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Robert Huckfeldt
University of California, Davis, rhuckfeldt@ucdavis.edu

Paul Johnson
University of Kansas, pauljohn@ku.edu

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Robert Huckfeldt
University of California, Davis

and

Paul E. Johnson
University of Kansas

This paper addresses the factors that give rise to both heterogeneous and homogeneous opinion distributions within political communication networks. We argue that the factors sustaining homogeneity and heterogeneity are not entirely symmetrical – heterogeneity is not necessarily explained by treating it as the flip side of homogeneity. Two primary questions guide the effort. If influence within a dyad depends on the distribution of opinions beyond the dyad, is dyadic influence contingent on the construction of the network within which the dyad is located? In particular, how does the micro-structure of the larger network affect the persuasiveness of communication within the dyad? We pursue an analysis based on agent based models of the communication process. The analysis points toward the importance of particular forms of small scale organization in preserving homogeneous opinion distributions. Homogeneity is more likely when network density is particularly high – when direct connections are more frequent among more agents. Correspondingly, when we observe homogeneity within communication networks in the natural world, the organization and reach of small scale social organization is likely to be key.

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When studies of public opinion consider interdependence within electorates, they typically focus on factors that give rise to persuasion and opinion homogeneity within groups at various levels. The null hypothesis has thus tended to be heterogeneity rather than homogeneity, and the arguments focus on factors that lead to agreement. Based on the tendency toward agreement within small scale social organization, this effort focuses instead on the factors that sustain disagreement and heterogeneity.

This effort views opinion heterogeneity within groups as a phenomenon that needs to be explained. Factors sustaining homogeneity and heterogeneity are not entirely symmetrical – heterogeneity is not necessarily explained by treating it as either the flip side of homogeneity, or as the error term in a statistical model. To the contrary, the factors that create and sustain opinion homogeneity are often seen as inexorable, while the factors that sustain disagreement are more likely to be seen as brittle and fleeting.

This paper's argument and its analysis centers on an agent-based model. Several questions guide the effort. If influence within a dyad depends on the distribution of opinions beyond the dyad, is dyadic influence contingent on the construction of the network within which the dyad is located? In particular, how does the micro-structure of the larger network affect the persuasiveness of communication within the dyad?

The Political Heterogeneity Problem

Social scientists have historically held divergent perspectives regarding the roles of persuasion and interdependence within micro-models of judgment and decision-making. These micro theories have, in turn, generated divergent expectations regarding the consequences of small scale social organization, friendship groups, and networks of political communication. Paradoxically, and for very different reasons, political economists and political psychologists have typically shared the expectation that political opinions should be homogeneous among associated individuals.

In a thirty year foreshadowing of arguments related to the new institutionalism within political science (Williamson 19xx, Ostrom 19xx), Downs (1957) argued that rational individuals could reduce information costs by obtaining reliable political information on the cheap through communication with others, but only if they obtained the information from politically expert individuals who share their interests. And hence the resulting expectation is that communication networks would be politically homogeneous, with political experts occupying an influential role among homogeneously clustered agents. Other analyses, inspired by the power of conformity (Asch 1956) and the discomfort of cognitive dissonance (Festinger 1957), view disagreement and heterogeneity as inherently unstable phenomena that inevitably give way to agreement and homogeneity over the long run.

The descriptive reality does not correspond to these expectations. While it is certainly the case that people who are located in shared micro-environments tend to be politically like-minded, it is also true that substantively significant levels of heterogeneity tend to persist. For example, the National Election Study included a network name generator in its 2000 post-election study. Respondents were asked to name up to four individuals with whom they discussed government, elections, and politics. Among those respondents who voted for Gore, 36 percent reported that one or more of their discussants voted for Bush. Among those who voted for Bush, 37 percent reported that one or more of their discussants voted for Gore. And less than half of both Bush and Gore voters reported that all their discussants voted for their favored candidates (Huckfeldt, Johnson, and Sprague 2004). Comparable levels of agreement and disagreement are demonstrated for major party supporters in other elections and other countries (Huckfeldt, Ikeda, and Pappi 2005; Huckfeldt and Sprague 1994).

This effort adopts a network perspective in addressing the potential for sustained political diversity within small scale social organization. Political behavior arises in particular contexts, characterized by the non-trivial details of the ways that communication networks are constructed. This argument does not deny the tendency toward shared political viewpoints among frequent associates, and it is not antithetical either to purposive action or to social influence via the psychological processes that are centrally related to processes of political communication. We simply argue that political preferences and political behavior, rational or otherwise, are embedded in "concrete, ongoing systems of social interaction" (Granovetter 1985: 487).

In this context, we locate the sources of heterogeneity at the intersection of phenomena occurring at two different levels. First, the maintenance of diversity depends on the structure of networks – particularly on the existence of open triads in which one actor is related to two other actors who are not related to each other. These are the network structures that underlie Granovetter's (1973) argument regarding weak ties, as well as Burt's (1992) analysis of the strategic manipulation of the bridges between otherwise self contained networks of communication. In contrast, our own effort is directed toward the consequences for persuasion.

Second, the maintenance of diversity depends on particular features of the persuasion process. This requires that we focus not only on larger network structures – dyads, triads, and beyond – but also on the individuals within the networks and the factors that limit interpersonal influence between individuals. Rather than turning to well travelled paths by focusing on the individual level factors giving rise to persuasion and acquiescence, we maintain an extra-individual structural focus. In particular, we consider the possibility that influence within any particular dyad is contingent on all the other dyads within which individuals are imbedded.

Agent-Based Models

Agent-based models employ a framework in which computer objects—objects that represent autonomous individuals—behave, interact, and adapt to one another (Epstein and Axtell 1996; Johnson 1996, 2002), and hence they provide an opportunity to consider macro-based outcomes based on micro-level patterns of interaction. The models define a collection of individual "agents" along with the setting in which the agents are embedded. The models explore the interaction among individual agents in order to uncover the complex combinatorial consequences of these interactions, thereby providing a vehicle to move seamlessly between the aggregate and interdependent, interacting agents. In this way, the aggregate consequences are not simply imposed on the agents. Rather, the behavior of the agents also produces aggregate outcomes, and they experience the consequences through interaction with other agents.

The resulting emergent properties of small scale social organization carry the potential to be surprising and counter-intuitive. A number of analyses have produced a series of expectations regarding the factors that prove to be influential in enhancing and inhibiting political influence and agreement among and between citizens (Baldassari 2007). In the analyses that follow, we construct a series of ABMs to simulate the dynamic consequences of these communication processes. Our goal is to identify the factors that give rise to the preservation of political diversity within networks, and ABMs are perhaps ideally suited to the task (Johnson 1999).

