_2 )</td>
<td>0.02</td>
</tr>
<tr>
<td>( \nu )</td>
<td>0.85</td>
<td>( k )</td>
<td>20</td>
</tr>
<tr>
<td>( N )</td>
<td>1,000</td>
<td>( r )</td>
<td>0</td>
</tr>
</tbody>
</table>

**Final Points on Unidirectional Models (Class 1)**

When initially describing Class 1 models, we described three different parameters that determine where the model equilibrium will lie. In Figures 4.2 through 4.4, we showed the effect of varying one of those parameters—the experience parameter. It is important to note that what it means to have a “small” or “large” experience parameter depends on the values of the other parameters. For example, slow memory decay could compensate for smaller values of \( \Delta_j \), resulting in an equilibrium in which close to 100 percent of people engage in behavior \( A \). This could occur at smaller values of \( \Delta_j \) than we showed here. Larger rates of information spread could also compensate for smaller experience parameters.

**Class 2 Models—Confirming Behavior: Both Behaviors Are Self-Reinforcing**

The second class of models is those in which both behaviors are self-reinforcing (confirming). That is, all experiences that result from engaging in behavior \( A \) have positive weights, and all experiences that result from behavior \( \bar{A} \) have negative weights (see Figure 4.5). As in unidirectional behavior (Class 1) models, it is possible for the default state to dominate if experience weights are small, memory decay is fast, and information transmission is slow. If the default state does not dominate, initial conditions will matter because whatever the initial condition is will be reinforced through the resulting experiences.
A behavior prototypical of Class 2 is a behavioral decision about joining one of two groups where membership in either group is not objectively better than membership in the other, or where decision makers tend to experience strong confirmation bias when evaluating the outcomes of their decision to join the group. Benefits of group membership may include social benefits derived from in-group cooperation. For example, choosing to follow and identify as a fan of a particular sports team could be considered a Class 2 behavior. Class 2 behaviors would also include those strongly influenced by a learning curve that results in an incentive to keep doing an already practiced behavior as opposed to novel alternatives that require investing practice time before achieving proficiency (Franz and Matthews, 2010).

Again, what we describe here is a highly stylized model—models specifically designed to capture opinion dynamics often capture phenomena such as individuals’ opinions becoming more entrenched with time, which our model does not capture (Hegselmann and Krause, 2002). Nonetheless, we believe it is useful to see how this simple, general model can produce dynamics found in a variety of different classical models.

Figure 4.6 shows an example of a Class 2 model where we started with nearly everyone (99.3 percent of individuals) engaging in behavior $A$ (corresponding to $S_{\text{init}} = 5$). Other parameters used for Figure 4.6 are shown in Table 4.3. Because the behaviors are self-reinforcing, behavior $A$ continues to dominate after many iterations. Figure 4.7 shows the same model with different initial conditions ($S_{\text{init}} = -5$). If we begin with nearly everyone (99.3 percent of individuals) engaging in behavior $\bar{A}$, then behavior $\bar{A}$ dominates for future iterations. Other parameters used for Figure 4.7 are shown in Table 4.3.
Table 4.3. Parameters Used in Class 2 Models (Figures 4.6, 4.7, and 4.10–4.14)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
<th>Variable</th>
<th>Value</th>
</tr>
</thead>
<tbody>
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<td>$S_{\text{ini}}$</td>
<td>+5 or –5, (described in the text)</td>
<td>$D'$</td>
<td>0</td>
</tr>
<tr>
<td>$\pi_1$</td>
<td>1</td>
<td>$\pi_2$</td>
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</tr>
<tr>
<td>$\rho_1$</td>
<td>0</td>
<td>$\rho_2$</td>
<td>1</td>
</tr>
<tr>
<td>$\Delta_1$</td>
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<td>$\Delta_2$</td>
<td>–2</td>
</tr>
<tr>
<td>$\eta_1$</td>
<td>0.02</td>
<td>$\eta_2$</td>
<td>0.02</td>
</tr>
<tr>
<td>$N$</td>
<td>0.85</td>
<td>$k$</td>
<td>20</td>
</tr>
<tr>
<td>$N$</td>
<td>1,000</td>
<td>$r$</td>
<td>0 (unless otherwise noted)</td>
</tr>
</tbody>
</table>

In Class 2 models, in which behaviors are self-reinforcing, if all individuals begin by exhibiting one behavior or the other, that behavior will very often persist. It is interesting to consider what happens to the system if, instead of having a homogeneous starting population, the initial condition contains clusters of individuals, some of whom engage in behavior $A$ and some of whom engage in behavior $\bar{A}$ as their starting condition.

The Watts-Strogatz (Watts and Strogatz, 1998; Kennel and Drake, 2009) networks, also known as “small-world” networks, are a useful class of model networks that we can use to
explore the stability of network clusters. Examples of this network structure are shown in Figure 4.8. In these networks, individuals can be thought of as being on a circular lattice, and they are connected to some number ($k$) of their nearest neighbors. Each connection then has some probability ($r$) of being rewired to a random node in the network. When this probability is zero (as shown on the left-hand side of Figure 4.8), nodes are connected only to their nearest neighbors, and when the probability is 1, the network is completely rewired.

**Figure 4.8. Watts-Strogatz (Small-World) Networks with Increasing Rewiring Probabilities**

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We will now show several simulations run on small-world networks. Figure 4.9 shows an example of how we initialize the small-world network for our cluster experiments. The network shown is much smaller than the network we ran our simulations on, but the structure is the same (nodes in a circle where each is connected to its nearest neighbors). In Figure 4.9, there are two initial clusters: one consists of blue nodes, which represent nodes initialized with a probability of doing $A$ close to 1; and the second consists of red nodes, which represent nodes initialized with a probability of doing $A$ close to 0.

