Social Networks 9 (1987) 109–134
North-Holland

COGNITIVE SOCIAL STRUCTURES

David KRACKHARDT *
Cornell University

There are problems within the area of network analysis that can be fruitfully explored with cognitive social structures (CSS). Such structures can be modeled as three-dimensional ($N \times N \times N$) network structures. A definition of such structures is presented, along with a review of some of the problems CSS might address. Three types of aggregations of CSS – Slices, Locally Aggregated Structures (LAS), and Consensus Structures (CS) – are proposed to reduce CSS to a tractable two dimensions for analysis. As an illustration, the CSS of a management team of a small manufacturing firm is analyzed comparing all three types of aggregations.

1. Introduction

Bernard, Killworth and Sailer (BKS) have generated a substantial controversy in the study of network analysis. They have shown repeatedly that behavioral measures of interaction are not very closely related to participants' self reports of this same interactions (e.g., Bernard and Killworth 1977; Bernard, Killworth, and Sailer 1980; Bernard, Killworth and Sailer 1982; Killworth and Bernard 1976; Killworth and Bernard 1979). In a review of this work, they conclude:

> Informants are inaccurate; memory does decay exponentially with time… . And on top of all this there appears to be systematic distortion in how informants recall just about everything. (Bernard, Killworth, Kronenfeld and Sailer 1984: 509)

This methodological challenge has not gone unanswered. Several social network scholars (Burt and Bittner 1981; Romney and Faust 1982; Romney and Weller 1984) have reanalyzed the BKS data using different assumptions about the structure of the data and the meaning of "similarity". Their conclusion has been that BKS were not correct in asserting that "… what people say … bears no useful resemblance to

* Johnson Graduate School of Management, Cornell University, Ithaca, NY 14853, U.S.A. I would like to thank Linton Freeman for his encouragement on this work and his helpful comments on earlier drafts.

0378-8733/87/$3.50

their behavior" (Bernard et al. 1982; 63). Freeman and Romney (1986) have reported evidence that indicates that the recollections people have may represent enduring patterns of interaction more accurately than individual instances of behavior. This is consistent with the work in psychology on schemas (Anderson 1980) that indicates that people may average individual stimuli to record an underlying pattern. Posner and Keele (1968), for example, found that people remember the average pattern of stimuli (called prototypes) over a longer period of time than they can remember any of the individual stimuli which made up the pattern.

The premise behind all of these arguments – a premise implied by the use of the term "accuracy" – is that recall is being used as a surrogate for or measure of behavior. There are two alternative ways of looking at this "problem", based on different premises or theories, that eliminate the BKS findings as a "problem" and open new avenues for approaching the study of networks. First, one might have a theory that relates people's perceptions to objective reality (behavior, in this case). Such a theory would account for bias or distortions or inconsistencies in the perceptions. For example, Lawler, Porter and Tenenbaum (1968) note that subordinates take more seriously any communication they have with superiors in organizations than the superiors do. One might wish to explain this difference by deriving a theory of self-aggrandizement in organizational interactions. One may further wish to focus on the observed discrepancies between recall and behavior as substantive meat to be explained by the theory (e.g. Freeman, Romney and Freeman in press), rather than simply error to be avoided, as implied by BKS. The goal of such an approach would be to uncover and explain sources of bias in recollections. This could prove to be a very fruitful search, comparable to what decision theorists have done in explaining observed "error" in rational decision making (Kahneman, Slovic and Tversky 1982).

The second alternative way of reinterpreting the BKS "problem" is to focus on the cognitive reconstructions themselves, apart from any relationship they may have to behavior. From this perspective, the BKS findings simply constitute evidence that one should not bother collecting behavioral data, since they do such a poor job of capturing the cognitions which live in peoples' heads.

Obviously, whether one is interested in discovering the behavioral patterns, the cognitive patterns, or the relationship between them is a function of the theory one is trying to articulate in the research. Clearly, there is room for explorations in all three realms. It will be argued here, though, that the preoccupation with the BKS accuracy problem is symptomatic of a bias towards behavioral patterns even though the theoretical base is frequently cognitive or psychological. To illustrate this bias, we will first discuss examples of research which draw from cognitive theory but then assume that the behavior patterns adequately reflect these cognitions. Following these examples, we will present a methodology and empirical case of cognitive patterns which, it is claimed, are better suited to address the cognitive models underlying these research efforts.

1.1. Examples of cognitively-based research

Perhaps the most prevalent and straightforward example of a cognitive model in network analysis is Heider's (1958) balance theory. In this theory, it is argued that people have a desire to believe that their friends are friends with each other. Others have extended the logic to include both asymmetric and symmetric ties, with the purpose of considering whether triads in networks are transitive (Cartwright and Harary 1956; Davis and Leinhardt 1972; Holland and Leinhardt 1971; Holland and Leinhardt 1976; Hubbell, Johnson and Marcus 1975; Johnson 1985; Johnson 1986).

The basic theoretical pillar on which this work rests is cognitive. Heider (1958) argued that people feel uncomfortable (dissonant) when they believe their friends do not like each other. To resolve this discomfort, the theory predicts that one will either discard a friend, or more likely, one will change one's perceptions of the relationship between friends to restore cognitive balance.

The asymmetric counterparts in triad analysis are also cognitively based: people feel uncomfortable when cyclical triads of deference are found. What is interesting is that the empirical work is not based on true cognitive triads. For example, for person A to be balanced in his/her friendship with B and C, then A must believe that B and C are friends. Whether B and C are actually friends is not necessary, in theory, for A to experience the balance predicted by Heider (cf. Krackhardt and Porter 1985). Similarly, if A does not perceive a cyclical triad of asymmetric relations among A, B, and C, then such a condition will not cause A any discomfort. Despite this cognitive basis for these theories, it is interesting to note that none of the empirical assessments of triad structures have measured such perceptions. In fact, this could be a reasonable explanation for why so many "unacceptable" triads are found in such empirical work.

Another highly visible example comes from a sociological tradition in social psychology. The roots of this tradition can be found in the work of W.I. Thomas during the early part of this century. His view of the social world is best summarized by his famous dictum: "If men define situations as real they are real in their consequences" (in E.H. Volkart 1951: 81).

Building on this work, Burt (1982) has developed a very interesting theory of individual behavior. It draws on the psychological perspective of actors having autonomous needs as well as a sociological perspective which argues that actors' interests are socially determined. The theory is complex and complete in its form, and it is beyond the scope of this article to describe it in any detail. Of particular interest here is Burt's assertion that the actor's perception of the position he/she holds in the network is critical in determining his/her interests and motivation. Specifically, ". [An actor's] evaluation is affected by other actors to the extent that he *perceives* them to be socially similar to himself" (p. 178, emphasis ours). Burt argues that Steven's law, which states that subjective perceptions are a direct power function of objective stimuli, can be used to translate the "objective" reality into an individual's perception of how similar all other actors are. As an empirical example, he calculates an "objective" structural similarity between elites in an invisible college based on questionnaire responses from these elites. He then translates this "objective" similarity into a perceived similarity using the formula derived from Stevens' work.

Burt is to be credited for admitting explicitly that perceived position in the network is crucial to the underlying theory. Moreover, this theory as a whole both creatively draws from many corners of social science and yet integrates them with impeccable logic. But we would like to draw attention to one small part of his operationalization of these ideas to make a point. The assumption that an actor's perceptions of similarity to others is a direct and derivable function of any kind to the "objective" similarity of others is tenuous. The study of attributions and perceptual distortions at a minimum must make us skeptical of any simple translation formula (e.g. Asch 1951; Jones et al. 1971).

These are two examples of many in which cognitive bases for the social network theory are not matched by the assumptions underlying the collection of data to evaluate that theory. What is recommended here is those studying cognitive networks should take a lead from psychological colleagues and measure perceptions of networks directly. That is, if one wants to know whether Heider's balance theory is operative, one should ask A if he/she perceives B and C to be friends. If one wants to know if A perceives B to occupy a similar role to A (in the sense that Burt is using the term "similar role"), then one should assess A's perception of the network in which A and B are embedded.

