

# **Nodal and Matrix Analyses of Communication Patterns in Small Groups**

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**Abstract:** This paper describes an analytic framework based on the methods of social network analysis pioneered by Nieminen (1974) and Freeman (1978/79) and used by structural anthropologists (e.g., Hage and Harary, 1996). It extends the methodology for use in evaluating computer-mediated communication in small groups and analyzes a sample dataset drawn from synchronous chat room interaction of five adults involved in a process of decision-making. The paper concludes with a discussion of possible applications of social network analysis to computer-supported learning, and limitations.

**Keywords:** computer mediated communication, evaluation

## **Introduction**

In educational and work settings, people form groups to foster the dispersion of existing expertise and to accelerate the generation of new knowledge. Some groups interact in ad hoc fashion, while in others, the pattern of activity is structured. Examples of purposefully engineered groups include Jigsaw (Aronson, 1978) Group Investigation (Sharan & Sharan, 1992) and PIES (Kagan & Kagan, 1998).

When investigating group interaction, instructors, researchers and designers of instructional environments have reason to describe or visualize the qualities of interaction among group members. They may also wish to quantify the number and types of interactions that take place among group members. This paper focuses on the latter interest, by describing a means of assessing patterns of interaction among group members. This method detailed in this paper is not meant as a substitute for qualitative analysis, but as a supplement to it. Additionally, the method may prove useful when put to use as a "sensor" in online learning communities, to help moderators, instructors or students themselves determine if certain group interactions are educationally desirable.

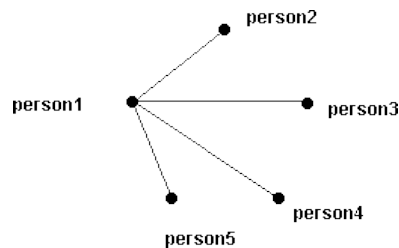
The idea of quantifying interactions among members of small groups is not new. For instance, Lotan, Cohen and Morphew (1998) suggest that simply counting the number of interactions among participants in a learning environment may help designers assess the success of group-work interventions. This paper expands on this idea by describing models of group interaction and means for assessing data streams' fit to these models. These models may be particularly useful for those interested in assessing interaction among members of online learning environments for the purposes of improving that interaction.

The paper is organized in the following way. First, we review two ways of representing patterns of interaction among members of groups: nodal networks and interaction matrices. We then describe a measure introduced by Nieminen (1974) and Freeman (1978/79) called *degree of adjacency* that is useful for describing the centrality of group members. After this, we discuss two network models...a "star" network (Freeman, 1978/79) and an "all-channel" network, and review how these models relate to social roles in learning environments. Finally, we conduct a sample analysis, discuss how such analyses might be useful, and describe limitations.

## Representing Networks

To represent relations between members in a group, Freeman (1978-79) used nodal networks, where a node or point represents each member of the group, and lines signify bi-directional connections between them. The figure below represents one of thirty possible models for five-person "transaction" networks identified by Freeman, where all connections funnel through a single node:

Figure 1. One of Freeman's (1978-79) thirty possible five-node transaction networks.



This particular network has one very interesting property. Four of its nodes (persons 2, 3, 4 and 5) are terminal points. This leads to inequality in the number of connections that each point holds. Borrowing from Nieminen (1974), Freeman (1978/79) refers to this quantification of connections as *degree of adjacency*, often represented as  $C_D(P_k)$ , which refers to the number of connections to a node ( $P_k$ ), and "is viewed as important as an index of its potential communicative activity." (Freeman, 1978/79, p. 221.) In the graphic above, person 1 is the most central member of our five-person group, since this person shares more connections than others do.

In addition to nodal diagrams, networks may also be represented in matrix form, with [1] representing the existence of links or connections between person-nodes, and [0] as their absence. More formally,  $C_D(P_k)$  may be expressed as:  $C_D(P_k) = \sum a(p_i, p_k)$ . Here,  $a(p_i, p_k)$  simply refers particular cells in a matrix defined by the networks' nodes. In such a matrix,  $a(p_i, p_k) = 1$  if  $p_i$  and  $p_k$  are connected in graph form. In the case of nodes 1 and 5, there is a connection, so  $a(p_i, p_k) = 1$ . If there is no connection, as is the case between nodes 4 and 5 in our network, then  $a(p_i, p_k) = 0$ . Following this,  $\sum a(p_i, p_k)$ , or  $C_D(P_k)$ , is simply the sum of row entries. So, the matrix in Table 1 below re-represents the information from our nodal diagram (Figure 1):

Table 1. Matrix with an adjacency ( $C_D(P_k)$ ) calculation for Freeman's "star" network.

	1	2	3	4	5
1	0	1	0	0	0
2	1	0	0	0	0
3	0	0	0	1	0
4	0	0	1	0	0
5	0	0	0	0	0

Now let us visualize another network. The five nodes below are fully-connected, or as Freeman (1978/79) described, "all-channel."

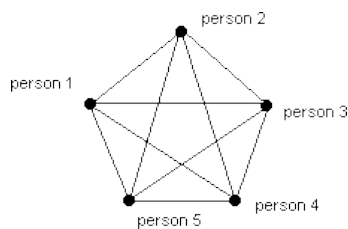


Figure 2. Freeman's "all-channel" network.

We when we compute adjacency measures for the net, we see that it has a higher total degree of adjacency, and that the connections are equally distributed.

Table 2. Matrix for Freeman's "all-channel" network.

