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New directions in the use of network analysis in research and product development evaluation

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In recent years, the use of social network analysis (SNA) has received increased attention in R&D evaluation. While SNA provides insights into communication and knowledge flows, its efficacy in evaluation methodology remains unclear. As Rogers *et al* (2001) discuss, the applicability of SNA in the evaluation of R&D is marked by several shortcomings, such as the weakness of understanding the content of ties and the inability to identify a generalizable concept of network effectiveness. This paper explores these issues through a discussion of two recent studies of social networks in R&D and concludes with an assessment of the results of these studies using the challenges outlined by Rogers *et al*.

WHERE DOES SOCIAL NETWORK ANALYSIS (SNA) fit in the toolbox for *research and product development (*R&D) evaluation? While the roots of SNA methodology and analysis reach back decades, the application of SNA within evaluation is relatively new. Nonetheless, the use of SNA in evaluation, including R&D evaluation, is rapidly drawing greater interest. Indeed, a recent issue of *New Directions for Evaluation* was dedicated to the topic of the use of SNA in evaluation, in general (Durland and Fredericks, 2005a). But as Rogers *et al* (2001) discuss in perhaps the most thoughtful review of the applicability of SNA for the evaluation of R&D, SNA offers both promise and peril.

The promise of SNA involves the potential to better understand complex systems of agencies, organizations and persons, particularly systems where some amount of coordination to achieve certain goals is in place. Despite the uncertainty about SNA in R&D evaluation, the importance of social networks in scientific research and R&D is readily acknowledged. A number of seminal efforts in the 1960s and 1970s initially served to illuminate the role of social networks in science, such as Price's (1965) study of citation networks, Zuckerman's (1967) examination of collaboration among Nobel laureates, Crane's (Alter and Hage, 1993; Crane, 1965, 1969) exploration of the invisible college hypothesis, and Allen's (1977; Allen and Cohen, 1969) examination of communication networks and knowledge flows. And since the early 1980s, there has been a tremendous increase in work on social networks in research. This growing literature has greatly expanded our understanding of social networks in research, including such topics as communication networks (Allen, 1970), knowledge flows (Almeida and Kogut, 1999), diversity (Reagans and Zuckerman, 2001), idea innovation chains (Hage and Hollingsworth, 2002), interorganizational networks (Powell *et al*, 1996) and complexity (Mote, 2005).

Given the relevance of social networks, it is clear that SNA could play a role in R&D evaluation. But we agree with Rogers *et al* (2001) that SNA, as it currently stands, may not be especially well-suited for addressing some key issues in evaluation. Despite the importance of social networks in R&D, much is still unknown. For instance, it is unclear exactly how networks operate. Further, are networks emergent and self-organizing or can they be structured and directed? Is an increase in network connections (ties) always good or is there an optimum

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level of ties? Similarly, what kind of network is appropriate — dense, clumpy, sparse? Also, it is necessary to distinguish between the operation of networks and network outcomes. And what do we expect as outcomes of networks? Is it to maximize efficiency, increase productivity, increase the dissemination of outputs, build critical mass around a topic, or all of these?

As one can see, the use of SNA can raise more questions than it can answer. As Rogers *et al* (2001) point out, a good first step for using SNA in R&D evaluation would be to look at what is being structured, not merely how it is structured. In this paper, we explore some new approaches to the use of SNA in R&D evaluation, approaches which expand the notion of what constitutes a network. In particular, we would suggest that it is necessary to move beyond thinking of networks as merely connections of people or organizations.[1] While there has been a great deal of work that looks at different types of networks, such as symbols (Carley and Kaufer, 1993) and meaning structures (Yeung, 2005), the majority of SNA typically focuses on people or organizations. Following this suggestion, this paper argues that SNA can be applied in ways that offer a more direct examination of the 'stuff' of R&D, such as knowledge, competencies and innovations. As we discuss in greater detail below, we move beyond simple descriptive exercises of who is connected to whom and attempt to uncover structure and dynamics that are hidden beneath the surface in R&D environments.

After a brief overview of SNA and its potential use in R&D evaluation, we discuss two recent studies that applied the use of SNA to R&D organizations in novel ways. First, we discuss the results of a study that utilized 2-mode network analysis to examine the interrelationships among knowledge competencies within a cluster of R&D projects in a large, multi-disciplinary, national laboratory. This study adopted the approach that collaborative research involves a range of specialties and skills, which can be viewed separately from the individuals involved in the collaboration process (Mote, 2005). These networks of competencies were shown to have structural characteristics which impact on the productivity of research projects. More importantly, the study assessed a number of network properties to determine which one was more effective for productivity. Second, we discuss the results of a current study that looks at the relationship between network positions of scientists and their perceptions of the research environment. This study combines data about project networks and ego networks with the responses to a research environment survey at a research organization consisting primarily of oceanographers and atmospheric scientists. With this data, the study is able to compare different types of network structures within the organization and how each affects the perceptions of researchers. In this manner, the study seeks to yield a better determination of what type of network has greater influence on the organizational 'health' of the research environment and vice versa.

The paper concludes with an assessment of the results of these studies using the challenges outlined by Rogers *et al* (2001). Specifically, it is argued that the studies presented in the paper move closer toward focusing on the content of ties and helping to determine what constitutes an 'effective' network. Finally, the paper discusses the implications for further research on the use of SNA in R&D evaluation.

