Increasing Consensus Through Shared Social Position and Interaction

Abstract

The formation of consensus among members of the society is complex. It is dependent on who has access to what information and how that information is inter-related. Consequently, it is expected that both shared social position, i.e.. similar pattern of interaction, and frequency of interaction should affect consensus. Consensus is defined in two ways - consensus in knowledge and consensus in behavior. Consensus in knowledge is measured as a function of shared knowledge relative to available knowledge. Consensus in behavior is measured as similar decision. A dynamic reflexive model of the individual and society is forwarded in which the interaction between individuals is key to the consequent construction of both the individual's cognitive structure and the social world. Using this model an attempt is made to determine on theoretic grounds expected differences in the impact of shared structural position and level of interaction on what information individuals acquire, the amount of information that they share and hence the level of consensus in knowledge and consensus in behavior. Data is drawn from a study of a group of undergraduates at MIT selecting a graduate resident or tutor for their living group. It is found that the coupling of high interaction levels and shared social position result in consensus in knowledge; although, not necessarily in consensus in behavior. Consensus in behavior is found to be a function of the exact pattern of information known to the individual. Consequently neither high levels of interaction nor shared social position guarantee consensus in behavior, i.e. guarantee that the exact ranking will be the same. It is argued that the way in which information is represented affects predictions about how known information affects behavior. It is found that when a frame structured knowledge representation scheme is used the voting behavior of the students is better predicted than when a list structured knowledge representation scheme is used. Using a frame structured knowledge representation scheme it is argued that consensus in behavior is a function of sharing concepts which are cognitively dense and of not having different critical concepts. It is shown that neither interaction nor shared position lead in the short run to individuals having the same level of density for shared concepts or having the same critical concepts. Together these finding explain why high interaction and shared position lead to consensus in knowledge but not consensus in behavior.

Increasing Consensus Through Shared Social Position and Interaction

Introduction

The formation of consensus among members of the society is a complex process. Understanding what conditions produce consensus is important. We might expect that the more individuals interact the more likely they are to concur. We might expect that individuals who share similar social roles, or have similar patterns of experience, are more likely to concur.

Consensus is a product of human social behavior. A model of human social behavior should provide insights into why consensus occurs and predict when consensus will occur. This paper examines the insights and predictions for consensus made by a model based on the constructural theory.

Constructuralism is the theory that the social world and the personal cognitive world of the individual evolve reflexively, and are continuously constructed as individuals acquire knowledge when they interact with other individuals, as they move through the series of tasks that constitute their daily experience (Carley, 1984, Carley, 1986a, Carley, 1986b). The model examined is a simplified version of this theory in which all communication is one to one and knowledge[1] is stored as a simple unconnected list of separable and discreet pieces of information (Carley, 1987a) -- see section 1. This model is referred to as the *1:1 list model*. It is implemented via simulation. Using this model an attempt is made to determine on theoretic grounds expected differences in the impact of shared structural position and level of interaction on what information individuals acquire, the amount of information that they share, and the degree to which they concur -- see section 3. The predictions of this model are then examined using the third east tutor selection data set -- see section 4. Measures of consensus are described in section 1.3. The third east tutor selection data set is based on a study of a group of undergraduates at MIT selecting a graduate resident or tutor for their living group (Carley, 1984, Carley, 1986a) -- see section 2. The prior study focuses on the way in which interaction levels and shared position affects the students general knowledge about what it means to be a tutor in that living group as they move through the tutor selection process. Finally, in section 4 the level of correspondence between model predictions and the data is analyzed.

---

[1] In this paper the terms information and knowledge are used interchangeably.

1. Theory and Model

Under the constructuralist theory individuals during their lives move through a set of tasks. The tasks being performed by the individual determines what information known by the individual is currently salient (Carley, 1986b). The tasks also provide opportunities for interaction with other individuals. Environmental factors, such as where the individual lives, also provide opportunities for interaction or make it impossible to interact. When the individuals interact they exchange information thus acquiring knowledge. Thus who you know is intimately related to what you know. As the individual acquires knowledge his task performance changes and his pattern of interaction changes. As individuals acquire knowledge the way they think about problems, their internal language, and the meaning they attach to different words change. Whether or not two individuals actually interact is a function of the opportunities for interaction and the individuals' propensities to interact with each other. These propensities are a function of the individuals' socio-cognitive position; i.e., of how much information the two individuals share relative to how much information they share with other members of the society, As knowledge is acquired by individuals they re-position themselves cognitively relative to the other members of the society. As changes occur in who shares what information the individual's propensity to interact with the other members of the social unit changes. For two individuals, the more information they share relative to the amount of information they share with others with whom they interact, the higher their propensity to interact with each other *ceterius paribus*. Since individuals continually move through a series of interactions their knowledge and interaction propensities change. However, since the amount of information one has increases with the number of interactions, the older the individual the less impact any one interaction has. This is true for two reasons. First, since interaction builds up the individual's knowledge base, the older the individual the more likely it is that the individual already knows the communicated piece of information **ceterius paribus**. And second, once the individual has a large amount of information the marginal impact of a new piece of information is in general extremely small.

Under the constructuralist theory the social world is an artifact due to many individuals being engaged simultaneously in the processes described above. Consequently, what is measured as 'social' depends on the number of individuals looked at and the way of combining individual responses. The social world is a wholistic entity perceivable as the pattern of regularities across the members of the society. Social knowledge is, roughly, that information which everyone shares (Carley, 1986b). Social structure is a set of groups that span the society and the ties between those groups. Social structure is thought of in terms of patterns of interaction. Individuals are said to have a shared social position if they are a member of the same structural group. All members of the society are simultaneously engaged in the process of interacting and acquiring knowledge. Consequently, as the individuals' acquire knowledge and enter and leave the society social knowledge evolves. Consequently, as the individuals' interaction propensities shift social structure evolves. Social knowledge and social structure co-evolve.

Under the constructuralist theory observable behavior such as diffusion and consensus are a product of the dynamic relationship between knowledge acquisition and interaction. In order to make specific predictions a simple model based on the constructural theory was devised. This model, the 1:1 list model, was previously used to explore conditions that lead to diffusion, knowledge acquisition, and consensus in knowledge (Carley, 1987a). It was shown that interaction is necessary for knowledge acquisition and leads to shared knowledge and the formation of consensus in knowledge. Further, it was shown that when high levels of interaction and shared position are coupled the propensity for shared knowledge leads to group homogeneity, the production of consensus in knowledge, and the maintenance of group boundaries.

Decision making tasks differ from other tasks in that at some point in time a decision must be made (Carley, 1986a). At that point information gathering stops and the decision is made on the basis of the known pieces of information. Then information gathering continues. Hence, future decisions can be different as can explanations of why the decision was made. The set of information known by the individual, relative to the decision making task, frames the individual's decision. Exactly how the decision is made depends on how information is stored cognitively. This calculation, i.e. the making of the decision, is mechanical. Therefore, if you knew what information the individual had at a specific point in time you could predict the individual's decision provided you had an accurate model of how information is cognitively stored.