2. Definition of cognitive social structure

Within the area of social networks, structure has taken on a specific meaning. The structure of any system is defined as a set of relational statements between all pairs of actors in the system. These statements can be summarized in a set of R matrices (one for each relation) of the form $\mathscr{R}_{ij}$, where $\mathscr{R}$ is the structure-defining relation, i is the "sender" of the relation, j is the "receiver" of the relation. Then, $\mathscr{R}_{ij} = 1$ if i is related to j in the form specified by $\mathscr{R}$; otherwise, $\mathscr{R}_{i,j} = 0$. If $\mathscr{R}$ is defined to be "approaches for help and advice", then one would interpret $\mathscr{R}_{3,12} = 1$ as meaning that Person 3 approaches Person 12 for help and advice.

The Cognitive Social Structure (CSS) of this system, then, would be represented as $\mathscr{R}_{i,j,k}$, where i is the "sender" of the relation, j is the "receiver" of the relation, and k is the "perceiver" of the relation from i to j. Again, $\mathscr{R}_{i,j,k}$ is binary in form. If we use the same coding as above, the $\mathscr{R}_{3,12,8} = 1$ would be interpreted as meaning that person 8 thinks that person 3 approaches person 12 for help and advice.

Thus, if there are N actors in a system to be described by R relations, then the social structure would be described by $RN \times N$ matrices, but the cognitive social structure would be described by $RN \times N \times N$ matrices.

A couple of characteristics of cognitive social structures become immediately apparent. First, and perhaps most obvious, the amount of information in a cognitive social structure far exceeds that in a traditional social structure. This creates inescapable practical data collection problems, since getting a respondent to voluntarily record his/her perception of every (i, j) dyad for each relation in a bounded system of actors is a formidable task. In cases where the bounded network is reasonably large, the task may be virtually impossible. But relatively small networks ($N < 50$) have provided useful insights in many studies of social and organizational phenomena. For example, Sampson's (1968) famous study of a cloister contained 18 monks; Roethlisberger and Dickson's (1939) classic study at Western Electric included a network analysis of 14 employees in a bank wiring room; Newcomb's (1961) University of Michigan housing experiment included 17 students. Networks of this size and considerably larger could be analyzed from a CSS perspective. The largest known CSS data set to date is that of Krackhardt and Kilduff (1986) who measured the perceptions of 48 employees about two relations among their coworkers, yielding a CSS of order $48 \times 47 \times 48$, $(i \neq j)$. Thus, while CSS data collection may be more difficult, it is certainly practicable and may well be worth the effort.

Second, contrary to what is implied in Burt's work, there is no implication in the definition that any "objective" relation in an (i, j) dyad has any correlation to the various k perceptions of that same dyad. They are conceptually distinct; correlations become a theoretical and empirical question to be explored by those interested in answering such questions. In a related way, no assumption is made about the perceptions being correlated with each other. The structure perceived by Person A may be very different from the structure as perceived by Person B. This also becomes an empirical question, to which we will return later.

3. Aggregations

The analysis of cognitive social structures poses unusual difficulties. How does one study a three-dimensional set of data? There are two potential answers to this. First, one can keep the data in its raw form, comparing it to other data in similar form. That is, one relation could be compared to another for consistencies or the lack thereof. For example, one could ask whether actors think that others choose to approach friends within an organization when they need political advice (cf. Allen 1978). A descriptive answer could be calculated from the following correlation:

$$\rho\left(\mathscr{R}_{1_{i,j,k}} \mathscr{R}_{2_{i,j,k}}\right) \quad \text{for all } i \neq j,$$

where $\mathscr{R}_1$ is friendship choice and $\mathscr{R}_2$ is "approach for political advice". There are severe analysis problems with this approach, however, most notably that these $N \times (N-1) \times N$ observations are not independent (thus making significance tests meaningless).

The second, more tractable, approach is to aggregate the $\mathscr{R}_{i,j,k}$ relation into a two-dimensional relation, $\mathscr{R}'_{i,j}$, using some set of rules. It is proposed here that there exist three basic kinds of reductions, each with its own set of rules and motivated by its own set of questions it tries to answer. These three aggregations, referred to here as Slices, Locally Aggregated Structures (LAS), and Consensus Structures (CS), are described below.

3.1. Slices

The simplest reduction is to take a "Slice" from the three-dimensional matrix, holding constant the "perceiver" dimension:

$$\mathscr{R}'_{i,j} = \mathscr{R}_{i,j,K}, \quad \text{where } K = \text{a constant.}$$

While simple, this reduction is also elegant and cuts to the heart of the value of CSS. For example, one can predict from a perceiver's "Slice" whether one is experiencing "balance", in the Heider sense. The information about whether k perceives all his/her friends to be friends with each other is present in k's Slice. Moreover, one can assess whether k's view of the whole network in which he/she is embedded is transitive (consistent) as defined by Holland and Leinhardt (1976) and further explored by Johnson (1985). In fact, the idea of consistency may be something imposed by psychological needs rather than a function of actual social order. For example, De Soto (1960) studied whether people could recall arbitrary relations between twelve fictitious actors. He found that people had a relatively easy time remembering these "influence" relations when they were asymmetric, transitive, and complete. "It is as if the S's had a theory about social structure..." (p. 102), he concludes, and this theory influences our memory of social structure. If this process is robust, then we should find k's Slices more balanced, more transitive, more ordered than "objective" social structure.

A more sophisticated analysis of Slices allows one to test Burt's theory in an interesting way. As discussed earlier, one tenet in his model is that actors' experience of role similarity to others is a function of how similar those others are. One assumption implied by Burt's method is that if two people are "objectively" structurally equivalent then each must *perceive* the other as structurally equivalent (appropriately attenuated by the Stevens' power function), *even though they may not even be aware that the other exists.*

In contrast to Burt's method, one could assess directly the perceptions of structural similarity. Instead of assuming that person A perceives person B to be structurally equivalent to A, one could take A's Slice out of $\mathscr{R}_{i,j,k}$, where $k = A$, and measure the extent of structural equivalence between A and B *as perceived by A*. Conversely, one could independently use B's Slice to measure B's perception of how structurally similar A is to B. These two assessments are not necessarily symmetric; indeed they are likely to be very different, especially when status differences exist.

These examples barely scratch the surface of questions which could be examined using Slices of CSS.

3.2. Locally aggregated structures

A second general approach to reduction of the CSS is to consider what might be thought of as diagonal slices, where $k = i$ or $k = j$:

Row Dominated LAS: $\mathscr{R}'_{i,j} = \mathscr{R}_{i,j,i}$,

or

Column Dominated LAS: $\mathscr{R}'_{i,j} = \mathscr{R}_{i,j,j}$.

We call these Locally Aggregated Structures (LAS) because the resulting relation between i and j depends on information provided by the most local of members in the network, namely i and j themselves. It should be immediately apparent that LAS reductions are exactly the type of data normally collected in traditional sociometry (Moreno 1960). That is, the row dominated LAS – $\mathscr{R}_{i,j,i}$ – represents the set of responses to the question: "who are you related to in this way?", and the column dominated LAS – $\mathscr{R}_{i,j,j}$ – contains the responses to the question "who is related to you in this way?".

While most network research only asks one of the two aforementioned kinds of questions for any relation, frequently both are asked and then combined in an attempt to increase the reliability of the measures. Since CSS data structures contain both forms automatically, one may combine the information further using either an intersection rule or union rule:

LAS from Intersection Rule: $\mathscr{R}'_{i,j} = \{\mathscr{R}_{i,j,i} \cap \mathscr{R}_{i,j,j}\}$,

LAS from Union Rule: $\mathscr{R}'_{i,j} = \{\mathscr{R}_{i,j,i} \cup \mathscr{R}_{i,j,j}\}$.

An LAS reduction would be recommended under several conditions. One obvious case is when it is appropriate to assume that i and j are the ones who best know whether the relationship in fact exists between them. This would be especially true when the relationship has no behavioral definition. For example, if one is interested in friendship relations, then the most appropriate definition might be that i and j are friends if i and j perceive that they are friends.

More behaviorally oriented relations, such as "talks to" or "interacts with", can also be reduced to LAS form. However, if the concern is for *accuracy* of the respondents' accounts of the network, then one is subject to the criticisms which Bernard, Killworth and Sailer raise.