**Figure 4.9. Labeling Points on a Small-World Network**

**Figure 4.10. A Class 2 Model on a Small-World Network with Two Initial Clusters (Each with 500 Nodes) and No Rewiring**
Figure 4.10 shows what happens if we have a small-world network with 1,000 nodes where we start with two groups of individuals—one group that begins engaging in behavior $A$ ($S_{\text{init}} = 5$), and another that begins engaging in behavior $\bar{A}$ ($S_{\text{init}} = -5$). Other model parameters are shown in Table 4.3. The heat map represented in Figure 4.10 shows the position on the circular network (clockwise from the top in Figure 4.9) from left to right, and the iteration in time (over the course of 100 iterations) from top to bottom. Note that, because the agents are connected on a circle, the agent represented at the left edge of the plot is connected to the agent represented on the right edge of the plot. Dark blue represents 100-percent probability that agents at the position engage in behavior $A$, while red represents 100-percent probability that agents at that position engage in behavior $\bar{A}$. Other colors represent intermediate probabilities. Notice that our initial condition was that agents 1 to 500 had 100-percent probability of engaging in behavior $A$ and agents 501 to 1,000 had 100-percent probability of engaging in behavior $\bar{A}$. Over time, we see some spots where agents 1 to 500 have less than 100-percent probability of engaging in behavior $A$, and some spots where agents 501 to 1,000 have less than 100-percent probability of engaging in behavior $\bar{A}$. We also see small boundary regions between the two groups where about half of agents engage in each behavior. However, we still see two distinct groups where each behavior dominates after 100 iterations.

Figure 4.11 shows the results of a simulation in which we decreased the initial group size from 500 to 100 agents. Other model parameters are shown in Table 4.3. In this case, we still largely see stable groups over the course of 100 iterations.

However, if we decrease the initial group sizes to 25 agents as shown in Figure 4.12 (other model parameters shown in Table 4.3), the groups quickly become unstable. Over the course of 100 iterations, we see the emergence of larger, distinct groups of agents where one of the two behaviors dominates. In the Watts-Strogatz model without rewiring, one of the key parameters
Clusters become unstable when the cluster size is similar to the network degree. When the cluster size is large compared with the network degree, many individuals near the center in the cluster will be connected only to others who are also in the cluster, and will therefore receive confirming information. In contrast, when the cluster size is on the order of the network degree or smaller, most individuals will be connected to (and influenced by) both individuals within and outside of their group, which will cause the clusters to become unstable. Other parameters, such as the experience weights, and the information transmission probabilities will also influence the stable cluster sizes. As shown in Table 4.3, in this series of analyses, each individual in the model is connected to 20 others (parameter $k$).

Until now, we have examined a Watts-Strogatz model network with no rewiring (i.e., each individual is only connected to his or her nearest neighbors). Figure 4.13 shows what happens at 10-percent rewiring (other model parameters shown in Table 4.3). At just 10-percent rewiring (whereby a random 10 percent of connections are rewired from a node that is physically close to another random node in the network) and initial conditions of two distinct groups, we see instability emerging over the course of 100 iterations.

Increasing rewiring further to 20 percent, as shown in Figure 4.14, results in one behavior taking over almost entirely by 100 iterations. In this example, behavior $A$ dominated (i.e., most individuals in the model ended up engaging in behavior $A$), but behavior $\bar{A}$ could have dominated just as easily.
Class 3 Models—Non-Confirming Behavior: Each Behavior Suggests the Other Is Better

Next, we will consider a class of models in which each behavior suggests that the other is better, as shown in the schematic in Figure 4.15. These models can exhibit several possible outcomes. As with the other classes of models, the default state may dominate. Other possible outcomes include an equilibrium and oscillation between the two behaviors.

Figure 4.15. In Non-Confirming Behavior (Class 3) Models, Each Decision Suggests the Other Is Better

A prototypical Class 3 behavior would be the choice of a service provider in an industry with low consumer satisfaction, in which negative experiences are relatively common and similar regardless of the particular provider. For example, if an area has only two cable providers (A and A) to choose from, and frustrating experiences are common with both, if someone chooses A, he or she will have experiences that suggest he or she should switch to A; and, if he or she chooses A, he or she will have experiences that suggest he or she should switch to A. Choices in other industries with relatively low customer satisfaction (Radhakrishnan, Grande et al., 2016), such as choice of airline or health insurance company, may exhibit similar dynamics. In the simple model here, observed and experienced outcomes influence agents equally, but we recognize that personal experiences in reality contribute more greatly to behaviors than do observed experiences.

Generally speaking, there are two main types of dynamics we might see in Class 3 models: oscillation—where behavior alternates between A and A—and equilibrium. Oscillation will be more likely when memory decay is fast, experience weights are large, and information transmission is fast. Equilibrium—a case in which population-level dynamics do not change with time—will more likely dominate when memory decay is slow, experience weights are small, and information transmission is slow. Intuitively, when each behavior suggests that the other is better, agents are having a negative experience (“Don’t do that again!”) regardless of their behavior. If memory persists, then once agents have tried both options, they will remember that they (or others they know) have a negative experience no matter what, and will tend to just choose randomly between the two options within the model.