The Modeling Strategy

The models analyzed in this paper have been implemented in Objective-C with the Swarm Simulation Toolkit (Minor, Burkhart, Langton, Askenazi 1996; also see http:www.swarm.org). They include two separate design components: a "selection process" that brings agents together for a one-on-one interaction, and a “persuasion process,” characterized by particular opinion adjustment rules that determine the outcome when an interaction occurs between two agents. The selection component is designed to parallel Axelrod's Culture Model (1997a, 1997b). We address this model first before adding the persuasion component.

The opinions of the agents are treated as integers. If there are three possible opinions about some particular issue, then the possible opinions on that issue are represented by the numbers 0, 1, and 2. Agents hold opinions on multiple issues. Hence, if there are five issues in the political sphere, we represent an individual’s stances on that collection of issues as a vector, such as (0,1,0,2,2), where each entry in the vector represents the agent's opinion on an issue.

As agents interact, opinions change, and we are interested in knowing if the opinion vectors of the interacting agents are homogenized. In order to do so, we employ measures of diversity at the observational level of individual agents, as well as at the level of the entire system – the diversity that is observed at the aggregate level. As Axelrod (1997a) demonstrates, it is entirely conceivable that individual citizens never encounter diverse opinions within their networks of interaction, even though diverse preferences continue to survive at the aggregate level.

At the aggregate level, it is possible to tally and summarize the features of agents. This allows the calculation of several summary measures, such as the average and variance of each opinion. We also calculate a system-wide diversity measure, ***entropy***, otherwise known as Shannon's information index. If there are F different issues and T different opinions on each issue, then the number of possible issue stances is T^F. This measure of entropy is normed to an interval where it equals 0 if all agents hold identical opinions and 1 if every possible combination of opinions is equally represented in the set (Shannon 1949; Balch, 2000).

In addition to tracking aggregate levels of diversity, we are also interested in whether individual agents encounter diversity. Social interaction among the agents comes in two forms – encounters and acquaintances (see Huckfeldt 1983). One agent encounters another agent as part of a stochastic process in which the probability of a dyadic encounter is dependent on availability, where availability depends on shared locations in space and time. In contrast to encounters, where the probability of an encounter depends on proximity and availability, the probability of an acquaintance depends on the existence of a shared opinion between two agents. When one agent encounters another agent, a choice is made regarding whether to become acquainted. This "choice" depends on the existence of a shared opinion, and in this way the models directly incorporate a self-selection component.[1]

Each agent keeps a running tally of its social interaction experiences – of its encounters and acquaintances. These can be collected and summarized to build indicators of the extent to which random encounters between strangers involve opinions held in common, as well as the extent to which agents agree with their acquaintances. For our models, we present three individual-level measures.

Acquaintance. For each other agent that is encountered through the process of random encounters, the agent checks to see if the two agree regarding a randomly chosen issue. Because such agreement is a precondition for acquaintance, the proportion of encounters on which there is a shared feature is kept as a moving average that we call "acquaintance." This can be treated as the individual agent's expectation – based on accumulated experience – that it will agree on a random issue with another randomly chosen agent. In other words, it provides a measure of the individual agent's expectation regarding the probability that a random encounter might become an acquaintance.

Harmony. When an interaction occurs between two agents, the agents "compare notes" and discover how much they have in common. Hence, the level of "harmony" is the proportion of opinions across all issues that are shared between two agents that are acquainted.

Identicality. Similar to "harmony", identicality is based on a comparison across all the opinions that are held by two agents that are acquainted with one another. For an individual agent, a moving average is retained for 20 interactions, and a 1 is added if another agent is identical, and 0 if it is not. A value of the moving average of, say, 0.70, indicates that seven-tenths of the others with which the agent has interacted are exactly the same as the agent itself.

In summary, "harmony" and "identicality" indicators reflect information regarding only those other agents with which a particular agent is acquainted, and hence they provide measures of the agents' networks of political communication. In contrast, the "acquaintance" measure is collected across all the other agents that are encountered by a particular agent, regardless of whether the encounter actually becomes an acquaintance. It is important to note that these measures are based on the experiences of individual agents. While agents cannot experience diversity when the aggregate is homogeneous – when entropy is complete – it is entirely possible for agents to experience homogeneity even when the aggregate is characterized by high levels of diversity. The measurement procedures thus described allow us to explore these possibilities.

Model Dynamics

[1] Hence, we conceive of an interaction sequence in which an encounter becomes a precondition for an acquaintance. Encounters are stochastic events within particular settings, and they may or may not lead to the formation of an acquaintance. In this way, encounters and acquaintances are specifically defined aspects of a more generally defined interaction process.

The model employs a square lattice on which agents are distributed, one per cell – see Figure 1. Each agent has a set of discrete-valued opinions – issue stances, party allegiances, candidate evaluations, and so on. For example, each agent might have a party allegiance taking on three possible values – Democrat, Republican, and independent. In an implementation of five opinions, each with three alternatives, an agent might be represented as (0,1,0,2,0); (1,2,1,0,1); (1,2,1,0,2); etc. At the outset, each agent has a vector of features in which each trait is assigned randomly from a uniform distribution.

At the beginning of the process, an agent is randomly selected, and a neighbor from the von Neumann neighborhood – consisting of cells on the east, west, north, and south borders – is randomly ***encountered***.[2] In the second step of this interaction sequence, an encounter is converted into an ***acquaintance*** with probability equal to their proportional agreement on the five opinions. (For example, if two agents share the same stance on 2 of 5 opinions, they form an acquaintance with probability .4.) If they form an acquaintance, the agents communicate regarding a randomly chosen issue on which they disagree, and the initiating agent copies the opinion of the other agent.

In Axelrod's (1997a, 1997b) analysis, using a very similar model, diversity is preserved only when neighbors have nothing in common, so that they do not become acquainted and hence cannot influence one another. In contrast, if two agents become acquainted in Axelrod's model, influence is automatic and heterogeneity is inevitably eliminated among acquainted agents. This means the end result is either that (1) all agents hold homogeneous opinions, or (2) the grid is divided into clusters of agents that are internally homogeneous absent any shared opinions with adjacent clusters, thereby creating a socially impermeable boundary.

Subject to the same restrictions, this model provides support for Axelrod's conclusion (Huckfeldt, Johnson, and Sprague 2004, chapter 6). Over the long run, heterogeneity within clusters disappears. When all the agents belong to a single cluster, this means that homogeneity is universal across all agents' issue stances. While the tendency toward homogeneity is greater for some parameter settings than others, it is powerful in all cases. Clusters of shared opinion develop which are completely isolated from one another because, lacking any point of agreement, individual members of one cluster cannot become acquainted with members of other clusters. Diversity is preserved in the aggregate sense, but ***none of the individual agents are acquainted with other agents holding divergent opinions*** – none of the agents experience diversity within their networks of acquaintance. Moreover, other analyses with a variety of modified selection mechanisms sustain the result – the basic structure of the model is remarkably robust with respect to the production of a stable homogeneous equilibrium.

