# ViSAGE: A *Vir*tual Laboratory for *S*imulation and *A*nalysis of Social *G*roup *E*volution

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We present a modeling laboratory, Virtual Laboratory for the Simulation and Analysis of Social Group Evolution (ViSAGE), that views the organization of human communities and the experience of individuals in a community as contingent upon on the dynamic properties, or *micro-laws*, of social groups. The laboratory facilitates the theorization and validation of these properties through an iterative research processes that involves (1) forward simulation experiments, which are used to formalize dynamic group properties, (2) reverse engineering from real data on how the parameters are distributed among individual actors in the community, and (3) grounded research, such as participant observation, that follows specific activities of real actors in a community and determines if, or how well, the micro-laws describe the way choices are made in real world, local settings. In this article we report on the design of ViSAGE. We first give some background to the model. Next we detail each component. We then describe a set of simulation experiments that we used to further design and clarify ViSAGE as a tool for studying emergent properties/phenomena in social networks.

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## 1. INTRODUCTION

Most social scientists regard actions of individuals as a key unit of analysis in the development of society. For this reason much work has gone into producing a computer modeling infrastructure that focuses attention on society as constituted by multiple and parallel autonomous actions, such as individual human choices or outcomes from institutional bodies such as juries or committees. The key technologies in this infrastructure are toolkits for building *agent-based models*, which describe and investigate the autonomous, adaptive, and reflexive nature of people [Epstein and Axtell 1996; Kohler and Gumerman 2000; North et al. 2006; Minar et al. 1996; Parker 2001]. Social change is a broad process, constituted by millions of actions by autonomous actors over long durations. Locating a significant unit of action in this large-scale process is, to say the least, a challenging problem. Are human actions so thoroughly situated or unique that social change cannot be explained by general laws of human action? The least we can do is postulate laws about how individuals take action and test if these can reproduce patterns *in silico* that match real world patterns of social change.

We have designed a simulation laboratory, ViSAGE (Virtual Laboratory for the Simulation and Analysis of Social Group Evolution), as a solution to the problem of understanding social change from an autonomous agent perspective. The laboratory does this by facilitating the creation of a class of models to understand social groups as the significant unit in determining human and social processes. The social constraints and patterning of units directly above the individual are emphasized in these models. In this article we report on the design of ViSAGE. We first give some background to the model. Next we detail each component. We then describe a set of simulation experiments that we used to further design and clarify ViSAGE and discuss future research.

### 1.1 The Virtual Laboratory Research Method

Methods for gathering, storing, and analyzing data of social phenomena are numerous and diverse. Social research methods range from highly qualitative and unstructured case studies such as grounded theory, where analytical categories are discovered during the research [Glasser and Strauss 1967], to highly quantitative studies that focus in on interaction among a few well-established variables across a wide population [Byrne 2002]. Regardless of how a study is structured methodologically, the tension and theme of social science, and the argument for qualitative analysis, is the relevance of changing contexts to human action [Miles and Huberman 1994]. To study changing contexts, one must have a method and tools for analyzing and conceptualizing patterns of behavior and social organization at varying levels and scales. The complexity of social existence is tied to the fact that in social settings the individuals who constitute a setting are themselves "living in," or attuned with, divergent and multiple social structures, such as in-group cliques or collective identities. Human activity is situated within overlapping material and social contexts. The potential of computer simulation in helping to understand social complexity lies in formalizing

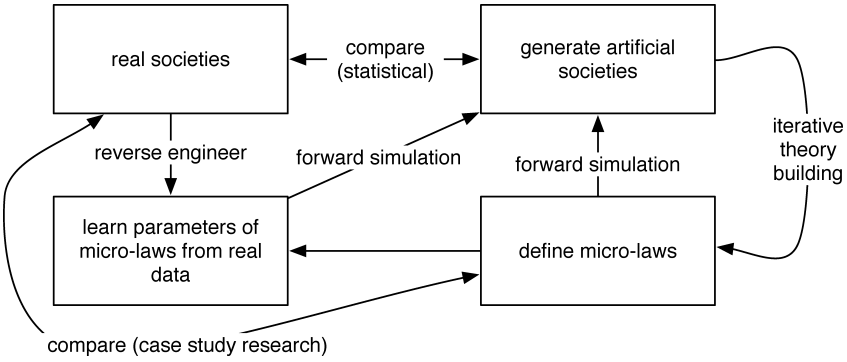


Fig. 1. ViSAGE is an experimental system design.

and exploring the various ways individuals are situated among other people, and inside groups.

In addition to understanding changing contexts, another benefit of using computer modeling and simulation is constructing formalisms for categorizing large sets of data and comparing human populations. For example, the recent explosion in data from online social networks has created a challenge in sampling data. Given that these data sets contain tens of millions of users, where does one bound the study? How does one go about dividing these populations into meaningful groups? ViSAGE can do such a classification by directing theory-building into micro-laws, which are then used to automatically learn characteristics of individuals and groups in the community. These data are learned about groups and therefore enable the researcher to intelligently compare and investigate classes of groups and communities. Once parameters are learned, actors, groups, and communities can be classified based on the model settings. These classes then can be used to drive case study research.

The purpose of ViSAGE, just as with any natural science laboratory, is to establish an experimental system where claims and insights about nature are supported through the iterative and collaborative creation of models, language, and practices. ViSAGE entails an iterative process (see Figure 1) where micro-laws are postulated and then formalized through forward simulation. An actor's actions are governed by micro-laws [Goldberg et al. 2003] which may be: personal attributes (e.g. some people like to go out with a bunch of people, but some would prefer one to one), the actions of other actors (e.g. the actor may join a group because his/her friend is a member of that group), and the influence of the community (e.g. some people take an action because it is expected by some communities). These micro-laws are then used to classify actors in real human communities. The learned distribution and range of classes are then used as input in forward simulation; the resulting artificial society compared to the real society. The micro-laws are then updated and reworked based on these comparisons. Finally micro-laws become the basis for case study research where social scientists seek to understand if and how the micro-laws exist in contextually rich local settings, by following the processes groups and individuals go through.

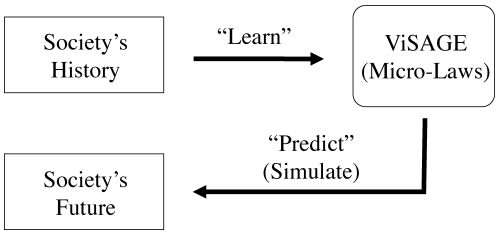


Fig. 2. Usage of ViSAGE.

The ability to locate inconsistencies and problems with existing theory, discover linkages among theories, and formalize directions for research projects improves and advances as this experimental system is used, becomes more organized, and the tools within that space made more efficient. This improved capacity for theory building and social inquiry based on the adoption and genealogical elaboration of instrumentation is known as rapid discovery social science [Sallach 2003; Collins 1994]. Analyses of ViSAGE results will work toward the development of rapid discovery social science in the following three ways:

(1) *Theory development.* The laboratory allows for the exploration and formalization of how different levels, scopes, scales, and dimensions of social reality interact. This is achieved through the automated display of patterns derived from agent-based processes.
(2) *Theory resolution.* Through the formalization of social existence and the rapid production of patterns *in silico* that correspond to theory, the laboratory will help researchers see the connections among different social theories and allow for novel synthesis of theories. Such synthesized theories can become a resource for the design of grounded case studies.
(3) *Theory display.* In order to develop new theories of social phenomena and resolve contradictory theories in a systematic and rapid fashion, novel ways of visualizing social structures and displaying complex data will have to be developed. ViSAGE will aid in that task.

## 1.2 Usage of ViSAGE

People can use ViSAGE as a tool for studying emergent behavior in social networks, and Figure 2 shows the general framework of using ViSAGE. To illustrate the value of ViSAGE, consider the case of designing an educational program to instill the values and skills of entrepreneurship and technology management in ethnic minorities. These values and skills could be taught to students through classroom learning and through a team business plan project over the course of a multi-week, immersive educational program. The purpose of using ViSAGE would be to study changes in the values of the students by modeling the dynamics of the social groups and their networks. To do so, we would gather communications and social network data among students and faculty using direct observation, participant reporting, interviews, and automated

logging of online communications. We would use this data to identify social groups and the characteristics of these groups as they change over time. This data is then reverse engineered using ViSAGE to categorize actors into two behavioral categories called ambition and leadership. The distribution and population of actors with different ambition and leadership configurations are our distributed theories of practice for the community from which our data was gathered. Micro-laws drive the evolution of the social group data and are a hypothesis about the real human practices that are a major component in how social groups develop. The result of our work would be presented to those responsible for the design and implementation of the educational program.

Thus there are three modes in which ViSAGE could be used: (1) as a tool for understanding the behavior of a society given its micro-laws; (2) as a tool to validate postulated micro-laws against observed evolution by simulating forward and comparing with the data; (3) as a tool for determining the micro-laws by searching for those parameters that through simulation, can be validated against the data.

## 2. BACKGROUND TO VISAGE APPROACH

While toolkits are developed for general use and can model a broad range of theories and perspectives, instruments that allow for the construction of several models of the same phenomenon around a set of specific theoretical assumptions are laboratories [Van der Veen et al. 2001; Sierhuis et al. 2003]. Grimm and Railsback [2005] note that modeling technologies are designed to be flexible and represent a diversity of problem classes to specific models that are meant to represent a single system or ecology. Flexible technologies, they say, for agent-based modeling are modeling toolkits or environments such as Repast [North et al. 2006], Swarm [Minar et al. 1996], or Ascape [Parker 2001]. An example of a specific model, on the other hand, would be the Village Project, which is large-scale model of pre-European land use and settlement patterns in Southwestern Colorado [Kohler et al. 2007]. Mid-range simulation technologies are good for comparing similar societies using a set of theories and frameworks. A good example of this is NOMAD, which has been used to study nomadic cultures in South and North America and in Africa [Kuznar and Sedlmeyer 2005]. These mid-range simulation technologies we refer to as laboratories since they entail stable sets of practices for theory building and testing.

ViSAGE is a laboratory for creating and experimenting on models of dynamic social group processes from an agent-based perspective and is therefore situated in an emerging field known as computational social science, or social simulation. It is also based on relationships among actors and the overlaps among groups, so there is a strong social network component to ViSAGE. We first give some background on social network analysis and how ViSAGE fits into this area of research and then we discuss the relationship to agent-based modeling.

### 2.1 Social Network Analysis

Over the last decades great efforts have been made to formalize and clarify the structure of social relationships as networks [Freeman 2004; Monge and

Contractor 2003; Wasserman and Faust 1994]. The proliferation of communications networks and technologies has supported this effort in two important ways. First, network technologies have given a formal approach to engineering communication and human interaction. Second, the existence and employment of these technologies by real human communities can allow for the gathering of large amounts of interaction data. Without a doubt, network technologies have increased our capacity to understand such structures by creating *informated* field sites [Zuboff 1988; Butler 1999; Kraut et al. 2004]. Telephone communications, email communications, and online community interaction, for example, have provided researchers with resources to quickly gather relational data.

The large amount of relational data that is generated by electronic social interaction requires new/different frameworks for categorizing and analyzing social structure. The opportunity for innovative research here is considerable. With such data comes the possibility of analyzing and interacting with new and more complex patterns. We have to ask ourselves what types of patterns are important in such an analysis with such data? How do we systematically explore such possibilities? One answer lies at the intersection of social network analysis [Wasserman and Faust 1994] and situated agent-based modeling [Sallach 2003; Epstein 1999].

The epistemological commitments of social network analysis as outlined by Linton Freeman in his history of social network analysis [Freeman 2004] are key for this new genre of categorization. A pure vision of network analysis makes claims about social groups and actors without looking at the attributes of these groups and actors. If an actor is male or female, European or North American, a manager or a shop floor technician..., it should not factor as much in the analysis. Such an epistemological commitment comes at the beginning stages of analysis; one cannot fully neglect the classic social divisions of race/ethnicity, gender, class, and age. Patterns are recognized at the network level first, which then gives meaning to these classic social categories. The social network analysis approach is further expanded through the use of computer modeling techniques, known as agent-based modeling (ABM), that formalize the specification and identification of actor attributes.