In our simulation model, payoffs of individuals’ behavior are independent of the behaviors of others. Oscillatory dynamics often occur in other types of ABMs in which the payoff function does depend on the behavior of others. One example of such ABMs are those that model free-
rider behaviors (such as vaccination), which can often display oscillations as well (Ma, Gonçalves et al., 2009). Free-rider behaviors occur when an individual benefits from the behaviors of others. Another type of ABM that often displays oscillatory dynamics includes models in which individuals benefit from being in the minority, and therefore tend to do the opposite of whatever behaviors are most common. An early example of this type of model is the classic El Farol bar problem, a game theory problem in which individuals have a positive experience if they go out to a bar that is not too crowded and a negative experience if the bar is too crowded (Arthur, 1994).

Figure 4.16 shows an example of a Class 3 model with the memory parameter set to zero. Other model parameters are shown in Table 4.4. We see oscillation between two extremes of nearly all agents engaging in behavior $A$, then nearly all engaging in behavior $\bar{A}$. Figure 4.17 shows the same results as Figure 4.16 plotted as a heat map. As in Figure 4.16, Figure 4.17 shows that individuals switch from engaging in behavior $A$ in one time step to engaging in behavior $\bar{A}$ in the next time step nearly all in unison.

Table 4.4 shows the parameters we used in our Class 3 model. Note that the oscillations we see in this model are largely dependent on assumption of discrete time steps—everyone engages in the same behavior, and then engages in the opposite behavior in unison. In a continuous time model, individuals engaging in behaviors at different points in time compared with their neighbors would dampen the oscillations.
When we increase the memory parameter from 0 to 0.3, we still observe oscillations, but not all agents engage in the same behavior at the same time as illustrated in Figure 4.18. Other model parameters are shown in Table 4.4. Note that we made the experience resulting from $A$ drive individuals more strongly to behavior $\bar{A}$ than we made the behavior resulting from $\bar{A}$ drive individuals toward $A$ (i.e., the absolute value of $\Delta_1$ is larger than $\Delta_2$; see Table 4.4). Therefore, individuals prefer $\bar{A}$ on average to $A$, which is why the fraction of individuals engaging in behavior $\bar{A}$ is higher on average than the fraction engaging in behavior $A$. (The red line in Figure 4.18 is higher on average than the black line.) Figure 4.19 shows the same data as in Figure 4.18, but plotted as a heat map so that we can see any groups that emerge in the network. First, note that like the memory = 0 case shown previously in Figure 4.17, we see strong oscillations...
horizontal lines indicating that, on average, individuals oscillate in time (which is shown vertically) between the two behaviors. However, unlike the previous case where the lines alternated between all red and all blue, the lines now alternate between mostly red and mostly blue. Second, notice that there are groups (seen as vertical strips in Figure 4.19) in which nearly pure oscillations persist for many iterations (i.e., we see the colors alternate from red to blue), and other groups in which the probability of engaging in either behavior does not change much from iteration to iteration (i.e., the color is yellow-green for many iterations, indicating a mix of behaviors $A$ and $\tilde{A}$). These features can be explained by the stochastic nature of the model.

Initially, the model displays oscillations like those seen in the case with no memory ($\nu = 0$). However, soon some individuals randomly engage in a behavior that is out of sync with most other agents (e.g., they make the same behavior two iterations in a row). This occurs when $\nu = 0.3$ because agents retain some memory of their previous negative experiences with both behaviors. When $\nu = 0$, agents just react to their most recent behavior. Agents who engage in an out-of-sync behavior then influence those around them, creating clusters of individuals who get negative information about both behaviors in the same time step and then begin to randomize their behaviors (green vertical streaks in Figure 4.19). Groups maintain more oscillatory behavior when they have no (or very few) individuals who randomly become out of sync with the group.

Figure 4.20 shows what happens as we further increase the memory parameter to $\nu = 0.85$. Other parameter values are shown in Figure 4.4. In this case, we see that oscillations dampen and the system reaches equilibrium very quickly. Figure 4.21 shows a heat map of this same case. Notice that there are no longer any clear oscillations between $A$ (red) and $\tilde{A}$ (blue). Vertical red streaks, where groups persist in behavior $\tilde{A}$, represent instances in which groups of agents remember a bad experience from behavior $A$ for many iterations.
Special Case of a Class 3 Model: The Influence of Rare, Bad Events

An interesting example related to Class 3 models occurs when there are fairly rare bad events (the non-confirming outcome of a behavior occurs only rarely relative to other Class 3 models we examined). For example, patients or providers choosing between two similar drugs that both have rare, negative side effects could fall into this category of behaviors. The previous examples used parameters that led to adverse outcomes each time individuals engaged in a behavior. Now we will consider adverse events that do not occur frequently, but have large experience weights, and are transmitted broadly throughout the network.

Table 4.5 shows the parameters we used in the rare, bad side effect model. Relative to our previous version of the Class 3 model, we decreased the probability of experiencing outcome 1, given that the individual engaged in behavior $A$ ($\pi_1$), and the probability of experiencing outcome 2, given that the individual engaged in behavior $A'$ ($\rho_2$) from 1 to 0.002; this makes both of these outcomes rare. We also introduce outcome 3, which is neutral (has no effect on propensity) and occurs with a frequency of 0.998 for both behaviors (which is why both $\pi_3$ and $\rho_3$ have value 0.998).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
<th>Variable</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S_{init}$</td>
<td>0</td>
<td>$D_i$</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>(for all individuals, $i$, corresponding to 50% of individuals engaging in behavior $A$ initially)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\pi_1$</td>
<td>0.002</td>
<td>$\rho_1$</td>
<td>0</td>
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<td>$\rho_2$</td>
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</tr>
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<td>$\rho_3$</td>
<td>0.998</td>
</tr>
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<td>$\Delta_2$</td>
<td>10</td>
</tr>
<tr>
<td>$\Delta_3$</td>
<td>0</td>
<td>$\eta_1$</td>
<td>1</td>
</tr>
<tr>
<td>$\eta_2$</td>
<td>1</td>
<td>$\eta_3$</td>
<td>0</td>
</tr>
<tr>
<td>$\nu$</td>
<td>0.95</td>
<td>$k$</td>
<td>100</td>
</tr>
<tr>
<td>$N$</td>
<td>1,000</td>
<td></td>
<td></td>
</tr>
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</table>

