

Social Networking in Organizations: The Network-Centric Organization

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INTRODUCTION

Organizations have long relied upon their formal structures (management direction), functional divisions of labor, and happenstance interactions for their members to develop and extend their *intensional* networks [2] in the conduct of their work. As organizational work becomes increasingly distributed across spatial, temporal, and organizational boundaries, formal structures, functional divisions of labor, and reliance on happenstance interactions become impediments to the development of such networks as resources for collaboration and work among its members.

My dissertation is titled “Uncovering the Network-Centric Organization” and reports on a 20-month study of a highly-distributed, ~125-person Division of a Fortune 100 aerospace corporation based on 31.5 hours of interviews, archival records, and – principally – 397.8 person-hours of recorded audioconference discussions (35 audioconferences involving an average of 12.6 participants each and averaging 54.1 minutes in duration). The collective transcript of these discussions (including codes embedded under a Grounded Theory approach) captures 18,345 individual utterances, only 227 of which I could not attribute to a specific person.

My approach to this research is grounded in social network theory, as applied to distributed work. The rationale for engaging remote organizational members in collaborative work is to make it possible – in theory – to draw from the expertise and experience of all organizational members. A Division with 125 members has 15,500 possible configurations of network ties for each collaborative interaction. I employ both qualitative (ethnography, Grounded Theory categorization) and quantitative methods (statistics, social network analysis) to uncover what factors drive the specific collaborative interactions observed. From these factors, and drawing from the research literatures of distributed work, social/organizational networks, and sensemaking theory, I am developing a model for a “network-centric” organization (defense planned for December 2008) which extends existing definitions of “network-centricity” beyond the scope of technological networks in organizations to facilitate the activation of social networks in the accomplishment of work.

For the rest of this position paper, I will describe two aspects of my dissertation research which appear particularly relevant for this workshop.

QUALITATIVE FINDING

Social networking systems fundamentally depend on facilitating social choices for interaction among people. They are of organizational interest to the extent they promote effective collaborations among people engaged in the conduct of their work. These systems enable their users to construct and publish an *identity* based on information each user wants other people to know about her/himself. On the basis of such identities, other people can make social choices to form an interactive relationship with a person. These systems also make visible such relationships as a form of *reputation* (what others know about a person and can share with others). In these systems, such choices are generally driven by affect generated in their offline lives or perceived homophily based on shared interests.

Organizational networking systems have additional sources of information which can contribute to the development of reputation among their members. My data includes discussions of social choices by a group assigning work to individuals and by individuals selecting their own set of collaborators for work activities. From this data, I have identified five types of reputational information used, and shared with others, to make these social choices. These types are:

- **Functional:** the nature of a person’s job, usually reflecting experience and expertise (no surprise, I know) relevant to the work to be accomplished. Several choices were made on the basis of low experience/expertise, e.g., “to give him a chance to learn about the needs of (two other subdivisions).”
- **Availability:** current situational factors in a person’s worklife (e.g., workload, vacation, medical leave, imminent deadlines, etc.) and homelife (primarily familial responsibilities with regard to children and parents) affecting their capacity to do the work at the time needed, e.g., “(He) just had a baby so let’s not take away from his sleep time at work (laughs).”

- **Coordinational:** evidence of superior understanding of how to get work done within the organization: e.g., "(I chose her) because she really knows the ins and outs of this stuff ... who does what and when ... and I wanted to make sure it was done right."
- **Responsiveness:** evidence of adherence to agreed-upon schedules for work deliverables, and timeliness of responses to emails, phone calls, etc.: e.g., "I wanted (name) but there's some urgency and he takes forever to get back to me."
- **Citizenship:** willingness and capacity to work for the organizational good without direct responsibility or benefit: e.g., "I like to have (name) or (name) ... they don't know anything about this stuff (but they) point out the language that doesn't make sense to them".

Collectively, these types of reputation constitute what I term “collaborative appeal” in making social choices about potential work partners when circumstances afford a choice.