Social network analysis: a brief overview

Before we move forward, it is important to ask a very basic question: What is a social network? Upon reflection, the question is not such a simple one. At its most basic, a social network is a set of relationships among actors. As mentioned earlier, the types of actors that are most often studied are people and organizations. But if we look closer at even the most simple of social relationships, such as between two people (or any actors), we see that the relationship can be quite complex. For instance, it is first necessary to determine the nature of the relationship. Are these two individuals friends, colleagues, co-workers, etc? Do the individuals like one another and are the feelings mutual? Are the individuals connected in more than one way, such as friends *and* co-workers? In addition, one can try to determine the nature of the connection, that is, what is shared (or not shared) between the two individuals, such as advice, information or other resources. When we extend these questions to a larger set of relationships, the answer to our initial question is not so clear. Indeed, these questions are further complicated when we inquire about the boundary of the network, that is, how far the pattern of relationships extends (Laumann *et al*, 1983).

It was questions like these that inspired the work of Jacob Moreno, a social psychologist who is typically credited as one of the originators of modern social network analysis (Freeman, 1996). In his various studies of social relationships, Moreno introduced the idea of drawing a picture of the social relationships, a sociogram. In general, a sociogram consists of a diagram of points and lines used to represent relations among persons, and Moreno used these sociograms to identify social leaders and isolates, to uncover asymmetry and reciprocity in friendship choices, and to map chains of indirect connection (Borgatta *et al*, 1975). Since Moreno's initial contributions, the social sciences have developed a range of theories and analytical tools for studying networks as structured relationships. While a sustained discussion of the history and the current state of the art of social network analysis is beyond the scope of this paper,[2] we do want to briefly discuss two issues in greater detail: types of networks and network measures.

Types of networks

As Kadushin (2005) discusses, those who study networks tend to focus on three types of networks: ego-centric, socio-centric and open system networks. Ego-centric networks are network relationships that are focused around a single individual and consist of that individual's relationships. These represent the types of networks and relationships that typically capture the public's imagination, such as the notion of six degrees of separation (Milgram 1967; Watts 2003) and have found practical application in such things as Friendster and Facebook. In ego-centered networks, members of the network are defined by their specific relations to the primary actor. It is often argued that an ego-centered approach to exploring networks is more appropriate when the population under study is large, or the boundaries of the network are hard to identify (Laumann *et al* 1983; Wellman 1979, 1982). In general, however, the ego-centered approach is most useful in illustrating the ability of individuals to utilize networks to gain resources, such as Granovetter's (1973) seminal study on the use of social networks to acquire important information for finding jobs.

Socio-centric networks, or what Bernard calls a "networks in a box" (Kadushin, 2005), are those networks that exist within some type of closed system, such as a classroom, an office, an organization or an industry, to name just a few examples. These types of networks are typically what we see in the social sciences under network analysis. In contrast, open system networks can best be described as those where the boundaries are difficult to delineate. In general, however, the analysis of both of these types of networks typically takes one of two different forms: intra-organizational (for example see Hage, 1974; McGrath and Krackhardt, 2003) and inter-organizational networks (for example see Alter and Hage, 1993; Mizruchi and Galaskiewicz, 1993).

Network measures

Since Moreno's original development of the sociogram, SNA has developed a number of measures that describe specific properties of networks and individuals located within the networks. One of the primary configurations Moreno observed was that of the sociometric star, that is, an individual chosen by many others as a friend (Borgatta *et al*, 1975). Over the years, this notion has been formalized into the concept of centrality, and a number of ways of measuring centrality have been developed which have been applied extensively in studies of networks. Building on Moreno's original insight, centrality measures are focused on the number and distance of ties a network actor has with other members of the network (Scott, 2000).

With regard to research evaluation, the use of centrality arguably has the greatest potential as it offers a good indicator of the flow of knowledge and communication between and among individuals, projects and departments

With regard to research evaluation, the use of centrality arguably has the greatest potential as it offers a good indicator of the flow of knowledge and communication between and among individuals, projects and departments. Four primary measures of centrality are typically utilized in network studies: degree centrality, betweenness, closeness and eigenvector centrality.[3] As Freeman (1978: 222) discusses, however, the first three measures of centrality — degree, betweenness and closeness — imply "three competing 'theories' of how centrality might affect group processes … centrality as control, centrality as independence or centrality as activity". The fourth measure of centrality — eigenvector centrality — can be considered an extension of degree centrality, reflecting that centrality is not simply a matter of your own network ties, but also the network ties of those to whom you are connected (Bonacich, 1987). Most simply, degree centrality is the number of nodes to which an actor is adjacent, and it offers an idea about the potential communication activity of an actor, that is, the higher the measure the greater potential for activity within the flow of communication (Freeman, 1978).

In contrast, closeness indicates the potential independence of an actor from the flow of communication. As Scott indicates, the simplest notion of closeness is calculated from the sum of the geodesic distance to *all other points* in the graph, and an actor is "close" if it lies at short distance from many other points (Scott, 2000). In this manner, an actor is centrally located but is not dependent on others as "intermediaries or 'relayers' of information" (Freeman, 1978: 224).

Betweenness is defined as the extent to which an actor is "between" two other actors (Scott, 2000), and it captures the capacity for an actor to play the role of intermediary in the network, connecting two actors that are not otherwise connected. Nonetheless, betweenness can be considered a measure of the extent that an actor can control the flow of information.

Finally, eigenvector centrality is a variant of degree centrality and "is proportional to the sum of centrality of the nodes it is adjacent to" (Borgatti and Everett, 1997: 257). In general, eigenvector centrality captures not only how many actors you "know", but how many actors they "know" as well. In this manner, an actor that is connected to many actors (high degree centrality) who are themselves well-connected (also with high degree centrality) has a high level of eigenvector centrality. Conversely, an actor who is connected only to actors who are less connected (isolates or near isolate) does not have a high level of eigenvector centrality, even if they have a high measure of degree centrality. In a sense, eigenvector centrality offers a measure of the diversity of an actor's network ties.