3.3. Consensus Structures

The final approach to CSS reduction is to consider the entire vector of perceptions of the (i, j) information in determining the (i, j) relation. In its most general form:

$$\mathscr{R}'_{i,j} = f(\mathscr{R}_{i,j,k_1}, \mathscr{R}_{i,j,k_2}, \ldots, \mathscr{R}_{i,j,k_n}).$$

A simple, practical version of a Consensus Structure (CS) is to use a Threshold function:

$$\mathscr{R}'_{i,j} = \begin{cases} 1 & \text{if } \frac{1}{N}\Sigma_k \mathscr{R}_{i,j,k} \geq \text{Threshold}, \\ 0 & \text{otherwise,} \end{cases}$$

where Threshold can take on any fractional value from 0 to 1. A Threshold of 0.5 would be interpreted as meaning that a relation exists from i to j if and only if a majority of the members of the network perceive that it exists.

This type of reduction has many possible applications. Perhaps the strongest motivation for looking at CS stems from the recent work of Romney, Weller and Batchelder (1986) and the field work of S. Freeman (1986). They have demonstrated that, given a few reasonable assumptions, the underlying "truth" about some statement is best predicted from a weighted average of each observer's perception or guess about its truth. While the computation of the weights is somewhat complicated and important (some people are deemed "smarter" than others – hence their vote counts more), this optimal solution can be approximated with the above simplified threshold function.

4. An empirical example

To demonstrate these aggregations and illustrate their differences, we collected data from a small manufacturing organization on the west coast. This 10-year old entrepreneurial firm produces high-tech machinery for other companies. They employ approximately 100 people, 21 of whom are part of management (supervisors up through president). The president invited us to collect data from this management team to help evaluate the effects of a recent organizational development intervention on the informal organization.

Each person was asked to fill out a questionnaire. They were not compensated, but they were told that they would be briefed on an overview of the results. All 21 respondents completed the questionnaire.

Included on the questionnaire was a series of items about who goes to whom for help and advice for work-related problems. For example, one question would read: "Who would Steve Boise go to for help or advice at work?" Below this was listed each of the other 20 managers. The respondents were asked to place a check beside the names of all the people that Steve Boise is likely to go to. The same question was repeated for each of the 21 managers.

The "advice" data constitute a complete Cognitive Social Structure as defined earlier. From these data, 21 Slices were extracted ($k = 1$ to

21), one Locally Aggregated Structure, and one Consensus Structure. The LAS was obtained by taking the intersection: $\mathscr{R}_{i,j,i} \cap \mathscr{R}_{i,j,j}$. That is, an advice relationship was deemed to exist if and only if both parties in the relationship agreed that it exists. The CS was derived using the following threshold function:

$$\mathscr{R}'_{i,j} = \begin{cases} 1 & \text{if } \frac{1}{21}\sum_{k=1}^{21}\mathscr{R}_{i,j,k} \geq 0.5, \\ 0 & \text{otherwise.} \end{cases}$$

The adjacency matrices which resulted from each of these aggregations – the 21 Slices, the Locally Aggregated Structure, and the Consensus Structure – are provided in Appendix A.

To give the reader an idea of what these networks look like, a sociogram for the Locally Aggregated Structure, the Consensus Structure, and one Slice ($k = 2$) are provided in Figures 11–3. [1] The arrows on the picture represent the relationship "goes to for help and advice", i.e. if person 1 goes to person 2 for help and advice, then the graph would display a line starting at person 1 and pointing to person 2. If they go to each other for help and advice, then arrow heads would appear at both ends of the line between persons 1 and 2.

Figure 1 shows the Locally Aggregated Structure. Two observations are immediately apparent. First, there is a degree of hierarchy, that is there are a number of noncyclical, asymmetric advice relations. Second, there are some centers of focus for advice, notably 2 and 21 (both are vice presidents). In Figure 2, the graph of the Consensus Structure, again we see a considerable degree of hierarchy, with 2 receiving the highest number of "advice" nominations. But 21 loses his prominence as a major recipient of nominations; instead, 18, 14 and 7 (the president) appear to be more central.

Individual perceptions – and consequent graphs – vary considerably. Figure 3 contains the graph of one person's picture (Person 15)

[1] The positioning of the actors in each of the sociograms was determined using a multidimensional scaling program. The input to this program was a proximity matrix defined as follows: The (i, j) element was computed as the the mean between the inverse of the path distance from i to j and the regular graph equivalence – or REGGE – score (White and Reitz, in press) between i and j. Experience has shown that this combination makes hierarchical graphs more readable and interpretable. The REGGE similarity scores result in a hierarchical arrangement, while the inverted distance scores tend to position the points to minimize the number of long, confusing lines which can crosscut the entire graph.

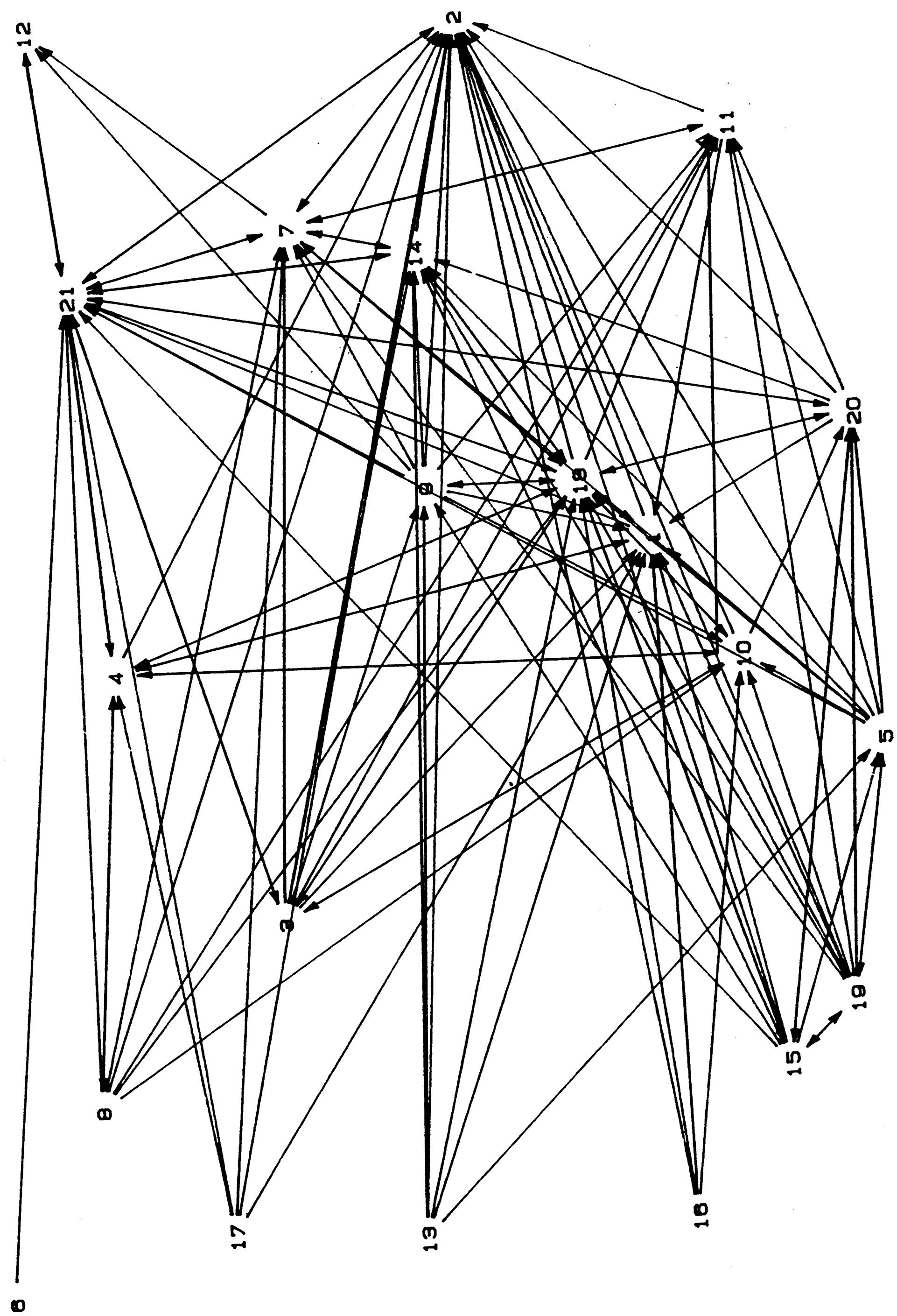

Fig. 1. Sociogram of locally aggregated structure.

