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OPINION FORMATION AND THE RESILIENCE OF DIVERSITY

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Abstract. This project explores agent-based models of the formation of individual opinions and collective judgments. The goal is to understand the effect of political communication on opinion formation and collective decisionmaking.

INTRODUCTION

The analysis begins by exploring the culture model originally proposed by Robert Axelrod (1997). Axelrod's model is highly tractable, and thus it is a good starting point. It has some fundamental weaknesses, however. One of the most important substantive weaknesses is that the model generally predicts the eradication of diversity over the long run.

The model predicts that all people (or almost all) will agree about all issues. Empirical studies by Huckfeldt and Sprague (1995) have found that disagreement can persist over the long run in sample data, and in addition they have found a relatively high degree of diversity among the networks in which there is social interaction.

As a result of the clash between the tendencies observed in the model and the empirical findings, we seek to adjust the model to generate patterns which seem more empirically likely. The new model should allow us to investigate the impact of additional variables. That model is generalized in a number of ways. The first generalization is to reconceptualize the "villages" in Axelrod's model as multi-member entities, rather than aggregates. This brings into play a factor called "parochialism", the tendency of an individual to seek communication with a narrowly defined sphere. The second reconceptualization is to consider the process of network formation for political discussion. We begin by allowing agents to be selective in their choice of discussion partners, and then we introduce the effect of changes in the agent's position among a number of environments.

All models are written in Objective-C using the Swarm Simulation System, an open source toolkit written in Objective C.

STATEMENT OF THE PROBLEM

Large scale social events result from the conglomeration of many micro events. The linkage between macro level stimuli and macro level outputs is uncertain because the impact of macro level events is filtered down to the individual level through a complex system in which individual decisions are made.

Theories of individual interaction in the formation of individual judgment, and eventually social judgment, can typically be categorized in two ways. The first holds that individual judgments are affected by their observations of social aggregates. Judgment is not driven by personal conversation, but rather by observation of mass behavior. It seems that descriptions of this sort are especially prevalent in models of mass political protest. Granovetter's threshold model links individual behavior to observations of aggregate levels of action (1978). Lohmann's model of revolutionary behavior presents a richer model of the way individuals react to the aggregates they observe, but for many purposes, the essential idea is the same.

We propose to work in a different direction, one in which the individual-level adjustment process is more prominent. Individuals are aware of each other, not simply by observing communal averages, but also as individuals. People exchange views and information, and they may change opinions in response to one another. If there were a useful model of this kind, it might help us to understand public opinion formation during an election or a policy debate. Following some insights of early work by McPhee and Smith (1962) and later explored by Huckfeldt and Sprague (1995), individuals are seen as parts of loosely knit, flexible networks in which information transmission occurs through political discussions. Individuals adjust their opinions on the basis of the perceived quality of the information from individual discussants and other factors. Adapting Huckfeldt's analogy, the formation of public opinion is like collecting the conclusions of thousands of individuals serving on different juries (Huckfeldt 1999).

This paper reports on preliminary effort to develop a perspective from which to design models of these processes and compare them. Along the way, some insights into the modeling process are afforded. The general modeling problems that seem most pressing are the following.

1. How can one differentiate "data" from that which is to be "reproduced?" In other words, how does one know what is to be assumed and what is to be derived? McPhee and Smith (1962) proposed to begin their model with known qualities of individuals. However, it may not be safe to assume that the results of empirical research about individuals reflect the actual underlying laws that guide individual action. Instead, the observed patterns reflect the outcome of a sifting-out process that may obscure evidence of some individual traits or create illusory indications of other traits.

2. How can one distinguish specification errors from emergent properties? The term "emergent property" arose from modern complex systems theory and it has captured the imagination of many writers. While the term is elusive and difficult to pin-down, it is meant to convey the sense that a model produces a pattern that is unexpected, but is somehow relevant or important. There is always the danger that these patterns might be artifacts of computer model design, rather than the substance of the problem itself. Hegselmann (1996, p. 222) notes, for example, that it can make a difference if a model is written so that the information state of all agents is temporarily frozen in order for all to adjust their behavior (synchronous updating) or if the effect of each agent's action is immediately known to each following agent (asynchronous updating). Choices in the structure of updating can produce some surprising patterns, which some might call emergent properties and others will call mistakes (Huberman and Glance 1993).

Technical Details

The simulations discussed here were done with the Swarm Simulation System (http://www.santafe.edu/projects/swarm). These models are written in Objective-C, an object oriented computer language, as is the Swarm toolkit itself. An object is a self-contained entity that is capable of maintaining data (the values of variables) as well as executing methods (sequences of commands). The Swarm toolkit supplies classes that can be used and, in many cases, subclassed to form new variants.

In the software development effort of which this paper is a part, a few important technical hurdles had to be overcome. The most important of these were the development of a new class that allows a number of agents to occupy positions in a two dimensional grid and also the integration of a procedure for iterative processing of Swarm programs.