The constructuralist theory is incomplete in the sense that it underspecifies certain facets. Two such critical factors are the determination of actual interaction and the way in which individual's cognitively represent information. According to the constructuralist theory actual interaction is affected by both opportunities for interaction and interaction propensities. In the model used in this paper actual interaction is a chance occurrence whose distribution is determined by the interaction propensities. Determining actual interaction is a critical facet of the model as it determines the rate at which individuals' knowledge bases and their socio-cognitive position will change. Section 3.4 contains a discussion of the impact of the procedure used to determine actual interaction on the model's predictions. The knowledge representation scheme is critical as it effects which information is salient, what information is communicated, whether or not communicated information is accepted by the receiver, how information relates to tasks, the mechanics of the decision process, and so on. The model in this paper uses a list structured knowledge representation scheme. Section 3.4 contains a discussion of the impact of using a list structured knowledge representation scheme on the model's predictions.

In order to develop the constructuralist theory and test propositions based on this theory a simulation system embodying the 1:1 list model was developed. Among the reasons that simulation is the appropriate modeling technique for the 1:1 list model are the following. First, according to the constructural theory there is a feedback loop between interaction propensity and shared knowledge. second, behavior is a function of the knowledge two individuals share relative to the knowledge they share with all others with whom they interact. Consequently, results calculated for two or even three individuals do not generalize to groups with more members. Therefore, it is important to look at realistically sized groups. And third, in social systems outside events occur so frequently that the system rarely reaches quiescence. Consequently, it is important to be able to predict near term behavior. Simulation is the ideal technique for looking at near term behavior.

The simulation system is referred to as CONSTRUCT1. Following is a description of that part of this simulation system that is used for the analyses in this paper. CONSTRUCT1 does have other features that allow the user to test other facets of the constructural theory.

1.1. The 1:1 List Model

In current network tradition, the society is modeled as a set of individuals connected into a multi-dimensional network by multiple ties (White, 1976, Boorman White, 1976, Burt, 1976, Burt, 1977, for example) ; At any point in time, there are $I(t)$ individuals in the society. Individuals are connected by two types of ties knowledge and interaction. All individuals in the society have the same cognitively based abilities. Individuals differ in terms of what information they actually know and in the opportunities available to them for interaction.

1.1.1. The Individual

Individuals are uniquely identified by two characteristics -- their propensity for interaction with the other members of the society and the information that they know. There may be factors other than knowledge and interaction propensities that comprise a human being -- e.g., motives and emotions. Herein the concern is with only those characteristics that are articulable, and hence communicable. To the extent that such factors are articulable then they too would come under the aegis of this model as they could be modeled as knowledge.

The individual, i, has a base propensity to interact with every other member of society, j:

$$0 \leq INTPRO_{ij}(t) \leq 1.$$

The individual must interact --

$$\sum_{j=1}^{I(t)} INTPRO_{ij}(t) = 1.$$

However, this interaction may be with himself $INTPRO_{ii} \geq 0$; e.g., when he is sleeping. The interaction propensity is a subjective facet of individual behavior; consequently, $INTPRO(t)$ is not necessarily symmetric.

The individual's life is modeled as a series of interactions. Each time period the individual interacts with someone, perhaps himself. The individual can interact with at most one other person during this time period. Actual interaction is thus symmetric and non subjective. Mass communication is outside the boundary of this model. Whether or not two individuals actually interact is a chance occurrence weighted by the initiating individual's propensity to interact with the individuals who are not already interacting with someone else. By definition if if there are an odd number of people in the society then each time period at least one individual will interact with himself. In this way, the propensity to interact and actual interaction are expected to be highly correlated, although not identical.

Each time the individual interacts the individual can acquire a piece of information and communicate a piece of information. Whom the individual interacts with is a function of the individual's propensity to interact with the other members of the society.

The individual, *i*, knows a set of information. At any point in time there are a number of pieces of information available to the members of the society for communication -- $K(t)$. Available information includes that information that is known by at least one member of the society. For each piece of available information, *k*, the individual either knows or does not know that information:

$$KB_{ik}(t) = \begin{cases} 1 & \text{if } i \text{ knows } k \text{ at time } t \\ 0 & \text{if } i \text{ does not know } k \text{ at time } t \end{cases}$$

The information known by the individual forms his knowledge base. Individuals do not forget information that they know; i.e.,

$$\text{if } \; KB_{ik}(t)=1 \; \text{ then } \; KB_{ik}(t+1) = 1.$$

Consequently, over time the size of the individual's knowledge base grows:

$$\sum_{k=1}^{K(t)} KB_{ik}(t) \leq \sum_{k=1}^{K(t+1)} KB_{ik}(t+1).$$

Note: the knowledge representation scheme described above is list structured. That is, each piece of information is distinct and unrelated to the next. There is no intrinsic way to link pieces of information together using this scheme.

There are two ways in which the individual can acquire knowledge -- *via* independent discovery or communication. If an individual is interacting with himself he can discover new information or reflect on known information. If an individual is interacting with someone else information is exchanged. An individual can only communicate a piece of information if it is currently in his knowledge base; i.e.,

$$i \text{ can communicate } k \;\; \textit{iff} \;\; KB_{ik}(t)=1.$$

All pieces of information known by the individual are equally likely to be communicated. An individual always accepts, i.e. learns, a communicated piece of information unless he already knows it. The level of shared knowledge, SK, is the intersection of the two individuals' knowledge bases:

$$SK_{ij}(t) = \sum_{k=1}^{K(t)} KB_{ik}(t) x KB_{jk}(t).$$

The relative level of shared knowledge for two individuals is their socio-cognitive position, SCS. This is defined as:

$$SCS_{ij}(t+1) = \frac{\sum_{k=1}^{K(t})KB_{ik}(t) \times KB_{jk}(t)}{K(t)}.$$

An individual's propensity to interact with another individual changes over time as their relative level of shared knowledge changes. The individual's interaction propensity changes through a small adjustment in the individual's previous interaction propensity. This adjustment is based on the relative socio-cognitive position of the two individuals:

$$Adjustment_{ij}(t) = SCS_{ij}(t) - \frac{\sum_{j=1, i \neq j}^{I(t})SCS_{ij}(t) + \sum_{i=1, j \neq i}^{I(t})SCS_{ji}(t)}{2 \times (I(t)-1)}$$

Then, provided that there are opportunities for the two individuals to interact, the individual's interaction propensity changes based on this adjustment. If the individual is now relatively more cognitively similar to that individual than to others, i.e., $Adjustment_{ij}(t) \geq 0$, then the interaction propensity increases:

$$INTPRO_{ij}(t) = \frac{INTPRO_{ij}(t-1) + Adjustment_{ij}(t) \times (1 - INTPRO_{ij}(t-1))}{\sum_{j=1}^{I(t)} INTPRO_{ij}(t)}.$$

Whereas, if they are less cognitively similar, i.e., $Adjustment_{ij}(t) < 0$, then the interaction propensity decreases:

$$INTPRO_{ij}(t) = \frac{INTPRO_{ij}(t-1) + Adjustment_{ij}(t) \times INTPRO_{ij}(t-1))}{\sum_{j=1}^{K(t)} INTPRO_{ij}(t)}.$$

In this way, interaction propensities track shared knowledge. This makes it appear at the social level that social structure, i.e. shared patterns of interaction, track socio-cognitive structure, i.e. shared patterns of knowledge. Note: it is possible for two individuals to communicate and yet their interaction propensities would decrease.

