International Journal of Communication 5 (2011), 682-720 1932-8036/20110682

IJoC
Network Theory

Multidimensional Networks and the Dynamics of Sociomateriality: Bringing Technology Inside the Network

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This article explores the theoretical implications of developing multidimensional social networks that include nonhuman technological elements. Using ideas from actor-network theory and sociomateriality, we develop a typology for multidimensional networks that includes multiple kinds of nodes and multiple kinds of relations. This typology includes traditional types of nodes, like people, and traditional types of relations, like "shares information with," along with types of nodes that are technological artifacts, like databases, and types of nonhuman relations, like embodiment. In this way, technology is moved inside the social network and becomes an inherent part of it. An illustrative case shows how the inclusion of nonhuman artifacts and relations in the networks of an automobile design firm significantly changes our understanding of the emergent dynamics in this sociomaterial network. These results are extended by an

[1] The authors wish to acknowledge the following funding sources that contributed to the development of materials presented in this paper: Army Research Institute W91WAW-08-C-0106/P00004; Army Research Laboratory under Cooperative Agreement Number W911NF-09-2-0053; Air Force Research Laboratory FA8650-10-C-7010; and National Science Foundation Grants: BCS-0940851, CNS-1010904, OCI-0904356, IIS-0838564, IIS-0838548, IIS-0841583, ITR 0427173. The views and conclusions contained in this document are those of the authors, and they should not be interpreted as representing the official policies, either expressed or implied, of the Army Research Laboratory, Air Force Research Laboratory, the National Science Foundation, or the U.S. Government. The authors also wish to thank Yun Huang for assistance with preparation of this manuscript, as well as anonymous reviewers, workshop participants, and Elena Pavan for helpful comments on the manuscript.

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Date submitted: 2011-03-02

exploration of how to develop multidimensional, multitheoretical, and multilevel models that include technological artifacts and relations.

In the 1950s, scholars began to explore the various ways that new technologies (e.g., hardware, software, routines, policies, etc.) enable and constrain people's communicative behavior in formal and informal organizational systems (e.g., Coleman, Katz, & Menzel, 1957; Leavitt & Whistler, 1958; March & Simon, 1958; Thompson & Bates, 1957; Woodward, 1958). By the late 20th century, researchers had accrued a good deal of empirical evidence to support hypotheses made in the 1950s and 1960s about the various ways that new technologies would alter social dynamics. Within formal organizational settings, for example, research by Barley (1990), Burkhardt and Brass (1990), Contractor and Seibold (1993), and others demonstrated the subtle, nuanced ways through which newly implemented computer-based technologies alter the flow of communication within networks and, hence, allow people to reconfigure formal organizational structures, decision making, and power relationships. Empirical evidence also mounted in support of the notion that new computer-based technologies could bring change to more informal communication networks (for a comprehensive review, see DiMaggio, Hargittai, Neuman, & Robinson, 2001). At the same time, scholars became interested in reversing the causal arrow, asking whether established networks could influence the effects of newly implemented technologies. A number of researchers showed, convincingly, that network dynamics could, indeed, shape what people thought about a new technology, as well as whether and how they would use it (Fulk, 1993; Karahanna, Straub, & Chervany, 1999; Kraut, Rice, Cool, & Fish, 1998; Rice & Aydin, 1991). The recognition that the causal arrows could plausibly go in either direction was embraced by advocates of a structurational perspective, who argued that technologies can simultaneously shape and be shaped by the social structures into which they are introduced (DeSanctis & Poole, 1994; Orlikowski, 2000).

All three sets of studies share the ontological position that technologies exist separately from people's social networks. In other words, they treat either technologies or networks as exogenous forces that impinge upon the functioning of the other. Such attempts to isolate causality make good sense in situations where people use a handful of distinct technologies, and where their interactions with technology are very different than their interactions with people. Indeed, in many of the contexts studied by the authors cited above, individuals interact with technology (such as telephone, fax, email) to reach other people, rather than interact with the technology in lieu of people. In other words, the people in these contexts are more likely to use technologies in ways that are distinct from how they "use" other people (Hollingshead & Contractor, 2002). Questions concerning the nature of causality seem less appropriate, however, when groups of people use multiple technologies simultaneously and switch the technologies they use frequently. In such situations, identifying what technology "causes" a particular network change becomes less intellectually interesting, because a given technology is often used interdependently with a wide swath of other pervasive and embedded technologies (Bailey, Leonardi, & Chong, 2010). Similarly, as technologies begin to store greater amounts of information that were once only held in the heads of people, individuals begin to "use" technologies in much the same ways that they "use" coworkers and friends (Su, Huang, & Contractor, 2010). These technologies are emerging as "social prosthetic systems" (Kosslyn, 2011, p. 182).