The Wrapped List Grid2d

The Swarm toolkit contains a number of libraries that help the user to design a simulation. There are libraries to manage collections of objects, to create random number generators and objects capable of generating observations from statistical distributions, to analyze and summarize observations, and also there is a space library which contains a set of classes that can be used to maintain records on the position of agents within two dimensional spaces. One limitation of the space library in the Swarm toolkit is the assumption that only one object can occupy a given position in a space. This is, of course, a standard premise in models based on cellular automata, and the assumption that only one agent can occupy a given location is perhaps logical in a model in which the cells in the grid are very finely grained. In such a model, it might be plausible to argue that it is physically impossible for more than one agent to be in one position at one time. (In fact, in the Heatbugs model, one of the "swarmapps" distributed to illustrate the usage of the Swarm toolkit, the impossibility of positioning multiple agents on a single cell is one of the critical elements of the model.)

If each cell in the grid is thought of as a household or village, the restriction on multiple occupancy becomes untenable. As a result, for the purposes of this project, a new class was developed that allows both multiple occupancy and user interaction with locations through the graphical user interface (GUI). The first steps toward this goal were taken by Sven Thomassen, who released a class he called MoGrid2d (ftp://ftp.santafe.edu/pub/swarm/users-contrib/anarchy/SvenSpaces-970805.tar.gz). MoGrid2d creates a subclass of the Swarm class Grid2d in which there is a Swarm List object at every position. After an instance of the MoGrid2d class is created, user code can then tell the space to add (or remove) objects at a particular position in the space and MoGrid2d handles the dirty work. If an agent tries to move onto a cell that has no current occupants, a new list object is created for that cell, and when the last agent leaves a cell, the list is destroyed.

The MoGrid2d class, however, does not completely solve the problem because it does not allow the user to interact with the entities in the grid, except to add or extract agents. It is not possible, for example, to ask a cell to report the average of agent opinions within the cell, or to describe the conditions of neighboring cells. The ability to dynamically create probes that reveal the internal states of objects is one of the key features of the Swarm library. MoGrid2d does not exploit that ability because it does not make it possible for users to interact with agents within these cells. Since the Swarm List class does not allow subclassing by users, it was necessary to redesign the multiple occupancy grid.

The solution used in this paper is a new class called WrappedListGrid2d. Like MoGrid2d, this class inherits from the Swarm Grid2d class. At each position in the WrappedListGrid2d object, one can insert an object or ask for an object to be retrieved. The object that are stored in the grid are "wrapped lists," meaning that they contain lists to hold the objects that are inserted, but they also can contain other information as well. As a result, the objects placed on the grid have more functionality than objects from the Swarm List class. These objects are designed to inherit certain generic features, such as the ability to add and remove agents from lists that they manage, but in addition they can respond to application-specific commands, which, for example, can ask the cell to gather information about the current members of the list or draw on graphs to represent a summary of the events within the cell. The WrappedListGrid2d class also contains some code designed to improve speed and efficiency. When a position in the grid is left empty by the movement of agents, the object in that cell is not destroyed, but rather it is removed and placed into a queue for recycling when agents move onto previously unoccupied cells.

DEALING WITH BATCH MODE PROCESSING

Our opinion is that procedures for managing repeated simulations and "parameter sweeps" ought to be a priority for the future development of the Swarm Simulation System. At the current time, Swarm is designed to allow users to run their programs in either of two modes. The first is the GUI (Graphical User Interface) mode in which the user directly interacts with the program through a point-and-click interface. By the convention, the object that manages the GUI is called the observer swarm. A "snapshot" of the screen from one simulation is shown in Figure 1. The Swarm GUI uses the tcl/tk toolkit (http://www.scriptics.com/software), which is a combined scripting language (tcl) and widget set (tk) that can be used to manage user interaction with a running program. The observer swarm creates a control panel object that has "start" and "stop" buttons that regulate events, and the user can design the code in the observer so that certain user clicks bring up "probes" that display information about the internal states of the agents and instruct them to perform particular tasks. In a GUI simulation, the observer is the top level swarm, which means that it not only manages the GUI, but also it initiates the creation of lower level objects and monitors their progress. The observer swarm can contain code to create various kinds of graph objects. The Swarm library contains methods that can be used to take "snapshots" of particular window displays (called "widgets") at predetermined times and save them in the png format (png is an open source pixmap format similar to the proprietary gif format familiar to internet users).

Swarm also has a batch mode. Simply put, in the batch mode, the simulation runs without displaying any graphics to the user during the simulation. Batch mode processing is required in order to conduct many replications of a single experiment or to conduct a "parameter sweep." The top level object is referred to as the batch swarm and it can create lower level objects and write reports on their activities to files. The Swarm development team has made significant strides in the so-called "serialization" of Swarm models, tools that can save summaries of the state of objects and make them available is a standardized format for statistical analysis. (Swarm supports saving of records inLisp format or the HDF5 format, which is an open-source data storage format supported by a number of advanced packages for graphical visualization of data).