1.1.2. Society

What group the individual is in does not have a direct impact on the individual's behavior. This is because all behavior is at the diadic level and controlled by the individual's interaction propensities. There appear to be group effects as group membership implies similar patterns of interaction. Hence, shared position does not cause but may be correlated with other social behavior such as consensus.

1.1.3. Decision Making

Relative to a decision there are a certain number of pieces of information available to the members of the society, $K_d(t)$. Note: $K_d(t) \leq K(t)$. These pieces of information have no special properties *vis-a-vis* communication. These pieces of information are used to evaluate decision alternatives. For each piece of information used to make the decision, k, each alternative, a, has a valuation, $AVAL_{ak}(t)$:

$$AVAL_{ak}(t)=\begin{cases} 1 & \text{if } k \text{ is true for } a \\ -1 & \text{if } k \text{ is not true for } a \end{cases}$$

It is being assumed that when an individual learns a piece of information he is also learning for each alternative whether or not that piece of information is true or not true.

The individual then calculates his evaluation of each alternative as:

$$RANK_{ia}(t)=\sum_{k=1}^{K_d(t)} KB_{ik}(t) \times AVAL_{ak}(t).$$

The individual uses this evaluation to rank the alternatives and to determine the top choice.

1.2. Operational Details

The simulation system is referred to as CONSTRUCT1. CONSTRUCT1 takes as input a description of the society and and can produce as output the characteristics of that society at later points in time. Input and output include such factors as the interaction propensities and the knowledge base. Various statistics on who interacts with whom, amount of knowledge that is communicated, and so on are also output. The society is described using the parameters defined in table 1.

EXNET can be used to set up the data bases containing a description of the society to be simulated. EXNET is an expert system which through a series of questions elicits from the user a description of the society. EXNET has various knowledge about societies and about the constructural theory. Thus, if the user is unable to answer a question EXNET will either elicit the information using a different series of questions or it will fill in gaps in the user's description of the society using default knowledge.

Table 1 -- Characteristics of Society to be Modeled

Length of Simulation	Number of People
Rate of Immigration	Number of Groups
Rate of Emigration	Number of Pieces of Knowledge
Rate of Inference	Start up Values for Immigrants
Rate of Discovery	Interaction Propensities
Size of Fixed Knowledge Base	Knowledge Base

Both **CONSTRUCT1** and **EXNET** are written in C (Kernighan, 1978) and run under the Berkeley 4.2 UNIX operating system (Kernighan, 1984). Additional details on **CONSTRUCT1** and **EXNET** are available on request. .

1.3. Measuring Consensus

The output from **CONSTRUCT1** can be analyzed to examine whether or not consensus occurs. Two different types of consensus are examined in this paper -- consensus in knowledge and consensus in behavior. Consensus in knowledge is *to what extent do people think about the problem in the same way*. Consensus in behavior is *to what extent do people act in the same way*.

Consensus in Knowledge: Consensus in knowledge is measured in two ways. First, it is measured as the percentage increase in shared knowledge over time. For each pair of individuals this is calculated as:

$$Increase\ in\ SK = \frac{SK_{ij}(END) - SK_{ij}(BEGIN)}{SK_{ij}(BEGIN)} \times 100 .$$

Second, it is measured as the degree of association between the two individuals' knowledge bases. For this, the chi-square based on the 2x2 table for shared and non-shared knowledge out of the total possible pieces of information available to the members of the society at that time $K(t)$. This measure is referred to as association.

Consensus in Behavior: Consensus in behavior is measured in four ways for each pair of individuals. First, do the individuals have the same first choice:

$$TopVote = \begin{cases} 0 \text{ if their top choice is not the same} \\ 1 \text{ if their top choice is the same} \end{cases} .$$

Second, how many of the top two choices do the individuals have in common independent of position:

$$TopLevel = \begin{cases} 0 \text{ if neither of the top two choices are the same} \\ 1 \text{ if one of the top two choices is the same} \\ 2 \text{ if both of the top two choices are the same} \end{cases}.$$

Third, do the individuals have the same last choice:

$$LastVote = \begin{cases} 0 \text{ if their last choice is not the same} \\ 1 \text{ if their last choice is the same} \end{cases}.$$

Fourth, how many of the last two choices do the individuals have in common independent of position:

$$LastLevel = \begin{cases} 0 \text{ if neither of the top two choices are the same} \\ 1 \text{ if one of the top two choices is the same} \\ 2 \text{ if both of the top two choices are the same} \end{cases}.$$

2. Third East Tutor Selection Data Set

The third east tutor selection data set is an extensive data collection composed of questionnaire, interview, observational, and historic data collected over a 3 month period -- see (Carley, 1984). The data set contains information on 42 undergraduates, all members of a single living group -- Third East -- going through a process of selecting a graduate resident or tutor for their living group. Appendix A contains that part of this data set which is used in this study.

Time Frame: The tutor selection process lasted approximately 2 and 1/2 months. Knowledge base data is drawn from interviews with the students conducted at the beginning of the process (prior to meeting the tutor candidates), and at the end of the process (after having chosen a particular candidate). Interaction data is drawn from questionnaire data collected during the middle of the process.

Interaction Propensity: Interaction propensity data was gathered via questionnaire. The students were asked to denote their level of interaction with all other members of the social unit on a five point scale (low to high). This subjective data was then recoded into a three point scale to minimize the impact of differing interpretations of the point scale and attitudes towards using extreme values. Where reported ties were asymmetric the data was averaged to produce a single symmetric tie -- (Carley, 1984). There was a 95.24% response rate on this questionnaire. The two students who did not respond had rare interactions with other students on the hall and spent most of their time talking to each other or studying. Consequently, the interaction matrix has only 40 entries.

Note: the length of the process, the fact that no students enter or leave the society (move out of the dorm during the middle of the term), and the fact that tutor selection is not the only topic of concern to the students during this period all suggest that there will be minimal change in the interaction patterns. As a participant observer in this culture I saw no major changes in the interaction patterns during this period. There were several minor changes in interaction propensities that were manifest by the following summer. For example, one couple spent increasingly less time together and another increasingly more time.

Social Structure: To extract social structure the subjective interaction data was processed using the block modeling program CONCOR -- (Breiger, 1975).[2] CONCOR was used to divide the individuals into 4 groups.[3]This was done by using CONCOR to spilt the group of 40 students into two groups and then each of these groups were split into two groups. These groups are referred to as -- g11, g12, g21, and g22. This convention reflects the splits, i.e. the first number refers to the first split and the second number to the second split.