The problem is, once again, that this implication contradicts the empirical record (Huckfeldt, Ikeda and Pappi 2005). Political homogeneity is not the ***inevitably*** stable

[2] Hence, there is no overlap in the opportunities for encounters among the agents. That is, none of the agents' opportunities for encounters are shared with the agents with whom they might interact. And thus, none of the agents' acquaintances will be the acquaintances of their acquaintances. This is usefully compared to the circular lattice of the small world model (Watts and Strogatz 200xx) in which each node is also connected to four other nodes. In the small world model, two of a central node's connected nodes share two nodes, and the other two nodes share one node. We will return to this issue below.

equilibrium outcome within patterns of political communication among and between citizens. Politically diverse individuals communicate with one another and are only ***sometimes*** persuaded by each other. Hence, the problem that we face is similar to the issue addressed by Abelson forty years ago. His dynamic models of social influence led to the prediction that "any compact group of individuals engaged in mutual dyadic interactions at constant rates will asymptotically tend toward complete homogeneity of attitude positions" (1964, p. 152). Later he observed that there is a "virtually inexorable consensus" (1979, p. 244) – one that he sought to avoid (with only limited success) by exploring various changes in the design of the model.

We address the problem by introducing an adaptation in the ways that individuals respond to differences of opinion. The key ingredient is a density dependent understanding of political communication *and persuasion* – an understanding that interprets dyadic effects on individual opinion and judgment in the context of preference distributions that occur within the larger networks of political communication experienced by particular agents.

Influence and Opinion Densities within Networks

A revised model includes two separate mechanisms – the original communication-interaction mechanism as well as an influence mechanism that depends on opinion densities within networks. In reconstructing the model, we pursue an emergent solution to the diversity problem – a solution generated by the logic of interaction and interdependence that is built into the model. The goal is to understand the process as a system in which diversity arises in a self-organizing way through an autocatalytic process – a system that transforms a wide range of inputs into a stable pattern of political heterogeneity, depending only on the information that agents accumulate through one-on-one interactions.

Moreover, we avoid models that require a highly specific set of initial conditions in order for diversity to be sustained. Similarly, we are interested in equilibria that might be locally stable – equilibria that do not come undone as a consequence of small random shocks. At the same time the model should allow for the model to be sensitive to initial conditions and random perturbations, both of which are particularly influential in complex non-linear systems such as the ones we are studying.

The theoretical motivation for this alternative framework is the expectation that dyadic interactions occur in a larger context that serves to moderate the reactions of the individuals within the dyad – a context created through the ongoing interactions of agents within their networks of interaction. In this alternative model, each dyadic interaction is thus interpreted within the ongoing series of all the agent's other dyadic interactions.

Hence, when agents interact within dyadic relationships, they bring a context with them that moderates their responses. Agents do not copy opinions from each other in an arbitrary or automatic fashion. Rather, agents change their opinions only when, upon reflection, there is sufficient support for the opinion that has been communicated through the interaction. We assume that such a sufficient reason is found when a majority within the agent's existing network of acquaintances hold the proposed opinion. In this way, the responses within dyads reflect the accumulation of individual experience, and the consequence of this accumulated experience is to create a pattern of autoregressive influence which serves to preserve diversity.

The Network Solution and Autoregressive Influence

This autoregressive model marks a relatively minor but theoretically dramatic departure from the earlier version of the model. The solution that we adopt recasts the problem of individual opinion change within the specifics of the networks that create the social contexts of political communication.

If you think that Obama is doing a great job on the economy, and one of your friends tells you that he is inept, how might you respond? According to the earlier model, you would simply change your opinion. But an alternative strategic response is to contextualize the information obtained from one informant by contrasting it with information provided by other informants. Hence if you like Obama's economic program, but your friend Nancy dislikes it, you might take into account the opinions of others regarding his capabilities. If all your other information sources suggest that Obama is an excellent manager of the economy, you might downgrade the credibility of Nancy's opinion. In contrast, if your other information sources tend to agree with Nancy, you are likely to reconsider your own opinion on the matter (see McPhee 1963).

In this way, any single piece of information is evaluated within the context of all the information that is available. The social influence of any single interaction ceases to be determinate, and the agent becomes an evaluator of information received through a successively autoregressive process of social interaction.[3]

Autoregressive Influence and the Micro-Structure of Networks

The incorporation of autoregressive influence within the model requires that current communication and information be evaluated in the context of past communication and information. Hence, the communication-interaction process occurs as before, but each agent maintains an ongoing record of past interactions, and they employ these records in formulating their responses to new points of view. In this way an agent accumulates a set of acquaintances that constitutes a communication network. When a particular acquaintance offers an opinion on a randomly chosen issue, the agent polls the other acquaintances with which agreement has occurred on more than one-half of the issues. If more than one-half of these acquaintances agree with the opinion being considered, it is adopted.

Hence, the autoregressive weighting scheme produces an advantage for opinions that are widely held within the agent's network of acquaintances. New opinions or novel preferences should take longer to win acceptance, and individual agents should be less susceptible to persuasion by opinions that constitute a minority position within the network.

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[3] We draw a distinction between autoregressive influence and autoregressive behavior. Behavior is autoregressive if your behavior reflects the behavior of those who surround you within the communication network. Influence is autoregressive if one informant's influence depends on the information you obtain from other informants.

Across a series of experiments, using a variety of communication-interaction modules, this autoregressive persuasion model leads to outcomes that are dramatically different from the earlier models in which persuasion is automatic (Huckfeldt, Johnson, and Sprague 2004). Diversity of opinion is retained, both within the agents' networks of acquaintance as well as across the aggregated system.

At the same time, one might argue that the stabilizing influence is a simple artifact of the model's decision rule in combination with the particular micro-structure of its interaction module. Agents have, at most, four possible acquaintances (up, down, left, right), and hence the requirement of a majority in favor of the new view amounts to a requirement of a two-thirds majority among remaining acquaintances for agents with four acquaintances, and unanimity among remaining acquaintances for agents with three or two acquaintances. Such super-majorities may be difficult to find, and hence, instead of demonstrating network-embedded resistance to change, we may be demonstrating the stabilizing impact of a larger-than-bare-majority decision rule.