We introduce this third outcome because we needed a common, neutral outcome in order to make the negative outcomes rare (because individuals always experience some outcome as a result of their behaviors). We also assume that information about this outcome does not transmit through the social network, and even if it did it would have no effect on the behaviors of others in the social network because we set its weight to zero. For the outcomes that do affect
propensity, we increased the fraction of individuals informed about each behavior $\eta_1$ and $\eta_2$ from 0.1 to 1. We did this because we made the outcomes with weights rare, so we need individuals to inform many others when they have these outcomes in order for there to be high enough levels of information sharing in the networks for us to discern the dynamics. We also increased the average number of social network connections, $k$, for similar reasons. In addition, we increased the value of the memory parameter, $\nu$.

Figure 4.22 shows an example of the dynamics that result when there are rare, bad outcomes. We begin with a fairly homogeneous initial condition in which individuals are equally likely to choose either behavior (horizontal band of green at the top of the figure), and see the emergence of groups of individuals who, when informed about the adverse outcome associated with one behavior, all engage in the other behavior (the emergence of patches of blue [all individuals in the cluster engaging in behavior $A$ for a period of time] or red [all individuals in a cluster engaging in behavior $\bar{A}$ for a period of time]). This homogeneity in choice, however, will break down once either (1) they collectively forget the adverse outcome or (2) members of the group learn about an adverse outcome associated with the behavior they are now currently engaging in. Note that globally, if we were to look at the fraction of individuals making either behavior, the model would appear to reach equilibrium (i.e., the fraction of individuals engaging in behavior $A$ would be relatively constant over time). However, we see rich dynamics at a more local level in the network.

Figure 4.22. Heat Map of Rare, Bad Events Model (Case of the Class 3 Model)

Class 4 Models—Dual-Outcome Behaviors: A Behavior with a Common Positive Outcome and a Rare Negative Outcome

Until now, we have considered models in which each behavior results in only one outcome. However, it will often be the case that a single behavior results in multiple outcomes, some of which have positive weights, and others that have negative weights. In other words, the same behavior may have both desirable outcomes that lead an individual to want to repeat the
behavior, as well sometimes having undesirable outcomes that lead an individual to not want to repeat the behavior. This type of behavior is represented schematically in Figure 4.23. Most real-world behaviors have many possible outcomes. Recall Figure 3.1 in Chapter Three, which showed the outcomes associated with vaccinating and not vaccinating.

**Figure 4.23. Dual-Outcome Behavior (Class 4 Models): Behaviors with Both Positive and Negative Outcomes**

In some cases, the dynamics of such models will be qualitatively similar to the classes of models we have already described, because one outcome will dominate for each behavior. However, for other models, the dynamics may be qualitatively different from the types of models we described earlier. One interesting example is a class of model in which the primary, common outcome associated with behavior $A$ affirms the behavior and has a moderate positive weight. However, there is a rarer outcome of behavior $A$ that has a large negative weight. An example might be a preventive behavior or a drug that works quickly and as intended for most people, but has a fairly rare, but very bad side effect, such as heart attack or stroke. A recently published example of this situation comes from the use of bisphosphonates to treat osteoporosis. Although the benefits of these drugs outweigh the potential costs, their use trades off a reliable benefit through reduced hip and spine fractures against a very rare side effect causing deterioration of the lower jaw (Kennel and Drake, 2009; Crandall, Newberry et al., 2014; Jha, Wang et al., 2015). Our ABM demonstrates that at short time scales the first outcome will dominate, while at longer time scales the rare, negative outcome will affect decision making.

Figure 4.24 shows the dynamics that result from a version of the simulation model with a common positive outcome and a rare negative outcome (such as a drug that typically works well, but has a rare adverse side effect). Table 4.6 shows the parameters we used in this model. Note that behavior $A$ initially spreads rapidly as individuals learn about the positive outcome (the initial rise in the black curve in Figure 4.24). However, as behavior $A$ becomes more popular, it is more likely that an individual in the population will experience the rare, bad event. Once these rare, bad events begin to occur, the behavior $A$ (taking the drug) quickly becomes less common. Behavior $A$ may briefly resurge as groups of individuals eventually forget the bad events, occasionally randomly engage in behavior $A$, and again spread the word about the common, positive outcomes.
Figure 4.25 shows a heat map of the same data shown in Figure 4.24. Initially, we see a quick transition from behavior $\bar{A}$ dominating (e.g., not taking the drug, illustrated in the top band of red) to behavior $A$ dominating (e.g., taking the drug, illustrated in the band of blue immediately below the red band at the top). Shortly thereafter, we see the emergence of groups of agents who learn about the adverse events that can result from behavior $A$ and switch back to engaging in behavior $\bar{A}$ (clusters switching to red). Eventually, these groups collectively forget the adverse outcome, and behavior $A$ (blue) will once again dominate. This process of “forgetting” can take a long time if others close to the group (i.e., who are linked to some members of the group) who are still engaging in $A$ continue to experience the adverse outcome. This effectively refreshes the group’s memory of the adverse outcome.
Table 4.6. Parameters for Class 4 Model