### 2.2 Agent-based Modeling (ABM)

Agent-based modeling is a powerful tool in the analysis of social networks and in social analysis at large. Agents can be either complex or simple [Billari et al. 2006]. They can have attributes that are exogenous or endogenous to a social network. For example, the *Agent Based Identity Repertoire* (ABIR) model, developed by Ian Lustick, focuses heavily on exogenous attributes, identity attributes, to define how the patterns become expressed in an artificial society [Lustick and Miodownik 2002; Van der Veen et al. 2001]. David Sallach's program of interpretive agents or situated agents, on the other hand, focuses much more on the ability of agents to see the structure that they are embedded within, and they are defined by how they see and interpret those structures or network locations [Sallach 2003; Sallach and Mellarkod 2005].

In the current implementation of ViSAGE, the agent attributes are mostly endogenous to the social network (we know nothing about the agents besides how they move in a particular social structure). Attributes of our agents are defined by where and how the agent persists in a particular location or position in a social network. Social theorizing in this model therefore consists of linking the persistence of a particular social location to particular agent behaviors. The complexity of such a view is limitless and therefore requires heavy investments in analytical tools that easily change the world-models that each agent has (how they see or experience and act in their social worlds) and help to visualize the various levels and units of analysis that emerge from the massive interaction of various and different world-models [Chattoe 2002].

### 2.3 Machine Learning

While much of the work in social network analysis and agent-based modeling involves growing networks, ViSAGE combines these approaches with machine learning techniques to reverse engineer the appropriate micro-laws (appropriate parameters in ViSAGE) of a community based on either the observed set of communications among actors without knowing semantic contents, or the observed social group evolution.

Most of the traditional methods of social network studies are labor intensive. People interview and analyze the data by hand in most of the cases. They usually spend a lot of time and can only work on a small amount of data. The results can more easily be subjective and less accurate, or even misleading. Marsden [1990] and Somekh and Lewin [2005] address some of the traditional research methods in the social sciences, but when there is a large amount of data or a lot of research objects, it is really painful for the sociologist to use those traditional research methods. Butler [1999] analyzes newsgroup data by hand and only works on a small amount of data. We apply social theories to ViSAGE as a tool to automatically find the appropriate miro-laws, so it is a powerful tool for sociologists to use for research.

Due to the growing popularity and interest in social network analysis (SNA), especially because of the booming exposure of online communities, researchers have started to use different methods to help them collect and study the structure of social networks as well as analyze the ranges/factors of social dynamics. Sanil et al. [1996] address model-fitting in a very limited setting using very simple models. Our work addresses the problem using a much more general setting, where models are constructed using ViSAGE; micro-laws can be learned from network data using these models. Snijders [2001] uses Markov chain Monte Carlo (MCMC) methods to simulate how the links among actors evolve. Other works also focus on the links among actors, for example Latent Space model [Hoff et al. 2002], Dynamic Latent Space model [Sarkar and Moore 2005], Probabilistic Relational Models [Adamic and Ader 2003; Getoor et al. 2003] (PRMs), and so on. In ViSAGE, the actors' actions are governed by micro-laws, and the changes of the relationships (links) among actors represent the actors' actions. Based on the paths of the actors' actions, we can use reverse engineering techniques to discover the appropriate micro-laws in

ViSAGE. Backstrom et al. [2006] use a decision-tree approach to determine some properties of the social network. The decision-tree approach is a deterministic process, which is different from our approach in using the stochastic process to determine actors' behaviors. The reason is that in social networks, even under the same environment, actors do not necessarily possess or reflect the same behaviors.

## 3. OVERVIEW OF THE LABORATORY

ViSAGE is an agent-based statistical simulation of social group formation and group change over time. In this section we provide an overview of the laboratory and how the components of the laboratory are related. There are four components in the laboratory: the resource model, the actor and group model, the membership model, and the action valuing model (Figure 3). The power of this laboratory is the ability to "rewire" the way components are related, where each configuration is a social theory in and of itself.

Agents in the system have two key attributes. The first attribute is the specification of the innate capacity, both mental and physical, of an actor to engage in social intercourse, which is part of the resource model. We call this variable *resources* (see Sections 4.2 and B.3). There is a limit on the ability of an actor to repeat preferred patterns of behavior; *resources* specifies this limit. Through participation in social groups, an actor's resources deplete. This depletion is intensified by the kind of group the actor is a member of. Thus, the manner in which groups are classified by the analyst is an important location of theorizing and experimentation and will have effects on the way the society of actors and groups changes on the whole.

The second attribute is a preference for specific kinds of groups, which is part of the membership model (see Sections 4.3.2 and B.6). This preference is subjective and intersubjective, which means that it is considered a personal preference, but it is also a preference that is socially learned. We assume that these preferences are consistently enacted functional patterns of behavior. Thus, preferences are building blocks of larger processes, be they for individual, social, cultural, and/or evolutionary ends. As default in the laboratory there are three categories that are defined by preferences for group size; small, medium, or large groups.[1]

In ViSAGE, groups are defined by how actors enter into them (see Section 4.1.2) and they are categorized in two different ways that are significant

[1]The choice of group size and three group sizes as default in ViSAGE was based on two factors. The first is availability of data. Group size was something that was easily available to us since we are using communications networks data and a clustering algorithm that puts actors into groups. We were also using chat room and newsgroup data so membership counts were, again, also readily available data. Group size was the easiest form of data to access. It is also logical that in some of these communications environments individuals use group size as a factor in choosing to enter the group. This is most prevalent in chat rooms and newsgroups. Communications networks such as email communications where we had to use a clustering algorithm to detect groups makes difficult the claim that actors are using the cluster information to take action. Three group size categories were chosen because more than three would make machine learning computationally difficult and we desired as many categories practicable.

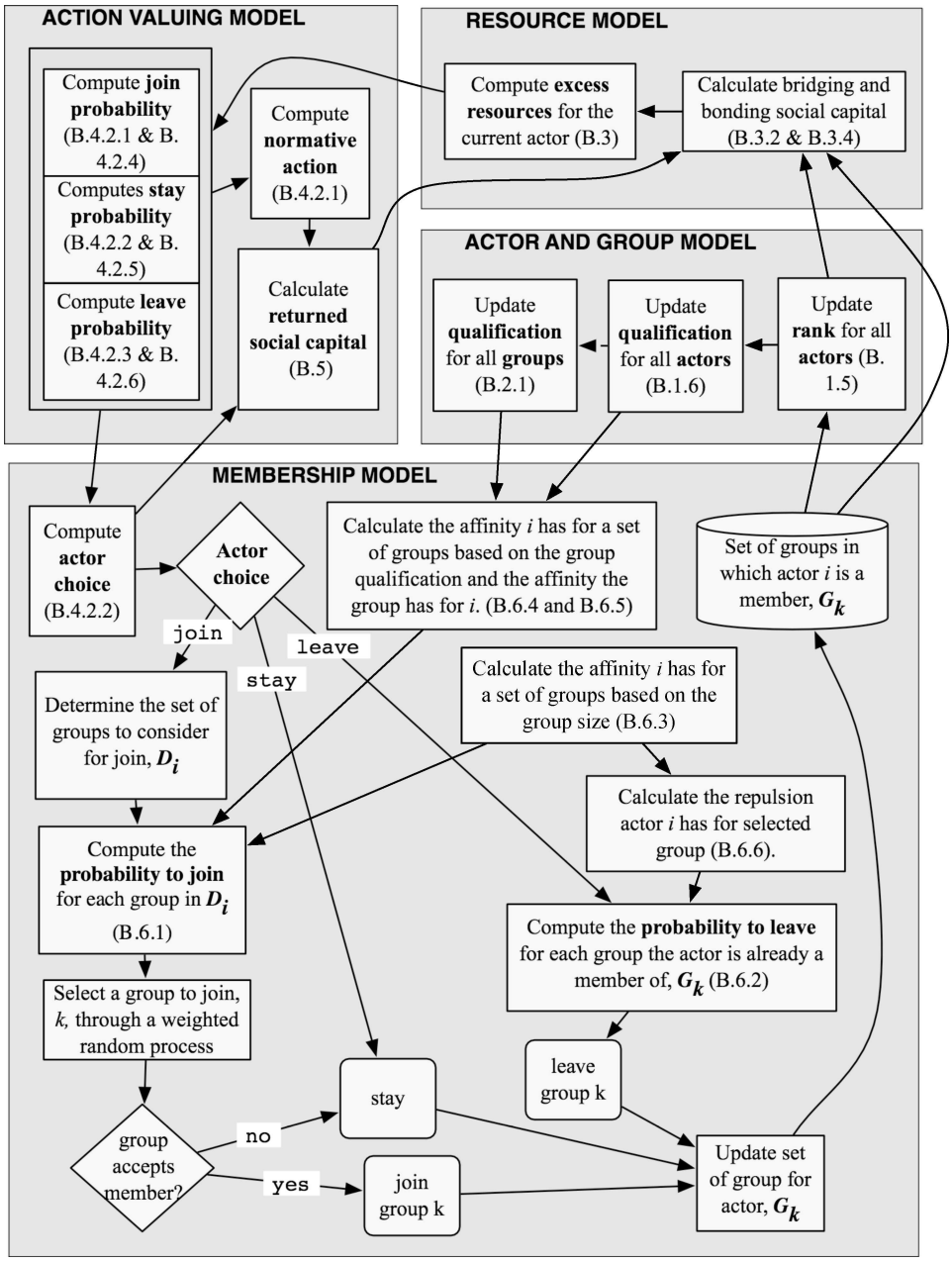


Fig. 3. Relationship of components in ViSAGE.

to actor preference and actor resources. In the current implementation of the system, actors prefer groups of relatively specific size: small, medium and large. Thus actors are classified into three types based on their preference for the size of groups.

The second class of group categories is much more involved. There are two measures that make up this class. The first is the bonding quality of the group and the second is the bridging quality of the group (these are further explained and defined in Sections 4.2 and B.3). Groups can be linked to many other groups, and thus facilitate bridging across a community, and/or be linked to groups that are in turn also linked, thus facilitating bonding in a community. Bridging and bonding are measured using standard network measures of degree and density [Wasserman and Faust 1994]. These two categories influence the intensity of resource depletion.

Actors and groups become associated (an actor becomes a member of a group, and a group gains another member) through a selection process that is initiated by the agent and then finalized by the group (see Sections 4.3 and B.6). First, the actor makes a choice based on the resources left over from their current affiliations—*excess resources*. Once the state of joining is entered (the decision to join is made) the actor locates a preferred group from the list of groups. The group then accepts or rejects an actor's attempt to join. Also at this time, an actor accepts or rejects a group based on a further set of preferences (see Section 4.3).

After a new social configuration is established (an actor becomes associated with a new group, leaves a group, or the properties of the actor's joined groups change) excess resources is calculated. The intensity with which resources are depleted is connected to the degree of bonding and bridging each group exercises. If an actor is a member of groups with high amounts of bridging and high amounts of bonding then their excess resources will be taxed. However, as specified in the action valuing model, an actor generates *returned social capital*, which lessens the impact of bridging and bonding costs. This is because social capital has been theorized as something that makes social intercourse easier and more efficient. Returned social capital is calculated by comparing the difference between an actor's choice given excess resources and a socially normative action that an actor should have taken given a level of excess resources (see Sections 4.4 and B.5).

### 3.1 Communicating Ideas

The data produced by the simulation laboratory may be used to generate displays both for finding new social theories and improving on the algorithmic models included in the system. ViSAGE therefore acts as a boundary object between two disciplines and should display results in a manner that allows for communication between disciplines. These displays may also be used to communicate social ideas to new audiences.

The system is designed to provide flexible plotting mechanisms in order to view and interpret the resulting data. Figure 4 shows the current default plots produced by the simulator. The group size distribution plot (a) shows the distribution of group sizes over time. This is useful in both determining when the system has reached a steady state and also the group sizes and group configurations that are preferred by the society.