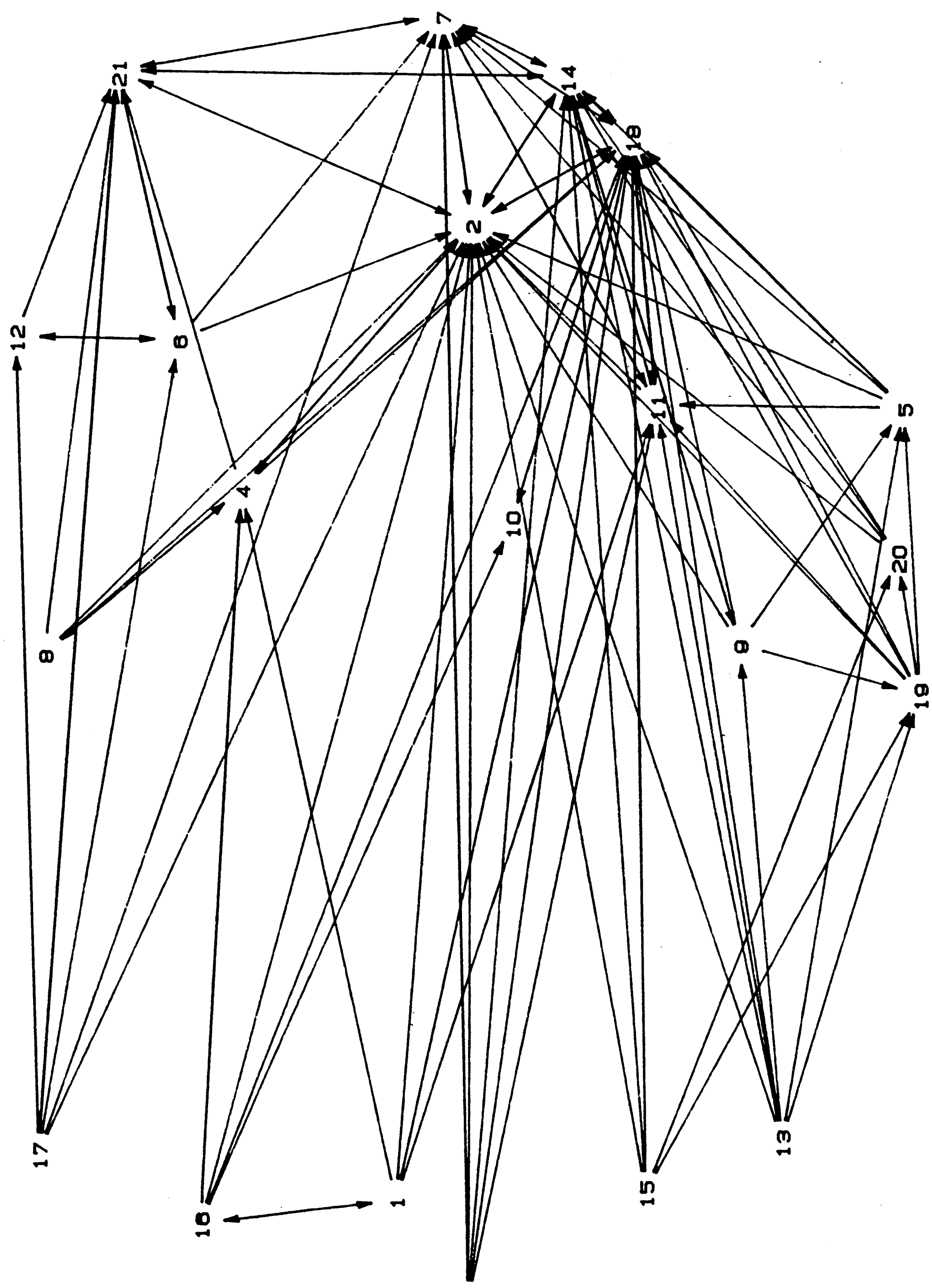

Fig. 2. Sociogram of consensus structure.

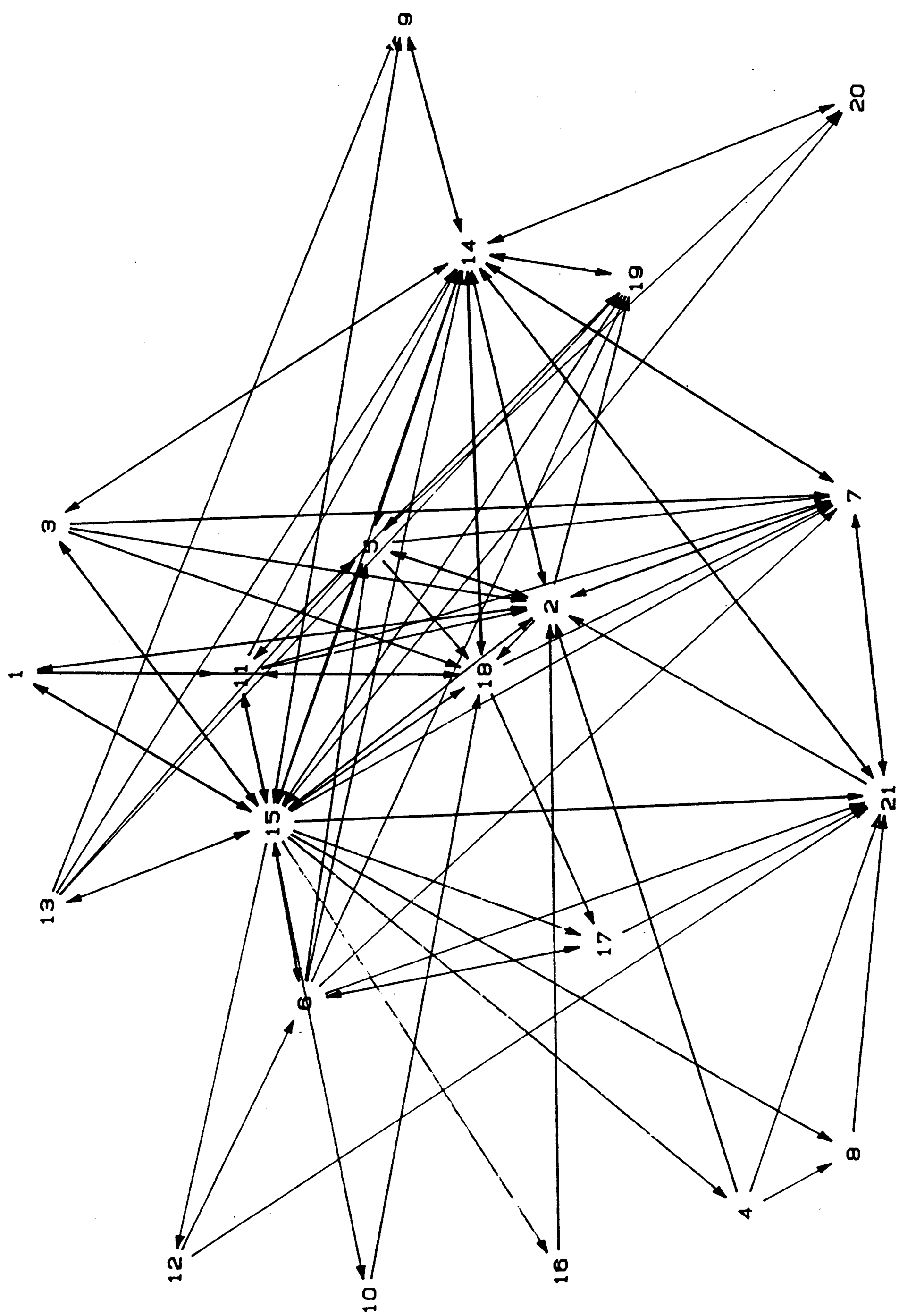

Fig. 3. Sociogram of person 15's slice.

which is considerably different from either the LAS or the CS picture. First, he puts himself in the middle, both giving advice to and seeking advice from many others; in the LAS, he was sought after by few, and in the CS graph, he was sought after by none for advice. Second, he perceives almost everyone both giving and getting advice; thus, he precludes any clear hierarchy in the structure, hierarchy which was obvious in both the LAS and CS pictures.