However, within Swarm itself there is no library with which to manage the repetition of simulations. Furthermore, in Swarm's batch mode, there is no capability of making graphical snapshots to summarize the state of events. In order to circumvent these limitations, two additional steps were taken in the present project. First, a generic simulation management tool called Drone, which was developed at the University of Michigan for the "CAR Group" (Cohen, Axelrod, Riolo), was used (http://aaron.physics.lsa.umich.edu/Software/Drone/). Because Drone was completed before the Swarm project reached maturity, some special effort is required to make the two work together. Second, a user-contributed class called BatchRaster (developed by Nelson Minar and Benedikt Stefansson in 1977: ftp://ftp.santafe.edu/pub/swarm/users-contrib/anarchy/batchraster-movies.tar.gz) was updated to work with Swarm 1.4.1 and later (ftp://ftp.santafe.edu/pub/swarm/users-contrib/anarchy/BatchRaster-990811.tar.gz). The BatchRaster class can create a portable pixmap record (in ppm format) of a two dimensional space. It records, pixel by pixel, the coloring of a two dimensional grid. Through this approach, pictures can be saved while the program runs in batch mode, without accessing the GUI interface that slows the processing significantly. Incidentally, because of the limitations imposed by Swarm's approach to batch processing, I've explored the development of a new class that sits above the observer swarm and can spawn one GUI simulation after another, recording data and taking pixmap snapshots of any Swarm widget (graph or raster). (An example of such a model can be found at this site: http://lark.cc.ukans.edu/~pauljohn/Swarm/RepeatingHeatbugsParameters-2.0.1x.tar.gz.)

APPLICATION

The model is designed for study of public opinion formation in a setting where the individual actors do not base their judgments on opinions they exchange directly. Huckfeldt and Sprague (1995) describe political interaction in terms that go something like this. People move around within their spheres of activity and, depending on where they are and what they are doing, they may meet people who may be inclined to discuss politics. The people are able to sort through their opportunities for political interaction. And, possibly on the basis of that interaction, people may alter their opinions. The agents are capable of selecting discussion partners and moving about in space.

Axelrod's Culture Model (ACM)

The simulations discussed here take Axelrod's culture model (Axelrod, 1997, Chapter7) as the baseline and then consider variations. There are a number of ways to implement the culture simulation in Swarm (two examples that I found most useful were by Rick Riolo, (ftp://www.pscs.umich.edu/pub/software/Swarm/axelcult-990712a.tar.gz) and Lars-Erik Cederman (http://www.sscnet.ucla.edu/polisci/faculty/cederman/S99/p209-1/code/culture.tar.gz)). The code that created the simulations described in this section is available (http://lark.cc.ukans.edu/~pauljohn/Swarm/cultureWrappedGridBatchRaster.tar.gz).

Axelrod's model conceptualizes interaction among agents in the following way. A square grid of agents, referred to as "villages," is created. Axelrod uses the term culture to describe a set of positions of a village on integer valued characteristics. The number of cultural issue dimensions or topics, called "features" in the culture model, and the number of positions on each topic, called "traits" in his model, can be varied.

The villages are fixed in position. They cannot move about. In that sense, they are like "real villages." In just about every other respect, they are not like real villages at all. There are no individuals in the villages--each village is conceived of as a unitary actor.

The simulation is scheduled as follows. An agent (village) is randomly selected and given the opportunity to interact with a randomly chosen neighbor. The set of neighbors is the so-called von Neumann neighborhood, which consists of the agents on the east, west, north, and south borders. Cells that lie on the outside boundaries of the grid have fewer neighbors with which to interact. Unlike some other simulation models that use a toroidal representation to make the grid wrap around and connect the opposite edges (Epstein and Axtell 1996), Axelrod reduces the interaction opportunities for actors on the edge. In Axelrod's model, one of the neighbors is selected at random, and then an interaction occurs with probability equal to the similarity of the opinions of the two agents. If the interaction occurs, then an issue on which the two agents disagree is selected at random and the agent's opinion on the issue is changed to match the other.

Axelrod made a number of observations on the basis of his model, the most striking being that, over the long run, there is not likely to be very much cultural diversity. While the tendency toward homogeneity is greater for some parameter settings than others, it is powerful in all cases. This conclusion poses a challenge at the outset for the current modeling exercise. If we are to formulate a useful model of political interaction and formation of small networks, and we want that model to be faintly realistic, we do not want the major implication of the model to be that diversity is unlikely to exist. One solution is to write agents who are individually resistant to environmental influences, but that is not the route explored here. Rather the emphasis is on developing a more intricate understanding of the formation of networks on formulation of public opinion.