This brief overview of network analysis is neither exclusive nor exhaustive, and is intended to provide a preliminary introduction to only some of the key concepts and metrics that have been developed in the literature but which are important for our discussion in this paper. In the following section, we provide a discussion of some examples of network analysis in science and R&D.

Social network analysis in R&D evaluation: the promise

As mentioned above, there has been a tremendous increase in studies on social networks in science and in R&D more broadly. These recent studies on social networks in science and R&D have encompassed a range of analyses, including studies of knowledge and learning networks (Bozeman and Corley, 2004; Liebeskind *et al*, 1996), inter-organizational networking of research organizations (Powell *et al*, 1996), and intra-organizational networks (Ahuja *et al*, 2003; Smith-Doerr *et al*, 2004).

Within this growing social network literature, a number of studies have produced important insights into the practice of science and research. For instance, Allen's (1970) study of the communication networks of individual researchers in different organizations found that the diversity of a researcher's network had an impact on productivity. Allen discovered that "high" performers not only had more intense communication networks, but also maintained a more diverse range of contacts, including those outside the researcher's respective field. Further, in a larger study, Allen (1977) confirmed that intensity and diversity of communication networks were directly related to increased R&D performance. In general, the role of these "gatekeepers" is an important one, as they are the individuals who frequently obtain information external to the group and then share it within the project team (Allen, 1970, 1977; Tushman and Katz, 1980). These results are consistent with those found in more recent studies. For instance, researchers with more "cosmopolitan" collaboration networks have been demonstrated to be more productive in terms of publications (Lee and Bozeman, 2005) and receiving research grants (Bozeman and Corley, 2004).

But one can question whether network centrality is really such a key factor. In a study on the Soar group, a virtual R&D project, Ahuja *et al* (2003) differentiated individuals on the basis of functional roles (users and developers) and status (faculty, senior researchers and students) and found that centrality was a stronger predictor of performance than individual characteristics. Yet, Reagans and Zuckerman (2001) explored the question of whether demographic diversity or network processes had a greater contribution to R&D productivity. The study found that diversity itself was not linked to productivity, but rather that two components of project teams, network density and network heterogeneity, were linked. As they argue, these network processes worked to enhance a team's coordination and learning capabilities. In this regard, these studies illustrate the critical network feature changes when one asks different questions about the network.

In summary, some of the more recent applications of SNA in the science and R&D literature suggest that networks not only are important, but also play a key role in research productivity and innovation. However, despite this wealth of research, it is still not entirely clear how network mechanisms might affect productivity, nor is it clear what constitutes an optimal network configuration for productivity and innovation. In the next section, we turn to recent discussions about SNA in the evaluation literature to highlight some of the issues with the use of SNA in R&D evaluation.

Social network analysis in R&D evaluation: the peril

In general, evaluation research is used to measure the effectiveness of different aspects of practice, such as a project, a program, a policy or a portfolio. When we use the terms 'project' or 'program' this could refer to the other units of analysis also. In this manner, the central objective of an evaluation, either formative or summative, is to identify objectives and measure progress towards them. Within this context, SNA in evaluation can take two forms: the evaluation of the role networks play in facilitating (or hindering) the achievement of program objectives or, by extension, an assessment of the development of networks as a program goal. The first role focuses on whether networks actually work or are effective (O'Toole Jr, 1997; Provan, 1995; Provan and Milward, 2001). This is seemingly a straightforward proposition although, as we discuss below, it is not suggested that SNA necessarily has any conclusive answers. The second role involves some assumptions about the effectiveness of networks that are often not questioned, that is, the development and growth of networks are typically assumed to be a positive outcome. Again, this is not altogether clear. To use a rather extreme example, we can look at Lee's (1969) classic study of the informal networks that women used to find a person to perform an abortion. Depending on your perspective in this particular social debate, the role of networks could be seen as either positive or negative.

With regard to the use of SNA in R&D evaluation, Rogers *et al* (2001) have put forth the most thoughtful discussion regarding the issues involved. Although the authors identify seven obstacles to the use of SNA in R&D evaluation, we would argue that several of the obstacles actually represent general challenges in R&D evaluation, such as inadequate performance measures. Indeed, many of the criticisms that the authors direct at SNA could just as easily be applied to many of the tools and approaches in R&D evaluation. Nonetheless, we have extracted from their review what we consider are the four primary challenges for the use of SNA in R&D evaluation:

1. SNA needs to focus on the content of ties rather than just structure.
2. SNA needs to develop a concept of "network effectiveness" in terms of its impact on the uses of knowledge.
3. SNA needs to examine more closely the heterogeneity and multiplexity within networks, what Rogers *et al* (2001) call "untidy" networks.
4. SNA needs to reformulate the typical evaluation questions.

In many respects, the first and third challenges are closely related, and can be put in the category of network specification. Typically, this involves the demarcation of the network's boundaries, the so-called boundary specification problem (Laumann *et al*, 1983). While most socio-centric SNA typically takes the social setting under study as the network boundary for ease of analysis, it is clear that networks do not begin and end at the office door. Further, we would argue that the operationalization of network ties is often given short shrift. Certainly, a great deal of work has focused on identifying and valuing the content of ties and what flows between them, such as Granovetter's (1973) distinction between strong and weak ties or Cross *et al*'s (2001) discussion of advice networks, but all too often ties are not adequately differentiated. In general, however, it should come as no surprise that SNA's primary focus is on social structure and patterns of interaction, as a fundamental assumption underlying all SNA is that structure determines and constrains behavior. Nonetheless, the need to pay greater attention to the specification of ties, the content of ties and the multiplexity of ties is warranted.