Thus, ubiquitous computing, both inside and outside formal organizations, is making it increasingly difficult to separate people's interactions with other people from people's interactions with technologies. Consequently, it may make more sense to begin treating technologies as endogenous to social networks, rather than as exogenous to them. In other words, instead of asking how technologies might change social networks (or vice versa, or both), the more appropriate question is, "What happens when a new technology becomes a part of a social network?" By "making technologies a part of a social network," we mean that the technologies are treated as nodes in the network, which are linked via specific relations to other nodes in the network. This move implies that researchers can no longer make an analytic distinction between technologies (or artifacts more generally) and people. They must begin to recognize that networks can be comprised of people and technologies, and that both types of nodes may, on occasion, play equivalent roles. Recently, proponents of a *sociomaterial* approach to studies of technology and communication have begun to provide us with the ontological foundations and theoretical language with which to make this conceptual shift (e.g., Leonardi & Barley, 2008; Orlikowski, 2007; Orlikowski & Scott, 2008; Pentland & Feldman, 2007).

At an ontological level, a sociomaterial approach to technology and communication suggests that communicative behaviors and technologies are indistinguishable phenomena (Baptista, 2009; Orlikowski & Scott, 2008). As Leonardi suggests: "technologies are as much social as they are material (in the sense that material features were chosen and retained through social interaction) and [communication patterns] are as much material as they are social (in the sense that social interactions are enabled and constrained by material properties)" (2009a, p. 299). Orlikowski argues that this ontological stance compels researchers to view the relationship between coordinated human action (the social) and the features of technologies (the material) that people use as central to the organizing process. In other words, a sociomaterial approach:

> . . . asserts that materiality is integral to organizing, positing that the social and the material are *constitutively entangled* in everyday life. A position of constitutive entanglement does not privilege either humans or technology (in one-way interactions), nor does it link them through a form of mutual reciprocation (in two-way interactions). Instead, the social and the material are considered to be inextricably related—there is no social that is not also material, and no material that is not also social. (2007, p. 1,437)

This sociomaterial approach draws heavily on the work of actor-network theory (Callon, 1986; Latour, 1987; Law, 1987) to stake this ontological claim of symmetry between human action and the actions of technology. Actor-network theory assumes the communicative actions that most social scientists would call "social" involve both people and technologies, and that the material features of a technology are developed and used in a system of social relationships. By abandoning the attempt to distinguish that which is social from that which is material, actor-network theorists consider the actions of humans and non-humans as part of a single network that is, itself, an actor, an "actor-network." Actor-network theory uses the term "actants" to denote human and non-human actors, and assumes that actants in a network take the shape that they do by virtue of their relations with one another. It assumes that nothing lies outside the network of relations, and, consequently, that there is no difference in the ability of technology, humans, animals, or other non-humans to act (Latour, 2005).

Although the sociomaterial approach is appealing at the ontological level, it is somewhat problematic at the empirical level, because technologies and communication patterns are relatively easy to distinguish (Edmondson, Bohmer, & Pisano, 2001; Pentland & Feldman, 2008). For this reason, Leonardi argues that “our current understanding of the nature of the relationship between routines and technologies evinces dissonance between our ontological specifications and our empirical observations” (2011, p. 164). In other words, although technologies and communicative behaviors can be seen, conceptually, as “constitutively entangled,” there are important differences between them in practice. For example, although a person might decide to retrieve information from his or her friend on one day, and from a technology (like a database) on the next day, it is unlikely that he or she would ever consider the technology his or her friend. Thus, although the sociomaterial approach provides an important way of thinking about technologies as parts of networks (as opposed to entities that exist independent of networks), this approach does not provide much guidance in specifying how researchers might depict sociomaterial relations empirically in ways that recognize these important differences.