Individual Knowledge Base: Based on interviews with the individual students a knowledge base was constructed for each student (Carley, 1986a). A student's knowledge base contains the information used by that student at that point in time to describe his perception of the tutorship position and the inter-relationships between these pieces of information. The student's knowledge was coded using both a list structured knowledge representation scheme and a frame structured knowledge representation scheme. The set of concepts used by the student to describe tutors and evaluate candidates comprises the knowledge base when a list structured knowledge representation scheme is used. In this case, the total available information, $K(t)$, is the set of concepts in the vocabulary list used to code the interview. There are 217 such concepts. Typical concepts are *Third Easter*, *fits in with hall*, *gnerd*, and *friendly*. The set of facts used by the student to describe tutors and evaluate candidates comprises the knowledge base when a frame structured knowledge representation scheme is used. A fact is defined as two concepts and the relation between them (Minsky, 1975, Carley, 1984, Carley, 1986a, Carley, 1986b). Typical facts are *a Third Easter would fit in with the hall* and *a gnerd is not friendly*. In this case, the total available information, $K(t)$, is the number of pieces of information in the union of all the maps coded from the end of the process. There are 1462 such facts. Regardless of the knowledge representation scheme used concepts are divided into four categories. These are: aspects, requirements, facts, and qualities. Under a list structured knowledge representation scheme concepts are not distinguished on the basis of type. Under a frame structured knowledge representation scheme aspects and requirements are treated as summation nodes and facts and qualities are treated as input nodes -- see appendix B for details.

---

[2]CONCOR is used to extract groups because I am looking for groups of individuals who are structurally equivalent. Note: no claim is being made that the groups extracted are the only groups, nor even the best representation of groups for this society. The claim is that they are one possible set of groups. And, that as a set of groups they exhibit the following properties: they span the society, they are disjoint, and they are nodes of structural equivalence. No claim is being made that this method of extraction is the best technique for locating nodes of structural equivalence.

[3]For more information on the structure of this society and alternate levels of grouping refer to (Carley, 1984, ch. 11).

Shared Knowledge: For each pair of individuals the number of pieces of information that they had in common at the beginning and end of the process were counted. Note: this is based on the intersection of their knowledge bases -- see (Carley, 1986a).

Voting Behavior: At the end of the process the field had been narrowed to 10 tutor candidates. The students then voted on these 10 candidates. For each student a preference ranking across the 10 candidates was constructed using the voting form (Carley, 1984, ch 9). When just voting behavior is looked at data for all 19 students whose interviews were coded at the end of the process is used, section 5.

Predicted Ranking: What knowledge representation scheme is used determines the way in which the predicted ranking is determined. When a list structured knowledge representation scheme is used all pieces of information, in this case concepts, have equal impact on the resultant decision. See section 1.1.3. When a frame structured knowledge representation scheme is used the impact of each concept is dependent on the way in which that concept is related to other concepts. See appendix B for details.

Consensus: In this paper only data for the 15 students for whom interviews were coded at both the beginning and end of the process are used in looking at consensus in section 4. This is because one of the measures of consensus in knowledge is the percentage change in shared knowledge over time.

3. Simulation Details and Predictions

Predictions were generated using CONSTRUCT1 in two ways -- pure simulation and data based simulation. These two approaches differ in the way in which interaction is treated, and the number of individuals whose behavior is simulated. Consequently, the groups differ. In pure simulation the initial interaction propensities is artificially constructed and a base of shared knowledge is used to maintain stability in interaction. In data based simulation the initial interaction propensities are based on the actual propensities drawn from the third east data set and stability in interaction is maintained by force. These differences will be described in more detail in sections 3.2 and 3.3 respectively.

3.1. Initial Description of Society

The initial description of the society is set so that it most closely reflects the condition on Third East during the tutor selection process. A summary of the initial description sans initial interaction propensities is in table 2.

Table 2 -- Initial Description of Society

Characteristic	Simulation 1	Simulation 2	Third East
Length of Simulation	150	150	3 months
Rate of Immigration	0.0	0.0	0.0
Rate of Emigration	0.0	0.0	0.0
Rate of Inference	0.0	0.0	unknown
Rate of Discovery	0.0	0.0	unknown
Size of Fixed Knowledge Base	25	infinite	100,000's
Number of People	12	15	42
Number of Groups	3	4	4
Number of Pieces of Knowledge	150	150	217/1462 .
Start up Values for Immigrants	none	none	undefined
Interaction Propensities	.3,.2,.1,.0	1-5	1-5
Knowledge Base	25%	25%	15%

No students moved in to or left the living group during the tutor selection process hence both the immigration rate and the emigration rate are 0. In order to look exclusively at the effect of communication the discovery and inference rate are set to 0.

The knowledge about tutor selection is modeled as a set of 150 pieces of information. So, $K(t)=150$. Tutor selection was a relatively unfamiliar task to the students on Third East. The students initially shared little knowledge about tutor selection. This is modeled by having each individual start out knowing only 25% of the available pieces of information, and what information they know is distributed randomly across the set of possible pieces of information.

As in the Third East case there are 10 alternatives. The valuation of these alternatives is set as follows: 3 alternatives are positive on 40% of the knowledge and negative on the other 60%, 4 alternatives are positive on 50% of the knowledge and negative on the other 50%, and 3 alternatives are positive on 60% of the knowledge and negative on the other 40%.

The behavior of these societies was simulated for 150 time periods. This time period was chosen as it allowed enough time for communication and hence knowledge acquisition without the system reaching quiescence.

3.2. Artificial Initial Interaction Propensities

In this case there are 12 individuals in the society. They are divided into 3 groups with 4 individuals in each group. For all pairs of individuals the out group interaction propensity is set to 0.01. Within group interaction propensities changes with group: group 1 0.30, group 2 0.20, group 3 0.10. Note: in this example group membership and interaction level are directly correlated.

It was previously noted that on Third East the interaction between dyads appeared, in general, not to change over the course of the tutor selection. To attain this stability in interaction a feature of the constructural theory is applied. Recall, according to the constructural theory if the individuals know many pieces of information the acquisition of one new piece of information has little impact on their interaction propensity. And, that what task the individual is performing determines which pieces of information are currently salient. Therefore, a base set of shared knowledge separate from the knowledge for the decision was constructed. In this base the number of facts shared by two individuals was proportional to their initial level of interaction. During the simulation only those pieces of information related to the decision are treated as salient, i.e., allowed to be communicated. The base described above is fixed and does not change during the course of the simulation. Consequently, communication of decision related pieces of information, since they do not constitute the entire knowledge base of the individual have minimal impact on interaction propensities.

When the initial interaction propensities are as described above the model predicts that as the level of interaction increases so does consensus in knowledge and shared knowledge -- see table 3. As the level of interaction propensity increases there is an increase in consensus in knowledge -- see columns 2 and 5. Consensus in behavior, however, does not increase as the level of interaction propensity increases -- see columns 6 through 9. Since interaction level and shared position are perfectly correlated it can also be argued that being structurally equivalent -- rows 2-4 -- also leads to consensus in knowledge but not consensus in behavior. Whereas, not being structurally equivalent -- row 1 -- leads to neither consensus in knowledge nor consensus in behavior. A consequence is that the coupling of high interaction propensities and structural equivalence leads to consensus in knowledge. This data suggests that consensus in behavior is a function of exactly what information is shared and not simply the level of shared knowledge.