To formalize these qualitative observations, centrality measures were calculated for each individual in each the three aggregations: their own Slice, the LAS and the CS. The centrality measures computed were: indegrees, outdegrees, and betweenness (L.C. Freeman 1977, 1979). [2]

Of interest here is the difference in patterns from one person to the next across the aggregations. As a simple example, see Table 1 which contains the centrality scores of Person 15 to whom we referred earlier. His own perception is that he is very active in the network: advice is sought from him by 12 people; he actively seeks advice from 20 others; and he is on the crossroads of this network as evidence by his 81.15 betweenness score. This self-evaluation is not shared by his coworkers (see second set of columns). Only three of the 12 indegrees he claims to have are confirmed (hence, his LAS indegree is three). Also, only nine of his 20 outdegree nominations are confirmed (LAS outdegree = 9). And finally, his betweenness in the LAS just about disappears (betweenness = 0.70). The Consensus Structure reveals that people generally think that no one approaches him for advice, that he goes to only five people for advice, and that he is not in between any other pair of people.

In addition to noting the differences in patterns across aggregations for particular individuals, it is instructive to know the general tendancy for the three aggregations to provide the same information about the structural centrality of actors. To this end, Table 2 reports the degree to which each of the three aggregations is correlated with the others on each of the centrality measures. As might be expected, there is redundancy in some of the measures, especially in the indegree and

[2] Betweenness was calculated in each of the three aggregations using Freeman's algorithm which is available in a package called UCINET. Each of the aggregations is asymmetric, and Freeman's algorithm requires symmetric adjacently matrices. Therefore, a temporary symmetric adjacency matrix was creased for each of the three aggregations by taking the union of the original adjacency matrix with its transpose. The betweenness scores reported in this paper were all based on these symmetrized matrices.

Table 1
Centrality scores (indegree, outdegree, and betweeness) for each individual (k) based on the three separate aggregations

k	k's Slice			Locally Aggr			Consensus		
	Indg	Outdg	Betw	Indg	Outdg	Betw	Indg	Outdg	Betw
1	18	6	2.81	12	4	10.97	1	5	0.67
2	20	3	43.67	18	2	18.23	18	5	56.66
3	12	15	11.06	3	9	1.29	0	5	0.00
4	12	12	2.71	6	7	2.07	4	4	3.09
5	9	15	6.36	3	10	3.69	3	5	0.78
6	2	1	0.33	0	1	0.00	3	4	4.43
7	13	8	5.01	11	6	8.80	10	5	12.09
8	1	8	2.29	1	7	0.87	1	4	0.63
9	10	13	26.17	4	9	8.76	2	5	0.00
10	13	14	19.42	8	5	4.53	2	1	0.00
11	14	3	40.78	9	3	3.15	7	4	3.07
12	8	2	0.93	3	1	0.00	2	2	0.00
13	0	6	9.38	0	6	0.20	0	7	0.17
14	19	4	17.01	10	4	2.76	12	5	10.32
15	12	20	81.15	3	9	0.70	0	5	0.00
16	0	4	2.83	0	4	0.11	1	5	3.00
17	1	5	14.63	0	5	0.28	0	5	4.43
18	17	17	19.64	15	12	13.95	16	5	38.26
19	4	11	12.22	2	10	1.44	3	6	2.07
20	12	12	65.35	6	7	1.60	2	4	0.42
21	18	11	7.86	15	8	31.59	8	4	14.53

outdegree between k's Slice and the LAS. These two strong correlations (0.90 and 0.87) are derivative of the fact that i and j's perceptions are used to calculate the (i, j) link in both Slices and LAS.

Table 2
Correlations between different aggregations of same centrality measures

	Locally Aggregated			Consensus		
	Indg	Outdg	Betw	Indg	Outdg	Betw
k's Slice						
Indg	0.90			0.65		
Outdg		0.87			0.03	
Betw			−0.01			0.14
Locally aggregated						
Indg				0.82		
Outdg					0.35	
Betw						0.60

The betweenness scores, on the other hand, are not correlated between the Slices and LAS ($r = -0.01$), nor between Slices and the Consensus structure ($r = 0.14$). Interestingly, the betweenness scores in the LAS and Consensus structures are strongly related (0.60).

Another peculiarity is the discrepancy between agreements on indegrees and outdegrees in the three aggregations. All these structures indicate a good deal of overlap in assessment of whom is approached most for advice (indegrees), with the lowest correlation being 0.65 between CS and Slices. Yet, the agreement on who seeks advice most is considerably lower ($r = 0.35$ between CS and LAS; $r = 0.03$ between Slices and CS).

4.1. Perceptions of structure as a function of centrality

Another interesting question is whether the position of the individual in the network affects his/her perception of the network. For example, does a person who is highly "central" in the network have a different view of the structure than a person on the periphery? Are people who are more connected more likely to have a "consensual" view of the structure than those who are on the periphery (cf. Romney and Weller, 1984)?

To answer these questions, the relationship between k's centrality and k's view of the structure was explored. While measures of k's centrality have been well-defined here (see Table 1), the question of what is meant by "k's view of the structure" needs clarification. What is needed is a standard against which k's view can be compared. No behavioral data are available for these managers, and thus we cannot use behavior as a standard as Bernard, Killworth and Sailer did. We can, however, ask the question how does the manager's view differ from other managers' views. In particular, we can ask three questions: (1) Are k's self-claimed ties to others confirmed by those others? (2) Are the ties which k claims exist between other (i, j) dyads confirmed by those others (i and j) in the network? And (3), does k's picture closely correspond to the "norm"? Each of these questions is explored in detail below.

The first question is whether one's own ties to others (and from others) are confirmed by those others. That is, what percent of the people I claim I go to for advice agree that I come to them for advice? What percentage of the people I claim come to me for advice agree that

Table 3
Correlations between percent confirmed ties and centrality

Percent Confirmed Ties on	Centrality of k based on								
	k's Slice			Locally Aggr			Consensus		
	Indg	Outdg	Betw	Indg	Outdg	Betw	Indg	Outdg	Betw
Indegree	0.50	0.02	−0.05	0.72	0.12	0.58	0.59	−0.04	0.50
Outdegree	−0.46	−0.60	−0.32	−0.26	−0.23	−0.17	0.06	0.53	−0.01

they in fact do approach me? The former is the percent confirmed indegree ties, the latter is the percent confirmed outdegree ties. Since the LAS, in our present analysis, is based on confirmed local ties, then this percentage figure is simply calculated as:

$$\text{Percent Confirmed Indegrees}_k = \frac{\text{Indegree}_{\text{LAS}_k}}{\text{Indegree}_{\text{Slice}_k}},$$

$$\text{Percent Confirmed Outdegrees}_k = \frac{\text{Outdegree}_{\text{LAS}_k}}{\text{Outdegree}_{\text{Slice}_k}}.$$

Table 3 shows the correlation between k's position and the proportion of k's confirmed ties. One should note that these correlations are not based on independent measures. For example, since the percent confirmed indegrees is the ratio of LAS_k indegrees to k's Slice indegrees, then one should expect a positive correlation between the LAS indegrees and percent confirmed indegrees; conversely, we should expect a negative correlation between percent confirmed indegrees and the dominator, Slice indegrees. We should observe the same for percent confirmed outdegrees. In fact, we find that percent confirmed indegrees is strongly correlated with LAS indegrees ($r = 0.72$), but we also see that it is positively related to Slice indegrees ($r = 0.50$). This latter positive relationship is supported in the consensus structure as well ($r = 0.59$), where little a priori statistical confounding exists. Moreover, being positioned in the middle (i.e. having a high betweenness score) in the LAS and CS also predict one's confirmation rate ($r = 0.58$ and 0.50, respectively). In other words, one's ability to report indegrees which will be confirmed appears to be more a function of position (receiver of many requests for advice and high betweenness centrality) than statistical artifact.