Generalization Of The Culture Model

The Swarm model described here uses the Axelrod culture model as a starting point in an effort to develop a more general simulation model. Put simply, we want to know how to redesign the model so that its most discouraging and unrealistic conclusions can be altered. We want a model that will 1) not have the long run tendency toward homogenization of public opinion (global diversity), and 2) will allow diversity to exist among people who interact (local diversity). Global diversity can be achieved by clumping together all similar agents and blocking their interaction with agents of other types. That does not provide local diversity, however, as the individual actors are likely to believe that the world is a very homogeneous place. On our list of structures that deserve investigation, we have ideas about ways to make the villages more interesting and "lifelike" by allowing multiple occupancy, varying definitions of the neighborhood of each agent, as well as movement among agents within a given grid or movement to another grid altogether. This report provides indications of the effect of changes in the introduction of multiple occupancy as the ability of agents to form "networks" by opening discussions with neighbors in a selective process.

It is necessary to develop a new diagnostic tool for the analysis of these models, however. Axelrod used concepts that are exclusive to single-agent-per-cell models. He used the principles of "zone" and "region" to summarize the development of patterns across the grid. A zone is a continguous region of cells that have at least one feature in common, while a region is a grouping of cells that are completely alike. In the model with multiple occupancy and mobility of agents, these summary indicators are not useful. Instead, I propose to use the summary measures of the perceptions of the individual agents as well as global indicators of diversity.

To summarize the perceptions of the agents, three measures were created. Each agent keeps a "running tally" of its experiences. For each prospective discussant, the agent records whether there was an interaction. The proportion of possible interactions that actually materialize is referred to as the perceived level of acquaintance. This is recorded as a 20 period moving average. The second and third measures summarize the similarity of an agent and the others with which it has had an interaction. The "harmony" moving average indicates the proportion of opinions that the two agents share, while the "identical" indicator is the proportion of people that the agent finds are identical to itself.

In addition to the subjective experiences of the agents, an objective measure of diversity is also calculated after each time the list of citizens is processed. This measure, known as entropy, or Shannon's information index, is a normed measure that is equal to 0 if all objects in a set are identical and 1 if there is an equal number of every kind (Shannon 1949; Baltch 1998). If there are F different features (issue dimensions) and there are T different traits (positions) for each feature, then the number of possible issue stances is T^F. If the proportion agents holding a given set of positions is p_j, then the normed entropy is given by:

$$NormedTotalEntropy = \frac{\sum_{j=1}^{T^F} p_j * \log_2(p_j)}{\log_2(1/T^F)}$$

Some caution is needed in interpreting the entropy values. The normed entropy measure depends on both the number of traits and the number of features. As a result, it can be tricky to compare across models where those variables differ. Furthermore, although the entropy depends only on the proportions of agents holding particular opinions, those proportions can be affected by the number of agents in the simulation. For example, if a distribution has 10 features and 10 types, then the number of possible observed types is a huge number, 10^{10}. If there are 100 agents, there are at most 100 different observed preferences, and so the calculated value of normed total entropy will be lower than a model that has 10000 agents.

To allow comparison across models that differ in the number of features, but have the same number of traits, I propose to calculate the entropy observed for each specific feature.

$$NormedFeatureEntropy = \frac{\sum_{i=1}^{T} p_i * \log_2(p_i)}{\log_2(1/T)}$$

An average of feature specific entropy measures can be compared across experiments, as long as the number of traits is the same.

One other technical issue is the scheduling of the actions of the agents. Axelrod's simulation was designed so that one agent is chosen at random for a possible interaction in each time period. As noted by Axtell et al (1996, p. 190), the outcome of the simulation over the long term can depend on seemingly unimportant assumptions such as this one. Because this project is intended to investigate the simultaneous interaction of many agents in a complex system, the scheduling of actions is done by randomly sorting the agents at each time period and then processing all of them in sequence. Each interaction reflects the impact of all previous interactions within the time step of the model.

What If They Really Were Villages?

Using the WrappedListGrid2d class described above, this model represents a square grid in which each cell can contain several individual agents. Each point in the grid is thought of as a household. As the simulation proceeds, the list of all citizens is randomly sorted and each agent is given the instruction to select a possible discussant and then initiate an interaction. As in the original Axelrod culture model, an interaction occurs with probability equal to the similarity of the cultures of the two agents.

To reproduce Axelrod's original results, one set of models is designed with one agent per cell and prospective discussant are selected at random from the four adjacent cells. The snapshot in Figure 1 shows a simulation of the Axelrod culture model (ACM) in a 10 by 10 cellular grid with 5 features (issues) and 5 traits (positions per issue). The "raster" displays on the right hand side (labeled "feature 0" and so forth) use color to indicate the trait (opinion) of the agent in that cell on that feature. The simulation stops when ten cycles through the list of agents are completed without any agent changing its opinion. This snapshot is taken at the end of the simulation. Each raster indicates that a single viewpoint is dominant and the normed entropy indicator is zero.