<table>
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<th>Variable</th>
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<td>$D_i'$ (for all individuals $i$)</td>
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</tr>
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<td>$\pi_1$</td>
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<td>$\rho_1$</td>
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<td>1</td>
</tr>
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</tr>
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</tr>
<tr>
<td>$\nu$</td>
<td>0.95</td>
<td>$k$</td>
<td>100</td>
</tr>
<tr>
<td>$N$</td>
<td>1,000</td>
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</table>
In this chapter, we describe our use of a national survey specifically designed to inform and parameterize a tailored version of our general ABM to create an ABM that models breast cancer screening behaviors. We will describe how we used the survey responses to estimate experience weights, the default propensity, and the memory parameter. The goal here is to use surveys for elements of the model in which survey responses are the only or best source of this information, such as knowledge of experiences within an individual’s social network and perceptions of risk. Furthermore, use of surveys allows us to connect these psychological variables with behavioral reports using within-subject analyses, which is not usually possible with publically available population-level statistics (e.g., mammography rates).

Very generally, such surveys contain sections in which we assess (1) respondents’ demographics and other factors that might influence their decision making beyond individual and social experience; (2) past personal behaviors; (3) future likelihood of making either decision $A$ or $\bar{A}$; (4) past personal outcomes; and (5) behaviors and outcomes from the social network.

Breast Cancer Survey Design

In our breast cancer screening work, we gathered information about respondents’ income, education, age, whether the respondent had health insurance, and whether a provider had recently recommended breast cancer screening. We chose these individual-level variables because they had been shown to influence screening rates in prior literature. In addition, we asked whether the respondent had ever had a mammogram; if so, we asked whether she had one in the prior year and in the year before that. Because we were interested in future likelihood of having a routine screening mammogram, we excluded women who reported that they had been diagnosed with breast cancer. A social network portion of the survey asked respondents to report on up to five women whom they knew personally and had ever been diagnosed with breast cancer, with follow-on detailed questions about each of these women (called alters). In our other work on influenza and vaccination, we used an alternate method for gathering social network information, collecting data on so-called egocentric networks, in which we ask detailed information about ten to 20 individuals whom the respondent knew well. We recommend using the egocentric network approach when asking about behaviors or outcomes that are relatively common. For example, had we been primarily interested in screening behavior in the social network, rather than cancer

\[\text{Breast Cancer Survey Design}\]

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diagnosis and outcomes, we would have used the egocentric network approach. However, because breast cancer diagnosis is relatively uncommon (affecting about 0.13 percent of women each year [National Cancer Institute, Surveillance, Epidemiology, and End Results Program, 2013]), we decided that restricting respondents to reporting on ten to 20 individuals whom the respondent knew well might cause us to miss diagnoses that were salient influencers of the respondents’ perceptions of breast cancer screening.

Estimating the Experience Weights and the Default Propensity for the Tailored Breast Cancer ABM

We used the survey data to estimate the weights placed on experience and the default propensity to get a mammogram. Figure 5.1 describes the final logistic regression model, which informed the baseline propensities and the propensity changes in our model. We modeled respondents’ reported future likelihood of having a mammogram\(^3\) as a function of age, education, income, insurance status, provider recommendation, past screening behavior, and indicators for knowing

![Figure 5.1. Specification of the Regression Model Used to Estimate Parameters for Breast Cancer Simulation Model](image)

\[^3\] Note that while our dependent variable is the likelihood of being screened in the next two years, we modeled the decision of annual screening in our ABM. We asked about biannual screening based on the most recent U.S. Preventive Services Task Force recommendations at the time (U.S. Preventive Services Task Force, 2009). However, from our survey, we found that many women were still receiving annual screenings, so we decided to model annual screening rather than biannual screening. Nowak and Parker (2014) describes in detail the sensitivity analyses we conducted to test the validity of using parameters we estimated from a statistical model predicting biannual screening to model annual screening.
someone who was screened and diagnosed with early-stage breast cancer, screened and diagnosed with late-stage breast cancer, not screened and diagnosed with early-stage breast cancer, and not screened and diagnosed with late-stage breast cancer. 4

Five terms in the regression model were significantly associated with future likelihood of having a screening mammogram: age, whether the individual has health insurance, whether their provider recommended screening, the respondent’s past screening frequency, and whether the individual described an alter who had received mammograms and was diagnosed with an early-stage breast cancer. The regression coefficients from the first three of these terms—age, health insurance status, and provider recommendation—inform the baseline propensities, $D^i$.

Two variables—the respondent’s past screening frequency and whether the individual described an alter who had received mammograms and was diagnosed with an early-stage breast cancer—informed the experience weights in our breast cancer ABM, $\Delta_j$. 5

Estimating the Memory Parameter for the Tailored Breast Cancer ABM

In this section, we will describe how we estimated the memory parameter, $\nu$—which represents a measure of how much information individuals retain about their previous experiences and the experiences of others they know. We noted that women were much more likely to report on diagnoses they had learned about recently and assumed that women were more likely to report on recent diagnoses because they were more likely to recall these more recent diagnoses. Figure 5.2 shows the frequencies with which women reported learning about a breast cancer diagnosis a given number of years ago. Assuming exponential memory decay, we fit an exponential curve to these data ($r^2 = 0.86$) and found a decay parameter of $\beta = 0.19$ (where we fit the model $y = Ae^{-\beta x}$). This corresponds to a half-life of about 3.6 years (roughly meaning that individuals would forget about half of their personal or social network experiences with screening and breast cancer after 3.6 years). Our model evolves in discrete time, so we estimated how much information an agent would retain in each time step (representing one year). We estimated the memory parameter to be $\nu = e^{-\beta} = 0.83$. A limitation of the approach presented here is that we used reports of women learning about breast cancer diagnoses up to 60 years ago, when the youngest members of our sample were only 40 years old. To test whether this affects the memory parameter estimation, we conducted a sensitivity analysis in which we limited ourselves to using only reports where $x \leq 20$. When we did this, the estimated value of $\beta$ was still 0.19 to two significant digits, giving us confidence in our estimate.