The group time distribution (b) displays the average time that each actor has spent in groups. A steeper slope in this curve indicates actors who are

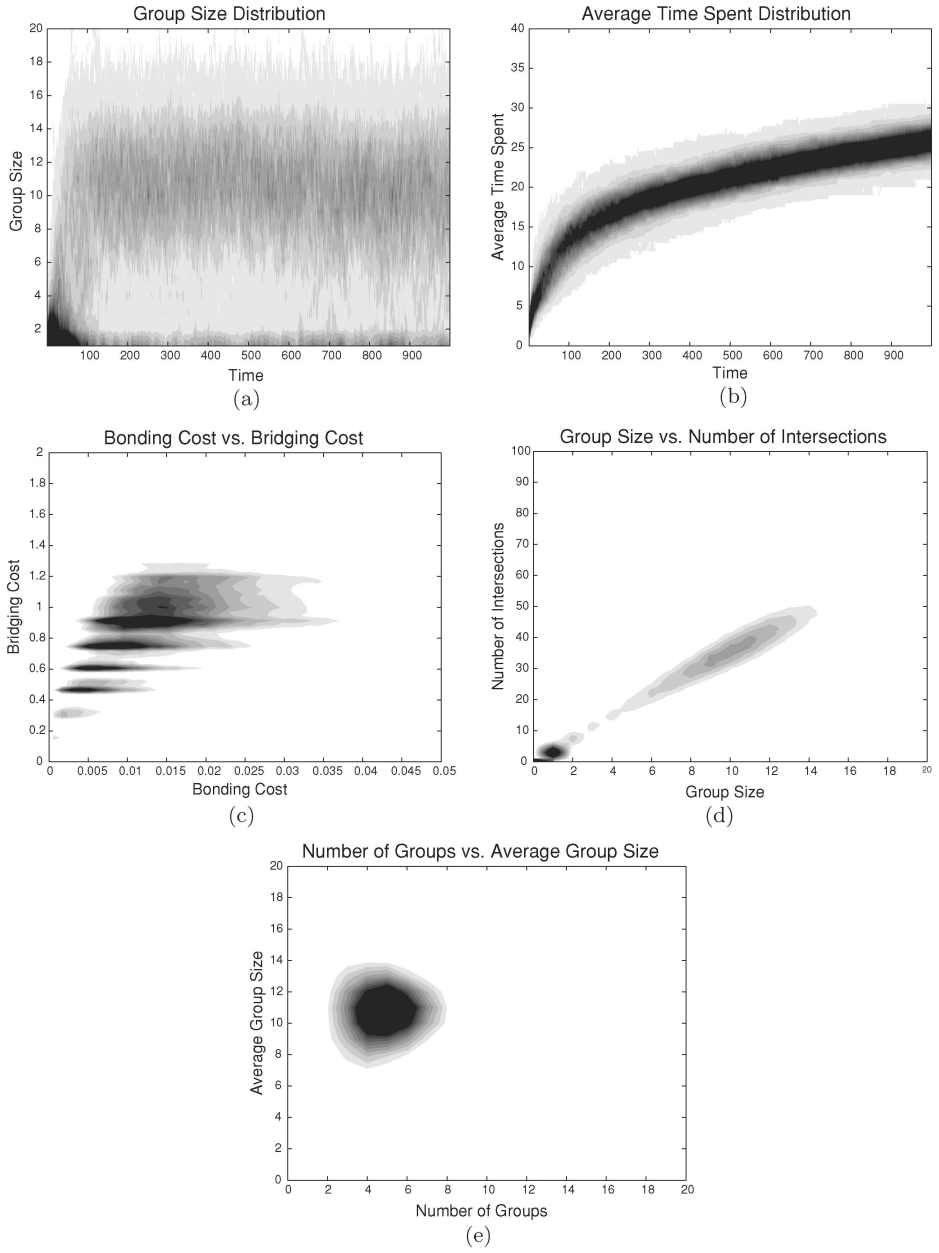


Fig. 4. Some output plots of the laboratory.

more static in their group membership, while a shallow slope shows that actors are exploring more of the group space instead of remaining in a few groups throughout the simulation.

The bridging and bonding plot (c) indicates where the actors are spending their resources in the society. If actors are using their resources more for

bridging, they are using resources to meet many people in the society. If actors are instead concentrating resources on bonding, they are spending resources to build very strong relationships with fewer people.

The group size versus number of intersections plot (d) shows the number of intersecting groups (i.e. groups that share at least one actor in common) for each group, plotted against the group size. Naturally, this plot will be increasing since a larger group size provides more opportunities for other groups to overlap. A steeper slope in this plot represents a more interconnected and cohesive society.

The group participation plot (e) shows the average group size and number of groups in which each actor participates. This plot simultaneously shows how active the actors are in the society and what sizes of groups the actors prefer. The further up and to the right of the graph, the more groups and the larger the group size, the more the society is one that values collective identification. Smaller groups and fewer groups indicate a society that does more bonding,[2] such as, if we are talking about online communications, chat room discussions.

## 4. VISAGE STRUCTURE AND FUNCTIONALITY

ViSAGE is comprised of four smaller, interrelated models:

(1) The *actor and group model*, which defines the properties of the actor and group objects,
(2) the *resource model*, which defines how the drive actors have to engage in the community changes,
(3) the *membership model*, which specifies how actors and groups associate or disassociate with one another, and
(4) the *action valuing model*, which defines how the individual, group, and community levels are related to one another.

In this section, we will describe each component of ViSAGE, how they operate, and how to use configuration parameters to simulate different types of societies.

### 4.1 The Actor and Group Model

Many parameters govern how actors decide whether to join or leave groups, and also which group the actor desires to join or leave. In this discussion, we will consider the parameters for a specific actor $i$. The current groups are represented by sets of actors $G_j$. These groups may overlap, since actors may belong to more than one group. Let $time_j^i$ represent the amount of time that actor $i$ has spent in group $j$. Figure 5 shows the actor and group model in VISAGE.

4.1.1 *Actor Type.* The laboratory allows the user to specify attributes of the actors in order to model different types of societies. The first important feature of actors is that each has a preference for the size of group he or she is willing to join. Similarly, some actors tend to join small emerging groups. We

[2]The term microcoordination may be more neutral here since it is difficult to image heated discussion or fights over, for example, politics as bonding. For this article, however, we keep the word bonding.

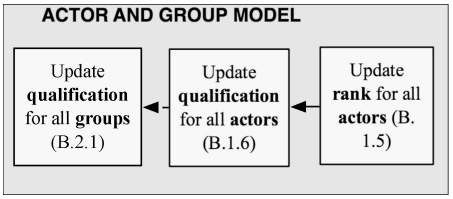


Fig. 5. Actor and group model in ViSAGE.

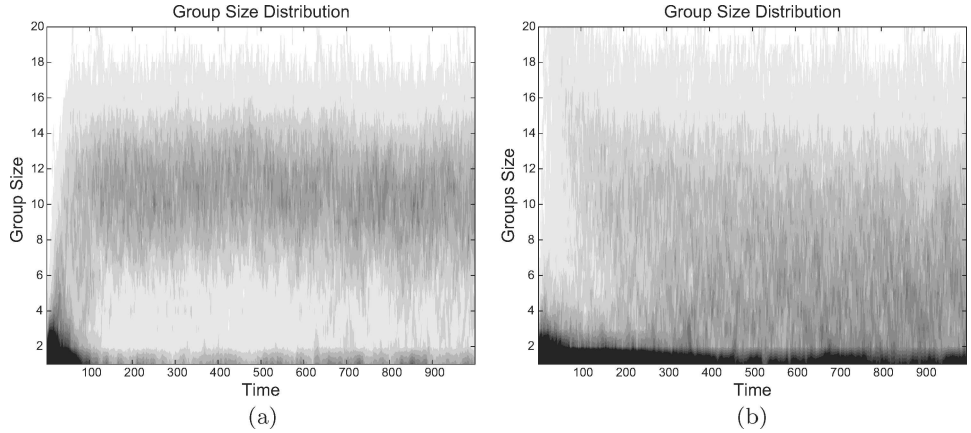


Fig. 6. The distribution of the group sizes changes between the default case of all socialites (a) and the case with equal amounts of leaders, followers, and socialites (b). These plots also show that the distribution of the group sizes for the default parameter settings stabilizes after the first 200 time steps.

call these actors leaders. The fraction of leaders is set using the *LeaderPercent* parameter. The actors who tend to join moderate sized groups are call socialites. The fraction of socialites in the society is specified by *SocialitePercent*, a number between zero and one. There is also a third group in ViSAGE, named followers, who tend to join large, well established groups. The fraction of followers is the remaining actors not specified to be leaders or followers. Providing different proportions of leaders, followers and socialites produces societal structures with different average group sizes (see Figure 6).

4.1.2 *Groups.* The way groups are implemented in ViSAGE is based on a theory of what makes a group. Thus an important part of using ViSAGE is deciding what counts as a group and how actors know that a group is a group. The parameter *Groups* defines the maximum number of groups possible in a simulation run, we call these *slots*. For our description of ViSAGE here, all slots are social groups, so actors evaluate a slot with no other actors influencing their choice to enter a group. Thus, in a simulation run, as default, new groups are not created and old groups do not disappear.

Future implementations of ViSAGE will make it easier to define how groups emerge and collapse in run-time. For example, a group collapses when all members of that group leave. Similarly, when an actor looks to join a group and

there are no suitable groups available then that actor will create a new group by entering into an empty slot. In this implementation a group is defined as a slot with one or more actors as members. An actor determines if there are no suitable groups available through the referencing process that is defined in Section 4.3.2.

4.1.3 *Rank and Qualification.* As actors spend more time in a group, their position in the group changes. There is a tendency for more senior members of a group to have a higher position within the group than junior members. Also, leaders should have a higher tendency to raise their position within the group than followers. A higher position requires more effort from the individual to participate in the group. All of these intuitive behaviors are included in ViSAGE in the form of an actor's rank and qualification. These parameters are not configured initially, rather they are attributes of actors that develop as the laboratory simulation progresses. We assume that every social group carries with it a sense of obligation, duty, or responsibility that is felt by each member.[3] At every time step, each group distributes its responsibilities among the actors present in the group. The amount of responsibility that an actor receives is referred to as the actor's rank. The rank of an actor is proportional to the amount of time that an actor $i$ has been a member of the group $G_k$:

$$r_k^i = \frac{time_k^i \delta^i}{\sum_{j \in G_k} time_k^j \delta^i}.$$

The quantity $\delta^i$ is large for leaders, moderate for socialites, and smaller for followers. This captures the property that leaders are more capable of advancing their rank within a group.

The measure of prestige of an actor is computed as a quantity known as qualification. The actor's qualification $q^i$, is determined as the average rank of the actor among all the groups of which the actor has been a member. The rank is weighted to give a stronger weight to ranks from larger groups. The qualification is used by groups to determine whether the actor should be allowed to enter the group:

$$q^i = \frac{\sum r_k^i |G_k|}{\sum |G_k|}.$$

Similarly, groups have a qualification, defined as the average qualification of actors currently participating in the group. For a group $G_k$ this is defined by the formula:

$$Q_k = \sum_{i \in G_k} q^i r_k^i.$$

The higher a group's qualification, the more attractive it will appear to other actors who are looking for a group to join. The interaction between the actor and group qualification determines whether an actor will be allowed to enter a

[3]This sense of duty or responsibility varies from group to group in real life, however, this variability is not yet a part of the current model.

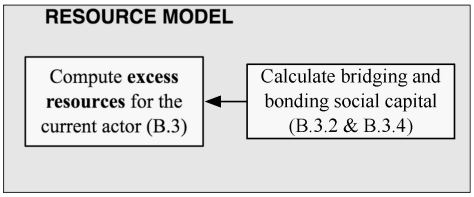


Fig. 7. Resource model in ViSAGE.

new group. Actors desire to increase their prestige by joining groups with high qualification compared to their own, but the groups want to keep their prestige by only allowing actors with high qualification to enter.

## 4.2 Resource Model

The physical and mental capacity an actor has to engage with others in order to be social, we refer to as an actor's *resources* ($R^i$). The resources of an actor represents the amount of time or energy that the actor is able to use in social endeavors. For the current implementation of ViSAGE the amount of resources given to each actor is constant. Figure 7 shows the resource model in VISAGE.