With regard to R&D evaluation, it is therefore essential to identify the appropriate network (and ties) for knowledge production. Typically, network studies focus on networks derived from advice networks (see Cross *et al*, 2001), friendship networks (see Zeggelink, 1995) or, more predominantly, communication networks (see Krackhardt and Porter, 1985). But a specific network structure or property has not been identified as critical for knowledge production. The situation is further complicated by the fact that we do not operate in only one network, but find ourselves operating in multiple networks concurrently (multiplexity).

The second challenge represents perhaps the most significant challenge to utilizing SNA: When is a network effective? Despite its importance, very little work has been focused on this issue (Provan and Milward, 2001). Arguably, one important reason for this shortcoming is the fact that the existence and development of networks is usually assumed to have positive outcomes, although these assumptions are typically not questioned. Certainly, an increase in the collaboration and cooperation that networks might foster is positive, but at what point does an increase in the number of ties become negative? Or at what point does having network ties which provide redundant information, a key point of Burt's (1992) concept of structural hole, become a drag on efficiency? This becomes an even larger problem when the development of networks becomes a programmatic goal (Schatz, 2003).

As suggested in the introductory paragraphs of this paper, it is essential to distinguish between effectiveness in terms of the network and network outcomes. As Borgatti (2005) suggests, the former depends on the specific research setting and goals. As Figure 1 indicates, Borgatti derives four types of network structures utilizing two strategic dimensions: mode of creativity (interactive or individual) and level of innovation (radical or incremental). Borgatti (2005) argues that radical innovation is facilitated by sparser and clumpier networks, while incremental innovation is better served with more dense networks. And what are the best measures to assess the effectiveness of the network? While most SNA has utilized centrality, our discussion above demonstrated that there are several types of measures of centrality, each suggesting a specific type of network dynamic. However, if we use Borgatti's hypothesis as a guide, we can begin to develop a more systematic framework for thinking about networks and R&D.

With regard to network outcomes, the choices are numerous and should be driven by the specific questions addressed in an evaluation. As Fredericks (2005) points out, questions and concerns about networks must be incorporated into the evaluation

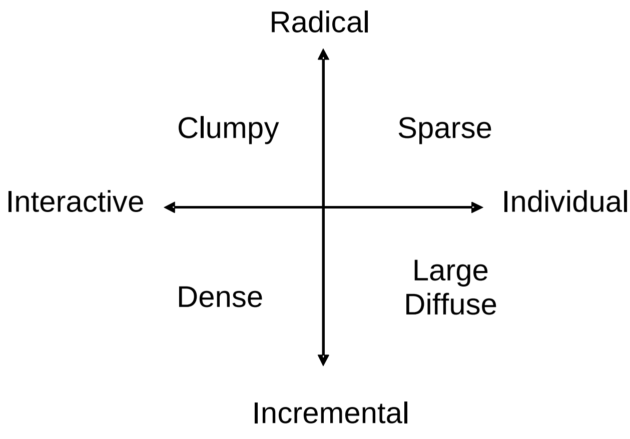

Figure 1. Types of network that facilitate innovation
Source: Borgatti (2005)

design. But again, the challenge is distinguishing between outcomes and the network itself, and what is the most effective network structure in achieving the desired outcomes. On this, the application of SNA is certainly muddled. For instance, a great deal of SNA has been utilized to examine business performance as the key dependent variable, such as sales, patents and innovation. However, the network variables utilized range from structural holes (Ahuja, 2000), strength of ties (Powell *et al*, 1996), network density (Valente, 1995), and centrality (Smith-Doerr *et al*, 2004), to name only a few. As this handful of studies demonstrates, there is still a great deal of diversity of thought on what are the key network variables.

Finally, the fourth challenge represents the most intriguing one, that is, reshaping some of the evaluative questions about networks. As Rogers *et al* (2001) discuss, most studies of networks are descriptive and explanatory, not normative. Of course, a justifiable reason is that if it is still unclear what an effective network looks like, then how can we determine how things should or ought to be, how to value them, which things are good or bad, or which actions are right or wrong? Clearly, this is a key issue that needs attention as the field moves forward.

Taking these challenges seriously, we would argue that a necessary first step is to move away from the focus on the individual. A great deal of SNA, particularly in the business literature, focuses on the identification of less connected individuals in networks and taking corrective action. Such a management orientation is not consistent with the questions we would like evaluation to address, nor would it be palatable in many publicly funded R&D settings. Hence, our suggestion is to better focus on a more appropriate network, the project network. A great deal of R&D is conducted within projects, often in a matrix-style organization framework, so focusing on this type of network provides a frame that captures the organizational ecology (Grabher, 2002; Mote, 2005). While the ties contained in this network do not represent or necessarily suggest actual communication linkages, these networks suggest the potential for communication and interaction centered on the research work. Further, the project affiliation network can depict the level of knowledge complexity contained within the projects and organization (Mote, 2005). In the subsequent sections of the paper, we present two recent network studies we have undertaken that utilize the project affiliation network and begin to address some of the challenges identified above.