The pattern for percent confirmed outdegrees is somewhat different. Interestingly, the numerator of the index, LAS outdegrees, is negatively (albeit not strongly) correlated with the index. The strongest predictor is the denominator, Slice_k, which is negatively correlated ($r = -0.60$) and could easily be due to methodological artifact. More interestingly, the percent confirmed outdegrees is positively related to CS outdegrees ($r = 0.53$). That is, if there is general consensus that one goes to many people for help and advice, then one is likely to have many of one's own outdegree nominations confirmed. It is as though a stereotype of being at the bottom (going to many others for help) gives rise to the expectation that one will go to particular individuals, and those individuals who are approached know it, confirm it.

But what predicts confirmation of ties *between all others* claimed by k (not just those ties k is connected to)? The answer, in part, depends on who is confirming the ties: the local dyad (i, j) or the group as a whole. In this case, we refer to the extent of confirmation of the entire set of ties as the degree of *agreement* with the structure, where the structure is defined as either the LAS (i.e. confirmed by the local dyads) or the CS (i.e. confirmed by the group as a whole). Agreement of k with the LAS structure is measured by correlating the $N \times (N-1)$ observations in k's Slice with the comparable observations in the LAS; agreement of k with the CS is similarly measured as the correlation between k's Slice and the CS.

These two agreement measures were correlated with each of the nine centrality measures (see Table 4). The only significant correlate with agreement with LAS is the betweenness of k in the CS ($r = 0.48$). That is, if k is in the middle of the consensus graph, then k is better able to reconstruct those advice relations which will be confirmed by the local dyads involved. What is particularly interesting here is that such CS

Table 4
Correlations between k's agreement with aggregated structures (LAS and Consensus Structure) and k's centrality

Agreement with	Centrality of k based on								
	k's Slice			Locally Aggr			Consensus		
	Indg	Outdg	Betw	Indg	Outdg	Betw	Indg	Outdg	Betw
LAS	−0.16	−0.22	0.03	0.15	−0.06	0.26	0.41	−0.08	0.48
Consensus	−0.52	−0.14	−0.08	−0.25	0.09	−0.13	0.12	0.08	0.18

centrality does *not* help in one's ability to reconstruct the CS ($r = 0.18$). The only reasonable predictor of one's ability to replicate the CS is one's own indegrees: the *fewer* people k believes approach him/her, the better k's picture agrees with the CS.

5. Conclusion

The above examples serve to point to the differences in the types and uses of aggregations one can derive from Cognitive Social Structures. This demonstration is by no means an attempt to be exhaustive of the possibilities for analysis, or even an attempt to guide the researcher in his/her analysis. Rather, it is hoped that this demonstration will spark interest, discussion, and expansion of questions and approaches to the study of social networks.

We started this paper by suggesting one response to the problem Bernard, Killworth and Sailer have exposed is to focus on the cognitive social structures as data in their own right, apart from their ability to mimic specific behaviors. Very little effort was made to ground the data presented here in behavioral terms. In fact, we are convinced by W.I. Thomas' logic. Perceptions are real in their consequences, even if they do not map one-to-one onto observed behaviors.

The veracity of this claim will depend on the results of empirical research, not on arguments made here or elsewhere. But the task of future research should not be to show that behaviors are more important than cognitions, nor that cognitions are more important than behaviors. Rather, our task will be to show the consequences of *each* – behavior and cognitions. In a step toward that goal, we have presented a way to model the cognitive social structure such that predictions on the cognitive side of this research can be formalized and pursued.

Appendix A

$$
\mathrm{LAS} = \begin{pmatrix}
010100000000000001001 \\
000000100000000000001 \\
110000101110010001001 \\
110000010110000001001 \\
110000100110010001111 \\
000000000000000000001 \\
010000000011010001001 \\
010100100110000001001 \\
110000100111010001001 \\
011100000000000001010 \\
110000100000000000000 \\
000000000000000000001 \\
110010001000010001000 \\
010000100000000001001 \\
110010001000010001111 \\
110000000100000001000 \\
110100100000000000001 \\
111100101110011000011 \\
110010100110011001010 \\
110000000010011001001 \\
011100100001010001010
\end{pmatrix}
\quad
\text{Consensus} = \begin{pmatrix}
010100000010000101000 \\
000100100000010001001 \\
010000100010010001000 \\
010000010000000001001 \\
010000100010010001000 \\
010000100001000000001 \\
010000000010010001001 \\
010100000000000001001 \\
010010000000010001100 \\
000000000000000001000 \\
010000100000010001000 \\
000001000000000000001 \\
010010001010010001100 \\
010000101000000001001 \\
010000000000010001110 \\
110100000100000001000 \\
010001100001000000001 \\
010000100110010000000 \\
010010000010010001010 \\
010000100000010001000 \\
010001100000010000000
\end{pmatrix}
$$

Slices:

$$
1 = \begin{pmatrix}
010100010000000101001 \\
100101110001000111001 \\
110000000111000011000 \\
110001010111000101001 \\
111000000110010111111 \\
111110011111111111111 \\
111011011110111111111 \\
100101100011000111011 \\
111011000010111111110 \\
001010011010111101110 \\
111010111000111101110 \\
110101010000011011011 \\
111011001110011111110 \\
111011111111101111111 \\
111011001010110111111 \\
110101010100000001010 \\
111110111011111101111 \\
111010111111111100111 \\
111011001110111111010 \\
111111011111111111100 \\
010001110001010011000
\end{pmatrix}
\quad
2 = \begin{pmatrix}
011100000010000101000 \\
000001100000000000001 \\
110001100000010000001 \\
110000010001000101001 \\
110000100000010101011 \\
010100000010000000001 \\
010000000000000000001 \\
110100000000000001001 \\
110000000000010001010 \\
010000010000000101000 \\
110000110000000001000 \\
010101000000000000001 \\
110010100000010001110 \\
010000100000000000001 \\
110011000000010001111 \\
110100010000000001000 \\
010001000000000000001 \\
110001100010000100001 \\
110000000000010000010 \\
110101100000010101001 \\
010001100000000000000
\end{pmatrix}
\quad
3 = \begin{pmatrix}
011010000010110001100 \\
101111110011110011101 \\
110101111111010011011 \\
010001110000000000000 \\
110000100010010011000 \\
010100100001010010011 \\
011101010010010011011 \\
011000000110010001001 \\
001010000000110000100 \\
011010110010110101110 \\
111010110100110001100 \\
010101110000010001001 \\
110000000010010001000 \\
011011111111101011111 \\
010000100010010001000 \\
000000000110010001000 \\
011011110001110001101 \\
011010110110110100100 \\
110000110110010011010 \\
011011000000110000100 \\
011101110001010010000
\end{pmatrix}
$$

$$
4 = \begin{pmatrix}
011110010110100111100 \\
100101110001010111001 \\
110000000000010000000 \\
110001010111000111011 \\
110000000010110001100 \\
110100100001000100001 \\
010001000000010011011 \\
011100100101000011011 \\
001010100000110000100 \\
111100010010000101000 \\
110110110000110001000 \\
010101010000000000001 \\
111010000000010101110 \\
011011101000101001111 \\
110010011100110101110 \\
111100010100000001000 \\
110101110001010001001 \\
111111110111110110111 \\
111010100110110101000 \\
111101110101011101000 \\
010101110001010011010
\end{pmatrix}
\quad
5 = \begin{pmatrix}
011110010110100101100 \\
101110110100110111101 \\
010010110100010101101 \\
110001110000000001001 \\
110001110110110111111 \\
010000100001010010001 \\
010001000000010001001 \\
110100100010000101001 \\
010010100000111011110 \\
010000110000000101010 \\
111010110000111001100 \\
010001110000010001001 \\
110010111110011001001 \\
010001100010000001001 \\
010010100010010001100 \\
110100010100000001000 \\
111011110001111000101 \\
000000000000000000000 \\
111010110110111111011 \\
010001110110111101100 \\
010001110001010011000
\end{pmatrix}
\quad
6 = \begin{pmatrix}
010000000000000001000 \\
000000100000000000001 \\
000000100000010000000 \\
010000010000000000001 \\
000000100000010000001 \\
000000000000000000001 \\
010000000000010000001 \\
000000100000000000001 \\
000000000000010000001 \\
000000100000000001000 \\
000000100000000001000 \\
000001100000000000001 \\
000010000000010000100 \\
000000100000000001001 \\
000000000000010001001 \\
010000000000000001000 \\
000001100000000000001 \\
001000100000010000001 \\
000010100000010000000 \\
000000100000010000001 \\
000000100000000000000
\end{pmatrix}
$$