4 For more detailed information about how we constructed model variables from measures in our survey, see the online supplemental information for Nowak and Parker (2014).

5 For additional details and full results of model regressions, see the online supplemental information for Nowak and Parker (2014).
Limitations

The use of a customized survey designed to parameterize the ABM provides a unique opportunity to inform key behavioral parameters within the model. That said, it is important to recognize several limitations in both the survey used to parameterize the model and the model itself. First, the survey was cross-sectional, and we therefore had to rely on intention to screen in the future rather than actual future screening behavior. Second, because the survey was at the individual level, we relied on those individuals’ reports about the breast cancer histories of those in their network, rather than having access to the alters’ true health histories. However, because the modeled agents act on their perceived network experiences, rather than actual network experiences, this approach closely mirrors reality. That said, an important extension of this work would be to collect both true health histories and perceptions of the health histories of others in the social network. This would allow us to model the effect of misinformation. In addition, in our ABM, we model decay in the level of impact of learning about a particular social network outcome. Empirically, we did not have sufficient statistical power to estimate how this impact depended on how long ago women learned about particular social network outcomes. Therefore, we instead measured the rate of decay of the fraction of women who recalled learning about a social network outcome. These are different processes, and they might lead to somewhat different population-level dynamics. Further discussion of limitations of this model can be found in Nowak and Parker (2014).
6. Other Modifications to the General ABM

In this chapter, we briefly describe some potential extensions we could make to add richness to our simple ABM, while addressing several current limitations. First, we discuss how the simulation model could be modified to allow the transmission of information about behaviors only or outcomes only, in addition to describing the transmission of information about coupled behavior-outcome events. Transmission of behavior-only or outcome-only information might occur frequently when there is a long delay between behaviors and outcomes, or when either the behavior (or outcome) is more readily observable by others than the outcome (or behavior).

Second, we describe two extensions to capture potential differences between groups of individuals representing different cultures. We discuss one example in which different cultures might spread information at different rates within the social network; we also discuss an example in which the different cultures interpret the same events in the social network differently. Understanding such cultural differences could help shed light on, say, regional differences in behaviors that can reduce risk of disease and disease rates (e.g., higher HIV rates in the South).

Transmission of Behavior-Only or Outcome-Only Information Through the Social Network

Figure 6.1 shows an example of how we could extend the model to include the transmission of behavior-only and outcome-only information. (Figure 6.1 highlights the transmission of behavior-only information; Figure 6.2 highlights the transmission of outcome-only information.)
Here, we revisit our example of the different behavior-outcome pairs that could result from an individual’s decision to vaccinate. Earlier, we identified behavior-outcome pairs that could be transmitted to the social network: ($E_1$) vaccinated, experienced illness and no side effect; ($E_2$) vaccinated, experienced neither illness nor side effect; ($E_3$) vaccinated, experienced both illness and side effect; ($E_4$) vaccinated, experienced a side effect but no illness; ($E_5$) not vaccinated, became ill; and ($E_6$) not vaccinated, did not become ill. Each behavior-outcome pair could have associated probabilities of being transmitted through the social network as (a) a behavior only, (b) a behavior-outcome pair, or (c) an outcome only. In Figure 6.1, the transmitted information is behavior-only (i.e., no information on outcomes). For clarity, we have grayed out the behavior-outcome pairs ($E_1$–$E_6$) to highlight the new types of information we have introduced. We introduced two types of behavior-only information (vaccinated [$B_1$] and not vaccinated [$B_2$]) and three types of outcome-only information (became ill [$O_1$], experienced a side effect [$O_2$], and did not become ill [$O_3$]).

To model the effect of receiving outcome-only or behavior-only information on an individual’s propensity for a particular behavior, we would need to introduce additional weights. For example, our original vaccination example in Chapter Three would have six different weights, $\Delta_i$, while the extended example shown in Figure 6.1 would have 11, because it would add the two behavior-only weights and three outcome-only weights. Allowing transmission of behavior- or outcome-only information can have important effects on whether people tend to copy or engage in different behaviors from others in their social network. For example, we would expect learning that someone was vaccinated and became ill to have a negative weight, because this behavior-outcome pair suggests that vaccination is ineffective. In contrast, we would expect learning only that someone was vaccinated to have a positive weight and
encourage vaccination. Similarly, learning only that someone became ill would also have a positive weight because it would increase perceptions of the risk of disease, in turn increasing perceptions of the need to be vaccinated.

Figure 6.2 shows the same behavior-experience example as Figure 6.1, but Figure 6.2 highlights the links between experiences and outcome-only information. Our three outcome-only types of information in this example are (1) became ill, (2) experienced a side effect, and (3) did not become ill.

**Culturally Specific Effects**

The next two sections describe a set of two extensions, each of which highlights how different cultures could influence the flow and interpretation of information through social networks.