2-mode networks and project ecologies[4]

Our initial aim of this first study was to utilize 2-mode network analysis to explore the impact of knowledge diversity, or complexity. Rather than simply looking at the sheer number of different departments represented in a project, the use of network analysis allows investigation of complexity within the social context of the laboratory. While a typical network analysis examines the interrelations between the same set of persons or entities (1-mode analysis), a 2-mode analysis looks at the relations between two equally interesting sets of persons or entities, such as groups or events (Borgatti and Everett, 1997). For instance, a 2-mode analysis can look at affiliation networks, which consist of sets of relations between individuals and events, such as women and social events (Borgatti and Everett, 1997), or co-membership of individuals in organizations, such as the analysis of overlaps in the corporate board memberships (Galaskiewicz, 1985). In the latter example, 2-mode analysis offers the ability to look at the network of relations between different groups based on the membership of individuals in two or more groups.

The network under investigation is not that of the researchers *per se*, but the interconnections between research departments and projects. In this manner, the study adopted the view that this social context operates much like Grabher's notion of a "project ecology" (2002) or Tuomi's "ecological framework" (2002). This "ecological" approach to intra-organizational networks encompasses a much broader conception of organizational and physical space to include "personal relations, localities and corporate networks on and around which projects are built" (Grabher, 2002: 246). Within the context of this study we viewed the project ecology as consisting of the project memberships, department affiliations, knowledge and competencies. In this manner, it is suggested that an organization's project ecology potentially represents another level of social structure that can be useful in an evaluation framework.

The data used in this first study came from a sample of scientific researchers in 20 research projects at a large national laboratory. The laboratory currently employs thousands of researchers in over two dozen disciplinary centers. The primary objective in this analysis was to explore the impact of a complex division of labor on research productivity. In the analysis, the research departments were assumed to represent different research competencies, and the number of departments represented in a given project was determined to be the complexity of labor in that particular project, similar to Larson and

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Gobeli's (1989) use of functional department. Hence, it is possible that a range of functional specialties could be represented within each department. Nonetheless, it is assumed that researchers from each of the departments lend something different — a competency, a skill, a cognitive map, etc — from researchers from other departments. Indeed, this paper suggests that conceptualizing research departments in this manner offers a good example of the kind of tacit knowledge that Von Hippel (1994) argues is limited and far from routine.

The network data consisted of the project and department affiliations of the researchers, and these affiliations were arranged in a 2-mode project-by-center matrix. The matrix (X) is arranged where $x_{ij} > 0$ if project i has a researcher from a department j and $x_{ij} = 0$ otherwise. Because most network analysis is geared towards 1-mode matrices, the study of 2-mode data introduces a number of challenges, in particular the graphical representation of correspondence analysis between the two sets of persons or entities. As Borgatti and Everett point out, "the distances in [2-mode] correspondence analysis are not Euclidian, yet human users of the technique find it very difficult to comprehend the maps in any other way" (1997: 247). Their primary solution is to treat the data as a bipartite graph and compute geodesic distances to be used in ordinary multi-dimensional scaling and other network measures. All social network measures and figures were derived using the software program Ucinet 6 and NetDraw 1.0 (Borgatti *et al*, 2002).

Figure 2 represents a multi-dimensional scaling of the network of connections between projects and departments. As such, the figure allows for visual identification of the structure of social relations among the projects and departments, as well as the key players within this intra-organizational network field. In the graphic, projects are represented with square nodes and departments with round nodes. It is possible to locate two distinct clusters of projects and departments on the left and right side of the diagram. As one would expect, the larger projects with personnel from a greater number of departments, such as projects 3, 4 and 17, are more centrally located in the larger cluster on the left. In contrast, a handful of projects, such as projects 9, 18 and 20, appear to act as intra-organizational intermediaries, bridging the larger cluster of projects and departments with the smaller cluster.

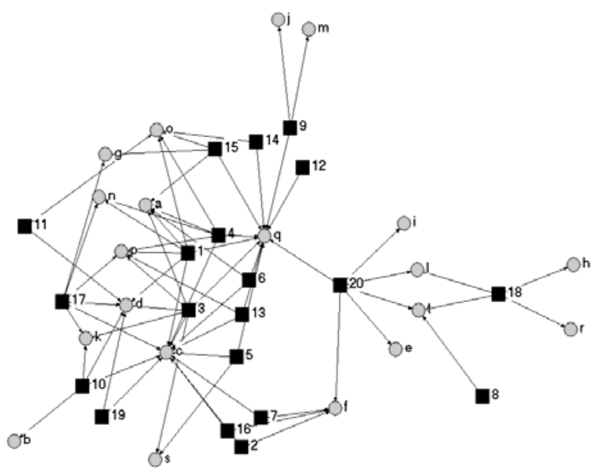

Figure 2. The network of projects and departments

In order to isolate the impact of complexity on productivity, at least on a superficial basis, a simple regression analysis was conducted using productivity as the dependent variable. Unlike most studies of R&D productivity that focus on individual performance, our study followed other recent studies in looking at network effects on the project or team performance (Reagans and McEvily, 2003; Smith-Doerr *et al*, 2004). In our analysis, productivity was defined as patents, papers, and hypotheses proven, and the data was self-reported by each project on an annual basis. In many ways, this way of measuring productivity is incomplete (Kerssens-van Drongelen and Bilderbeek, 1999; Mote *et al*, forthcoming), but this is a larger issue that affects R&D evaluation in general. The results of the regression are displayed in Table 1. Each model represents the insertion of a different measure of centrality into the regression.