The ability of an actor to function in the society is also contingent upon the social resources they has accumulated over time. These social resources are known as social capital. The social capital of an actor has the affect of making social intercourse easier and more efficient for that actor [Putnam 2000]. Therefore we understand social capital to be something that makes joining and staying in groups more probable. Thus, social capital is an individual property. That is, as an actor's social capital increases, it consumes less resources to participate in groups within the society. ViSAGE has three different notions of social capital built into it: bridging social capital ($L^i_{br}$), bonding social capital ($L^i_{bo}$), and returned social capital ($C^S_i$).

*Bridging social capital* represents the amount of resources the actor uses to branch out in society, and thus increase visibility [Putnam 2000]. A good indicator of this is simply the number of groups that the actor is involved with, so

$$L^i_{br} = |G : i \in G|.$$

*Bonding social capital* depends on the actor's rank, or prestige, in each group. As actors spend more time in a group, their rank tends to increase. The intuition is that an actor will use more resources in order to maintain membership as the rank increases. Bonding social capital is then a measure of the knowledge and experience an individual has about a social group, and it is developed by individuals spending a great deal of time with one another [Putnam 2000]. Thus we have that the bonding level is the total of all the ranks of an actor:

$$L^i_{bo} = \sum_{G_k : i \in G_k} r^i_k.$$

The *returned social capital* $C^S_i$ of an actor is generated from a negotiation between an individual's action and the norms of the community. This definition is defined more precisely in the valuing action model, Section 4.4.

In the simulation, the desired interaction of human and social capital presents itself when actors decide whether to join or leave a group, or to perform no action in the current time step. The decision depends on the actor's excess resources. The excess resources is what is left of the actor's resources after participating in society for that time step. The cost of participation in each group is contingent upon the bridging component and a bonding component. The simplest formula for the excess resources is:

$$R_E^i = R^i - \phi^i L_{br}^i - \psi^i L_{bo}^i,$$

where $\phi^i$ is the bridging coefficient, $\psi^i$ is the bonding coefficient, and $L_{br}^i$ and $L_{bo}^i$ are the levels of bridging and bonding the actor is currently experiencing. These coefficients may be set to constants, by setting *BridgingCostType* and/or *BondingCostType* to zero. In this case the coefficients are set with the parameters *BridgingParam1* and *BondingParam1*. However, this simplistic model for excess resources does not use the concept of social capital. As described earlier, an individual's social capital is a sort of social lubrication which makes it easier for the individual to participate in society [Putnam 2000]. In order to incorporate this idea into ViSAGE, the user must set *BridgingParam1* and *BondingParam1* to one. This creates equations for the coefficients which function as follows:

$$\phi^i = \frac{BridgingParam1}{1 + C_i^S}, \quad \psi^i = \frac{BondingParam1}{1 + C_i^S}.$$

In this case, as an individual's social capital increases, the costs of participating in society will decrease, allowing the individual to have more participation in society.

The excess resources are used by the actor to determine what action to take. If the amount of excess resources is positive, the actor will tend to use that excess in joining another group. If the excess is negative, the actor will tend to leave a group in order to reduce the needed cost. If the excess is near zero, the actor may decide to remain in all of the same groups for the current time step.

This decision is made with the assumption that the actor makes a choice that optimizes their excess resources to zero. Ideally, the actor would always choose to perform the action that would make their excess resources in the following time step as close to zero as possible, since this creates a state of stability. However, we assume that the actors sometimes make nonoptimal decisions, which is more realistic. In a society, some actors will overextend themselves and others will function at a level below their actual abilities. We include this in the laboratory with a randomized choice behavior that tends to optimize to zero but leaves the opportunity for actors to seek nonoptimal states.

### 4.3 Membership Model

The membership model (see Figure 8) determines how an actor moves from one social configuration to another. This section specifies this process in two parts, how an actor decides on what action to take, and how the actor executes that action.

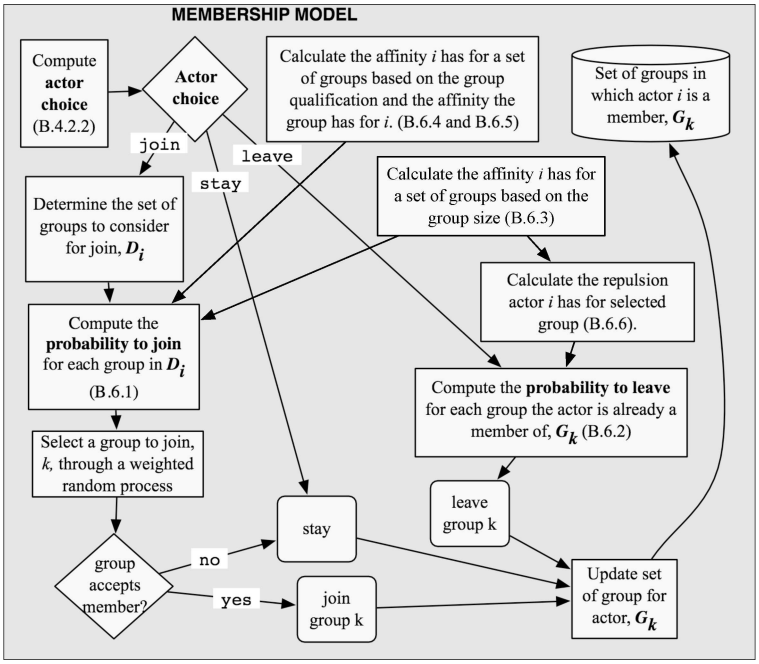


Fig. 8. Membership model in ViSAGE.

4.3.1 *Deciding Actors' Actions.* Figure 9(a) shows the default probablility of joining, leaving, or remaining in the same groups based on the actors excess resources. The parameters *Aplus* and *Rhoplus* change the shape of the joining probability function, and similarly *Aminus* and *Rhominus* affect the leaving probablility, while *Azero* and *Rhozero* affect the probability of taking no action. The parameter *Threshold* affects all three curves. The equations for these curves are specified in Section B.4 in the appendix.

4.3.2 *Performing Actors' Action.* At each time step, every actor decides to leave one group, join one group, or remain in the same groups. In order to decide which group to join or leave, the actor takes into account the size and qualification of the group. Each class of actors (leaders, followers, and socialites) has a different size preference. The size preference is defined by a function representing the relative preferences of each group size. The parameters *Theta*, *GammaLeader*, *GammaSocialite*, and *GammaFollower* determine the shape of the equation by the following formula:

$$SizeAff_k^i = \frac{1}{\Gamma \times Theta^{iclass_i}} \times (|G_k| + 2)^{(iclass_i - 1)} \times e^{-(|G_k|+2)/Theta},$$

where $iclass_i$ is 1, 3, or 5, if the actor is a leader, socialite, or follower, respectively, $|G|$ is the number of actors in group $G$, and $\Gamma$ is equal to the parameter value *GammaLeader*, *GammaSocialite*, or *GammaFollower*, depending on the actor's type. The parameter *Theta* is also defined in the configuration

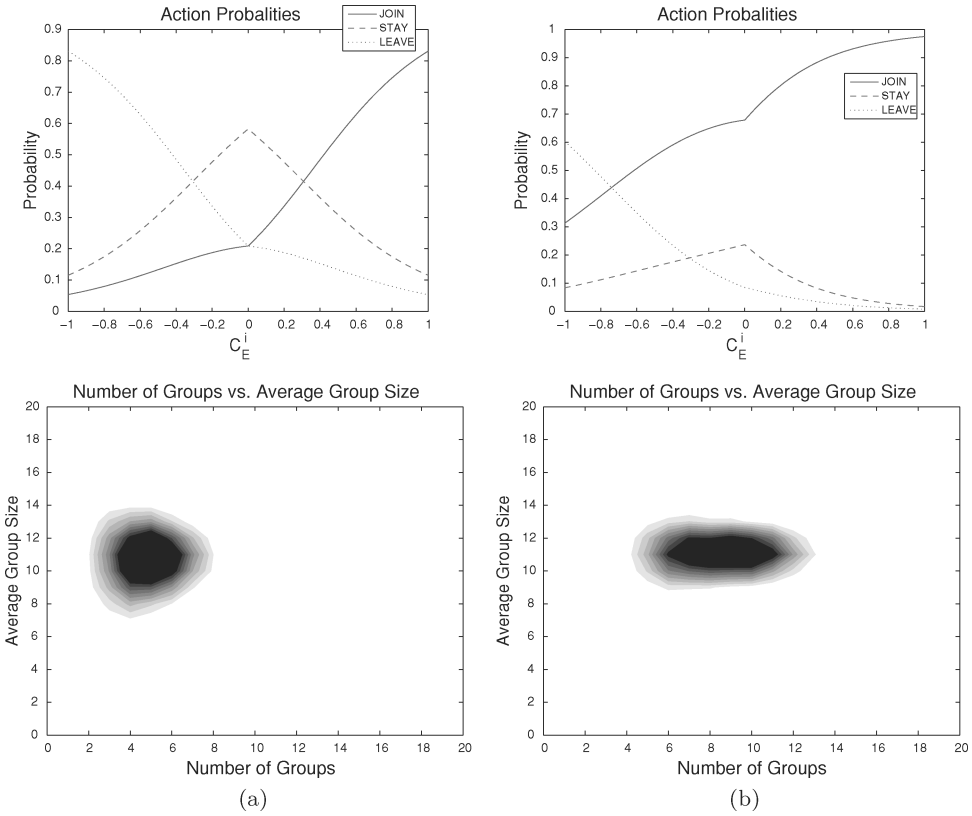


Fig. 9. The action probability functions and resulting number of groups versus average group size per actor for (a) the default parameters with $Aplus = 1.0$ and (b) $Aplus = 8.0$.

file. Figures 10 and 11 show the default size preference functions and also the changes that take place if *GammaSocialite* or *Theta* are changed.

4.3.2.1 *Leave One Group* In this case, the actor determines the repulsion toward each group. The actor tends not to leave a group where the rank in that group is high relative to the rank in other groups. The actor also will be more likely to leave groups that are not in a size preferrable for the type of actor (leader, follower, or socialite). Thus an appropriate formula for the repulsion of actor $i$ toward group $k$ is defined by:

$$Rep_k^i = \left(1 - \frac{r_k^i}{\sum_{i \in G_j} r_k^j}\right)(1 - SizeAff_k^i),$$

where $SizeAff_k^i$ is the size affinity of the actor to the group described previously. With probabilities in proportion to the repulsions, the actor then chooses the group to leave, and exits that group.