Alternatively, one might expect that the effect of the autoregressive mechanism would depend on the low levels of network density that are built into the model (Granovetter 1973; Burt 1992). The restrictions of the simple von Neumann neighborhood create networks in which an agent's acquaintances are unable to become acquainted with any of the agent's other acquaintances. All the triads in the simplest model are, by definition, open triads—none of an agent's acquaintances are acquainted with any of their other acquaintances. Hence the aberrant message communicated by a particular agent is less likely to be reinforced by other agents who are entirely independent of the messenger.

In contrast, if the agents' networks of encounters were potentially of higher density so that many of the acquainted agents shared similar patterns of acquaintances with other agents, one might expect that disagreement would disappear. That is, no one would ever encounter diverse preferences because every communication network would, at least potentially, become entirely self-contained and likely to reinforce political messages, thereby creating political homogeneity.

We consider this problem in several ways. First, we jettison the von Neuman neighborhood in favor of locating each agent in the middle of a Moore neighborhood – a 3x3 grid where the agent randomly encounters any one of the other eight agents in the neighborhood with equal probability. This creates significant levels of overlap between the agent's neighborhood and the neighborhoods of the other agents. All agents share at least two neighbors with each of the other agents in their neighborhoods. (See Figure 1.)

Autoregressive Influence in Moore Neighborhoods

This analysis is based on one hundred agents located on a 10x10 lattice, where the agent is located in the middle of a Moore neighborhood. As in previous analyses (Huckfeldt, Johnson, and Sprague 2004), each agent maintains an ongoing record of past interactions, and they employ these records in formulating their responses to new points of view. Each time one agent encounters another agent, it counts the number of opinions held in common with this other agent, and an acquaintance is formed with probability equal to the proportion of shared opinions. In this way an agent accumulates a set of acquaintances that constitutes a communication network. When a particular acquaintance offers an opinion on a randomly chosen issue, the agent polls the other acquaintances with which agreement has occurred on more than one-half of the issues. If more than one-half of these acquaintances agree with the opinion being considered, it is adopted.

Hence, the autoregressive weighting scheme produces an advantage for opinions that are widely held within the agent's network of acquaintances. At the level of the agent's network, the autoregressive feature of the model rewards majority opinion as it punishes minority opinion. Thus, new opinions or novel preferences should take longer to win acceptance, and individual agents should be less susceptible to persuasion by opinions that constitute a minority position within the network.

The adoption of a larger neighborhood with correspondingly higher levels of network density does not change the outcome. Diversity of opinion is retained, both within the agents' networks of acquaintance as well as across the aggregated system. A summary of 100 runs is presented in Table 1. The simulation stops after the entire list is processed 10 times without a single change of opinion by any of the agents. In each of the 100 runs of the model, the level of entropy is in the middle ranges when the simulation stops. The variance of the opinions is also far from zero. Furthermore, the experiences of the agents indicate that they are located in diverse acquaintanceship networks, as illustrated by the harmony and identicality measures.

There is not a great deal of variety in the time paths of summary statistics across runs of the model. Consider the example time paths illustrated in Figure 3. Note that, because opinions are randomly assigned at the outset, the entropy level starts at a high value. As the simulation proceeds, the agents accumulate experience with their neighbors. The agents begin to adjust their opinions in response to new input and the stabilizing impact of autoregressive influence is made evident. First, the level of acquaintanceship is lower than in the previous models, reflecting the fact that the opinions of the randomly paired agents are less similar. Encounters still occur, however, because agents frequently have at least one opinion in common. As a result, agents regularly encounter other agents with which they disagree on a randomly chosen issue. Second, only a relatively small proportion of networks are composed of dyads with identical preferences. Finally, the average proportional agreement with any acquaintance (harmony) is only slightly above one-half. That value, which is consistent with earlier empirical results, indicates that there is a considerable level of agreement among the networks, but by no means complete homogeneity.

Agents on Multiple Lattices

Agents still have, at most, eight possible acquaintances in the context of the Moore neighborhood. Hence, the requirement of a majority in favor of the new view still requires substantially greater than 50 percent in favor of the new view.[4] We address this problem by subjecting the autoregressive model to a more challenging test. As before, the agent's neighborhood is defined as a 3x3 grid, but agents are located on two separate lattices – a “home lattice” and a “work lattice” (Figure 2). In this model, there are five separate lattices consisting of 10x10 "home" lattices, and each day all the agents spend at least part of their time at home.

[4] The ratios are 4/7 , 4/6, 3/5, 3/4, and 2/3 for majorities in reference groups of 7, 6, 5, 4, and 3.

Some agents also travel to a cell in three separate 5x5 "work" lattices. These agents begin each day at home, but travel to work at some time during the day before returning home. Across these alternative environments, the agents continue to encounter other agents at random, and acquaintances continue to form with probability equal to the proportion of shared opinions. When presented with disagreement on an issue, an agent will adopt the acquaintance's opinion if more than one-half of its agreeable acquaintances support that new opinion instead of the agent's existing opinion. Each "day"—one trip through the list of all agents—requires ten time steps within the simulation.

At the outset, agents have formed few acquaintances and they are simply wandering about, forming acquaintances, accumulating experience, and keeping records. After a few iterations, patterns of influence begin to appear. The averages across 100 runs of the model are presented in Table 2. Out of 500 agents, the number of agents persuaded to change in each day is typically less than 10, and that number declines as the networks stabilize. The average duration of the simulation is about 7,871 timesteps, or 781 "days" (trips through the list of all agents).

The time paths of the measurement variables for one sample run are plotted in Figure 4. As in other runs, the diversity measures stabilize after a relatively small number of periods: agents report neither complete homogeneity nor complete heterogeneity. Note that entropy—indicating diversity—starts at a relatively high level but settles down into a steady state in the middle range, while agent experiences of homogeneity increase. As the harmony measure shows, agents experience agreement with acquaintances about two-thirds of the time – across two-third of all issues; and less than one-third of the agents' acquaintances hold identical sets of opinions.

The results of this model address the concern that the stabilizing impact of the autoregressive influence is an artifact of the small (eight acquaintances is the maximum) networks that are allowed in the earlier design. The average number of other agents that are encountered by each agent in this revised model is 39, and the average number of agreeable acquaintances is 22. These results drive home an important point: diversity is not being preserved by isolating agents from opinions with which they disagree. Rather, diversity is preserved within the networks – both large and small, high density and low density – by providing agents with an autoregressive decision rule for accepting or rejecting the opinion of a discussant.

Autoregressive Influence in Small Groups

Perhaps the most demanding test for the autoregressive influence model is to consider it within the confines of a small group where everyone has an opportunity to encounter everyone else within the group, but no one has an opportunity to encounter anyone beyond the group. We implement this scenario by locating twenty agents in each cell of a 10x10 grid. The agents are equally probable to experience random encounters with any other agent in the cell, but they are unable to encounter agents in other cells. This would appear to be a very demanding test of the autoregressive influence model, and one might well expect to see homogeneity within the cells. In fact, this is not the uniform outcome.