In this article, we argue that making technologies endogenous to networks will offer researchers the ability to begin thinking about networks composed of different types of nodes (e.g., persons, databases, books, etc.), and about where the relationships among these varying nodes also differ (e.g., one might have a friendship relationship with another person, but an information-retrieval relationship with a database). We call these “multidimensional networks.” This approach stands in contrast to the more traditional approaches, outlined above, which treat networks and technologies as objects that exist separately. Although we focus our attention on computer-based artifacts in this article, one could easily substitute the word “non-human” for our use of “technology.” That is, any non-human actor, no matter whether it is a policy, a routine, a chemical, or a drug, can be brought, conceptually, inside a social network, just like a technology. In so doing, the resultant network ceases to be a simple *social network*, and it should, instead, be considered a *multidimensional network*.

The remainder of this article is organized into three parts. First, we develop a general typology of multidimensional networks. Second, we illustrate our arguments by applying this typology to analyze a case study of the implementation of a new computer-based simulation technology into the work of automotive engineers. Though this is not a test of our theory, we show that traditional unidimensional network approaches provide a limited—and in some cases, flawed—explanation of the implementation process, while multidimensional networks allow us to more fully explain these dynamic network processes. Finally, we discuss recent theoretical and methodological developments in the field of network analysis that offer considerable promise in advancing a multi-theoretical, multilevel approach to the analysis of multidimensional networks at scale.

Conceptualizing Multidimensional Networks

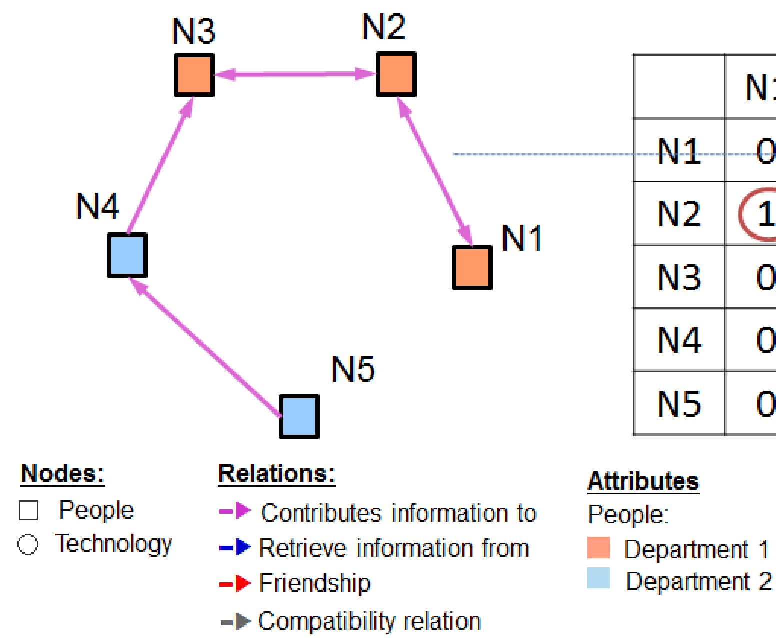
While much has been learned from the large corpus of published research on unidimensional networks, there is little doubt that unidimensionality is a significant oversimplification of the rich complexity that exists in most social networks. As a general analytic system, network analysis can be applied to both an amazingly diverse set of objects and a similarly diverse set of relations. However, in most instances, any single study typically looks at networks comprised of only one type of node and, at most, a handful of relations among these similar objects. Of course, the primary objects of study for social networks are people and their social, communicative, and other human relations. But increasingly, even the ties among people are created, maintained, and dissolved because of their interactions with nodes in the network that are technologies such as Web sites, documents, and tags. Of course, there are multiple types of relations that often create complex patterns. Some relations might be appropriate for ties among humans, but not for ties among non-humans. Other relations might similarly be appropriate for ties among technologies, but not humans. And some relations, such as friendship, might not be appropriate for connections between humans and non-human entities. In this section, we explore these types of network multidimensionality, examining the inclusion of different types of objects in networks and defining multiple types of relations on the multimodal objects.