3.3. Actual Initial Interaction Propensities

In this case there are 15 individuals in the society. These are the 15 individuals previously identified as those members of Third East for whom interviews from both the beginning and end of the process were calculated. The individuals are divided into the four groups previously identified. The interaction propensities for these individuals are a scaled version of the reported subjective interaction values. Let $INTSUB_{ij}$ be the subjective interaction level reported by individual, i. Then, the initial interaction propensity is calculated as:

Table 3 -- Model Predictions Using Artificial Initial Interaction Propensity[4]

Int Level	Assoc	SK BEGIN	SK END	Increase in SK	Top Vote	Top Level	Last Vote	Last Level	N
0.01	0.93	9.33	36.12	319.73	0.40	1.50	1.00	1.38	48
0.10	23.97	12.17	49.00	306.24	0.50	1.17	1.00	1.50	6
0.20	25.85	10.17	51.50	441.96	1.00	2.00	1.00	1.67	6
0.30	29.75	8.50	51.67	521.03	0.50	2.00	1.00	1.33	6

if $INTSUB_{ij} > 1$

$$INTPRO_{ij}(BEGIN) = INTSUB_{ij}^2 + INTSUB_{ij} \quad \text{for } i \neq j.$$

And,

if $INTSUB_{ij} = 1$ $INTPRO_{ij}(BEGIN) = INTSUB_{ij}$.

Self Interaction is initially defined to be

$$INTPRO_{ii}(BEGIN) = 0.$$

Then the maximum level of reported subjective interaction is calculated as:

$$MAXINT = \text{Maximum of} \sum_{j=1}^{15} INTPRO_{ij}(BEGIN) \quad \text{across all } i.$$

Then the individual's interaction propensities are adjusted so that the conditions of the model hold. That is,

$$INTPRO_{ij}(BEGIN) = \frac{INTPRO_{ij}(BEGIN)}{MAXINT} \quad \text{for } i \neq j.$$

The initial level of self interaction is set as:

$$INTPRO_{ii}(BEGIN) = 1 - \sum_{j=1, j \neq i}^{15} INTPRO_{ij}(BEGIN).$$

This scaling has two important features. One it stretches the scale out thus separating the impact of the different levels of interaction. Second by using the maximum interaction to scale the results individuals who interacted less overall end up with higher levels of self interaction.

[4] The numbers in tables 3 through 8, 10, and 11 are the average values for the dyads in the group. For example, in table 3 column 2 row 2 23.97 is the average level of association for the 6 dyads who have an initial interaction level of 0.10.

In this case, in order to maintain stability in the interaction propensities the interaction propensities were never recalculated but left at the initial values. The scheme used in the previous section, of providing dyads with a base of shared knowledge that is proportional to their initial level of interaction, was prohibitive in this case. It was prohibitive as the number of pieces of information necessary to generate a base was beyond the maximum number of cases CONSTRUCT1 can handle at this time. Both procedures for maintaining interaction stability have the same basic impact on the results.

When the initial interaction propensities are as described above the model predicts that as the level of interaction increases so does shared knowledge -- see table 4. As the level of interaction propensity increases there is a corresponding increase in consensus in knowledge -- refer to columns 2 and 5. Consensus in behavior, however, does not increase as the interaction propensity increases -- refer to columns 6 though 9.

Table 4 -- Model Predictions Using Actual Initial Interaction Data for Interaction Impact

Int Level	Assoc	SK BEGIN	SK END	Increase in SK	Top Vote	Top Level	Last Vote	Last Level	N
1	0.80	8.43	33.43	332.74	0.57	1.86	0.57	2.00	7
2	2.06	10.45	35.92	262.95	0.87	1.42	0.66	2.00	38
3	3.99	10.36	41.22	307.87	0.89	1.55	0.69	2.00	36
4	5.02	9.69	42.06	353.27	0.94	1.75	0.56	2.00	16
5	10.19	9.50	45.38	404.28	0.88	1.25	0.75	2.00	8

In this simulation, shared position and interaction propensities are not correlated. Referring to table 5 we see that membership in a structural group does not guarantee consensus in knowledge but does appear to be related to consensus in behavior. On average individuals who share a position tend to have more consensus in knowledge than do individuals who do not share a position -- contrast rows 5 and 6. Within a split, the coupling of high levels of interaction propensity and shared position leads to consensus in knowledge -- compare g11 with g12 and g21 with g22. Shared position does not guarantee consensus in behavior. On average, however, there is more consensus in behavior among members of the same group than there is between individuals who are not structurally equivalent -- contrast rows 1 through 4 with row 5.

Table 5 -- Model Predictions Using Actual Initial Interaction Data for Group Impact

Group	Int Level	Assoc	SK BEGIN	SK END	Increase in SK	Top Vote	Top Level	Last Vote	Last Level	N
1	3	3.90	9.17	31.17	246.44	0.50	1.50	1.00	2.00	6
2	4.2	10.87	13.00	49.33	302.78	1.00	2.00	1.00	2.00	3
3	3	2.00	10.50	39.83	300.33	1.00	1.17	0.33	2.00	6
4	4.3	2.75	8.83	42.00	407.08	1.00	1.50	0.50	2.00	6
OUT		3.63	10.12	39.20	305.47	0.87	1.55	0.65	2.00	84

3.4. General Predictions and Qualifications

Both simulations predict that:

- As interaction propensities increases consensus in knowledge increases.
- There is no systematic relationship between shared position and consensus in knowledge.
- The coupling of high interaction propensity and shared position leads to consensus in knowledge.
- Neither interaction propensity nor shared position predicts consensus in behavior.
- Individual who are members of the same group, however, are slightly more likely to exhibit consensus in behavior.

When the critical facets of the model are considered these predictions must be somewhat qualified. Recall that the two critical facets are the procedure by which actual interaction is determined and the use of a list structured knowledge representation scheme.

The procedure for determining actual interaction affects the rate at which information is exchanged and the level of feedback between shared knowledge and interaction propensity. The weighted chance determination of actual interaction reduces the feedback. Consequently, this scheme decreases the rate at which information is exchanged and knowledge acquired. This in turn somewhat mitigates the effect of using a list structured knowledge representation scheme.

The use of a list structured knowledge representation scheme has two main consequences. First, since there are no links between pieces of information all pieces of known information are equally likely to be communicated and must be accepted. This leads to a fairly fast rate of knowledge acquisition. In turn, this leads to higher levels of consensus in knowledge and consensus in behavior than would be seen if a knowledge representation scheme with links between pieces of information were used. A specific consequence of the fast rate of knowledge acquisition is that the impact of interaction is somewhat reduced as it takes large differences in interaction propensities to evoke even small differences in the rate at which knowledge is acquired. This suggests that the relationship between interaction and consensus in knowledge in the case of the second simulation should be even stronger than it appears. This also suggests that the coupling of high interaction propensities and shared position should have an even stronger effect on consensus in knowledge than that exhibited in tables 3 through 5 above. Second, since there are no links between pieces of information the alternative evaluations had to be passed with generic facts. This produces higher levels of consensus in behavior than would have been seen if a network structured knowledge representation scheme were used.