The results of the regression analysis indicate that R&D productivity is significantly affected by the number of departments, as one would expect, but the impact of measures of centrality is mixed. More specifically, the regression coefficients for the number of departments are both positive and significant across most of the models. In Model 6, however, the regression coefficient for the number of departments is substantially reduced and no longer significant. Rather, the regression coefficient for eigenvector centrality is both larger and significant, although only at $p < 0.1$. Further, the R-square for the model is higher than that for Model 1. Also of interest is the result on the regression on betweenness, with a

Table 1. Linear regression of scientific productivity (papers and patents) on measures of complexity

Model/network measure	1	2	3	4	5
Personnel, number of	0.015	–0.427	–0.606	–0.090	0.002
Departments, number of	0.638**	1.049*	0.641**	0.952**	0.588*
Standardized complexity	–	–0.353	–	–	–
Degree centrality	–	–	0.623	–	–
Betweenness	–	–	–	–0.371	–
Closeness	–	–	–	–	0.096
Eigenvector centrality	–	–	–	–	–
R^2	0.422	0.453	0.427	0.499	0.427

Note: N = 20, * < 0.1, ** < 0.05

negative regression coefficient, which suggests that the role of intermediary does not lend itself to increased productivity.

The results of the study suggest that the complexity of labor is indeed an important factor that contributes to research productivity, but our analysis highlighted that the impact of complexity might be tied to network structure. In this manner, the use of network analysis proves to be a useful tool for providing a broader view of the relationship between complexity and productivity. The most interesting findings were those from the regression analysis on the impact of eigenvector centrality and betweenness on productivity. Indeed, the results of these two measures indicate that a strategy of connecting projects to departments that are, in turn, well-connected to other projects might be more advantageous than a strategy of having projects act as bridges between distinct clusters of departments. When one takes into account the changes that have occurred in R&D organizations in recent decades, these findings make intuitive sense. In the past, R&D, particularly basic research, was largely pursued separately by functional departments. In this manner, functional departments constituted separate and unconnected communities of interest. However, the organization of R&D along strictly functional lines has declined and the move to more project-oriented R&D has achieved a significant amount of cross-functional integration. As functional lines have eroded, more R&D workers interact and share a common language (Dougherty, 1992).

Within this milieu of greater cross-functional integration, the role of intermediary (as measured by betweenness) becomes less important as a strategy for increasing R&D productivity. Interestingly, Ahuja (2000) similarly found that an increase in structural holes — defined as gaps between discrete groups of people (Burt 1992) — has a negative impact on the innovation output of the intermediary firm in an inter-organizational network. Rather, the capacity for innovation and productivity is increased not just by connecting to more functional areas, but connecting to other functional areas that are, in turn, also connected to a large number of functional areas (a project's eigenvector centrality). For example, this suggests that connecting to other central projects might have a multiplier effect on absorptive capacity by increasing the capacity for acquiring new knowledge and developing innovations. In short, a project's productivity is in part a function of the productivity of the other projects to which it is connected.

To summarize, the analysis in this study suggests that one needs to take into account the network structure of the projects and departments, which represents the constellation of people and competencies, as a complement to other network and group processes in an R&D setting (as discussed in Brown and Eisenhardt, 1995; Reagans and Zuckerman, 2001).

Networks and the research environment

In this subsequent study, we sought to examine the relationship between the social network positions of scientists and their perceptions of the research environment. As Jordan (2005) highlights, an important question in the R&D literature focuses on how organizations can support and encourage high performance, and the work environment has also been identified as a key factor for research success by Balachandra and Friar (1997). Yet, most network studies typically look at social networks in isolation, without taking into account the interaction between the network and the organizational environment, particularly how network position might affect scientists' perception of the research environment. Although a handful of studies have explored this connection, such as Smith-Doerr *et al* (2004) and LaBianca *et al* (1998), this remains an area that is largely unexplored. Hence, we were interested in better understanding the interaction between social networks and the organizational research environment and how these might facilitate or inhibit network behavior and patterns that are conducive for higher performance.

To explore this relationship, our study utilized data from a research environment survey which was administered to a small research organization that is a subunit within a large, mission-oriented agency. The organization consists of approximately 70 physical scientists who are organized into three divisions that encompass satellite meteorology, oceanography, climatology and cooperative research with academic institutions. In addition, the organization has a complex physical structure, consisting of one primary office, a nearby secondary office and several smaller offices scattered around the country but typically located within a major university. With a charter to develop operational algorithms and applications, the scientists develop satellite-derived land, ice, ocean and atmospheric environmental data products in support of all of the parent agency's mission goals. In addition to actively developing new data products, the scientists currently provide support to nearly 400 current satellite-derived products for various users on a routine basis. In addition, the scientists actively work with the numerical modeling communities of many government agencies to support the development of new methods for the assimilation of satellite data. Finally, much of the work of these scientists is conducted in close partnerships with other agencies, academic institutes and industry.

The research survey utilized in this analysis has been administered and tested in a number of R&D settings (Jordan, 2005; Jordan *et al*, 2003, 2005; Jordan and Streit, 2003), including national laboratories. For the survey, the research environment has been characterized as a set of specific organizational attributes previously identified by researchers as important for conducting high-quality and relevant research. Key attributes of organizational structure and management practices within the research environment were

Table 2. 36 key attributes in the work environment survey

Development of human resources	Creativity and cross–fertilization	Internal support systems	Set and achieve relevant goals
People treated with respect	Time to think and explore	Good research competencies	Sufficient, stable project funding
Optimal mix of staff	Resources/freedom to pursue new ideas	Good equipment/ physical environment	Good planning and execution of projects
Management integrity	Autonomy to make decisions	Good salaries and benefits	Good project-level measures of success
Teamwork and collaboration	Cross–fertilization of ideas	Good allocation of internal funds	Good relationship with sponsors
Good internal project communication	Frequent external collaborations	Informed and decisive management	Reputation for excellence
Management adds value to work	Relevant research portfolio	Rewards and recognizes merit	Management champions fundamental research
High-quality technical staff	Commitment to critical thinking	Efficient laboratory systems	Good lab-wide measures of success
Good professional development	Identification of new opportunities	Laboratory services meet needs	Clear research vision and strategy
Good career advancement opportunities	Sense of challenge and enthusiasm	Overhead rates not burdensome	Invests in future capabilities

identified and defined through an extensive literature review and input from 15 focus groups that included bench scientists, engineers and technologists, as well as their managers, across various R&D tasks (Jordan *et al*, 2003). In total, 36 attributes in four discrete categories (see Table 2) were identified. For each attribute, researchers were asked to rate the existence of the attribute within the organization in terms of percentage time true on a scale of 0% to 100%.