Unidimensional Networks

Networks consist of objects that are connected to each other in the world by some type of relationship; they also consist of the symbolic representation of those connected objects, such as in maps that represent connections among blogs in the blogosphere (Adamic & Glance, 2005; Kelly, 2010). Unidimensional networks, sometimes called unimodal, uniplex networks, consist of a single type of object or node and a single type of relation. Typically, in social networks, nodes are people, sometimes broken down into different kinds of categories, like school children (Goodreau, 2007) or members of various corporate boards of directors (Stevenson & Radin, 2009). But it is entirely possible to have nodes other than humans and still have social networks. For example, Faust and Skvoretz (2002) compared 42 networks of four different types of social species: humans, non-human primates, non-primate mammals, and birds. It is also quite common to have non-human networks, as with road maps that show the connections among cities. These examples illustrate that, while scholars have looked at networks of diverse nodes, each of these studies typically look at only one type of node (humans, primates, birds, etc.).

Relations describe connections among objects that specify which objects are linked, and which are not. Relations can also be signed to indicate whether they are positive or negative, like amity and enmity. They can also be valued, so as to show how much of the relationship exists, as in monthly, weekly, or daily communication contact. Relations can also be directional, as in the relation, “gives money to,” or they can be non-directional, as in the relation, “is friends with.” There is nothing inherently wrong with unidimensional networks. Decades of work in the social sciences has revealed considerable information about how they operate (Easley & Kleinberg, 2010; Jackson, 2008; Monge & Contractor, 2003; Newman, 2010). But they do have a number of limitations. Perhaps most serious is the fact that they oversimplify reality. Most communicative and social processes contain multiple types of relations. For example, in organizational communication contexts, people are often thought to have relations with others about getting work done, about innovation, and about social maintenance (Farace, Monge, & Russell, 1977). Unidimensional examination of these three networks would require three separate analyses, ignoring the relations among them. Consider a simple illustration of a network that might include multiple types of nodes and relations. Figure 1 presents a unidimensional network. Suppose that there are two possible kinds of nodes, people and technologies (as shown in the legend), but only one is shown in the network, people, making it *unimodal*. Several possible relations are also shown in the legend, but only one is included in the network, friendship, making it *uniplex*. Also shown in Figure 1 is the adjacency matrix, which shows the nodes as row and column labels, and relations as the cell entries indicating the link between each pair of nodes.

Relation Network



Adjacency Matrix

	N1	N2	N3	N4	N5
N1	0	1	0	0	0
N2	1	0	1	0	0
N3	0	1	0	0	0
N4	0	0	1	0	0
N5	0	0	0	1	0

Figure 1. Unidimensional (Unimodel and Uniplex) Network and Adjacency Matrix.

Attributes are characteristics of the nodes. Common attributes in social networks are features like gender, race, age, and education. In Figure 1, people's attributes are shown, which consist of the departments to which they belong, represented by orange and blue color codes.

Unimodal Multiplex Networks

Unimodal multiplex networks contain two or more kinds of relations on a single type of node. For example, Lee and Monge (in press) studied two sets of relations among the nongovernmental organizations that comprise the field of information and communication technologies for development. The two relations that they studied in this one set of organizations were (1) project implementation and (2) knowledge-sharing. In addition to studying the networks defined by the two relations separately, Lee and Monge were able to examine how structural patterns in one network influenced structural patterns in the other network. A representative finding here was that "organizations with repeated collaboration in implementation networks are likely to have ties in knowledge-sharing projects as well."

Figure 2 shows a unimodal, multiplex network. Though there are two possible types of objects in the legend, this network is unimodal, so it contains only one type of object—in this case, people (it could just as easily have been the other mode, technologies). Three possible types of relations are shown in the legend, but only two exist in the network, "friendship," and "contributes information to." Again, people's attributes, their departments, are shown.