**Culturally Specific Information Transmission Patterns**

Figure 6.3 demonstrates how different cultures can differ in how information is transmitted over social networks. In this example, three cultures (shown in the blue, gray, and pink circles) all use the same three outcomes (depicted by the blue, green, and red nodes) to inform their decision making, but have different beliefs about how much information people should share with others about these different outcomes. In the first culture on the left, the red outcome is highly stigmatized and individuals either do not talk about that experience or they share that experience with only one other individual. An example of this type of experience could be contracting a sexually transmitted disease. The green outcome is shared frequently in the network (this could be a positive experience, such as getting a pay raise at a job). The blue outcome is shared with a moderate number of individuals. In the second, middle culture, people believe that it is extremely important to share information about the red outcome with others (for
example, educational programs could have been used to destigmatize the sexually transmitted disease, and highlight the importance of individuals with the disease sharing their experience with others to help spread awareness and slow the disease spread); they talk relatively little about green (perhaps, if this is an experience like getting a pay raise, this culture values humility more than the first culture, in which people share this experience widely) and again share blue a moderate amount. In the right-hand culture, individuals always share outcomes with the same three close friends, regardless of which outcome they experience.

_Culturally Specific Interpretation of Information_

In our general ABM, we implicitly assumed that all individuals have the same beliefs about what outcomes can result from a particular behavior, and that all individuals would react to the same information in similar ways. However, in reality, individuals often have different beliefs about the causal relationships between behaviors and outcomes, which cause them to respond to the same information in different ways (Rindos, Carneiro et al., 1985; Durham, 1991). Figure 6.4 shows one potential hierarchy of beliefs about causality. At Level 3, we have beliefs about frequencies of different outcomes—this level represents the same processes captured in our general ABM. Consider, for example, vaccination behavior: At Level 3, individuals consider the
likelihood of becoming ill without vaccination, the vaccine’s efficacy (likelihood of becoming ill even with the vaccine), the severity of the vaccine-preventable illness, and the likelihood and severity of different side effects associated with the vaccine. These beliefs may be common within groups of individuals, or may vary from one individual to another based on the individual’s past experiences and experiences they learn about in their social network. Next, at Level 2, we have the beliefs about what types of outcomes result from a particular behavior. For example, some individuals may believe a vaccine to be associated with autism, regardless of whether scientific evidence supports this association, while others do not. Level 2 beliefs may be common among members of a particular culture or subculture. At the deepest level, which we are calling Level 1, individuals hold beliefs about what types of causal relationships are possible. These are the most fundamental lenses through which the individual views the world and are likely to include the general principles from the individual’s scientific, cultural, and/or religious understanding of the world. In the case of vaccination, a Level 1 belief would be a scientific understanding of how the immune system works. In general, we would expect that beliefs at Level 2 are less difficult to change than beliefs in Level 1, so long as they are consistent with Level 1 beliefs. For example, when considering vaccination, at Level 2, individuals change their awareness and beliefs about what side effects might be associated with a vaccine.

To model behaviors influenced by the hierarchy shown in Figure 6.4, we would generally model multiple types of decisions \( d \), simultaneously (as different cultures or groups might focus on different decisions to affect an outcome of interest). To do this, we would introduce the variables shown in Table 6.1.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>( S_{i,d,n} )</td>
<td>Propensity of individual ( i ) for choice ( A ) for decision ( d ) at iteration ( n )</td>
</tr>
<tr>
<td>( D_{i,d} )</td>
<td>Default individual-level propensity for choice ( A ) for decision ( d )</td>
</tr>
<tr>
<td>( B_{i,d} )</td>
<td>The set of cause-effect relationship beliefs individual ( i ) has</td>
</tr>
<tr>
<td>( f_i )</td>
<td>Fundamental beliefs individual ( i )</td>
</tr>
<tr>
<td>( R_i )</td>
<td>The set of all relationships ( j ) that are not inconsistent with fundamental beliefs ( f )</td>
</tr>
</tbody>
</table>

Figure 6.5 shows how we could mathematically implement the hierarchy shown in Figure 6.4 in our simulation model. At Level 3, the model operates much as our previous model does, where individuals are influenced by their own personal outcomes and by the outcomes of others they know personally. We assume that individuals are influenced only by outcomes \( j \) that they believe are relevant to decision \( d \), which are the outcomes in the set \( B^i_d \). At Level 2, we assume that there is a process (which we are calling some function \( g \)) that changes the outcomes (or behavior-outcome pairs) \( j \) in the individual’s set \( B^d_j \). We assume that there are two primary
processes by which this can occur: First, an individual can learn from others that a relationship between decision $d$ and outcome $j$ exists (link D in Figure 6.4; for example, hearing from a friend, family member, or even a celebrity that vaccines can cause autism). Second, the individual can observe $d$ and $j$ co-occurring in his or her own experience or the experience of those he or she knows and infer that a relationship might exist (links E and F in Figure 6.4; for example, knowing a child diagnosed with autism shortly after receiving vaccinations). (Note: The relationships between a decision $d$ and an outcome $j$ do not need to be truly causal; we only need to assume that some individuals in the model may believe there to be a causal relationship.) At Level 1, we assume that individuals will change their fundamental beliefs with some probability that is a function of the beliefs of individuals they know personally or others in the network from whom they receive information. We assume that this process occurs by some function $h$—for example, individuals might adopt the Level 1 beliefs most common in their neighbors.