4.3.2.2 *Enter One Group.* If the actor decides to enter a group, a selection process begins between a group and the actor. First, the actor generates

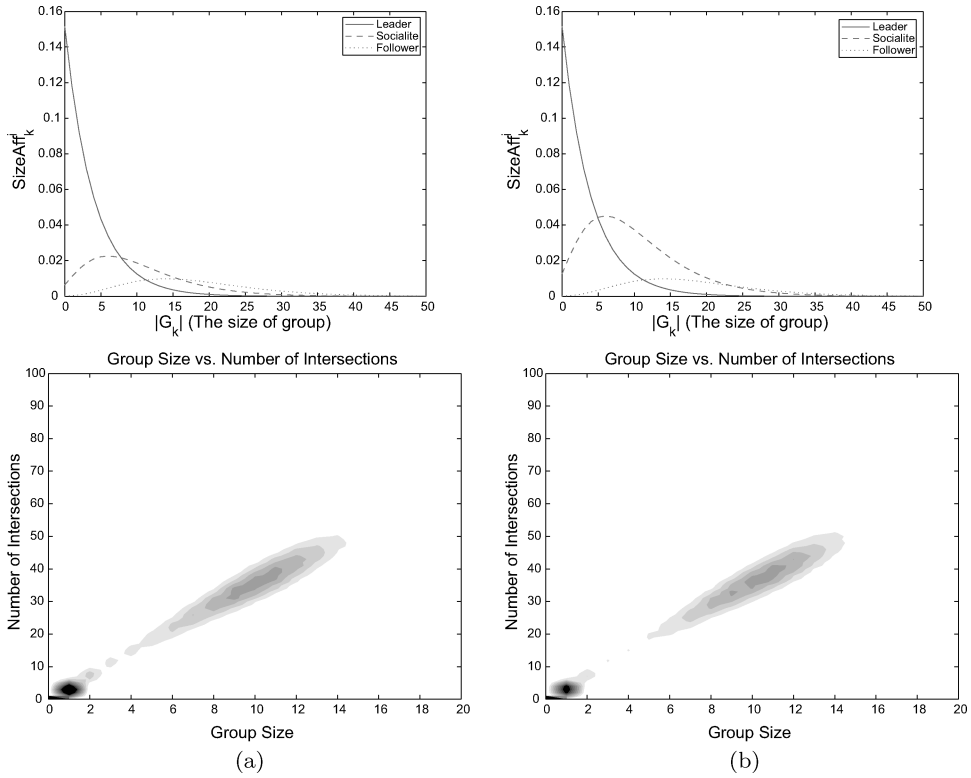


Fig. 10. The size preference functions and resulting group sizes for (a) the default simulation with *GammaSocialite* = 6 and (b) with *GammaSocialite* = 3.

a list of possible groups to join, $D_i$. This can be done either through a random process or by references through individuals whom the actor already knows (individuals who are members of the actor's current groups). This behavior is controlled through the parameters *ShareAllFrac* and *ShareProb*. *ShareAllFrac* specifies the fraction of actors who are willing to share information about the other groups they are members of, such as the group identity and members of the group. These actors may not share all their information, however. The *ShareProb* specifies the proportion of groups that the sharing actors will disclose when asked by the joining actor. $D_i$ is generated as follows:

(1) Actor $i$ produces a list of all its group comembers, $M_i$.
(2) Using *ShareAllFrac* and *ShareProb*, actor $i$ generates a list of possible groups, $D_i$, from $M_i$.
(3) If $D_i$ contains no groups, then set $D_i$ to all possible groups.[4]

[4]Alternatively one can change this algorithm to define what counts as a group and what doesn't. For example, an actor can create a new group here by setting $D_i$ equal to an empty slot. Or one can set $D_i$ here to be a random set of slots with one or more actors. This effectively sets what a group is and is not, by excluding a slot from any set of groups.

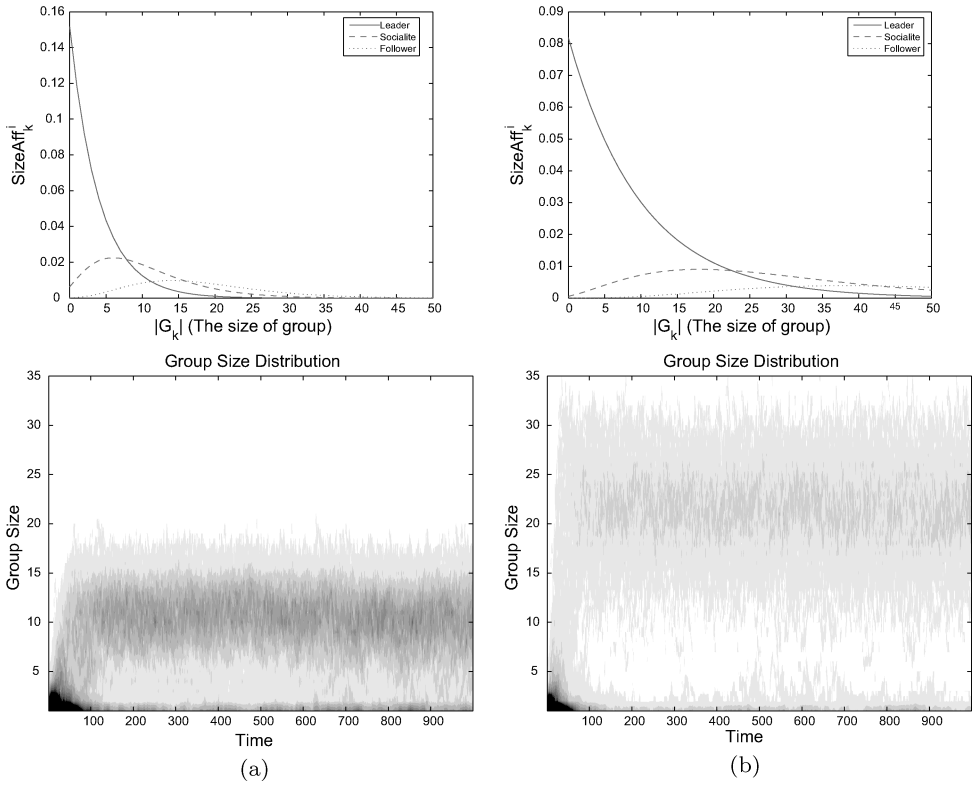


Fig. 11. The size preference functions and resulting group sizes for (a) the default simulation with $Theta = 4$ and (b) with $Theta = 10$.

Once $D_i$ is determined, the actor will choose a group according to both the size affinity described previously and the qualification affinity. The process of joining a group:

(1) After establishing the list of possible groups, $D_i$, each group is given a probability weight ($PJ^i_k$) based on the properties of an actor, $i$. The *group join probablility* ($PJ^i_k$) is the probability that actor $i$ joins a group $k$, where the *size affinity* ($SizeAff^i_k$) and *qualification affinity* ($QualAff^i_k$) indicate actor $i$'s preference for different properties of group $k$:

$$PJ^i_k = \frac{SizeAff^i_k * QualAff^i_k}{\sum_{j \in D_i} SizeAff^i_j * QualAff^i_j}.$$

See Section B.6.4 for specifications of $QualAff^i_k$.

(2) Actor $i$ will randomly pick one group $k$ from the list of possible groups based on the probabilites $PJ^i_k$ and will attempt to join it. Before the actor can join, the group $k$ has the right to reject actor $i$'s attempt to join based on the group's affinity for the actor, $ActorAff^i_k$ (see Section B.6.5 for details). The actor gains membership if a randomly generated number, $R \in [0, 1]$, $\leq ActorAff^i_k$. Therefore, a higher qualification of actor $i$ increases the chance

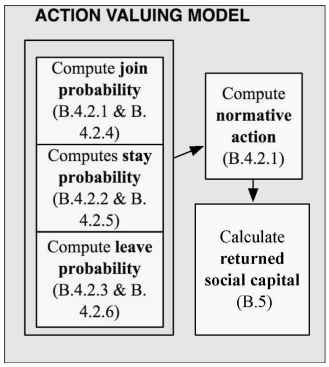


Fig. 12. Action valuing model in ViSAGE.

that group $k$ will accept actor $i$. If group $k$ rejects actor $i$, actor $i$ will instead perform the `stay` action in this time step.

4.3.2.3 *Perform No Action.* In this case, the actor does not join or leave any groups. Even though the actor has not chosen to perform any action, this may affect its social capital as described in the next section.

## 4.4 Action Valuing Model

Actors, when reflexive or aware of their actions, make decisions based on some beliefs about the world. These beliefs are said to be *socially constructed*. The idea of social construction is understood through what is termed the object-subject schema [Bloor 1999] or structure and agency [Giddens 1984]. The basic idea here is that for any action there is a mechanism internal to the individual that drives the action but is limited and expanded by the social and physical environment where the action occurs. Figure 12 shows the action valuing model in VISAGE.

4.4.1 *Structure and Agency.* Actors make choices based upon their own beliefs about how the world ought to operate and the world either operates in that manner or resists responding to an action in the way imagined by the actor. As is generally accepted, knowledge is not perfect nor can it ever be perfect and therefore the world will never respond exactly as imagined by an actor. Complicating this is the fact that humans never have a fully formalized mental model of a given context, be it social or natural, to keep track of or, even, notice how well reality corresponds to perception. The relationship between belief and action, which is key to understanding social behavior, is a complex phenomena that is contingent upon (1) the degree to which an actor is present or reflexive in his or her choices and (2) the ability of that belief to be revised in light of changes in the world structure, that the belief is coupled with.

It is important to note that the real world can be perceived along many dimensions, even other beliefs, which we understand to be structure. If enough people believe in something over time it becomes an object or a structure. Money is a good illustration. One cannot eat money, it has no natural value on its own.

An American Dollar, for example, might also not have any value in a different economy, inside a different social, cultural, and political context. Thus money is a deeply social object that is embodied in a physical system of relationships, which are further suspended by social relationships. This structure is something inside of which individuals have to make choices, and about which there are specific rules. However, if enough people decide to bend these rules then the rules can and do change. It is commonly held that this is not the case with natural systems such as the biology of the cell or the physics of the quark. It is believed that belief cannot change the way such systems operate. Thus the relationship between belief, action, and structure is even further made complex because structure is contingent upon (1) the reality of how actions probe structure, (2) the manner in which actors perceive structure, and (3) that certain structures can change based on the perceptions and actions of other actors.

4.4.2 *Constructing Value.* The back-and-forth between action and a structure resisting that action is productive along different dimensions. For one, through this process social practices are developed that actively shape a structure to generate an objective or physical benefit. For example, following Burt [1992], if an actor, say a person in a supply chain, seeks out structural holes and seeks to fill structural holes then he or she will, in Burt's theory, allocate more capital [Burt 1992]. On the other hand, social practices generate solidarity among the community of actors who deploy these practices. For example, if an actor seeks to fill structural holes and a community perceives that as a good practice, then the community will have positive feelings towards that actor.

The latter is the focus of our laboratory. In ViSAGE, social practices are specified using the idea of structure and agency. Using the variable *returned social capital* ($C_i^S$) we track the positive and negative feeling directed toward a certain actor. These perceptions influence the actor's capacity to interact in the community.

4.4.3 *ViSAGE Specifications.* We provide the tools in ViSAGE to simulate the tension between structure and agency, a social practice, through a series of functions and parameters beginning with the action probabilities described in Section 4.3.1. The action probabilities evaluate a real-world variable (in this case it is excess energy) from the points of view of a structure and of an individual actor, an agent. The idea here is that two social things, one defined as structure and the other as agency, are brought into tension. One is the belief of the individual (we call this actor choice, $Act_c$) and the second is the common practices of the society (we call this normative action, $Act_n$) concerning how that reality ought to translate into action and how action generates a socially perceived value.

These two actions, calculated from the action probabilities, are then processed in the agency and structure table. Table I shows an example of the agency and structure table. This table is a tool for formally specifying the practices and habits of a given society. How the Agency and Structure Table is specified in ViSAGE is presented in appendix B.5.5, and how to use this table to update the returned social capital ($C_i^S$) is discussed in appendix B.5.

Table I. The Agency and Structure Table

| | | "structure" $Act_n$ | | |
|---|---|---|---|---|
| | | `join` | `stay` | `leave` |
| "agency" $Act_c$ | `join` | 1 | −1 | −1 |
| | `stay` | 0 | 1 | −1 |
| | `leave` | 0 | 0 | 2 |

In our current implementation of ViSAGE, the table increases or decreases an actor's returned social capital based on their own subjective criteria and the best choice based on the accepted norm of the community. The idea of the Structure and Agency Table is to model a socially constructed value, which in the following example is social capital. While the Structure and Agency Table need not be turned on to run instances of ViSAGE, we hold that understanding values and the practices of valuing in a society, are critical for understanding and modeling how social groups function.

## 5. THEORY BUILDING IN VISAGE: THE SOCIAL CAPITAL MODEL

In order to develop ViSAGE further we ran a series of experiments. While these experiments can be used to make insights about social complexity the goal of these simulation experiments is to better understand how ViSAGE operates to further design it, clarify it, and make it usable. In this way, these experiments are a first iteration in our iterative experimental system design (Figure 1).

### 5.1 Modeling Social Capital Practices

The idea that a community's social structure, its social network properties, is a resource for producing wealth and positive social outcomes and can be quantified or indexed has come to be called *social capital* [Putnam 2000] or *relational wealth* [Diwan 2000]. The concept, because of its generality, has been widely criticized and has had multiple interpretations [Kadushin 2004; Portes 1998]. In order to model social capital, we make use of the network measures of social capital—individual-level bridging social capital and individual-level bonding social capital—formalized in ViSAGE based on Borgatti et al. [1998], which was discussed in Section 4.2. We then specify a pair of value practices using the ViSAGE agency and structure framework. Finally, using these value practices, we define an experiment and present the results.