4. Results

The data does tend to support the model -- see tables 6 and 7. Although the correlation is not perfect, as the level of interaction propensity increases so does the level of consensus in knowledge -- refer to columns 2 and 5 in table 6. Interaction propensity is not related to consensus in behavior. Shared position does not determine consensus in knowledge -- refer to table 7 columns 2 and 5. And, in the case of the percentage increase in shared knowledge, column 5, it is the case that the coupling of high interaction propensity and shared position does lead to consensus in knowledge. This does not appear to be the case for association, however. Shared position does not determine consensus in behavior.

There are a few cases where the model is not directly supported. First, in table 6 although low levels of interaction propensity do tend to correspond to lower levels of consensus in knowledge and higher levels of interaction propensity to higher levels of consensus in knowledge the relationship is not direct. For example, for both association and increase in shared knowledge the levels are opposite the predictions of the model. More importantly, when the interaction level is 1 the level of increase in shared knowledge is too high. Second, the level of association for groups g11 and g12 is in direct opposition to that predicted by the model -- see table 7 column 3 rows 1 and 2. The reason that the data in these cases does not correspond directly to the model may be attributable to the procedure for collecting what information the individual knows about the candidate. In the model, once an individual knows a piece of information that information is never forgotten. Hence, an individual's knowledge base can only increase with time. When collecting data on what an individual knows we are at best sampling the known information (Carley, 1987b). Hence, unless the coding procedure always adds to information at later times that discovered at earlier times this condition will

Table 6 -- Data for Interaction Impact
Using Concepts

Int Level	Assoc	SK BEGIN	SK END	Increase in SK	Top Vote	Top Level	Last Vote	Last Level	N
1	17.90	23.28	33.00	52.85	0.43	1.28	0.43	1.43	7
2	23.44	25.68	26.76	16.37	0.28	1.60	0.32	1.92	38
3	26.18	26.14	31.42	28.47	0.22	1.61	0.28	1.69	36
4	24.67	29.31	33.12	23.45	0.19	1.44	0.56	0.51	16
5	31.05	27.00	38.50	54.54	0.12	1.75	0.62	2.12	8

Table 7 -- Data for Group Impact
Using Concepts

Group	Int Level	Assoc	SK BEGIN	SK END	Increase in SK	Top Vote	Top Level	Last Vote	Last Level	N
1	3.0	40.28	23.83	29.67	40.50	0.50	1.83	0.17	2.33	6
2	4.3	22.96	27.33	40.33	49.72	0.00	2.00	1.00	1.67	3
3	3.0	8.90	20.50	18.17	-0.12	0.17	1.67	0.17	1.83	6
4	4.2	48.96	24.67	30.17	37.15	0.00	1.17	0.33	1.33	6
OUT	2.9	23.15	27.01	31.28	26.36	0.26	1.56	0.38	1.76	84

not be met. Since the coding procedure for extracting information did not do this, the apparent size of knowledge bases can decrease. This can affect the level of consensus in knowledge measured.

5. What Does Determine Consensus in Behavior?

According to the model and the data neither interaction propensity nor shared position determines consensus in behavior. Examination of the model suggests two reasons why this might be the case.

First, according to the constructuralist theory individuals are generally in an information gathering mode and at some point are forced to stop and make a decision. The decision is based on the information available to the individual at that point in time. Thus, the theory would predict that, provided there is a limit to the amount of information related to that decision topic, the longer the information gathering process the more likely it is that the individuals will make the same decision. Further, the theory predicts that as long as the opportunities for interaction and the interaction propensities are recurrent[5] eventually everyone will learn everything that is to be learned and everyone will make the same decision. In fact, the longer the model is run the greater the consensus in behavior as well as the consensus in knowledge. Consequently, it is the case that after a long enough period high interaction propensities lead to not only consensus in knowledge but also consensus in behavior.

Second, behavior is a function not of how much information the individual knows but of what information the individual knows. Even with a list structured knowledge representation scheme two individuals who differ on only one piece of information may rank the alternatives differently. With a list structured knowledge representation scheme two individuals will rank the alternatives the same provided that the number of positive/negative pieces of information known by one individual is proportional to the number of positive/negative pieces of information known by the other individual. That is, the i and j will generate the same rank order if

$$RANK_{ia}(t)=\beta RANK_{ja}(t)$$

Thus it is simply the number of positive versus negative pieces of information that determines behavior. However, a list structured knowledge representation scheme, at least in the case of Third East, is not a good predictor of individual behavior -- see table 8. Using a list structured knowledge representation scheme the correlation between predicted and observed ranks is 0.348, 0% of the 1st place votes are predicted exactly, 5% of the time the 1st place vote was predicted to occur in the top two, 26% of the time in the top three and 42% in the last three.

Other knowledge representation schemes are expected to lead to other conclusions. In a network structured knowledge representation scheme behavior is a function of the way the information is inter-related and not simply the amount of information. Such schemes include frames (Minsky, 1975, Charniak, 1972), scripts (Schank, 1977, Abelson, 1976, Abelson, 1969), schemes (Anderson J., 1973, Bobrow, 1976), transition networks (Collins, 1975, Clark, 1977, Wyer, 1979), semantic nets (Simmons, 1973, Schank, 1973), and schemata (Rumelhart, 1976, Tesser, 1977, Tversky, 1980).

Previously, an operationalization of Minskian frames was developed and used to code the Third East's students knowledge about tutors (Carley, 1984, Carley, 1986a, Carley, 1986b). Using this

---

[5] Given a set of individuals with a set of ties between them the network is recurrent if a piece of information discovered by one individual can eventually reach every other individual in the society.

Table 8 -- Predicting Voting Behavior

	Correlation	Win	Place	Show	Lose	TOTAL
List Prediction	0.348	0 0.0%	1 5.2%	5 26.3%	8 42.1%	19
Frame Prediction	0.729	8 42.1%	11 57.9%	15 78.9%	1 5.2%	19

representation scheme knowledge acquisition is a function of both what you know and whom you know (Carley, 1986b). Consequently, the rate at which information is acquired is slower than when a list structured knowledge representation scheme is used. Using this frame structured knowledge representation scheme the correlation between predicted and observed ranks is 0.729, 42% of the 1st place votes are predicted exactly, 58% of the time the 1st place vote was predicted to occur in the top two, 79% of the time in the top three and 5% in the last three. Thus, at least for the Third East data, the frame structured knowledge representation scheme leads to better predictions of actual behavior than does the list structured knowledge representation scheme.

It has been suggested that the network characteristics of the frame affect the individual's behavior (Carley, 1984, Carley, 1986c). One such characteristic is the cognitive density of the various nodes, i.e. concepts. A concept's density is measured as the number of facts that contain that concept. Cognitively dense concepts are expected to play an important role in the way an individual makes a decision. For example, via inference and other cognitive mechanisms, it is expected that values will propagate through the network. Two mechanisms are expected to be at work here. First, cognitively dense nodes control the valuation of the network as a dense node that is positive may propagate this positiveness to many other nodes. Second, cognitively dense nodes to the extent that they bring together earlier valuations serve to sum or multiply together the valuation of many other nodes. Consequently, it is expected that cognitively dense nodes will control and have the greatest impact on the decision that is made. Using the Third East data it is found that for requirements, those nodes that sum the effects of earlier nodes, that in general the higher the cognitive density the greater the expected impact of that node on the resultant decision -- see table 9.