Table 3 shows the levels of entropy, acquaintance, identicality, and harmony for the entire population of agents, as well as for the separate cells. First, it is clear from Part A that opinion heterogeneity is maintained in the aggregate, although the level of entropy is higher than those of Tables 1 and 2. Moreover, the aggregated levels of harmony and identicality are also higher, indicating higher levels of issue agreement in Table 3.

Second, the results within each of the 100 cells of the grid are shown in Part B of Table 3. In this instance these measures are not based on the experience of the agents through the simulation, but rather on a census of the conditions that existed at the end of the simulation. These results are notable for their heterogeneity. In some instances, opinions become homogeneous. In other instances, the agents polarize into two groups that are internally homogeneous but share no opinions in common with the opposite group. For example, the level of identicality ranges from .10 to 1.00. This means that, in some instances, the agents in a cell become entirely homogeneous, in other cells there are only minimal levels of identicality, and the mean for the entire grid is .44. In contast, the number of opinion clusters varies from 1 (when ever agent holds opinions that are identical to each other agent in the cell) to 8. And the largest opinion cluster varies from 4 agents to 20 agents.

Social network models usually emphasize “connectivity.” Connectivity plays a role in our models, but it appears it is not the most important component in persuasion and homogenization of opinion. Diverse agents may interact forever without changing, as long as each has recourse to a group of others with whom they agree (and thus resist the influence of persuasion). Because of the simultaneous importance of connection and persuasion, we have found it difficult to summarize the essence of the process in a simple directed graph.

Two “persuasion graphs” are displayed in Figure 5. In these particular example cells, all of the agents have at least one opinion in common, so they can all interact dyadically. As a result, we don’t draw lines for interaction. Rather, a line represents membership in the “confirmation group” for an agent who encounters a new point of view. A line from agents 0 toward 1 indicates that if 1 encounters a new opinion, then 0 would be one of the agents to whom 1 would look for confirmation. In our simulations, all stable networks are fully recursive—if one agent is in the confirmation network for another agent, the converse is also true. However, when considering triads, the same is distinctly not true.

One interesting pattern is displayed in Figure 5a. There are 3 distinct clusters of agents who rely on each other when new opinions are presented. Because of the dynamical processes that are assumed in this model, it seems very unlikely that a slight modification in the opinion pattern could upset this arrangement of opinion. The situation might be different in Figure 5b, where we see that there are some weak links between the isolated groups. These links share a majority of opinions with the two separate groups and they may act as conduits to “tip” the opinion networks in a more homogeneous direction.

What does this suggest? Clearly, initial conditions, defined both with respect to the initial random interactions and to the initial random distributions of opinions, are profoundly important to the equilibrium outcome. To reiterate Granovetter's insight, behavioral outcomes depend on "concrete, ongoing systems of social interaction" (Granovetter 1985: 487). In this particular instance, these systems of social interaction unfold as a consequence of communication patterns, constrained by rules of interaction, that lead to particular patterns of behavior which in turn constrain future patterns of communication.

Autoregressive patterns of influence do not necessarily create opinion heterogeneity within small self-contained groups, but neither do these small self-contained groups foreordain homogeneous opinion distributions. Combined with the random perturbations that are part of the model, the inherent nonlinearity of autoregressive influence leads to complex patterns of communication and behavior with outcomes that cannot be predicted. This lack of predictability is striking. The rules governing interaction relatively simple and well understood, but the equilibria are highly unstable and dependent on initial conditions (Boudon 1987).

Conclusion

What have we learned from this analysis? First, the effect of auto-regressive influence with respect to the adoption of socially communicated opinions is quite robust with respect to small scale social organization. In general, the model shows that it is possible to sustain opinion diversity with respect to the small scale organization of social networks, even under fairly extreme conditions. This is not to say that opinion homogenization never occurs. In some circumstances, under particular sets of conditions, it is possible to generate homogeneous opinion distributions.

The circumstance in which we are able to generate homogeneous opinion distributions occurs when the potential for network density is extremely high. In this situation, each agent shares an environment with 19 other agents, and each of the other 19 agents share exactly the same environment. Moreover, none of the agents is able to encounter agents beyond this shared environment, and the probability of encountering any one of the other agents within the shared environment is equally probable. In short, this is small group politics with a vengeance.

Under these conditions, it is possible to generate homogeneous opinions, but it not particularly likely. To the contrary, the typical result in such an environment is that agents develop communication networks that, while reflecting their own opinions, also demonstrate persistent heterogeneity. In this world, opinion formation is endogenous to social communication at the same time that the formation of communication networks is endogenous to agents' opinions. And the end result is that, while agents are imbedded in networks that reflect their opinions, heterogeneity persists, and agents continue to experience diversity.

It is much more difficult to generate homogeneous opinion distributions when the density of encounter networks is reduced. Heterogeneous distributions are generated when all agents are located on 10x10 grids within either von Neumann or Moore neighborhoods. Diversity is also preserved, within Neumann and Moore neighborhoods, when agents are distributed over five "home" grids coupled with random patterns of assignments to additional "work" grids. While these arrangements affect the speed and reach of communication, they do not alter the diversity-producing consequences of auto-regressive influence.

None of this should be interpreted to call into question the efficacy of small scale organization within networks of political communication. Small scale organization is, after all, capable of producing opinion homogeneity. Rather, in order to preserve homogeneous opinions within communication networks, it appears that a fairly extreme form of small scale organization is necessary. Correspondingly, when we observe homogeneity within networks in the natural world, the organization and reach of small scale social organization is likely to be key.

Political diversity and disagreement among associated individuals does not survive in all societies at all times, but the survival of disagreement among associated individuals is not a rare event, and political homogeneity within communication networks is not an inevitable consequence. Just as important, diversity of experience and opinion, both in the small and in the large, is likely to arise even if no individual actively and intentionally seeks to cultivate diversity.