The empirical work of Putnam [2000] shows that there has been a structural change in American communities since the middle of the 20th century. In general this change has been in the form of how bridging and bonding social capital is distributed among social groups. Putnam [2000] shows several trends. In the 50s and 60s small groups with memberships of about two to seven, such as dinner parties and bowling teams, functioned to bridge individuals across the community. Large groups with memberships of eight and up, such as community volunteer organizations and bowling leagues, served a bonding function, bringing community members into contact. In the 80s and 90s the function of community social groups flip-flopped from midcentury. Small groups served a bonding function, making already existing relationships even stronger. Large groups served a bridging function that connected individuals

Table II. Stay is Valued

| | | $Act_n$ | | |
|---|---|---|---|---|
| | | join | stay | leave |
| $Act_c$ | join | 0 | 0 | 0 |
| | stay | 1 | 1 | 1 |
| | leave | −1 | −1 | −1 |

Table III. Accordance Valued

| | | $Act_n$ | | |
|---|---|---|---|---|
| | | join | stay | leave |
| $Act_c$ | join | 1 | 0 | −1 |
| | stay | 0 | 1 | 0 |
| | leave | −1 | 0 | 1 |

Table IV. Civic Class

| | | Norm | | |
|---|---|---|---|---|
| | | join | stay | leave |
| $Act_c$ | join | 1 | 0 | −1 |
| | stay | 1 | 2 | 1 |
| | leave | −2 | −1 | 0 |

to a broader national or world-wide community. In the last half of the 20th century the place-based community lost out as an organizational focus of social capital. How did this happen? While Putnam argues that, primarily technologies constrained the expressive actions of a civic minded cultural practices, he also points to generational change: the development of cultural practices with different values about creating relations with others.

Ortner [2003] argues that the proliferation of the manager professional class in the second half of the 20th century was a primary force in the development of late capitalism. While Putnam sees civic mindedness, a cultural practice that encodes an ethic of reciprocity and place, as the necessary force in developing the place-based social capital that existed at mid-century, a cultural practice of individual prosperity, one that seeks to create global relationships, relationships to global capital, rather than community relationships is the foundation of the post-industrial society, a society that Putnam points to as a sign of the collapse of the American community [Putnam 2000].

5.1.1 *Civic Social Capital Practices.* The civic practices for generating social capital (civic class) are specified in Table IV and are derived from adding Table II and Table III together element-by-element. In this culture, actors believed that staying in groups and having loyalty, is the honorable or good thing to do. This is specified by returning a positive number if an actor chooses to stay in a group, and a negative number if this actor chooses to leave a group (see Table II). Table II represents the social fact in this particular society that there is a perceived value in sticking with one's existing social groups, as would be an ethic observed in a community-oriented culture. Also, as there is value in loyalty to existing groups there is also an ethic of following social norms, of maintaining coordination with the community's values. This is represented

Table V. Join is Valued

| | | $Act_n$ | | |
|---|---|---|---|---|
| | | `join` | `stay` | `leave` |
| $Act_c$ | `join` | 1 | 1 | 1 |
| | `stay` | 0 | 0 | 0 |
| | `leave` | −1 | −1 | −1 |

Table VI. Self-Interest Valued

| | | $Act_n$ | | |
|---|---|---|---|---|
| | | `join` | `stay` | `leave` |
| $Act_c$ | `join` | 0 | 0 | 1 |
| | `stay` | 0 | 0 | 0 |
| | `leave` | −1 | 0 | 0 |

in Table III. Adding these two tables together element-by-elements gives the model of civic social capital practices.

5.1.2 *Manager Social Capital Practices.* The manager practices for generating social capital (manager class) has two specifications similar to the civic class. In this culture, actors believe that joining new groups is the good thing to do. If an actor joins, a positive number is returned, and if they leave, a negative number is returned (Table V). Again this follows a modern ethic of networking or building social capital. Second the manager works in his or her own self interest. Therefore actors break norms when it is in their interest and coordinate with norms when that is in their interest. An actor is benefited by going against the view that he or she should leave a group. A simple interpretation is that joining always provides more social capital than leaving and therefore going against the situated norm to leave a group is valued at a higher society-wide level. On the other hand if an actor leaves when both the situated norms and the society-wide value are to join, the actor is not benefited (Table VI). Adding these two tables together gives the manager social capital practice.

## 5.2 Experiment

Robert Putnam claims that communities in the United States have lost place-based social capital while gaining function-based social capital [Putnam 2000]. Place-based social capital is characterized by the presence of many small groups, such as a card game group or a dinner party, that function to bridge across a community, and the presence of many larger groups, such as town hall meetings or volunteer groups or community work groups, that function to bond a community. In this view small groups, which we define to be between two and seven, will have a relatively high degree and low density and large groups, which we define to be eight to twenty, will have a relatively high density and low degree. Characteristic of place-based social capital is that small groups bridge and large groups bond [Putnam 2000].

To test the hypothesis that social capital has decreased from midcentury to late-century American communities we ask if a civic class community generates

Table VII. Manager Class

| | | $Act_n$ | | |
|---|---|---|---|---|
| | | *join* | *stay* | *leave* |
| $Act_c$ | *join* | 1 | 1 | 2 |
| | *stay* | 0 | 0 | 0 |
| | *leave* | −2 | −1 | −1 |

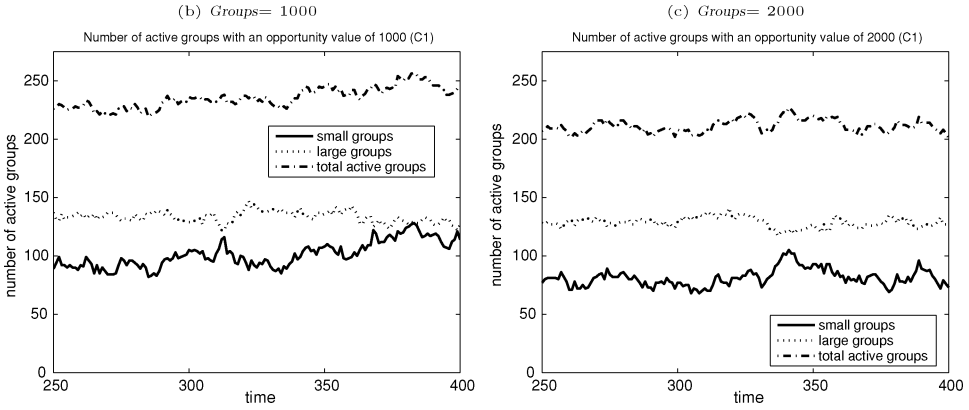


Fig. 13. Number of groups in civic-minded agent community.

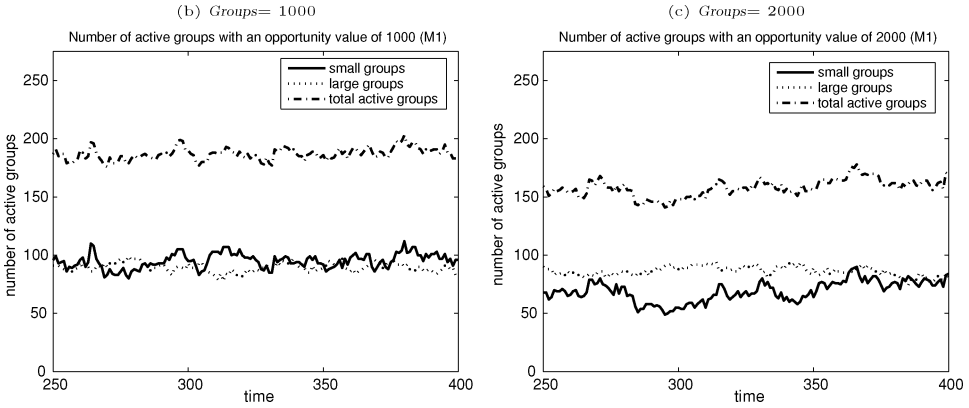


Fig. 14. Number of groups in manager-professional agent community.

social capital in the manner previously discussed, while the manager class community does not. We ran a total of four simulations classifying the output of each into a number of small and large groups (Figures 13 and 14) and by the local-level bridging social capital (Figure 15) and the local-level bonding social capital (Figure 16) of large and small groups. These figures were extrapolated and simplified from the standard ViSAGE output plots shown in Figures 4(a)–(e) after observing changes of these properties over time. Each society was initialized with no social structure, with no actors in groups. Therefore each society began with a null social structure with all actors isolated. For

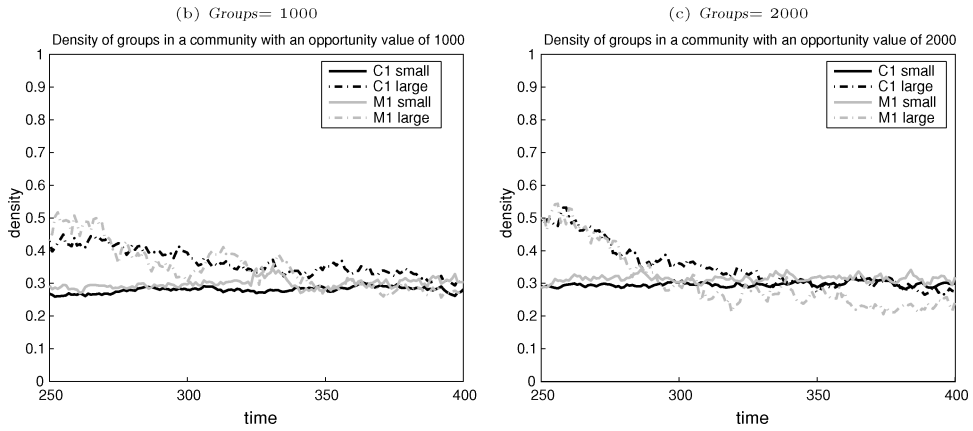


Fig. 15. Density for small and large group classification; C1 = Table IV and M1 = Table VII.

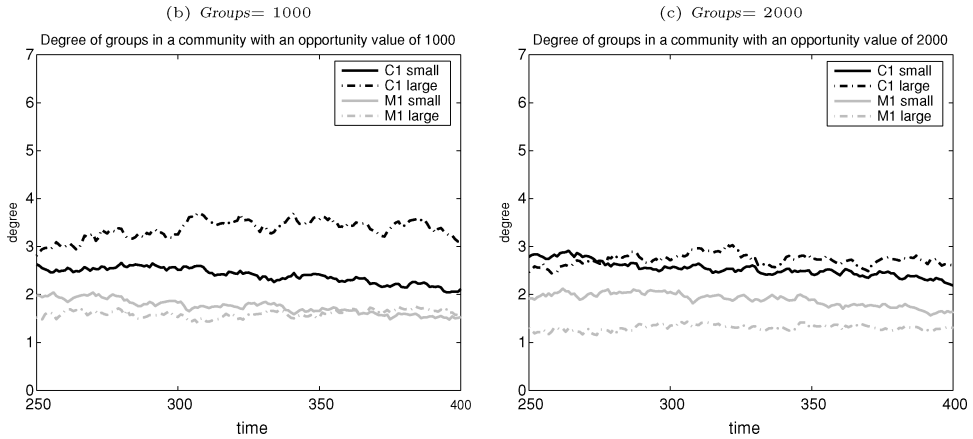


Fig. 16. Degree for small and large group classification; C1 = Table IV and M1 = Table VII.

a further comparison among societies constituted from these different practices we tested how each of these societies grew inside an environment that affords different possibilities for forming groups, which we call *opportunity values (OV)*. Opportunity values are modeled using the *Groups* parameter in ViSAGE, which gives agents more opportunities to form active groups. Table VIII shows the hypotheses in which societies, constituted by manager practices or constituted by civic practices, have higher social capital values for each social capital category.