QUANTITATIVE METHOD

One of the challenges of analyzing “real world” social networks is the complexity of networks constructed from such data. While node-level metrics (e.g., the several forms of centrality) and network-level metrics (e.g. size, density, centralization, etc.) can be calculated, network analysts also rely on visualizations for meaningful interpretations. Network hubs (with high degree), for example, were identified in network visualizations before the discovery of power laws and scale-free networks gave increased understanding of their role in real-world networks.

Traditional sociograms quickly become difficult to interpret meaningfully, so a means of decomposing them and visualizing the resulting parts in a meaningful way is useful. For my dissertation research, I am applying spectral analysis to sociomatrixes constructed from the transcript data described earlier and visualizing the results via the Open Source R statistics environment.

Spectral analysis is an eigendecomposition method suitable for large one-mode networks. Other eigendecomposition methods include factor analysis, principal components analysis, correspondence analysis, etc. Eigenvector centrality is a network-equivalent of these methods. However, these methods typically only utilize the largest-magnitude (“principal”) eigenpair¹ and often transform the data to eliminate negative eigenvalues. Spectral analysis, on the other hand, does not transform the data and does not limit its analysis to a single eigenpair. Instead it preserves

¹ An eigenpair is the combination of an eigenvalue and its associated eigenvector. The eigenvector centrality of a network node is its value in the eigenvector associated with the largest eigenvalue after decomposition. The sign of an eigenpair is determined by the sign of its eigenvalue; the “intensity” of an eigenpair is reflected by the absolute value of the eigenvalue.

the entire dataset encoded into the original sociomatrix, partitions the network data in meaningful ways, and enables the partitions to be easily visualized to facilitate analysis.

The importance of not transforming the data lies in the relatively recent recognition that positive eigenvalues are associated with *clustering* effects in networks and negative eigenvalues are associated with *bi-partitioning* effects. The interpretation of these effects, in the context of interaction and collaboration provide information pertinent to reputation and collaborative appeal.

Nodes identified by partitions of positive eigenpairs reveal organizational members who interact/collaborate with each other at a similar “intensity,” reflected by the relative magnitude of the relevant eigenvalue. Nodes identified by partitions of negative eigenpairs reveal organizational members who have similar patterns of interactions/collaborations with other members, at a similar intensity, but *not* with each other. Network models based on transitive closure (e.g., “the friends of my friends become my friends”) suggest that people who interact/collaborate with the same people ought to interact/collaborate with each other. Network models based on structural holes theory suggest negative eigenpairs reflect asymmetries in some organizational aspect (e.g., power, information flow, rank, trust, etc.). In either case, information is revealed which can contribute to each individual’s *collaborative appeal*.

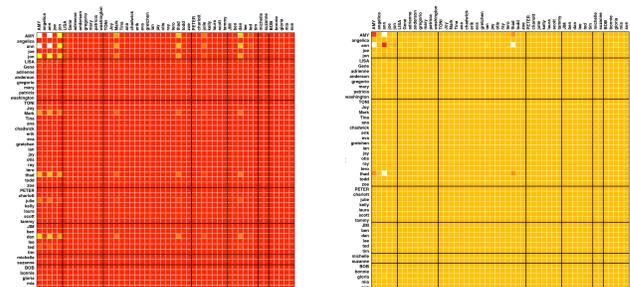


Figure 1. Example visualization of principal eigenpairs, positive (left) and negative (right). Zoom to view. Positive eigenpairs identify individuals through high values in the matrix cell at the intersection of their names. Negative eigenpairs identify individuals by a characteristic square pattern of high values at the NE and SW corners of the square and low values at the NW and SE corners.

To illustrate how such eigendecompositions can be usefully visualized, Fig. 1 shows “heat map”-style visualizations (albeit limited here due to space constraints) of two eigenpairs of teleconference interaction data. The white/yellow-colored matrix cells identify the highest values of collaborative interaction; reds identify minimal at this intensity to low values. The black lines were manually added to identify functional sub-divisions in the organization. The different eigenpairs identify different (though possibly overlapping) subsets of organizational members at different levels of interaction.