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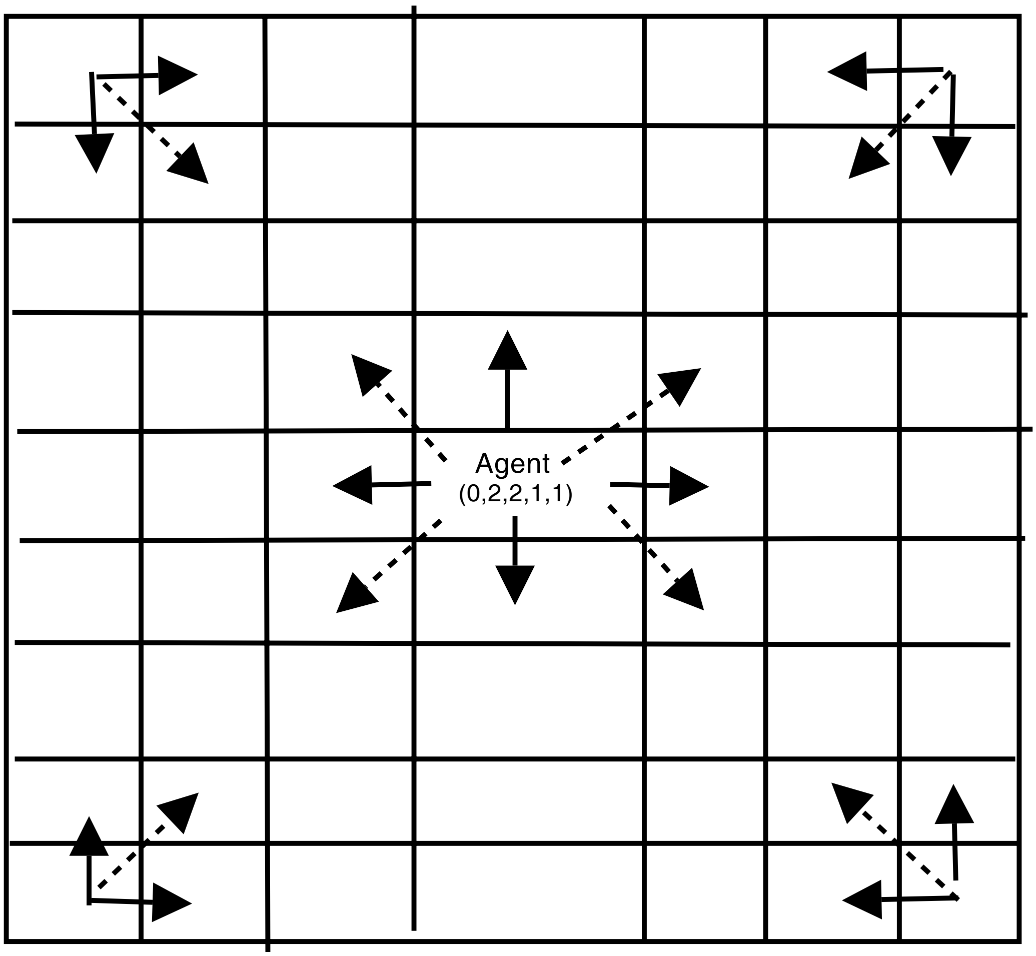
Figure 1. Agents in von Neumann and Moore neighborhoods.



Basic Model:

- A single agent in each cell
- An opinion vector each agent, e.g. (0,2,2,1,1) for 5 opinions
- Solid lines represent von Neumann neighborhoods
- Dashed lines represent additional cells of Moore neighborhoods

Figure 2. Multiple home grids and work grids.