## 5.3 Results and Discussion

The results verified three of our four hypotheses (see Table IX). We focus here on the results from the bridging social capital measures because the bonding social capital results, while confirming our expectations, were too close to give a good

Table VIII. Which Practices Generate Higher Values?

| $OV$ | $C_j^{br}$ Small | $C_j^{br}$ Large | $C_j^{bo}$ Small | $C_j^{bo}$ Large |
|---|---|---|---|---|
| 1000 | Civic | Manager | Manager | Civic |
| 2000 | Civic | Manager | Manager | Civic |

Table IX. Civic Practices Generate the Highest Bridging Social Capital Measures

| $OV$ | $C_j^{br}$ Small | $C_j^{br}$ Large | $C_j^{bo}$ Small | $C_j^{bo}$ Large |
|---|---|---|---|---|
| 1000 | Civic | Civic | Manager | Civic |
| 2000 | Civic | Civic | Manager | Civic |

analysis.[5] The civic-produced-societies had much higher bridging social capital values for both large and small groups. We were incorrect in predicting that manager societies would have large groups with a higher degree than large groups in civic societies. There are several reasons for this. The most direct reason is because the civic societies produced more groups in total than the manager societies (between 25 and 40 percent more) there was simply more likelihood of linking with a diversity of other groups. An indirect explanation for these results is that the groups with the right kind of qualifications and sizes were not available to the actors who were seeking them, which could have allowed the manager practices to yield expected results. For example, the networks into which most agents were initialized would rarely trigger the norm `leave` and therefore there were fewer moments when agents could break the rules and generate large returns of social capital. The overall result is fewer available resources to put manager agents into a `join` state, which means fewer groups overall. The implication of this result, in terms of the model, is that we would have to take much more into consideration about the real-world initial states of communities and the context in which these practices occur. In this sense our simulation points us towards the need for real-world empirical studies and to design ways for initializing groups and group membership at the start of the simulation. To further validate and test the manager and civic practices and their impact on social capital measures, we must formalize the possible social structures in which these practices occur. Real-world data is needed.

5.3.1 *Thinking about the ViSAGE Design.* What did we learn about ViSAGE from these experiments and going through this first theory-building iteration? The main insight concerns the choice of a hybrid agent-based and parameter learning design for the laboratory. Proponents of agent-based modeling (ABM) argue that ABMs are more transparent and easier to understand since changes in the system are governed by the actions of individuals, which are observable and testable at the individual level [Grimm and Railsback 2005; Epstein 1999]. This is bottom-up design. On the other hand, parameter learning

[5]We will better understand these results if we develop measures that make bridging and bonding more sophisticated measures. For now our measures are simple network measures, which give too general a result to see subtle differences in the communities.

or equation-based modeling (top-down) approaches are computationally easier to deal with in reverse engineering or learning parameters from real data. We believe that we can to a better job in the trade-off between the transparency of ABM and the power of parameter learning. At this point parameter learning requirements overshadowed the design process of ViSAGE (for example, in the implementation of the criteria actors use to choose groups). The aspects that control individual choice are distributed into equations (e.g. *ShareAllFrac* and *ShareProb*) relating components, rather than in algorithms within the components themselves, and this produces simulation results that are difficult to understand and describe. From our simulation experiments we see that as we begin to use ViSAGE with real data, the question about what choices individuals are really making when entering groups and what information they are using to enter a group will take precedence. At that point ViSAGE will take on more of a agent-based approach. At the same time a commitment to machine learning requires that agent choices are suitably general. As the ABM perspective takes precedence there will be resistance from those doing machine learning to keep the models simple as to maintain the possibility of computation.

## 6. CONCLUSION

In this article we have given a full view of our simulation laboratory, ViSAGE. We did this by giving some background of social simulation and the purpose of the laboratory, described each component of the laboratory in detail, included an appendix that outlines each function and parameter, and gave an example. Our hope is that the use of ViSAGE will enable computer scientists and social scientists to study patterns of social organization and development across various populations by establishing an experimental system through which population-level patterns are understood through the action of individuals.

Our ongoing work addresses the problem of using observed society dynamics to identify the model parameters in ViSAGE (reverse engineering), which ought to be of interest to the computer science community. These inferred parameters could then be used to simulate forward to depict the dynamics of real societies, leading to a better understanding of this complex phenomenon.

## APPENDIX

## A. CONFIGURATION FILE

### A.1 Parameters

(1) *Actors*: the total number of actors in the population
(2) *Groups*: the maximum number of groups during the simulation
(3) *TimeSteps*: the simulation time
(4) *LeaderPercent*: the fraction of population that are *Leader*
(5) *SocialitePercent*: the fraction of population that are *Socialite*
(6) *SCTableR0*, *SCTableR1*, *SCTableR2* indicate the value of the table of updating socail capital

(7) *Aplus*, *Azero*, *Aminus*, *Rhoplus*, *Rhozero*, *Rhominus* and *Threshold* are constant for computing the probabilities $p_+$, $p_0$ and $p_-$
(8) *BridgingCostType*, *BridgingParam1*, *BridgingParam2*, *BridgingParam3* are constant for computing the bridging cost
(9) *BondingCostType*, *BondingParam1*, *BondingParam2*, *BondingParam3* are constant for computing the bonding cost
(10) *InteractCostType*, *InteractParam1*, *InteractParam2*, *InteractParam3* are constant for computing the interaction cost
(11) *ExcessType*, *ChangeBegin*, *ChangeAmount* are constant for computing the excess capital
(12) *InitSocCap*: the initial value of social capital per actor
(13) *Theta*, *GammaLeader*, *GammaSocialite*, *GammaFollower* are constant for computing *SizeAff*
(14) *QualRange*, *QualSensitivity* are constant for computing *QualAff* and *ActorAff*
(15) *ShareAllFrac*: the fraction of population that share all the information
(16) *ShareProb*: the average percentage of information each actor shares if the actor doesn't share all the information
(17) *PenaltyFun*: The switch of using a different penalty function.

### A.2 Default Values

| Name | Default | Name | Default |
|---|---|---|---|
| *Actors* | 500 | *InteractCostType* | 1 |
| *Groups* | 2000 | *InteractParam1* | 0.0 |
| *TimeSteps* | 1000 | *InteractParam2* | 1.0 |
| *LeaderPercent* | 0.0 | *InteractParam3* | 1.0 |
| *SocialitePercent* | 1.0 | *ExcessType* | 1 |
| *SCTableR0* | 2.0 1.0 0.0 | *ChangeBegin* | 500 |
| *SCTableR1* | 1.0 0.0 −1.0 | *ChangeAmount* | 0.0 |
| *SCTableR2* | 0.0 −1.0 −2.0 | *InitSocCap* | 0.25 |
| *Aplus* | 1.0 | *Theta* | 4.0 |
| *Azero* | 0.75 | *GammaLeader* | 1.0 |
| *Aminus* | 1.0 | *GammaSocialite* | 6.0 |
| *Rhoplus* | 1.0 | *GammaFollower* | 120.0 |
| *Rhozero* | 1.0 | *QualRange* | 0.9 |
| *Rhominus* | 1.0 | *QualSensitivity* | 0.75 |
| *Threshold* | 0.5 | *BoundedMaxFrac* | 1.0 |
| *BridgingCostType* | 1 | *BoundedMinFrac* | 1.0 |
| *BridgingParam1* | 0.3 | *BoundMax* | 1.0 |
| *BridgingParam2* | 1.0 | *BoundMin* | 0.0 |
| *BridgingParam3* | 1.0 | *ShareAllFrac* | 1.0 |
| *BondingCostType* | 1 | *ShareProb* | 1.0 |
| *BondingParam1* | 0.8 | *PenaltyFun* | 0 |
| *BondingParam2* | 1.0 | *BondingParam3* | 1.0 |

## B. LIST OF FUNCTIONS AND VARIABLES

### B.1 Actor Properties

B.1.1 $time_k^i$. The amount of time actor $i$ spends in a group $k$.

B.1.2 $rclass_i$. A real number representing actor $i$'s class.

B.1.3 $\delta_i$. The bounded size preference of actor $i$.

$$\delta_i = (e^{rclass_i} - e^{-rclass_i})/(e^{rclass_i} + e^{-rclass_i}).$$

B.1.4 $iclass_i$. An integer number representing actor $i$'s class.

$$iclass_i = \begin{cases} 1 & : \text{Leader, if } \delta_i < -0.5 \\ 5 & : \text{Follower, if } \delta_i > 0.5 \\ 3 & : \text{Socialite, otherwise} \end{cases}.$$

B.1.5 $r_k^i = \frac{\rho_k^i}{\sum_{j \in G_k} \rho_k^j}$. Indicates the rank of actor $i$ in group $k$, where $G_k$ is the set of all actors in group $k$ and $\rho_k^i = time_k^i * (2 - \delta_i)$.

B.1.6 $q^i = \frac{\sum r_k^i * |G_k|}{\sum |G_k|}$. Indicates the qualification of actor $i$, where $|G_k|$ is the size of group $k$; the number of actors in group $k$.

### B.2 Group Properties

B.2.1 $Q_k = \sum_{i \in G_k} q^i * r_k^i$. The qualification of group $k$.

### B.3 Excess Resources

The excess resources ($R_E^i$) for actor $i$ is

$$R_E^i = R^i - \phi^i L_{br}^i - \psi^i L_{bo}^i.$$

B.3.1 *Resources.* The internal mental and physical resources or capacity each actor has to engage in social activities at the current time step, $t$.

$$R^i = \begin{cases} C_i^S - \eta, & \text{when } ExcessType = 0 \\ 1 - \eta, & \text{when } ExcessType = 1. \end{cases}$$

$$\eta = \begin{cases} 0, & \text{when } t \leq ChangeBegin \\ (t - ChangeBegin) * ChangeAmount, & \text{when } t > changebeginP. \end{cases}$$

B.3.2 *Bridging Social Capital.* $L_{br}^i = |G : i \in G|$.

B.3.3 *Bonding Social Capital.* $L_{bo}^i = \sum_{G_k : i \in G_k} r_k^i$.

B.3.4 *Bridging Coefficient.*

$$\phi^i = \begin{cases} BridgingParam1, & \text{when } BridgingCostType = 0 \\ \dfrac{BridgingParam1}{(BridgingParam2 + C_i^S)^{BridgingParam3}}, & \text{when } BridgingCostType = 1. \end{cases}$$

B.3.5 *Bonding Coefficient.*

$$\psi^i = \begin{cases} BondingParam1, & \text{when } BondingCostType = 0 \\ \dfrac{BondingParam1}{(BondingParam2+C_i^S)^{BondingParam3}}, & \text{when } BondingCostType = 1. \end{cases}$$

B.3.6 $C_i^S$. The returned social capital of actor $i$. The default initial value is *InitSocCap*. See section B.5 for the specification of returned social capital.

## B.4 Action Probabilities

B.4.1 *Normative Action.* $Act_n = \max(p_+, p_0, p_-)$.

B.4.2 *Actor Choice.* $Act_c = random(p_+, p_0, p_-)$.

B.4.2.1 $p_+ = \frac{p'_+}{p'_+ + p'_0 + p'_-}$.

B.4.2.2 $p_0 = \frac{p'_0}{p'_+ + p'_0 + p'_-}$.

B.4.2.3 $p_- = \frac{p'_-}{p'_+ + p'_0 + p'_-}$.

B.4.2.4 $$p'_+ = \frac{Aplus}{1+e^{-Rhoplus\times\left(\frac{R_E^i}{Threshold}-1\right)}}$$

B.4.2.5 $$p'_0 = Azero \times e^{-Rhozero\times\frac{|R_E^i|}{Threshold}}.$$

B.4.2.6 $$p'_- = \frac{Aminus}{1+e^{Rhominus\times\left(\frac{R_E^i}{Threshold}+1\right)}}.$$

## B.5 Returned Social Capital Models

The returned social capital function, $f_{\Delta C_i^S}(C_i^S, Act_n, Act_c)$, specifies how an actor's returned social capital changes at each time step.

$$f_{\Delta C_i^S}(C_i^S, Act_n, Act_c) = PenaltyW(Act_n, Act_c) \times Penalty(C_i^S) + RewardW(Act_n, Act_c) \times Reward(C_i^S).$$

B.5.1 $$Penalty(C). = \begin{cases} -0.35 * (0.01C + (1.99C)^{1.05}), & \text{if } PenaltyFun = 0 \\ -0.35 * (C^{0.5} + 100C), & \text{if } PenaltyFun = 1 \\ -0.35 * (C^2 + 100C), & \text{if } PenaltyFun = 2 \\ -1/(1 + e^{(5.0-10C)}), & \text{if } PenaltyFun = 3 \end{cases}.$$

B.5.2 $Reward(C) = -Penalty(1.0 - C)$.