	1	2	3	4	5
1	0	1	1	1	1
2	1	0	1	1	1
3	1	1	0	1	1
4	1	1	1	0	1
5	1	1	1	1	0

These representations of network interactions relate to theoretical approaches to learning. For instance, the pattern shown earlier in Figure 1 is consistent with the transmission model of learning, where information flows almost exclusively from one resource. On the other hand, the "all-channel" or fully-connected model is suggestive of some models of cooperative learning. Interestingly, both the star and all-channel models may be consistent with dynamic models of participation, such that proposed by Lave (1991) and Rogoff (1990). Here, learners have peripheral roles early on, but under guidance of an expert other (or others) gain increasingly legitimate roles in the social structure.

How might apprenticeship and increasingly legitimate participation manifest themselves in these sorts of networks? Possibly, in the initial stages (time 0) of an apprenticeship situation, the interaction patterns might more closely resemble a "star" representation—they would hold fewer degrees of adjacency. As time passes (time1, time2, etc), students' participation shifts from peripheral to central, degrees of adjacency would likewise increase.

## Analysis of Online Data

We turn now to the analysis of interaction data captured from an online chat room. Two university professors and three graduate students used this "virtual" communication medium as they discussed the design of an instructional environment in late 1998. This exchange consisted of 94 interactions among the five participants.

Let us explore the question of whether all group members are equally participating in a small group. One way to approach this is to ask if the pattern of interactions conforms to the pattern of Freeman's all-channel five-node network. In this ideal network, the pattern of interaction among group members is symmetrical and equal. Since we know the number of total interactions among group members (94), we can compute the expected values for each cell (Table below).

Table 3. Expected cell values for 94 interactions, given an "all-channel" network.

[illegible]

In the matrix above, antecedent behavior is marked by columns; subsequent behavior in rows. Therefore, the cell in Table 3 above in bold may be read, "LindaL responds to FredM 4.7 times."

In fact, as the actual data presented in Table 4 below shows, LindaL responded 12 times to utterances made by FredM, the largest number of responses in this dataset. (Note: seven utterances in which persons "responded to" themselves were eliminated from the data trace.) At the other extreme are the patterns of interaction centering on KarenH; her five utterances—the smallest gross number in the group—were followed by utterances from JeffR.

Table 4. Actual cell values for 94 interactions.

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78	79	80	81	82	83	84	85	86	87	88	89	90	91	92	93	94	95	96	97	98	99	100
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To compute degree of adjacency ( $C_D(P_k)$ ), we can convert the data matrix in Table 4 above to a table of binary responses. We do this by assigning all non-zero data in the table a "1." Summing across rows, we find that that degree of adjacency for this data is different from that expected in an all-channel net, where the vector would be [4,4,4,4,4]:

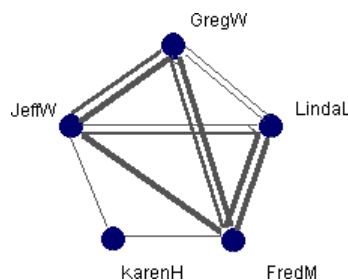
Table 5. Matrix and adjacency ( $C_D(P_k)$ ) calculation for binary data.[illegible]

We can also test the data to determine if there is a statistical difference between the actual data and that expected under the hypothesis that the group performed as an all-channel network. Indeed, a one-sample t-test of expected minus actual responses rejects the null hypothesis of no difference between expected values and actual values,  $p < .000001$ . In other words, if we take communicative interaction as proxy for network adjacency, then this group did not function in a way consistent with Freeman's all-channel network during the period observed.

Visual inspection of the matrices in Tables 4 and 5 does little to disconfirm the statistical result. Looking across the bottom row and last column of the matrix, we see that KarenH’s participation is marginal.

The story seems even more straightforward when we represent the connections in the form of a weighted graph. Here, connections between members are drawn as lines in the direction of their flow. The lines are weighted to reflect relative connection strengths, with darker lines reflecting more responses. Absence of lines means no interaction.

Figure 3. Interaction paths for actual data presented in Table 4 above.



In examining this graph, three points strike especially hard: KarenH appears to be very weakly connected to the group, having connections with only two of its members. Also, the relationship between GregW and LindaL is not particularly strong. Finally, FredM appears to be the most central member of the group, with the heaviest lines connecting him and three of the group's four other members. Interestingly, these visual patterns resonate with reality: FredM, in addition to being the group member with the strongest communicative connections, was also its leader. KarenH was one of the three graduate students in the group and by far the most junior.

## **Applications**

Let us put aside our roles as researchers and designers of online learning environments. If we imagine for a moment that we are instructors concerned with facilitating the interactions within networks of students, the absence of all-channel group interaction might be a problem to solve, rather than a mere curiosity. The nodal and matrix representations of patterns of group interaction, along with the statistical analysis of these patterns, might prove as useful screening devices, if they were part of a real-time or near-real-time social network analysis toolkit. Instructors could use a social-network analysis to analyze whether or not work- and learning groups were functioning appropriately, given a particular model of learning. Student teams could likewise access the tool to self-assess their communicative processes. While it is beyond the scope of this paper to describe the implementation of such a tool, its design follows directly from the principles outlined in this paper.

## **Limitations**

While the methods described in this paper (and proposals for tools based upon them) may well hold potential, it is important to understand their limits. Absent some understanding of the actual relationships among group members, knowledge of communicative structure of the group may not be particularly useful. Indeed, it may be misleading. For instance, in the case given above, KarenH's lack of participation might be perfectly appropriate given her status as "junior" graduate student. Were she a facilitator who was "fading" her influence on the group, in a manner consistent with the cognitive apprenticeship model of Collins, Brown and Newman (1989), her level of participation might also be appropriate. The point is that these judgements cannot be made in the absence of richer data about who KarenH is and her role in the group. The methods described here give us little purchase on that problem. Still, in combination with richer data, this approach may prove useful.

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