With regard to network questions, the survey included a name generator and a project affiliation question. Because of the lack of detail in the name generator responses, we have not included this data in our current analysis. The research environment survey was administered to all scientific and technical staff of the research organization. Out of 81 potential respondents, 64 surveys were completed, yielding a response rate of 79%. Of the 64 respondents, 58 were scientists and six were technical staff.

Figure 3 represents a multi-dimensional scaling of the network of connections by project affiliation, with each node representing an actor within the organization and the lines indicating ties defined as co-membership in projects. As such, the figure offers one possible way for visualizing the structure of social relations among the projects, as well as the key players within this intra-organizational network field. For example, it is possible to identify one, and possibly two, distinct clusters of scientists by project affiliation, such as the dense cluster of connections in the middle of the network graph. However, such graphs, while interesting, provide little in the way of useful information without further analysis.

Network measures: centrality

In exploring the relationship between network structure and perceptions of the research environment, we principally examined the role of network centrality on perceptions. In general, centrality details the prominence of actors and the nature of their relation to the rest of the network primarily through calculating the number and distance of ties a network actor has with other members of the network (Scott, 2000). However, rather than using centrality measures to focus on individuals, we are more concerned with centrality as an indication of the potential flow of knowledge and communication between projects.

Of the four measures of centrality, closeness was found to have the greatest impact on perceptions. After calculating the measures of closeness for each person in the network, we grouped the respondents into two categories (low closeness and high closeness) using mean closeness. In utilizing ANOVA to compare the two groups of scientists on the 36 items on the research environment survey, we found that there were statistically significant differences on six

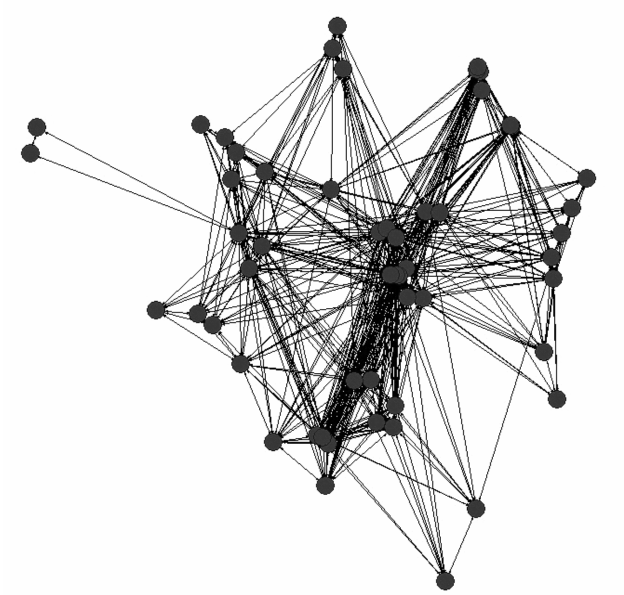

Figure 3. The network of connections by project affiliation

Table 3. ANOVA table for items with significant differences in perceptions by closeness

Attribute in the research environment and overall ratings	Low closeness	High closeness	Significance
People are given the authority to make decisions about how to do their jobs	3.76	4.43	0.00****
People show a commitment to critical thinking	3.35	4.17	0.01**
My management adds value to my work	2.82	3.74	0.01***
There is teamwork and collaboration	3.42	4.04	0.02**
There is good planning and execution of research projects	3.27	3.83	0.03**
My management has a clear research vision and strategies	3.06	3.7	0.03**
External collaborations and interactions occur frequently for this project	3.18	3.78	0.06*
People are treated with respect as individuals	3.88	4.43	0.06*
My management maintains an integrated and relevant research portfolio	3.28	3.83	0.07*
My management rewards and recognizes merit	3.39	3.96	0.08*
Overall, I would rate my research/work environment as ...	4.79	5.43	0.06*
Overall, the organization is a great place to work	3.76	4.13	0.08*

Note: **** $p < 0.0001$, *** $p < 0.001$, ** $p < 0.05$, * $p < 0.1$

of the items (see Table 3). On an additional four times, the differences were approaching significance. In addition, those in the high closeness group also reported higher ratings on two overall questions regarding the research environment, which were approaching significance. However, it is interesting to point out that on all of these items, the high closeness group reported a significantly higher mean percentage time true. The statistically significant items are listed before the four near significant items and two overall ratings in the list below.

In one respect, this kind of finding should be reassuring to management because it means that those who have more visibility of what is occurring across the organization are most likely to perceive a higher percentage time true on a number of desirable attributes. In addition, these results strongly suggest that network position, in this case closeness, is associated with positive perceptions on a number of key organizational attributes.

Because individuals with high closeness are in a relatively better position than others to monitor the information flow in the network and have the best visibility into what is happening in the overall network, we wanted to explore what type of research is pursued by those with high closeness. To do this, we first categorized projects by the research goal for each project, which we defined as the orientation of the project toward either current products or new product development. Next, the projects were disaggregated on the basis of the closeness measures of the individuals involved with the project. If more than 60% of the individuals in a project had low closeness (based on mean closeness), the project was categorized as “low closeness”. Conversely, if more than 60% of the individuals in a project had high closeness, the project was categorized as “high closeness”. For projects that had an equal number of individuals with low and high closeness, more or less, the project was categorized as “mixed closeness”.