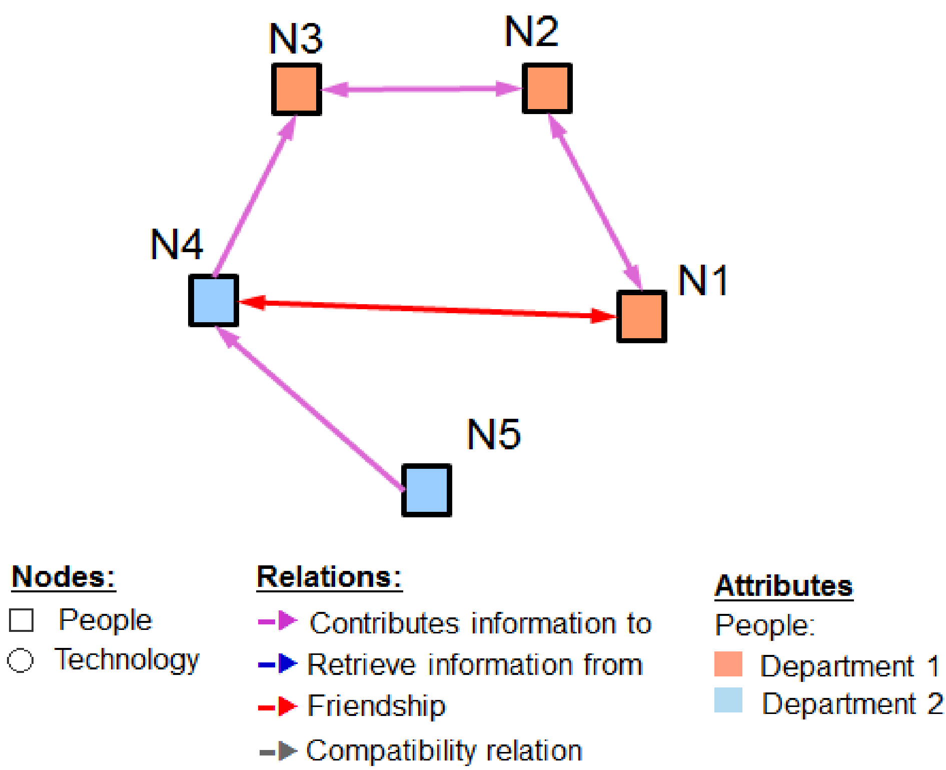


Figure 2. Unimodal, Multiplex Network.

Multimodal Uniplex Networks

Multimodal networks contain two or more different kinds of nodes. The simplest are bimodal (two-mode) networks. Multimodal uniplex networks contain two or more types of nodes connected by a single relationship. Often, two-mode social networks consist of a set of people nodes and a set of event nodes, traditionally called affiliation networks because they record which people were affiliated with which events. Davis, Gardner, Gardner, and Wallace (1941) described 18 Southern women who belonged to a social club and attended one or more of 14 social events during the 1930s. The matrices containing these network data can be divided into two one-mode matrices to show (1) the number of times each pair of women attended the same events, or (2) the number of women each pair of social events had in common. They can also be represented as a bimodal (or bipartite) matrix, where the two types of nodes are included into a single matrix with rows being the women and columns being the social events or vice versa. Figure 3 shows a multimodal (bimodal) uniplex network. The two types of nodes are people and technologies, and the single relation is "contributes information to."