A replication of this model for various values of the parameters matches the substantive highlights of Axelrod's results (see Table 2). For each setting of the parameters, the table indicates the averages of the model's duration (number of iterations), the total and feature-specific entropy values at the stop time, as well as averages of the perceptions of the individuals. The perceived acquaintance value represents the proportion of the time that the agent has tried to initiate a conversation and succeeded. The other two measures summarize interactions. Harmony is the percentage of features that the agent shares with acquaintances. The Identical percentage is the percentage of acquaintances that are identical with the agent on all features. To summarize the results, there is not much diversity in models with a small number of features and adding to the number of features reduces diversity still further. Increasing the number of traits increases diversity somewhat, but not in a striking way.

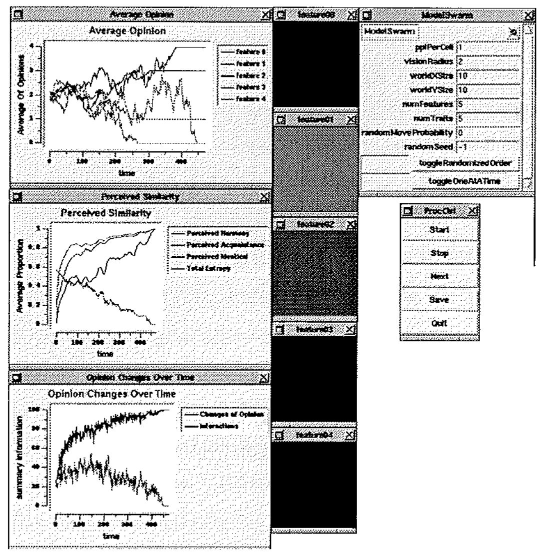

FIGURE 1. Culture model: one person per village. (see electronic version for color image)

The entropy figures are abstract and perhaps a brief illustration of their meaning will help. Consider a single feature that has 5 possible values. If we have 100 agents and they are distributed (20,20,20,20,20), then the feature-specific entropy value is 1.0. Some other distributions, and their entropy values, are provided for comparison purposes.

TABLE 1. Entropy values of opinions.

Distribution of opinions	Entropy Value
(97,1,1,1,0)	0.12
(99,0,0,0,1)	0.034
(70,0,0,0,39)	0.37
(50,0,0,32,18)	0.63

When the entropy level is so small as in the runs in Table 2, one is probably safe in concluding that only a trivial amount of diversity remains after the model reaches its resting state.

Does increasing the number of agents in each cell change the prediction of the model? When there are many agents in each cell, then each agent chooses a prospective discussant in the following way. First, with a given probability, the agent decides whether to select the discussant from its own village. If the agent decides to look for a discussant elsewhere, then one of the four neighboring villages is chosen at random, and a random occupant is selected from that village. The "parochialism" factor, the probability that the agent will choose a discussant from its own village, can vary from 0 to 1. If it is set at 1, then each village is autonomous and there is no homogenization across villages. On the other hand, if the parochialism factor is 0, then nobody ever talks to anybody in their own village. If it is set at 0.2, then the agent is equally likely to stay in the village as to initiate an interaction with a person from one of the four neighboring cells. It is not known how high the parochialism factor must be in order to sustain diversity across cells. Certainly 1 is sufficient. Experimentation found that 0.2 is too small, in the sense that entropy declined to 0, as in the original ACM. By raising the parochialism factor to 0.5, the homogenization of opinion is somewhat reduced, but certainly not blunted. Figure 2 shows what happens in one run with 5 features, 5 traits, and 10 agents per cell. The model takes a significantly larger amount of computer time (duration), but the result is the same, complete homogeneity. We have not yet found any level of parocialism below 1.0 that can sustain diversity.

A summary of 100 replications of these computations is presented in Table 2, along side the original culture model. The left side of the table presents results for the "no parochialism" model, which means that an agent is equally likely to look for a discussion partner in its own cell or in a neighboring cell. The right side of the table summarizes results for a model in which each agent looks within its own cell with probability 0.5, and looks in the neighbors with equal likelihood after that. One can see that after raising the parochialism factor, there is only a sight increase in long-run diversity. Entropy in a model with five agents per cell (features=5, traits=5) is increased from 0 to 0.0077, a statistically significant increase by any test, but certainly not a substantively significant increase.