$$
7 = \begin{pmatrix}
010100010010000111000 \\
101101110011010111001 \\
000001100010010011001 \\
010001010000000011000 \\
010001100010010011000 \\
010100100000010010001 \\
010001000011010011001 \\
010100100010000011001 \\
010001100010010011000 \\
000001000000000011000 \\
010001100000010011000 \\
000101010000000010001 \\
000001100010010011000 \\
111111111111101011111 \\
000001000000010011010 \\
110101010100000010010 \\
010000100000010001001 \\
111101110110010110011 \\
110001100000010011000 \\
010001000000010011000 \\
010001110001010010000
\end{pmatrix}
\quad
8 = \begin{pmatrix}
011000000110000101000 \\
000000100000010000001 \\
110000000110010001000 \\
110000010101000001001 \\
011000101000110000101 \\
010000100001010000001 \\
010000000010010001001 \\
010101100110000001001 \\
011010100000010001101 \\
011000100000000101000 \\
011000100000010001000 \\
010101000000000000001 \\
011010101010010101100 \\
011010101000100001101 \\
010010100010010101100 \\
110100000110010001000 \\
010001100001000000001 \\
010000100110010000000 \\
011010101010010001000 \\
011010101000010101000 \\
010001100000010000000
\end{pmatrix}
\quad
9 = \begin{pmatrix}
011010011110101001100 \\
101110111000111001101 \\
110000101110010001000 \\
110001010000000000000 \\
110000100010000010010 \\
000100011001000000001 \\
011010001000011001101 \\
010000001001000000001 \\
110001110111010111001 \\
001010000000100001100 \\
011010100000111001100 \\
000101000000000010001 \\
110010101010010001100 \\
010000101010001001011 \\
010000101010010001010 \\
110100000100000000000 \\
010011000001110000101 \\
010000101010010000010 \\
110000100010010001010 \\
010010100010111001100 \\
011000100000010010000
\end{pmatrix}
$$

$$10 = \begin{pmatrix} 010100000110000001000 \\ 100100110110010011000 \\ 010000100110010001000 \\ 000000010111000001000 \\ 001000000110010001110 \\ 000000110001000010001 \\ 010000000010010001001 \\ 010000000110000001000 \\ 001010000100011001100 \\ 111110010010101111110 \\ 110100110100000001000 \\ 000101110000000010001 \\ 000010000110011001100 \\ 000010101000101001110 \\ 000010101000010000110 \\ 010100010100000001000 \\ 010001100001000000001 \\ 111110110111111110110 \\ 001010001110011001010 \\ 000000100111010001000 \\ 010001100001010011000 \end{pmatrix} \quad 11 = \begin{pmatrix} 010100000110000101000 \\ 000101100111000101001 \\ 000000100010010000000 \\ 000000010110000001000 \\ 000000100010010000100 \\ 000000100000000000001 \\ 010000000010010000001 \\ 000100000110000000000 \\ 010000000110010001000 \\ 000000110000000000000 \\ 110000100000000000000 \\ 000000100000000000001 \\ 000010000010011000100 \\ 010000000010000001000 \\ 000000100000010001000 \\ 010000000000000000000 \\ 000000100010000000001 \\ 010000100110010000000 \\ 010010000010010000000 \\ 010000000110010001000 \\ 000000100000000000000 \end{pmatrix} \quad 12 = \begin{pmatrix} 010100000000000101000 \\ 000101100001010000001 \\ 000000000000010000000 \\ 010000010000000000001 \\ 010000100001010001101 \\ 010000100001000010001 \\ 101111011111111111111 \\ 110101100001000011001 \\ 011011100001110001101 \\ 110000100010000101010 \\ 000000100000000001000 \\ 000000100000000000001 \\ 110010000010010001110 \\ 010000100000000000001 \\ 010000100000010001000 \\ 110100000000000001000 \\ 010001100001010000001 \\ 010000100010010000001 \\ 011010100000011001010 \\ 111110100010110101101 \\ 000000100001010010000 \end{pmatrix}$$

$$13 = \begin{pmatrix} 010000000010000001000 \\ 000000100000000001000 \\ 010000000010010001000 \\ 010000000000000001000 \\ 000000000000010001000 \\ 000000100000000000001 \\ 000000000000010000001 \\ 000001100000000000001 \\ 000000100000010000000 \\ 000000100000000001000 \\ 000000100000000001000 \\ 000001000000000000001 \\ 110010001000010001000 \\ 000000100000000000000 \\ 000000000000010000000 \\ 010000000000000001000 \\ 000001100000000000001 \\ 100001000000000000000 \\ 010000000000010001000 \\ 010000000000010000000 \\ 000000100000000000000 \end{pmatrix} \quad 14 = \begin{pmatrix} 010011001000110101100 \\ 000000100000010000001 \\ 010010001000010000101 \\ 000000000000000000000 \\ 111101111111111111111 \\ 010000100000010000001 \\ 010001000000010001001 \\ 111001100010010101001 \\ 110010100000111001111 \\ 000000000000010001000 \\ 000000100000010001000 \\ 010000100000010000001 \\ 100010001000010101100 \\ 010000100000000001001 \\ 010000100000010001110 \\ 100100010000010001000 \\ 111111111111111101111 \\ 010000100100011000000 \\ 000000000000010001010 \\ 000010101000011001100 \\ 011000100000010000000 \end{pmatrix} \quad 15 = \begin{pmatrix} 010000000010001001000 \\ 100010100000011001100 \\ 010000100000011001000 \\ 010000010000000000001 \\ 010000100010011001110 \\ 000010100000011010101 \\ 010000000000010000001 \\ 000000000000000000001 \\ 000000000000011000000 \\ 000000000000000001000 \\ 010010100000011001100 \\ 000001000000000000001 \\ 000010001000011000100 \\ 011010101000001001111 \\ 111111111111110111111 \\ 010000000000000000000 \\ 000001000000000000001 \\ 000000100010011010000 \\ 000010000000011000000 \\ 000000000000011000000 \\ 010000100000010000000 \end{pmatrix}$$

$$
16 = \begin{pmatrix}
010000000000000001000 \\
000000100000000001001 \\
010000000000010001000 \\
010000010000000000000 \\
010000000000010001000 \\
000000100000000000001 \\
000000000000000000001 \\
010000000000000000001 \\
000010000000010000100 \\
000000000000000001000 \\
000000100000000001000 \\
000000100000000000001 \\
000010001000010000100 \\
000000100000000000001 \\
000000100000010000000 \\
110000000100000001000 \\
010000000000000000001 \\
010000100000000000000 \\
000010000000010001000 \\
000010000000010001000 \\
000000100000000000000
\end{pmatrix}
\quad
17 = \begin{pmatrix}
010000000000000000000 \\
100000100000000000000 \\
000000100000010000000 \\
010000000000000000000 \\
000000000000010000000 \\
000000000001000000001 \\
010000000000010001001 \\
110100000000000000001 \\
000000000000010000000 \\
000000000000000001000 \\
000000100000000001000 \\
000100000000000010000 \\
000000000000010000000 \\
010000100000000001001 \\
010000000000010000000 \\
010000000000000000000 \\
110100100000000000001 \\
010000100000000000001 \\
000000000000010000000 \\
000000000000010000000 \\
010000100000000000000
\end{pmatrix}
\quad
18 = \begin{pmatrix}
010100000010000101000 \\
101111111111110101101 \\
110000100110010101000 \\
110000000110000101001 \\
000000000010010001000 \\
010000100000000000001 \\
010000000011010001011 \\
010100100110000001001 \\
010000000000010001000 \\
001000000010000101000 \\
110000000100010001000 \\
000001000000000000001 \\
000010101110010001110 \\
010010101110001001111 \\
010000000000010001110 \\
110000000100000001000 \\
000000100000000000001 \\
111110111110111100111 \\
011010001110110001000 \\
010010001110011001101 \\
010001100001010001000
\end{pmatrix}
$$