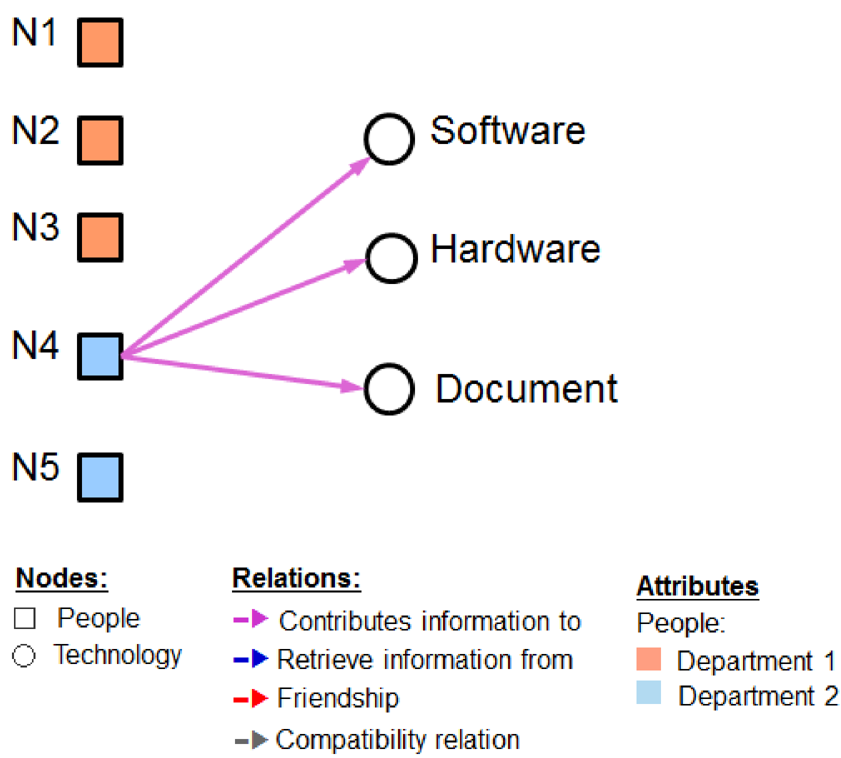


Figure 3. Multimodal Uniplex Network.

Multidimensional Networks (Multimodal Multiplex)

Multidimensional networks have both multiple nodes and multiple relations, and thus, they are sometimes called multimodal multiplex networks. Scholarly research on multidimensional networks is rare. One notable exception is the research on the evolution of the biotechnology industry by Powell, White, Koput, and Owen-Smith (2005). Their research examines six different sets of nodes (heximodal) and four different relations (quadriplex). The six types of nodes are dedicated biotechnology firms (DBFs), universities and other research and development firms, government regulators, pharmaceutical companies, venture capitalists, and others. The relations were research and development, finance, commercialization, and licensing.

Figure 4 shows a multidimensional network with two different types of nodes, people and technologies, and four different types of relations: (1) contributes information to, (2) retrieves information from, (3) friendship, and (4) compatibility. Only two of these four relationships (contributes information to and retrieves information from) are shown in the Figure. This is because the links in these networks only exist between different types of nodes; that is, between people and technologies, but not among people or technologies. Since the figure does not have relationships only among the people, no friendship ties are shown. Likewise, because the figure does not show relationships among technologies, there is no way to show a compatibility relationship between a hardware product and a piece of software.

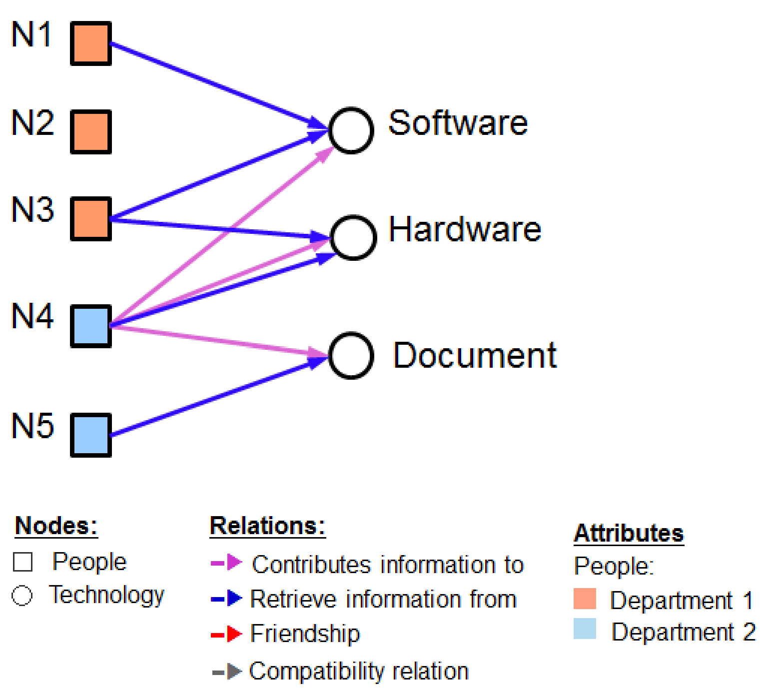


Figure 4. Multidimensional Network: Two (or more) Relations

Between Two (or more) Types of Nodes (Objects).