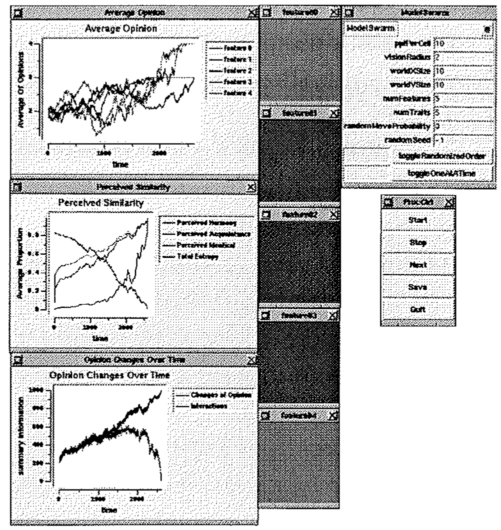

FIGURE 2. Culture model: ten agents per cell

What If There Are Small Endogenous Networks?

In a second set of simulations, the agents are given the power to be selective about their discussion partners. The model is supposed to represent a part of the logic of interaction outlined by Huckfeldt and Sprague (1995). At a given moment, people have an opportunity to discuss issues with people that are physically accessible to them. At work, church, home, or elsewhere, one finds a group of possible discussion partners and then chooses among them. The agent in this model has a limited ability to choose the most appealing discussion partner, which in this case is the expected similarity of opinion with the agent (but it could be enriched to include other personal traits, such as expertise).

The world and the agents are created through the same random process as described for the culture model. If there is only one agent per cell, then the agent simply makes a list of the four neighbors and chooses to discuss with the one who is expected to be the most agreeable. If there are many agents per cell, then the agent builds a list of possible discussants by taking a random selection from its own cell and one from each of the four neighbors. (Parochialism was not investigated in

TABLE 2. Culture simulation (averages of 100 runs).

Total Entropy					
Agv.FeatureEntropy					
Pct.Acquainted					
Pct. Harmony	No Parochialism			Parochialism=0.5	
Pct.Identical	Traits=5			Traits=5	
Features=5	Ppl/Cell=1	Ppl/Cell=5	Ppl/Cell=10	Ppl/Cell=5	Ppl/Cell=10
	549.38	2300.4	4814.6	2209.28	4805.66
	0.001	0	0	0.0077	0
	0.0053	0	0	0.009	0
	0.99	0.99	0.99	0.99	0.99
	0.99	0.99	0.99	0.99	0.99
	0.97	0.99	0.99	0.96	0.99
Features=5	Traits=10			Traits=10	
	Ppl/Cell=1	Ppl/Cell=5	Ppl/Cell=10	Ppl/Cell=5	Ppl/Cell=10
	628.12	2518.4	5665.53	2525.02	5515.57
	0.028	0.000012	0	0.000012	0
	0.13	0.000062	0	0.000078	0
	0.92	0.99	0.99	0.99	0.99
	0.98	0.99	0.99	0.99	0.99
	0.96	0.98	0.99	0.98	0.99
Features=10	Traits=5			Traits=5	
	Ppl/Cell=1			Ppl/Cell=5	
	715.2			3540.13	
	0			0	
	0			0	
	0.99			0.99	
	0.99			0.99	
	0.96			0.98	
Features=10	Traits=10			Traits=10	
	Ppl/Cell=1			Ppl/Cell=5	
	854.3			4136.2	
	0.00036			0	
	0.0036			0	
	0.99			0.99	
	0.99			0.99	
	0.96			0.98	

this model.) The agent then sorts them according to their agreeability and considers the most agreeable one (or a randomly chosen one among those equally most-agreeable) for a possible interaction. As in Axelrod's original model, an interaction occurs with probability equal to the similarity of the two agents. This is operationalized by selecting a single feature (issue) and testing to find if the two agents have the same trait (position). If they do, then one of the issues on which they disagree is randomly selected and the agent copies that position from the discussion partner.

At beginning of the simulation, no two agents have met, and so all of them assume the others are equally attractive and choose randomly among them. As the simulation proceeds, each agent keeps an internal record summarizing its experiences with other individuals. If they interact, which means they share opinions on all of the issues, then the agent can make a record of the similarity of the other's opinions with its own. In the future, when an agent is considering a list of possible discussants, these records are consulted and used to rank them potential discussants.

If another agent is not in an agent's diary, then the agent has to make a guess about how agreeable the other is likely to be. Intuition might lead one to expect that this assumption will play a pivotal role in the development of the model. If each agent assumes that any stranger is completely disagreeable, then the agent will choose to interact with a stranger only when the list of possible discussants includes only strangers or acquaintances who are totally disagreeable. On the other hand, if the agent assumes that strangers are quite likely to be agreeable, then the agent may choose to interact with them when there are in fact more agreeable acquaintances.

One of the surprises to be found in the numerical analysis of this model is that, as long as one does not assume strangers are highly likely to be agreeable, then it makes little difference what one assumes about them. Consider the model depicted in Figure 3. This shows the same 10 by 10 grid as in the culture models. The only difference is that the agents are selective and, furthermore, they assume that an unfamiliar agent is completely disagreeable. In contrast to the total homogeneity induced by interaction in the ACM, in this model a fairly high amount of diversity is preserved. Lest one think that the distrust of strangers is a driving force in this model, compare it with Figure 4, which shows what happens with the same agents when it is assumed that a stranger will agree on one half of the issues (when there are 5 features, half means 2 because of rounding).