B.5.3 $PenaltyW(Act_n, Act_c) = 1/\left(1 + e^{((1+SCTable(Act_n, Act_c))\times 5)}\right)$.

B.5.4 $RewardW(Act_n, Act_c) = 1/\left(1 + e^{((1-SCTable(Act_n, Act_c))\times 5)}\right)$.

B.5.5 $SCTable(Act_n, Act_c)$.

$$= \begin{cases} SCTableR0[1], & \text{when } Act_n = \texttt{join} \text{ and } Act_c = \texttt{join} \\ SCTableR0[2], & \text{when } Act_n = \texttt{join} \text{ and } Act_c = \texttt{stay} \\ SCTableR0[3], & \text{when } Act_n = \texttt{join} \text{ and } Act_c = \texttt{leave} \\ SCTableR1[1], & \text{when } Act_n = \texttt{stay} \text{ and } Act_c = \texttt{join} \\ SCTableR1[2], & \text{when } Act_n = \texttt{stay} \text{ and } Act_c = \texttt{stay} \\ SCTableR1[3], & \text{when } Act_n = \texttt{stay} \text{ and } Act_c = \texttt{leave} \\ SCTableR2[1], & \text{when } Act_n = \texttt{leave} \text{ and } Act_c = \texttt{join} \\ SCTableR2[2], & \text{when } Act_n = \texttt{leave} \text{ and } Act_c = \texttt{stay} \\ SCTableR2[3], & \text{when } Act_n = \texttt{leave} \text{ and } Act_c = \texttt{leave} \end{cases}.$$

## B.6 Actor and Group Fitting

B.6.1 *Group Join Probablility.* The probability for actor $i$ to join group $k$ where $D_i$ is the set of groups that actor $i$ can possibly join.

$$PJ_k^i = \frac{SizeAff_k^i * QualAff_k^i}{\sum_{j \in D_i} SizeAff_j^i * QualAff_j^i}.$$

B.6.2 *Group Leave Probablility.* The probability for actor $i$ to leave group $k$ based on a set of groups of which the actor has membership, $G_k$.

$$PL_k^i = \frac{Rep_k^i}{\sum_{i \in G_j} Rep^i{}_j}.$$

B.6.3 *Size Affinity.* The affinity an actor, $i$, has for a group, $k$, based on the actor's preferred size.

$$SizeAff_k^i = \frac{1}{\Gamma \times Theta^{iclass_i}} \times (|G_k| + 2)^{(iclass_i - 1)} \times e^{-(|G_k|+2)/Theta},$$

$$\Gamma(iclass_i + 1) = \begin{cases} GammaLeader, & \text{if the actor is a leader} \\ GammaSocialite, & \text{if the actor is a socialite} \\ GammaFollower, & \text{if the actor is a follower.} \end{cases}$$

B.6.4 *Qualification Affinity.* The affinity an actor, $i$, has for a group, $k$, based on a comparison between the actor's qualifications and the group's qualifications.

$$QualAff_k^i = QualRange + (1 - QualRange) \times (1 + \tanh(\xi))/2,$$

$$\xi = \begin{cases} QualSensitivity \times (Q_k - q^i)/q^i, & \text{if } q^i \neq 0 \\ QualSensitivity, & \text{otherwise.} \end{cases}$$

B.6.5 *Group's Actor Affinity.* The affinity a group, $k$, has for an actor, $i$, based on a comparison between the group's qualifications and the actor's qualifications.

$$ActorAff_k^i = QualRange + (1 - QualRange) \times (1 + \tanh(\xi))/2,$$

$$\xi = \begin{cases} QualSensitivity \times (q^i - Q_k)/Q_k, & \text{if } Q_k \neq 0 \\ QualSensitivity, & \text{otherwise .} \end{cases}$$

B.6.6 *Repulsion.* The repulsion actor $i$ has for a group, $k$, based on a set of groups the actor is currently associated with, $G_k$, and size preference.

$$Rep_k^i = \left(1 - \frac{r_k^i}{\sum_{j \in G_k} r_k^j}\right) \times (1 - SizeAff_k^i).$$

## C. OBTAINING VISAGE

At present ViSAGE is available at no charge under the MIT open source software license by contacting Hung-Ching Chen (chen3@cs.rpi.edu). We intend to make ViSAGE available online in the near future.

## REFERENCES


ADAMIC, L. AND ADER, E. 2003. Friends and neighbours on the web. *Social Netw.*, 211–230.

BACKSTROM, L., HUTTENLOCHER, D., KLEINBERG, J., AND LAN, X. 2006. Group formation in large social networks: Membership, growth, and evolution. In *ACM International Conference on Knowledge Discovery and Data Mining*. 44–54.

BILLARI, F., FENT, T., PRSKAWETZ, A., AND SCHEFFRAN, J., Eds. 2006. *Agent-Based Computational Modelling: Applications in Demography, Social, Economic and Environmental Sciences*. Physica-Verlag Heidelberg.

BLOOR, D. 1999. Anti-latour. *Studies Hist. Philos. Sci. 30*, 1, 80–112.

BORGATTI, S. P., JONES, C., AND EVERETT, M. G. 1998. Network measures of social capital. *Connections 21*, 2, 10.

BURT, R. S. 1992. *Structural Holes: The Social Structure of Competition*. Harvard University Press, Cambridge, MA.

BUTLER, B. S. 1999. The Dynamics of cyberspace: Examining and modelling online social structures. Ph.D. dissertation, Carnegie Mellon University.

BYRNE, D. 2002. *Interpreting Quantitative Data*. Sage Publications, Thousand Oaks, CA.

CHATTOE, E. 2002. Review: computational techniques for modelling learning in economics. *J. Artif. Soc. Social Simul. 5*, 1.

COLLINS, R. 1994. Why the social sciences won't become high-consensus, rapid-discovery science. *Sociol. Forum 9*, 2, 155–177.

DIWAN, R. 2000. Relational wealth and the quality of life. *J. Socio-Econ. 29*, 305–340.

EPSTEIN, J. M. 1999. Agent-based computational models and generative social science. *Complexity 4*, 5, 41–60.

EPSTEIN, J. M. AND AXTELL, R. 1996. *Growing Artifical Societies: Social Science From the Bottom Up*. Brookings Institution Press.

FREEMAN, L. C. 2004. *The Development of Social Network Analysis: A Study in the Sociology of Science*. Empirical Press, Vancouver.

GETOOR, L., FRIEDMAN, N., KOLLER, D., AND TASKAR, B. 2003. Learning probabilistic models of link structure. *J. Mach. Learn. Res.*, 679–707.

GIDDENS, A. 1984. *The Constitution of Society: Outline of the Theory of Structuration*. University of California Press, Berkeley.

GLASSER, B. AND STRAUSS, A. 1967. *The Discovery of Grounded Theory: Strategies for Qualitative Reserach*. Aldine Publishing Company.

GOLDBERG, M., HORN, P., MAGDON-ISMAIL, M., RIPOSO, J., WALLACE, W., AND YENER, B. 2003. Statistical modeling of social groups on communication networks. In *Proceedings of the 1st Conference of the North American Association for Computational Social and Organizational Science*.

GRIMM, V. AND RAILSBACK, S. F. 2005. *Individual-Based Modeling and Ecology*. Princeton series in theoretical and computational biology. Princeton University Press, Princeton, NJ.

HOFF, P., RAFTERY, A., AND HANDCOCK, M. 2002. Latent space approaches to social network analysis. *J. Amer. Statis. Assoc.*, 1090–1098.

KADUSHIN, C. 2004. Too much social capital? *Soc. Netw. 26*, 75–90.

KOHLER, T. A. AND GUMERMAN, G. J. 2000. *Dynamics in Human and Primate Societies: Agent-Based Modeling of Social and Spatial Processes*. Oxford University Press, New York, NY.

KOHLER, T. A., JOHNSON, D. C., VARIEN, M., ORTMAN, S., REYNOLDS, R., KOBTI, Z., COWAN, J., KOLM, K., SMITH, S., AND YAP, L. 2007. Settlment ecodynamics in the prehispanic central mesa verde region. In *The Model-Based Archaeology of Socionatural Systems*, T. A. Kohler and S. E. van der Leeuw, Eds. SAR Press, Santa Fe, NM.

KRAUT, R., OLSON, J., BANAJI, M., BRUCKMAN, A., COHEN, J., AND COUPER, M. 2004. Psychological reserach online: Report of board of scientific affairs' advisory group on the conduct of research on the internet. *Amer. Psych. 59*, 2, 105–117.

KUZNAR, L. A. AND SEDLMEYER, R. 2005. Collective violence in darfur: An agent-based model of pastoral nomad/sedentary peasant interaction. *Math. Anthr. Cult. Theory: Int. J. 1*, 4, 22.

LUSTICK, I. S. AND MIODOWNIK, D. 2002. The institutionalization of identity: Micro adaptation, macro effects, and collective consequences. *Studies Compar. Int. Devel. 37*, 2, 24–53.

MARSDEN, P. V. 1990. Network data and measurement. *Ann. Rev. Sociol. 16*, 435–463.

MILES, M. AND HUBERMAN, A. 1994. *Qualitative Data Analysis: An Expanded Sourcebook*. Sage Publications.

MINAR, N., BURKHARDT, R., LANGSTON, C., AND ASKANAZI, M. 1996. The Swarm simulation system: A toolkit for building multi-agent simulations. Tech. rep., Sante Fe Institute.

MONGE, P. R. AND CONTRACTOR, N. S. 2003. *Theories of Communication Networks*. Oxford University Press, Oxford, UK.

NORTH, M. J., COLLIER, N. T., AND VOS, J. R. 2006. Experiences creating three implementations of the Repast Agent Modeling Toolkit. *ACM Trans. Model. Comput. Simul. 10*, 2, 1–25.

ORTNER, S. B. 2003. *New Jersey Dreaming: Capital, Culture, and the Class of '58*. Duke, University Press.

PARKER, M. T. 2001. What is Ascape and why you should care? *The J. Artif. Soc. Social Simul. 4*, 1, http://www.soc.surrey.ac.uk/JASSS/4/1/5.html.

PORTES, A. 1998. Social capital: Its origins and applications in modern sociology. *Ann. Rev. Sociol. 24*, 1–24.

PUTNAM, R. D. 2000. *Bowling Alone: The Collapse and Revival of American Community*. Simon and Schuster, New York, NY.

SALLACH, D. L. 2003. Social theory and agent architectures: prospective issues in rapid-discovery social science. *Soc. Sci. Comput. Rev. 21*, 2, 175–195.

SALLACH, D. L. AND MELLARKOD, V. S. 2005. Typifying situations: Contextualizing and cohering action. In *Proceedings of the North American Association for Computational Social and Organizational Science (NAACSOS'05)*. Notre Dame, IN.

SANIL, A., BANKS, D., AND CARLEY, K. 1996. Models for evolving fixed node networks: Model fitting and model testing. *J. Math. Sociol. 21*, 1-2, 173–196.

SARKAR, P. AND MOORE, A. 2005. Dynamic social network analysis using latent space models. *ACM SIGKDD Explorations Newsletter*, 31–40.

SIERHUIS, M., CLANCEY, W. J., SEAH, C., TRIMBLE, J. P., AND SIMS, M. H. 2003. Modeling and simulation for mission operations work system design. *J. Manag. Inform. Sys. 19*, 4, 85–128.

SNIJDERS, T. 2001. The statistical evaluation of social network dynamics. In *Sociological Methodology Dynamics*, M. Sobel and M. Becker, Eds. Basil Blackwell, London, UK, 361–395.

SOMEKH, B. AND LEWIN, C., Eds. 2005. *Research Methods in the Social Sciences*. Sage Publications Ltd.

VAN DER VEEN, A. M., LUSTICK, I. S., AND MIODOWNIK, D. 2001. Studying performance and learning with ABIR. *Social Sci. Comput. Rev. 19*, 3, 263–280.

WASSERMAN, S. AND FAUST, K. 1994. *Social Network Analysis: Methods and Applications*. Cambridge University Press, Cambridge, UK.

ZUBOFF, S. 1988. *In the Age of the Smart Machine*. Heinemann.

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