$$
19 = \begin{pmatrix}
010100110000000101000 \\
001000100000010001000 \\
010000100000010001000 \\
110000000000000100000 \\
010000100010010001110 \\
000000100001000010001 \\
011000000010010000001 \\
110000000000000001000 \\
000010000000011000110 \\
000000000010000001000 \\
010000100000010000000 \\
000001000000000010001 \\
010010101010010001110 \\
011000100010000001000 \\
010000000010010001110 \\
110000000000000001000 \\
010001100001000000001 \\
111000100110010000000 \\
111010100110011001010 \\
010000100110010001000 \\
010001100000010000000
\end{pmatrix}
\quad
20 = \begin{pmatrix}
010000000000000000000 \\
000000100000010001000 \\
010000000010010001000 \\
010000000000000000001 \\
000000000000010001010 \\
000000100000000000001 \\
000001000010010000010 \\
010000000000000001001 \\
000000000000010000010 \\
000000000000000001010 \\
010000100000000001010 \\
000000000000000000001 \\
000000000000010001010 \\
001010101000100001111 \\
000000000000010001010 \\
010000000000000000000 \\
101001100001000001011 \\
010000110010010100011 \\
000000000010010001010 \\
110001010011011111001 \\
010100100001010010010
\end{pmatrix}
\quad
21 = \begin{pmatrix}
011100010010000001001 \\
001100110010010101001 \\
110100000110010001011 \\
110001010001000001001 \\
010000000000010001011 \\
010100010001000010001 \\
011000000010010011001 \\
011101000111000111001 \\
111011010011010111101 \\
010100110010000001000 \\
111100110000000001001 \\
010101010000000010001 \\
011010001000010001110 \\
011010111011001011111 \\
010010001000010001111 \\
111101010110000011011 \\
010001110001010000001 \\
111101110110010010011 \\
011010000010011011011 \\
111111111111111111101 \\
011101110001010011010
\end{pmatrix}
$$

References

Allen, Robert
1978 "Study on the choice of targets to influence in organizations". Unpublished doctoral dissertation, University of California, Irvine.

Anderson, John R.
1980 *Cognitive Psychology and Its Implications*. San Francisco: W.H. Freeman and Company.

Asch, S.E.
1951 "Effects of group pressure upon the modification and distortion of judgments". In Harold Guetzkow (ed.) *Groups, Leadership and Men*. New York: Russell and Russell.

Bernard, H.R. and P. Killworth
1977 "Informant accuracy in social network data II". *Human Communications Research 4*: 3–18.

Bernard, H.R., P. Killworth and L. Sailer
1979 "Informant accuracy in social network data IV: A comparison of clique-level structure in behavioral and cognitive network data", *Social Networks 2*: 191–218.
1982 "Informant accuracy in social network data V: An experimental attempt to preduct actual communication from recall data". *Social Science Research 11*: 30–66.

Bernard, H.R., P. Killworth and L. Sailer
1984 "The problem of informant accuracy: The validity of retrospective data. *Annual Review of Anthropology 13*: 495–517.

Burt, Ronald S.
1982 *Toward a Structural Theory of Action*. New York: Academic Press.

Burt, Ronald S. and William M. Bittner
1981 "A note on inferences regarding network subgroups". *Social Networks 3*: 71–88.

Cartwright, D. and F. Harary
1956 "Structural balance: A generalization of Heider's theory". *Psychological Review 63*, 277–293.

Davis, J.A. and S. Leinhardt
1972 "The structure of positive interpersonal relations in small groups". In J. Berger, M. Zeldith, Jr. and B. Anderson (eds.), *Sociological Theory in Progress*. New York: Houghton-Mifflin.

De Soto, Clinton B.
1960 "Learning a social structure". *Journal of Abnormal Psychology 60*: 417–421.

Freeman, Linton, C.
1977 "A set of measures of centrality based on betweenness". *Sociometry 40*: 35–41.

Freeman, Linton, C.
1979 "Centrality in social networks: Conceptual clarification". *Social Networks 1*: 215–239.

Freeman, Linton, and A. Kimball Romney
1986 "Words, deeds and social structure". *Human Organization,* January.

Freeman, Linton C., A. Kimpball Romney and Sue Freeman
in press "Cognitive structure and informant accuracy". *American Anthropologist*.

Freeman, Sue
1986 "Structural complexity and the recall of events". Paper presented at the Sunbelt Social Network Conference, Santa Barbara, February.

Heider, F.
1958 *The Psychology of Interpersonal Relations*. New York: John Wiley.

Holland, P.W. and S. Leinhardt
1971 "Transitivity in structural models of small groups". *Comparative Group Studies 2*: 107–124.
1976 "Conditions for eliminating intransitivities in binary digraphs". *Journal of Mathematical Sociology 4*: 315–318.

Hubbell, Charles H., Eugene C. Johnsen and Marvin Marcus
1975 "Structural balance in group networks". Institute for the Interdisciplinary Applications of Algebra and Combinatorics Monograph Series, Vol. 2, Santa Barbara: University of California.
Johnsen, Eugene C.
1985 "Network macrostructure models for the Davis–Leinhardt set of empirical sociomatrices". *Social Networks 7*: 203–224.
1986 "Structure and process: Agreement models for friendship formation". *Social Networks 6*: 257–306.
Jones, E., D. Kanouse, H. Kelley, R. Nisbett, S. Valins and B. Weiner
1971 *Attribution: Perceiving the Causes of Behavior*. Morristown, New Jersey: General Learning Press.
Kahneman, D., P. Slovic and A. Tversky
1982 *Judgment Under Adversity: Heuristics and Biases*. Cambridge: Cambridge University Press.
Killworth, P. and H.R. Bernard
1976 "Informant accuracy in social network data". *Human Organization 35*: 269–86.
1979 "Informant accuracy in social network data III: A comparison of triadic structures in behavioral and cognitive data". *Social Networks 2*: 19–46.
Krackhardt, David and Martin Kilduff
1986 "Culture, cultural construals and social networks: The task of organizing diversity". Paper presented at the 50th Annual National Meeting of the Academy of Management, Chicago.
Krackhardt, David and Lyman W. Porter
1985 "When friends leave: A structural analysis of the relationship between turnover and stayers' attitudes". *Administrative Science Quarterly 30*: 242–261.
Lawler, Edward E. III, Lyman W. Porter and A. Tenenbaum
1986 "Managers' attitudes toward interaction episodes". *Journal of Applied Psychology 52*: 432–439.
Moreno, J.L. (ed.)
1960 *The Sociometry Reader*. New York: Free Press.
Newcomb, Theodore M.
1961 *The Acquaintance Process*. New York: Holt, Rinehart and Winston.
Posner, M.I. and S.W. Keele
1968 "On the genesis of abstract ideas". *Journal of Experimental Psychology 77*: 353–363.
Roethlisberger, F.J. and W.J. Dickson
1939 *Management and the Worker*. Cambridge, MA: Harvard University Press.
Romany, A. Kimberly, Susan Weller and William Batchelder
1986 "Culture as consensus: A theory of culture and informant accuracy". *American Anthropologist 88* (2): 313–338.
Romney, A.K. and K. Faust
1982 "Predicting the structure of a communications network from recalled data". *Social Networks 4*: 285–304.
Romney, A.K. and S.C. Weller
1984 "Predicting informant accuracy from patterns of recall among individuals". *Social Networks 6*: 59–77.
Sampson, S.F.
1968 "A novitiate in a period of change: An experimental and case study of social relationship". Unpublished doctoral dissertation, Cornell University.
Volkart, E.H.
1951 *Social Behavior and Personality*. New York: Social Science Research Council.
White, Douglas R. and Karl P. Reitz
in press "Rethinking the role concept: Homomorphisms on social networks". In Linton C. Freeman, Douglas R. White and A. Kimball Romney (eds.), *Research Methods in Social Network Analysis*.