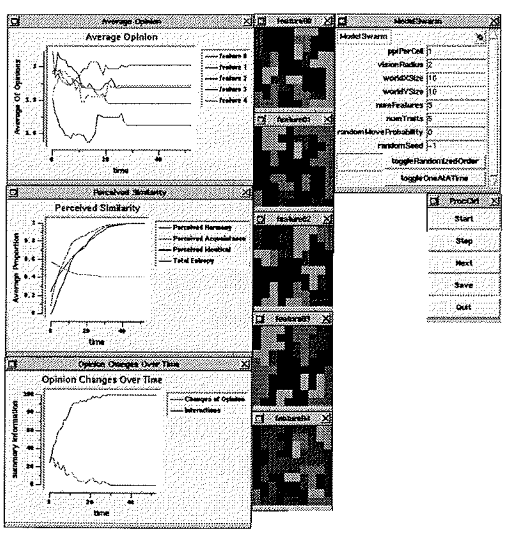

FIGURE 3. Small endogenous networks with one agent per cell.

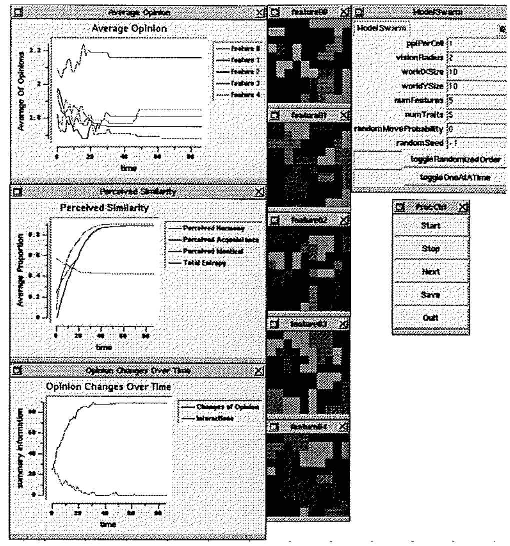

FIGURE 4. Small endogenous networks with strangers assumed agreeable.

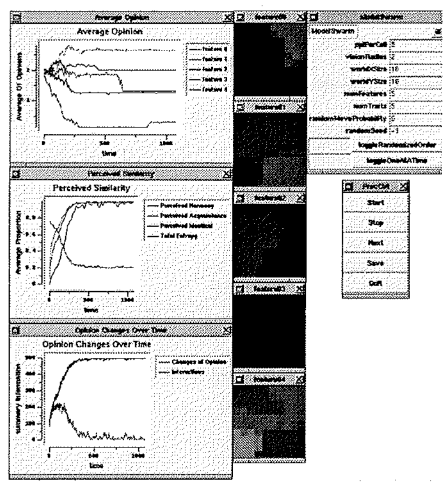

FIGURE5. Small endogenous networks with strangers assumed agreeable (5 agents per cell).

Curiously, when agents are added to the model, the diversity-enhancing effect of individual selection is reduced. When there are 5 others per cell, diversity is significantly reduced, as shown in Figure 5. These calculations used a parochialism level of 0.5. The level of diversity drops to a lower level, but it does not vanish over the long run. The effect of increasing the number of people in each village is to make it more likely that any given agent will be confronted with a list of strangers or undesirable acquaintances. This exposes the agent to the buffeting influences that cause homogeneity in the ACM. The summary statistics for a batch of these models are presented in Table 3.

In these small network simulations, the level of diversity is significantly higher than in the different variants of the culture model. Adding agents to each cell increases the chance of "unselected" interactions and thus allows the homogenizing tendencies of the culture model to operate. There is one highly interesting pattern that is illustrated in these models. Even when their society is in fact quite diverse, the individual agents perceive a great deal of homogeneity within their sphere of activity. The perceived rates of acquaintance and harmony with acquaintances rise much more quickly than the entropy level declines.

TABLE 3. Voluntary networks model (averages of 100 runs).

		Traits=5			Traits=10		
		Ppl/Cell=1	Ppl/Cell=5	Ppl/Cell=10	Ppl/Cell=1	Ppl/Cell=5	Ppl/Cell=10
Features=5	Duration	60.67	2657.77	1675.5	68.75	2205.6	2470.45
	Tot.Entropy	0.42	0.2	0.044	0.39	0.16	0.097
	Avg.FeatureEntropy	0.94	0.67	0.17	0.96	0.63	0.36
	Pct. Acquaintance	0.88	0.99	0.99	0.11	0.98	0.97
	Pct.Harmony	0.9	0.99	0.99	0.35	0.99	0.98
	Pct. Identical	0.88	0.99	0.99	0.11	0.99	0.97
Features=10	Duration	69.78	11,648.03		103.51	6285.84	
	Tot.Entropy	0.19	0.13		0.18	0.085	
	Avg.FeatureEntropy	0.94	0.78		0.95	0.63	
	Pct. Acquaintance	0.98	0.99		0.34	0.99	
	Pct.Harmony	0.98	0.99		0.46	0.99	
	Pct. Identical	0.98	0.99		0.34	0.99	

WHERE TO GO NEXT?