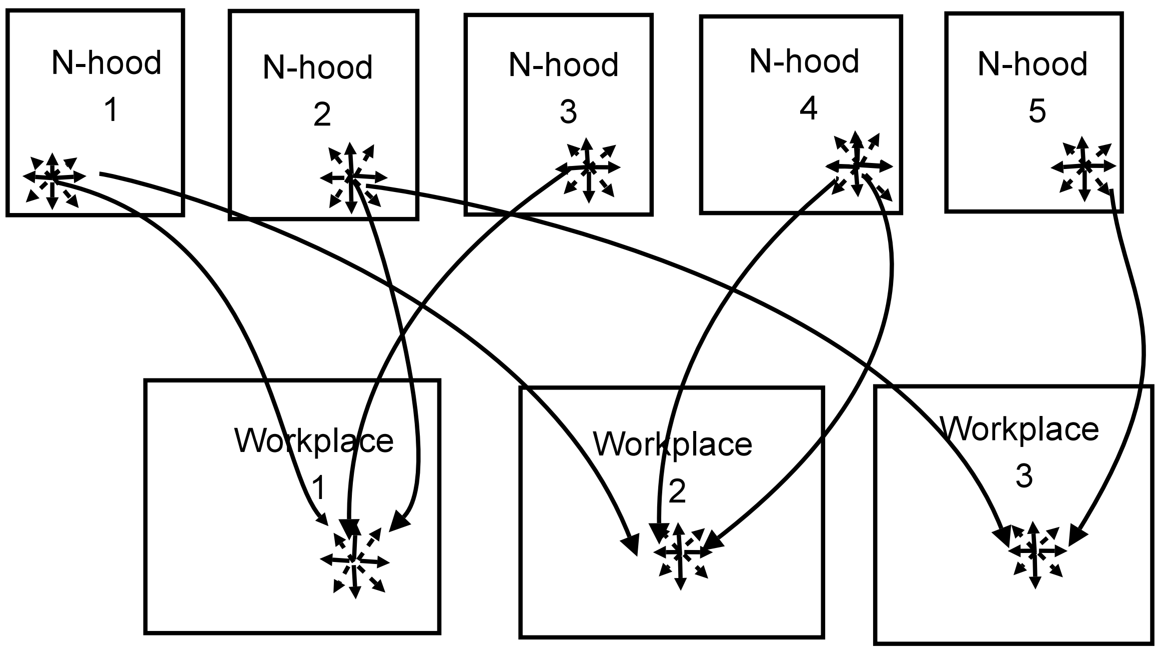


Figure 3: Diversity in one 10x10 home grid with Moore neighborhoods

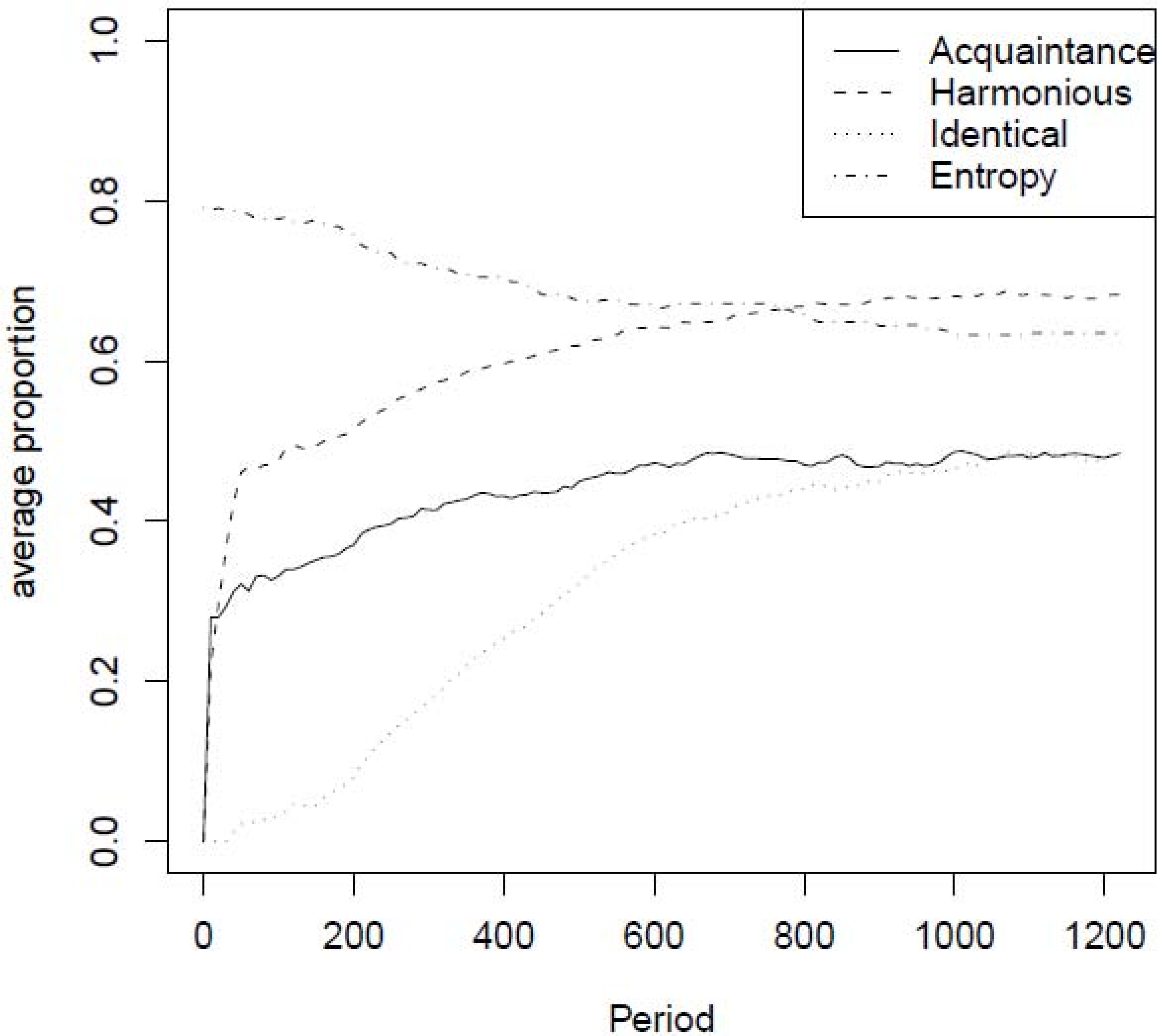


Figure 4: Diversity with 5 home grids and 3 work grids

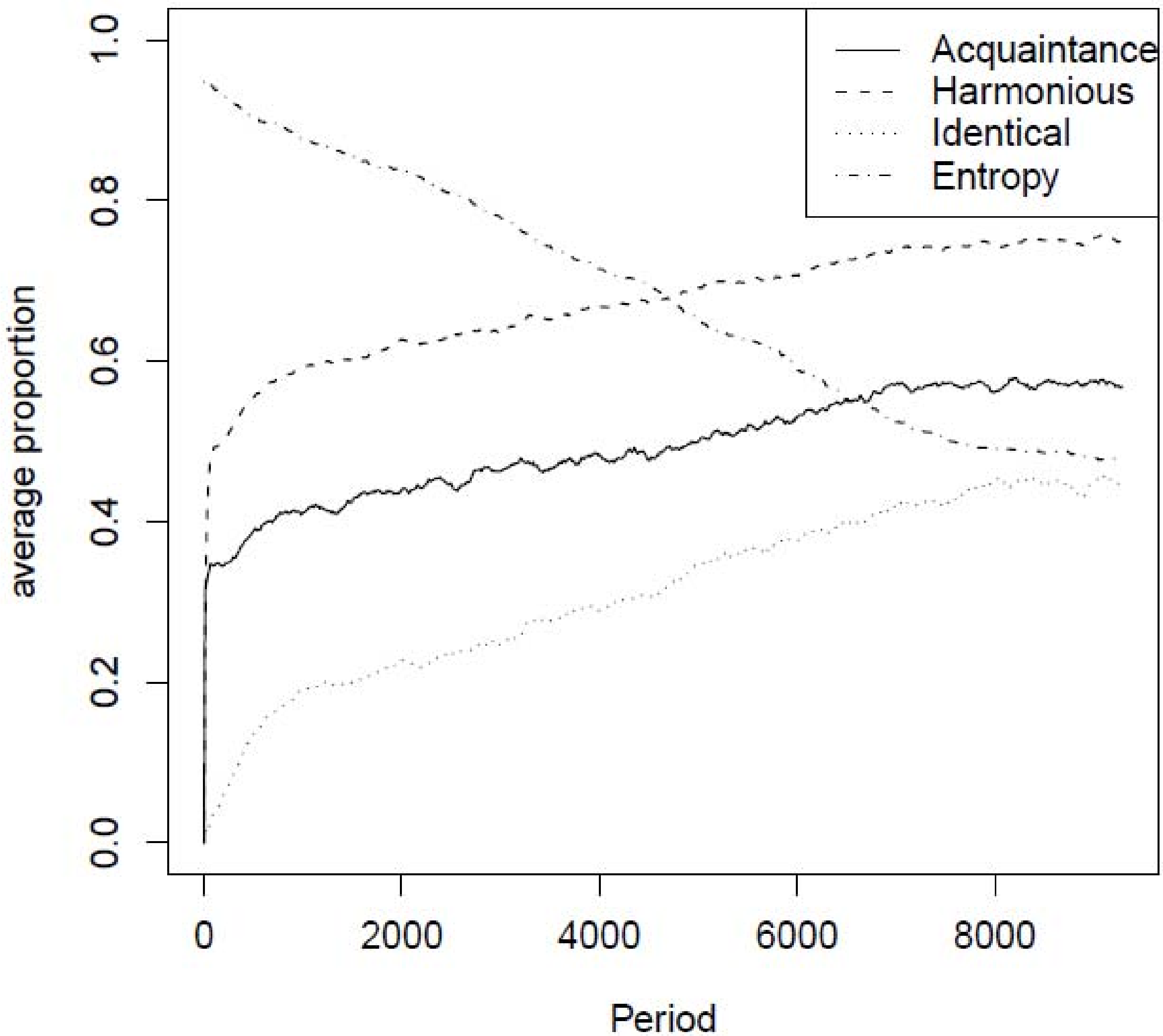
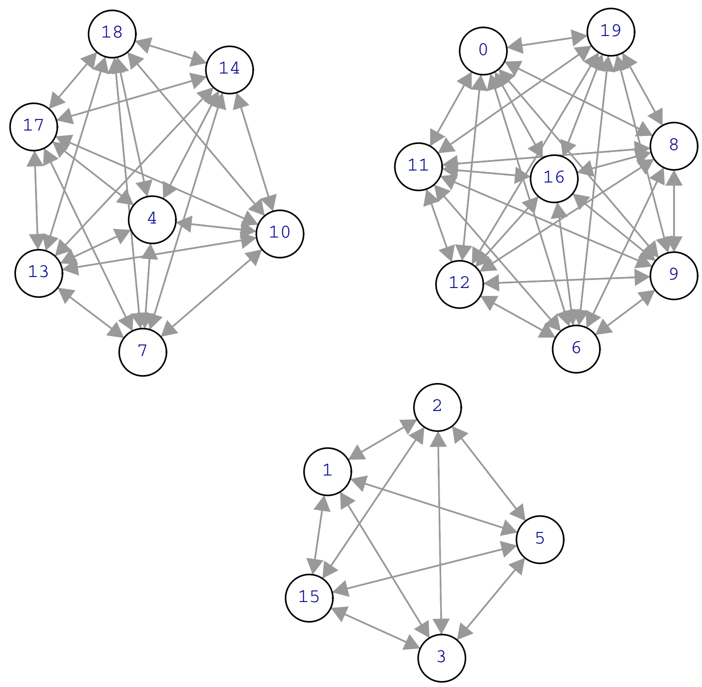