When the frame structured knowledge representation scheme is used the pattern of observed consensus is similar to that predicted by the model. Contrast tables 10 and 11 with 6 and 7.

Table 9 -- Correlation Between Density and Impact

	Requirements			Facts		
	Corr	AvgImpact	AvgDensity	Corr	AvgImpact	AvgDensity
Johann	0.8S	1010.46	15.50	-0.84	757065.67	2.08
Lorenzo	0.43	1.91	13.07	-0.83	745762.58	1.87
Ian	0.98	85.58	9.00	-0.93	870056.93	0.83
Zebadiah	0.81	325,73	11.78	-0.82	768364.86	1.76
Edith	0.94	68.78	9.91	-0.88	813559.98	1.43
Ernest	0.88	196.83	9.23	-0.89	836160.37	1.12
Castor	0.90	191.96	12.08	-0.86	768362.67	2.07
Zaccur	0.84	258.67	10.73	-0.85	807911.41	1.60
Aaron	0.68	464.79	15.19	-0.80	598874.17	3.50
Lowell	0.76	840.20	13.40	-0.83	711870.82	2.36
Jaques	0.76	251.92	11.50	-0.87	785312.89	1.60
Eunice	1.00	350.88	12.25	-0.94	892656.41	0.68
Ishtar	0.92	112,76	9.75	-0.92	853108.63	0.95
Jubal	0.93	178.14	10.71	-0.90	864407.84	0.77
Deety	0.95	393.10	14.31	-0.82	672319.64	2.72
Woodie	0.88	277.36	12.40	-0.84	740115.59	1.95
Maureen	0.94	153.42	11.58	-0.83	751413.41	1.60
Hazel	0.87	298.14	11.00	-0.91	824860.57	1.40
Manni	0.88	380.80	12.73	-0.79	711866.02	2.38

Moreover, when a frame structured knowledge representation scheme is used cognitive density is not related to the level of interaction propensity or shared position -- see column 10 in tables 10 and 11. There are a few cases where the model is not directly supported. First, in table 10 although low levels of interaction propensity do correspond to lower levels of consensus in knowledge and higher levels of interaction propensity to higher levels of consensus in knowledge the relationship is not direct. Second, the level of association for groups g11 and g12 is in direct opposition to that predicted by the model -- see table 11 column 3 rows 1 and 2. And third, the average percentage increase in shared knowledge for structurally equivalent individuals is not higher than that for non structurally equivalent individuals -- see table 11 column 7 contrast rows 1-4 with 5. The reason that the data in these cases does not correspond directly to the model may be attributable to the procedure for collecting what information the individual knows about the candidate. In the model, once an individual knows a piece of information that information is never forgotten. Hence, an individual's knowledge base can only increase with time. When collecting data on what an individual knows we are at best sampling the known information (Carley, 1987b). Hence, unless the coding procedure always adds to information at later times that discovered at earlier times this condition will not be met. Since the coding procedure for extracting information did not do this, the apparent size of knowledge bases can decrease. This can affect the level of consensus in knowledge measured.

Table 10 -- Data for Interaction Impact.
Using Facts

Int Level	Assoc	SK BEGIN	SK END	Increase in SK	Top Vote	Top Level	Last Vote	Last Level	D	N
1	268.43	93.86	113.86	46.96	0.43	1.28	0.43	1.43	0.86	7
2	257.11	96.89	110.18	34.44	0.28	1.60	0.32	1.92	0.90	38
3	313.16	75.06	117.03	77.88	0.22	1.61	0.28	1.69	0.88	36
4	291.40	63.00	110.00	95.16	0.19	1.44	0.56	0.51	0.68	16
5	314.13	85.50	127.12	94.62	0.12	1.75	0.62	2.12	0.91	8

Table 11 -- Data for Group Impact
Using Facts

Group	Int Level	Assoc	SK BEGIN	SK END	Increase in SK	Top Vote	Top Level	Last Vote	Last Level	D	N
1	3.0	421.47	86.33	102.00	27.10	0.50	1.83	0.17	2.33	0.88	6
2	4.3	196.06	59.33	147.67	159.18	0.00	2.00	1.00	1.67	0.90	3
3	3.0	155.66	147.50	110.33	-21.79	0.17	1.67	0.17	1.83	0.95	6
4	4.2	518.37	47.50	106.17	139.27	0.00	1.17	0.33	1.33	0.83	6
OUT	2.9	273.06	81.75	114.53	64.00	0.26	1.56	0.38	1.76	0.85	84

Putting these findings together suggests that consensus in behavior is a function of having not only the same information but also having that information connected in the same way. Since cognitively dense concepts play an important role in determining behavior, similar behavior should occur if two individuals have the same dense nodes and these concepts get evaluated in the same way. Since neither interaction propensity nor shared position determines which concepts are dense it is thus not surprising that they do not determine consensus in behavior.

The evaluation of a concept is a function of both what other concepts the focal concept is related to and the value of these concepts. Since value propagates through the conceptual network it seems likely that there will be a set of critical concepts that dominate the overall evaluation of the network. See appendix B for the determination of critical concepts. Thus it is expected that consensus in behavior is a function of having both the same dense concepts and the same critical concepts. This is a point for future research.[6]

6. Conclusion

The constructuralist theory was reviewed. Based on this theory the 1:1 list model of individual behavior was developed. Using this model a series of predictions about consensus were made. Using the Third East data set the predictions of this model were examined. In general these predictions held. The findings include the following:

- High interaction leads to consensus in knowledge.
- High interaction, in the short run, does not lead to consensus in behavior.
- Shared position is not necessary for consensus in knowledge.
- Shared position is not necessary for consensus in behavior.
- Shared position reinforces high interaction so the two together produce consensus in knowledge but not necessarily consensus in behavior.

It was found that consensus in behavior is a function not of how much one knows but of what one knows. That is, the exact pattern of information known to the individual determines consensus in behavior. It was demonstrated that different knowledge representation lead to different explanations as to why consensus in behavior occurs. A frame structured knowledge representation scheme exhibits the same pattern of consensus behavior as does a list structured knowledge representation scheme. However, the frame structured knowledge representation scheme is a better predictor of behavior than is a list structured knowledge representation scheme. This suggests that to understand consensus in behavior it is important to understand the inter-relationship between information. In future work on consensus in behavior some form of network structured knowledge representation scheme such as the frame structured one used herein should be considered. When the frame structured knowledge representation scheme is used it appears that consensus in behavior is a function of sharing concepts which are cognitively dense and of not having different critical concepts.

As a result of this work the constructural theory can now be extended. The main extension is

[6] Or put in a table showing correlation between votes and number of same dense nodes and number of same critical nodes. In this case add to the previous tables: criticality in impact of int. in impact of shared position Also create a new table with correlation between presence of dense nodes and vote and presence of criticality and vote.

the addition that individuals use a network structured knowledge representation scheme. This detail makes it possible to draw a correspondence between tasks and knowledge thus permitting predictions about what information will be salient when, and when particular information will not be accepted even if it is communicated. In order to do further theory building a second generation model is called for in which a network structured knowledge representation scheme is used.