After finding that the introduction of multi-agent villages and parochialism does not solve the "diversity problem", we introduced the additional detail of selective interaction. By giving the agents the ability to select among possible discussion partners, we put a damper on the pressures toward conformity that exist in this artificial society. Global indicators say that diversity does exist in the large, but it does not survive in the small. In the local networks there is complete consensus. We have solved only half of the problem.

We have isolated two important avenues for research on this problem. The first avenue is to introduce a series of "worlds" and allow the agents to move among them. For example, each agent can have a home world, one in which it interacts with family members. That agent could also have a work world, a place where it interacts with a (possibly variable) set of other agents. The agent's movement among these grids can be scheduled so that agents do not necessarily encounter the same agents. Perhaps by causing a greater degree of mixing, the homogenizing tendencies will be ameliorated. The empirical motivation for this change is the finding that people look for others with which to discuss public affairs within a proscribed individual sphere. Many people discuss politics with folks at work, church, or in their neighborhoods, and thus they are exposed to a greater mixture of opinions than the one-world model describes. If the homogenizing tendencies are not ameliorated by the introduction of multiple grids, perhaps then allowing agents to move about in one or more of the grids will get the job done.

The second avenue for further work is to make a richer model of individual opinion change. So far, we have been faithful to the Axelrod approach, which says that an agent will adopt a new attitude with certainty if it interacts with another agent. What if the individual's response to exposure to different ideas is tempered by the individual's experience? We propose to have each agent keep a list of opinions expressed by other agents. When the agent is presented with a view that is different from its own, the agent should ignore the input if it is grossly at variance with the opinions of others in its list.

By creating an individual evaluation process that incorporates personal experience, we open the door to the inclusion of "opinion leader" effects. The empirical research indicates that people respond both to the opinions of people that generally agree with them and the opinions of people they perceive to be well informed and articulate. In order to model this phenomenon, we can introduce an "intelligence" variable for each agent and reveal that to the other agents. It should then be possible to attempt to stimulate "blips" in public opinion, events that can cause a sudden flare of support for a particular position that may be short lived.

Comments and Conclusion

The models introduced here have some strong elements that deserve emphasis. First, the wrapped list grid offers a workable way to move agents in-and-out of multi-agent cells that are distributed in a grid. Second, the measurement of opinion diversity in the model is a significant enhancement. Entropy, used as an objective, society-wide index of diversity offers an easy-to-calcuate index that summarizes the change in public opinion over time. The individual-level experience variables, the personal summaries of diversity experienced in one's own environment, offer an interesting contrast to the entropy measures.

On a substantive level, one important conclusion is the following. If people are exposed in a completely unstructured way to interaction with ideas that may differ from theirs in a significant way, it seems that the total homogenization of public opinion is to be expected.

How must one redesign the agent-based model to avoid that conclusion? Apparently, it is not enough to stipulate that there are village-like clans of agents who interact only sparingly with the outside world. By adding additional agents, the homogenization is slowed, but not stopped.

On the other hand, by supposing that agents are able to recognize potential discussion partners and select among them, we arrive at a more satisfying conclusion that the following things can coexist.

1. Agents are able/willing to change their minds in response to input from outside.

2. Substantial social diversity exists.

3. In a long-running social system that is not subjected to external shocks, agents are seldom observed to change their opinions.

However, the endogenous local network model also implies

4. Individual agents believe that most people think like they do about most things, which we would rather avoid.

The next step in our agenda is to consider modifications of the model so that diversity can exist in both the large and the small. This drive is inspired by both empirical and normative reseach problems. The empirical problem is that the prediction of the model does not match reality very well. According to the survey data, people seem to discuss political affairs in relatively (certainly more than expected) heterogeneous networks.

The normative problem is perhaps more important. Theories of democratic government generally presuppose that the citizens can discuss and learn from one another. One of the "sales pitches" for these theories as prescriptions for government is that free interaction can allow diversity to exist and, in fact, contribute to the decision making process. If the predictions of the Axelrod Culture Model are true, theories of democracy will have to be re-examined. Supposing that the long run tendency of social interaction is to produce nearly complete consensus and a rigid set of dividing lines between groups that block interaction, then free government will tend more toward consociationalism (Lijphart, 1968, 1977) than pluralism.

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