The network data visualized in Figure 1 is derived from the 35 weekly teleconferences in which Division members engage in consensual, collective sensemaking about how the Division will operate in the future as it incorporates more and more facilities distributed around the world. These teleconference loosely follow an announced agenda, but Division members at all levels are permitted to contribute to the discussion and deviations from the agenda for substantive discussion of non-agenda topics is encouraged. The 18,345 individual contributions to the discussions were grouped together into 2,935 “multi-interacts” in which 2-11 people co-contribute to discussion of a particular issue. For each multi-interact, a network “tie” is created among all co-contributors (a “clique”) and the results aggregated into the overall network. The principal positive eigenpair in Fig. 1 identifies 6 Division members who co-contributed the most to discussions (AMY, ann, jon, and dan at one site, and Mark and thad at another site)². The principal negative eigenpair reveals AMY and ann have similar patterns of co-contribution with the others, but they tend not to co-contribute to the same multi-interact. Similarly, ann and thad tend not to co-contribute to the same discussions. AMY is ann’s supervisor so, when AMY speaks, ann listens. It’s easy to understand the bi-partitioning in this case.

The case of ann and thad is a bit different. It was ann’s functional job to facilitate the meetings and to get people talking. However, from interview data, thad was somewhat new to the Division and he felt his contributions beyond “just the facts” would be a distraction, a waste of other people’s time and, possibly, would make him look stupid. He was nonetheless assigned to participate and he did so minimally, often with monosyllabic responses to direct questions even when encouraged to tell people what he thought about issues relevant to his work. As facilitator, ann tried to get thad to contribute more but was ineffective.

The transcript data revealed that sometime around weeks 18-19 of the study, ann’s functional colleagues (AMY and jon) began working together in asking thad questions to get him to contribute more. Apparently, ann, AMY, and jon had recognized the problem with thad and they contrived a different approach ... which worked because thad began contributing more.

The apparent recognition of thad’s reticence and sharing of this recognition among ann’s colleagues constitutes another form of reputation operating in the Division. It’s unlikely that this shift in practice would have been noticed, had the spectral analysis not focused attention on explaining the bi-partitioning effect between ann and thad.

² Name length here identifies the site from which the person participated. Capitalization reflects rank in the Division: AMY is a Sr. Manager, Mark is a Manager, and thad is an employee.

SOCIAL NETWORKING IN ORGANIZATIONS

It’s clear that Division members draw upon many different kinds of information, both that which is known personally and that which is shared by others, in working together. Not all such information can be represented effectively in a technology system, but some can. Functional reputation, for example, could be generated from a compilation of each person’s work activities. The Division actually collects and maintains such functional data, albeit in a project/activity-centric way. By this, I mean that people can search for particular projects or work activities and discover a list of people contributing to them. However, the same information could also be provided in a people-centric form by generating a list of projects/activities for each Division member, thereby constituting a source of reputational information. Similarly, availability could be gleaned from organizational scheduling/calendaring systems.

The methods used in the spectral analysis above could also be applied here, more for identifying people who have worked together (and who don’t work together as much as they do with similar others) than for generating visualizations. From the functional data described above, network representations of co-participation in the same work activities or projects could be constructed in the same fashion as my teleconferencing multi-interacts. The values in the interaction matrices resulting from eigendecomposition could be converted to z-scores, rather than visualized, those above a specified threshold (say, ≥ 3 standard deviations from the mean) identify people at the same “intensity” of co-participation. The result is a ranked ordering of subsets of organizational members who have worked together before, as well as a ranked ordering of people who have worked together with similar others, but not each other to the same degree. In either case, similar patterns of work activities suggest the people within each subset have worked together on the same things and, so, likely have similar areas of expertise and experience. Such ranked subsets could provide a neutral source of reputational information since it’s derived from records of work activities rather than from the opinions of others.

Overall, as organizations increasingly depend on self-directed work, their members have increasing opportunities to choose their work partners, drawing from a variety of information cues to determine their collaborative appeal. Organizations can facilitate such choices by making information about past, present, and planned work activities accessible in a people-centric manner, i.e. with an emphasis on who is working together rather than what is being done. In this way, organizations may realize improved performance and job satisfaction among its members.