Figure 6.6 shows three types of Level 1 fundamental beliefs (belief in humoral theory of disease (MacDonald, 2005), belief in the law of attraction (Hicks and Hicks, 2006), and a belief in the germ theory of disease) with associated cause-effect relationships. Note that while certain cause-effect beliefs may be most strongly associated with one particular fundamental belief, individuals with other fundamental beliefs may adopt them if they do not violate key assumptions of their culture. For example, individuals could adopt the idea that garlic and chamomile can treat cold symptoms with a belief in germ theory because there is a mechanism of action that could at least be plausible within germ theory. For example, if an individual from the germ theory culture learns from someone in the humoral theory culture that people should drink...
chamomile tea when they have a cold, the germ theory individual could assume that chamomile tea can help the immune system fight infection and accept the suggestion as a plausible treatment. The idea that lettuce can worsen symptoms, and certainly the idea that bloodletting can relieve cold symptoms would probably be unlikely to be adopted by individuals in the germ theory culture. Similarly, cause-effect relationships most strongly associated with the law of attraction culture might be accepted and adopted by individuals in the germ theory culture when they have a plausible mechanism (e.g., the idea that avoiding stress can help you avoid catching a cold is consistent with germ theory if one assumes that stress can weaken the immune system).

These refinements to the model: incorporating behavior-only or outcome-only information transmission, as well as incorporating the influence of culture on social learning, are just two of many possible extensions to the general modeling framework. As with our existing models, these extensions could usefully be informed using tailored primary data collection, such as the survey conducted for the breast cancer study.
This report presents a general ABM for modeling social learning and describes dynamics that can result from the model for different classes of generic behaviors. We examined different classes of behaviors, including the following classes of two mutually exclusive behaviors $A$ and $\bar{A}$ (such as vaccinating or not vaccinating):

1. The outcomes of both $A$ and $\bar{A}$ suggest that $A$ is the better behavior, such as the emergence of a new dominant technology. We found that if memory, information transmission, and the effect of learning about network outcomes are relatively large, most individuals in the network will end up engaging in behavior $A$. If these parameters are small, most individuals will revert to a default behavioral state.

2. The outcome of behavior $A$ suggests that behavior $A$ is a good choice and outcomes from $\bar{A}$ suggest that $\bar{A}$ is a good choice, as would be the case with membership in one of two equally attractive groups (e.g., becoming a fan of different sports teams). This type of social learning mechanism can lead to distinct clusters of behavior in the population if there are few long-range connections between individuals and if initial conditions include large, relatively homogeneous clusters of individuals either engaging in behavior $A$ or $\bar{A}$. Small clusters and large numbers of long-range social network connections can destabilize initial clusters.

3. The outcome of behavior $A$ suggests that behavior $\bar{A}$ is the better choice and the outcome of behavior $\bar{A}$ suggests that $A$ is the better choice, as may be the case with two unsatisfying cable service providers. This results in dynamics in which individuals alternate between behaviors $A$ and $\bar{A}$. If individuals are highly connected, they may switch from one behavior to another in groups. If they are not, they may switch as individuals.

4. Behavior $A$ results in many positive outcomes that reinforce behavior $A$, but occasionally lead to very bad side effects that suggest behavior $\bar{A}$ is better—that is, behavior $A$ leads to some outcomes with positive influence and other outcomes with negative influence. An example of this would be a medication that is generally helpful, but with a rare and severe side effect. In this case, behavior $A$ will initially spread rapidly in a population, but may temporarily decrease in frequency, or stop entirely as individuals begin to experience adverse outcomes.

Additionally, we note that while our general ABM can produce dynamics reminiscent of those that might result from many different types of behaviors, the general ABM will need to be tailored when it is used to model any particular behavior. We discussed how we created a tailored ABM of breast cancer screening behavior. We also described other ways we might tailor the general ABM in the future. These included an extension to examine a case in which anecdotal information from the social network is sometimes transmitted as information about a behavior only, is sometimes transmitted as information about an outcome only, and is sometimes
transmitted as a behavior-outcome pair. In addition, we described two extensions of the model that could be used to explore the role of culture in social learning. First, we described how individuals in different cultures might have different preferences and beliefs for how much information individuals should share with others about their own behaviors and outcomes. Second, we described a belief hierarchy that illustrates how individuals in different groups or cultures might have distinct models of causality related to behavior. For example, they might have different beliefs about disease causality, which act as alternate lenses through which they interpret information they learn about in their social networks.

So far, we have mostly applied the ABM approach presented in this report to problems in health policy; however, the approach could be useful for studying any system in which social learning may occur. While most of our past and ongoing research focuses on preventive medicine, like other theories of social networking, we believe it can be used in other cases. For example, a currently funded project for the National Science Foundation, *IBSS: An Agent-Based Model of the Role of Income Tax Evasion Perceptions*, led by Raffaele Vardavas, applies a similar approach to tax evasion perceptions and behavior. Other potential examples include (1) law enforcement, where individuals learn about which illegal behaviors lead to arrest and punishment; (2) insurance decisions, where individuals may be more likely to select policies that cover the types of events that happen to people they know; and (3) product marketing and loyalty, where customers learn from their experiences, as well as the positive and negative product experiences of people they know when deciding what products to buy.

In our current ongoing work on breast cancer screening (*The Impact of Provider Social Networks on Breast Cancer Screening*, funded by NIH/National Cancer Institute), influenza vaccination (*Modeling the Coupled Dynamics of Influenza Transmission and Vaccination Behavior*, funded by NIH/National Institute of Allergy and Infectious Diseases), and tax evasion, described above, we are exploring ways to leverage social learning ABMs to examine how social networks facilitate or impede the effects of various policies or communication strategies (such as those aimed at increasing vaccination rates or reducing excessive use of cancer screening in overscreened populations). We hope that such models as those described in this report can improve our ability to predict effects of policy and communication strategies and can ultimately lead to policy and communication strategies that more effectively modify behavior because they carefully consider the crucial role of social learning, and therefore work with, rather than against, ways in which social networks naturally influence behavior through social learning processes.