It may be that when a network structured knowledge representation scheme shared position will be found to have a greater impact on consensus. Note: it was found that the coupling of high interaction levels and shared social position result in consensus in knowledge; although, not necessarily in consensus in behavior. Under the constructuralist theory consensus in knowledge is a function of amount of information known. Whereas, consensus in behavior is a function of the pattern of information known. Consequently, we might expect that if shared position leads to individuals acquiring information in the same pattern then given that high interaction leads to acquiring the same information we might expect that the coupling of shared position and high interaction might in fact lead to consensus in behavior. Whether or not this is in fact the case is a point for future research.

These findings suggest that the level of consensus in a society can be manipulated. Specifically by limiting or providing opportunities for interaction and by increasing or decreasing the interaction propensities the level of consensus in knowledge can be manipulated. Further, the longer the individual's gather information prior to making a decision the more likely consensus in behavior is to result. This, of course, depends on there not being an isolated group or individual in the society. Long intense interactions between individuals with no communication barries are thus likely to produce both consensus in knowledge and consensus in behavior. In the long run, influence and persuasion is simply a function of interaction.

This research also suggests that there may be specific pieces of information whose communication will have a greater impact on the formation of consensus than will other pieces of information. The cognitive property of such pieces of information has not been determined. Determination of such properties is important for understanding how one individual can influence and persuade another when time is limited.

If in fact, as this research suggests, behavior is a function of knowledge then determination of a sufficient knowledge representation scheme is important. With such a representation scheme we would be able to determine what cognitive properties information must possess to evoke specific social behavior. Such a representation scheme will enable us to better understand the relationship between interaction and social position on consensus, persuasion, the construction of meaning, the development of norms, and other social behavior.

References

Abelson, R.P. and Reich, C.M. (1969). Implicated Molecules; A method for extracting meaning from input sentences. In Walker, D.E. and L.M. Norton (Eds.), *Proceedings of the International Joint Conference on Artificial Intelligence.* : .

Abelson, R.P. (1976). Script Processing in Attitude Formation and Decision-Making]. In Carroll, J.S. and J.W. Payne (Eds.), *Cognition and Social Behavior.* Hillsdale, NJ: Lawrence Erlbaum Associates.

Anderson J. and G. Bower. (1973). *Human Associative Memory.* Washington DC: Winston-Wiley.

Bobrow D. G. and D. A. Norman. (1976). Some principles of memory schemata. In Bobrow, D. G. and A. Collins (Eds.), *Representation and Understanding: Studies in Cognitive Science.* New York, NY: Academic Press.

Boorman, S.A. and H.C. White. (1976). Social Structure from Multiple Networkes. II Role Structures. *American Journal of Sociology, 81*, 1384-1446.

Breiger, R.L, S. A. Boorman, and P. Arabie. (1975). An Algorithm for Clustering Relational Data with Applications to Social Network Analysis and Comparison with Multidimensional Scaling. *Journal Mathematical Psychology, 12*, 328-383.

Burt, R.S. (1976). Positions in networks. *Social Forces, 55*, 93-122.

Burt, R.S. (1977). Positions in multiple network systems, part one: a general conception of stratification and prestige in a system of actors cast as a social topology. *Social Forces, 56*, 106-131.

Carley, K.M. (1983). *Construct 1 - Technical Notes* (Tech. Rep.). Carnegie-Mellon University,

Carley, K.M. (1984). *Constructing Consensus.* Doctoral dissertation, Harvard,

Carley, K.M. (1986). An Approach for Relating Social Structure to Cognitive Structure. *Journal of Mathematical Sociology, 12(2)*, 137-189.

Carley, K.M. (1986). Knowledge Acquisition as a Social Phenomenon. *Instructional Science, 14*, 381-438.

Carley, K.M. (1986). Language: Society's Chronicle. ASA meetings and Sociological Abstracts.

Carley, K.M. (February 1987). Separating the Effects of Structure and Interaction. CMU Social and Decision Sciences Working Paper Series.

Carley, K.M. (1987). Formalizing the Social Expert's Knowledge. CMU Social and Decision Sciences Working Paper Series.

Charniak, E. (1972). *Toward a Model of Children's Story Comprehension*. Doctoral dissertation, Massachusetts Institute of Technology,

Clark, H.H. and Clark E.V. (1977). *Psychology and language: An introduction to psycholinguistics*. New York, NY: Harcourt Brace Jovanovich.

Collins, B.E. and Loftus, E.P. (1975). A spreading-activation theory of semantic processing. *Psychological Review, 82*, 407-428.

Kernighan B.W. and D.M. Ritchie. (1978). *The C Programming Language*. Englewood Cliffs, NJ: Prentice-Hall.

Kernighan B.W. and R. Pike. (1984). *The UNIX Programming Environment*. Englewood Cliffs, NJ: Prentice-Hall.

Minsky, M.A. (1975). A framework for representing knowledge. In Winston, P. (Ed.), *The Pshchology of Computer Vision*. New York, NY: McGraw-Hill.

Rumelhart, D.E. and A. Ortney. (1976). The representation of knowledge in memory. In Anderson, Spiro and Montague (Eds.), *Schooling and the Acquisition of Knowledge*. Lawrence Erlbaum Associates.

Schank R. and Colby K. (1973). *Computer Models of Thought and Language*. San Francisco, CA: W. H. Freeman.

Schank, R. and R. Abelson. (1977). *Scripts Plans and Goals and Understanding*. New York, NY: Wiley.

Simmons, R. (1973). Semantic networks: Their computational use for understanding english sentences. In Schank, R. and Colby K. (Eds.), *Computer Models of Thought and Language*. San Francisco, CA: W. H. Freeman, Publisher.

Tesser, A. (1977). Toward a theory of self-generated attitude change. In Berkowitz, L. (Ed.), *Advances in Experimental Social Psychology*(10 ed.). New York, NY: Academic Press.

Tversky, A. and D. Kahneman. (1980). Causal Schemas in Judgments Under Uncertainty. In Fishbein, M. (Eds.), *Progrss in Social Psychology*. Hillsdales, NJ: Erl-Baum.

White, H.C., S.A. Boorman, and R.L. Breiger. (1976). Social Structure from Multiple Networks. I. Blockmodels of Roles and Positions. *American Journal of Sociology, 81*, 730-780.

Wyer, R.S. Jr., and D. E. Carlston. (1979). *Social Cognition, Inference, and Attribution*. Hillsdale, NJ: Lawrence Erlbaum Associates.

APPENDIX A -- DATA

Not Included

APPENDIX B -- PREDICTING VOTING

Not Included

d13.mst
interaction

Increasing Consensus Through Shared Social Position and Interaction

Kathleen Carley

Assistant Professor of Sociology
and Information Systems
Carnegie-Mellon University

10 September 1987

 This work was supported in part by the National Science Foundation grant No.IST-8607303.