Figure 5: Directed persuasion networks: An infinite Variety

(a)



(b)

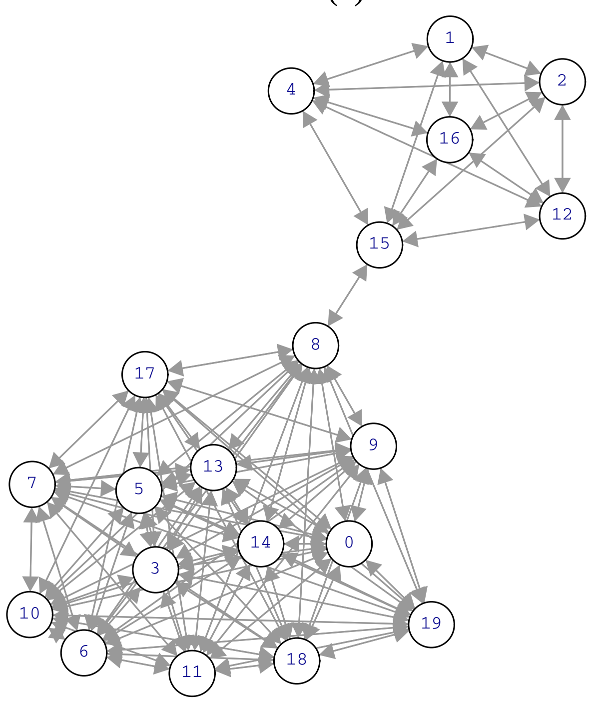


Table 1. Diversity with Moore Neighborhoods on the 10 x 10 Grid

	Mean Across 100 Simulations	Std. Dev. Across 100 Simulaitons
Experiment Summaries		
Iterations	1285.8	273.991
TotalEntropy	0.61744	0.03400
Variance of Opinion		
Issue: 1	0.6347	0.100699
2	0.6307	0.081715
3	0.6282	0.087529
4	0.6257	0.094818
5	0.6298	0.094985
Summaries Across Agents		
Acquaintance (mean)	0.48951	0.039445
Harmony (mean)	0.69828	0.03490
Identical (mean)	0.48456	0.05859
N. of Contacts (mean)	6.3796	0.15536
N of Contacts (std.dev.)	1.6975	0.07886
N of “friends”: (mean)	2.5527	0.363167
N of “friends”: (std. dev.)	1.7879	0.229525

Table 2. Diversity Across 5 Home Grids and 3 Workplaces with Moore Neighborhoods

	Mean Across 100 Simulations	Std. Dev. Across 100 Simulaitons
Experiment Summaries		
Iterations	8809.3	1698.480756
totalEntropy	0.447824	0.09489
Variance of Opinion		
Issue: 1	0.5489	0.203196
2	0.54778	0.208084
3	0.53084	0.21107
4	0.52544	0.19480
5	0.48842	0.19688
Summaries Across Agents		
Acquaintance (mean)	0.564913	0.081606
Harmony (mean)	0.765975	0.046533
Identical (mean)	0.50326	0.082521
N. of Contacts (mean)	38.62	1.913635
N of Contacts (std.dev.)	12.301946	0.80917
N of “friends”: (mean)	22.18112	4.234838
N of “friends”: (std. dev.)	11.11455	1.875112

Table 3. Small Groups of 20 Agents in Each Cell.

A. System-wide Summary of the 10x10 Grid

	Values at Completion
Experiment Summaries	
Iterations	2940
Normed Entropy	0.902
Variance of Opinion	
Issue: 1	0.5489
2	0.54778
3	0.53084
4	0.52544
5	0.48842
Summaries Across Agents	
Acquaintance (mean)	0.559
Harmony (mean)	0.826
Identical (mean)	0.741
N. of Contacts (mean)	17.533
N of Contacts (std.dev.)	2.2224
N of "friends": (mean)	8.353
N of "friends": (std. dev.)	4.571

B. Cell level summaries within the 10x10 Grid, based on the distribution of opinion when the model stabilizes.

Indicator	Mean	Std.Dev.	Minimum	Maximum
Identical	0.55	0.24	0.10	1.00
Acquaintance	0.83	0. 18	0.35	1.00
Harmony	0.68	0.17	0.33	1.00
Clusters	3.30	1.28	1.00	8.00
Largest Cluster	11.69	3.36	4.00	20.00
Entropy	1.34	0.52	0.00	2.88
Normed Entropy	0.81	0.18	0.00	1.00

Table 3 (continued).

C. Correlation matrix for cell level indicators.

Pearson's r	Ident.	Acq.	Harm.	Clust.	Largest	Entropy	Normed Entropy
Identical	1.00	-0.50	0.98	-0.73	0.71	-0.79	-0.39
Acquainted	-0.50	1.00	-0.51	0.06	0.18	-0.08	-0.32
Harmony	0.98	-0.51	1.00	-0.70	0.70	-0.85	-0.77
Clusters	-0.77	0.06	-0.63	1.00	-0.71	0.77	0.38
Largest Cluster	0.71	0.18	0.70	-0.71	1.00	-0.92	-0.75
Entropy	-0.96	-0.08	-0.77	0.91	-0.92	1.00	0.58
Normed Entropy	-0.39	-0.32	-0.38	0.25	-0.75	0.58	1.00