In exploring these results further, we looked at the relationship between closeness and the orientation of research projects, differentiating between those working on current products or new products. The cross-tabulation in Table 4 shows the association between projects based on closeness composition and product orientation. Projects were classified as either high, mixed or low depending on the number of project members with high closeness, which was defined as a closeness measure above the mean. As Table 4 illustrates, a large number of projects oriented toward new product development also had more projects with higher numbers of project members with high closeness. While closeness composition neatly fits the definition for ordinal variable (as it is ranked from low to high), the variable for product orientation is less clear as an ordinal variable (and seems more akin to a nominal variable). However, one could argue that if the interest is in innovation, product orientation is more clearly an ordinal variable as new product development would be ranked higher for that purpose. In testing the strength of this association, we used several measures of association for

Table 4. Projects by closeness composition and product orientation

		Product orientation		Total
		Current product	New product development	
Closeness composition	Low closeness	5	5	10
	Mixed closeness	9	7	16
	High closeness	9	21	30
Total		23	33	56

ordinal by ordinal tables, including Kendall's tau-c and Somers' d, which showed only a slightly significant association between closeness composition and product orientation.

As the results of this study suggest, network position is related to perceptions of the research environment. In this respect, the combination of network analysis with an organizational survey, such as the research environment survey, offers a path for identifying optimal intra-organizational network structures. While Borgatti (2005) suggests that a network structure best suited for new product development would be one where project members have high closeness, our study highlights that the self-emergent properties of this particular network have organized in such a manner that individuals with high closeness do, in fact, tend to be clustered around new product development.

Conclusion

In this paper, the framework and methods of SNA and two case studies were presented to illustrate the application of SNA in assessing R&D, and science and technology, more broadly. The case studies presented were not evaluative studies, but rather explorations of the use of SNA in ways that more broadly took into account the context of R&D. Hence, there are no clear evaluative lessons to draw from the case studies. Rather, the case studies suggest ways of looking at network structures and properties that might be useful within an evaluative frame. However, as the case studies highlight, there is still considerable work to be done in pinpointing network structures and properties that are most meaningful in the context of R&D. Unfortunately, the social network literature is not altogether clear in identifying the optimal network configuration and network outcomes. However, some recent contributions have begun to recognize that different kinds of R&D need different kinds of network configuration (Borgatti, 2005; Mohrman *et al*, 2006). Much more work of this nature needs to be done in order to more effectively utilize SNA in both evaluation and program planning.

In conclusion, we share Rogers *et al* (2001) general argument that SNA offers both promise and peril for R&D evaluation. While we agree that there is nothing inherent in SNA for revealing R&D value, we would argue that SNA represents a method that is useful in uncovering structures that have a decided impact on R&D. Science is inherently a social process, so networks are part of the fabric of how science is performed and knowledge transferred. Understanding the process will provide a leading indicator for future performance and a management lever for improving the process. But to make SNA useful for R&D evaluation, and evaluation in general, it is critical to think more systematically about the integration of SNA into evaluations (a point echoed by Fredericks, 2005), as well as expand our understanding of what constitutes a 'good' network. On this score, our optimism is tempered by an acknowledgement of the considerable hurdles of accommodating SNA for evaluation. As Rogers *et al* (2001) point out, many significant issues need to be dealt with before we see a wider utilization of SNA.

A primary question for evaluators and program managers should be this: What are we expecting to get out of networks in the first place? The efficacy of SNA in evaluation should be driven by an understanding of what networks facilitate and foster in the first place. In general, a better understanding of the role of social networks can help maximize the use of resources, better coordinate work patterns, and better manage an organization's intellectual and human capital. Of course, a strategic understanding of networks is important from the beginning of a program in order to provide measurable goals and objectives for an evaluation of the networks. Concomitant with continued exploration of SNA is the need to develop more appropriate performance measures for R&D. In terms of measuring knowledge, the use of papers, patents and publications — the standard measures — are simply not adequate. As we have argued elsewhere (Mote *et al*, forthcoming), these are lagging indicators and demonstrate only a part of the growth of knowledge.

Even without the incorporation of clear goals and objectives for a network, the use of SNA can still provide evaluators with an assessment of the interactions and workflow that currently exist. In our two case studies, we have attempted to illustrate the application of SNA to the project affiliation network, which we argue provides a good object of analysis for any knowledge-based organization or program. And we have also demonstrated that it is important to look at the network actors' perception of their research environment. While a network configuration may appear positive (such as those with high closeness working on new product development), does the network match up with researchers' perception of what makes a good work environment? Do those with high closeness have favorable perceptions of the research environment, particularly on those items that we think are favorable to fostering network connections and activity? All too often, the role of the organizational context in fostering or inhibiting the desired type of networks is overlooked.

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Notes

1. Interestingly, this echoes a comment by Brieger (1976) that "despite the increased attention accorded to the empirical study of social networks among scientists, there has been remarkably little concern for the possibility of using network phenomenology itself as a guide".
2. For more detailed overviews and introductions to social network analysis, see Durland and Fredericks (2005b); Brass *et al* (2004); Borgatti (2003).
3. Network centralization (or global centrality) is a related measure that assesses the degree to which an entire network is focused around a few central nodes (Scott, 1991).
4. A more comprehensive discussion of this study can be found in Mote (2005).

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