The absence of relations among the people or among the technologies is not unlike the bimodal example of Southern women attending social events described previously in the discussion of bimodal uniplex networks. In that case, a relation existed when a woman attended a certain social event. We discussed how these bimodal relations could be used to infer either ties among women (how many events they attended in common), or ties among events (how many women attended pairs of events). However, that study did not directly measure relations among women, such as friendship, or among events, such as a thematic connection. The reason for this omission is not necessarily because the authors did not consider those relations to be important. Instead, their omission reflects a limitation of traditional network analytic methods that were used to study bimodal networks. These methods typically required that relations only exist between different types of nodes (or modes) and not include relations among similar types of nodes. But most empirical contexts involving multidimensional networks would greatly benefit from the ability to depict ties among the same types of nodes. Figure 5 depicts such a multidimensional network. This figure includes the friendship relation among people and the compatibility relation among technologies. Recent methodological developments (Robins & Wang, 2011) address the limitations indicated above that had restricted analysis only to relations between different types of nodes and highlight the potential for simultaneously analyzing networks where relations can also exist among nodes of the same type.

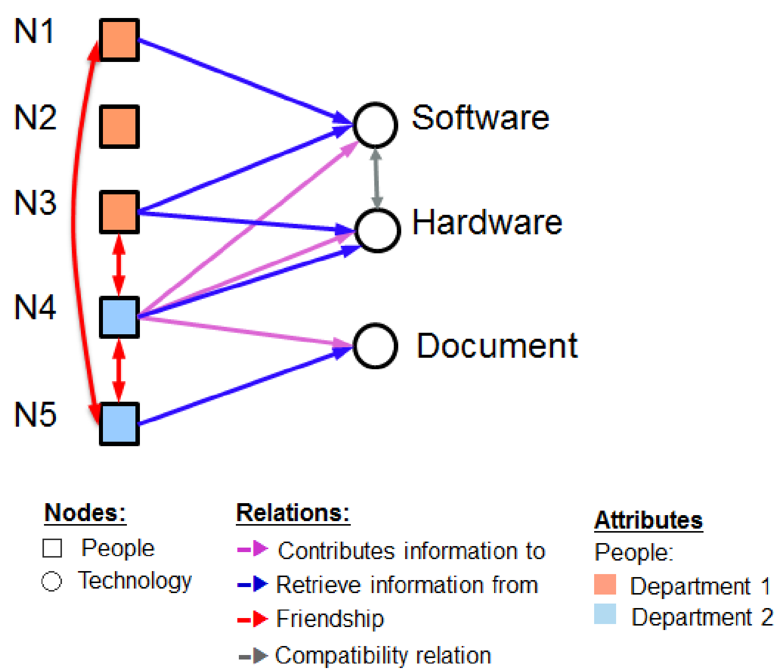


Figure 5. Multidimensional Network: Two (or more) Relations/ Two (or more) Types of Nodes.

Multidimensional networks: Micro and macro variations. Historically, communication and other social networks have been examined from a static, single-point-in-time, cross-sectional perspective. In fact, each type of network described in this typology can be studied from a dynamic perspective (Breiger, Carley, & Pattison, 2003). Burt's (2000, 2002) research on tie decay is one of the earliest examples, though it was done in the context of unidimensional networks. Burt found that the personal networks of banker relationships tend to decay over time, though this was mitigated somewhat by the level of embeddedness of the nodes. Kivran-Swaine, Govindan, and Naaman (2011) show how network structure—strength of ties, embeddedness and status—influenced when people dissolved ties with others on Twitter by "unfollowing" them. Powell et al.'s work, mentioned above, looked at two-mode networks to see how different types of firms (e.g., DBFs and pharmaceutical firms) changed in link structure over time.

When network scholars have thought about network dynamics, they have tended to focus on the *micro level*. Research shows that networks grow by adding individual nodes, or links, or both, and that they decline the same way, by losing nodes, or links, or both. For example, Lescovec, Kleinberg, and Faloutsos (2007) examined the extent to which densification and network diameters change as networks add nodes and links. However, rather than focus on individual nodes and links, we can focus on entire modes of objects and types of relations. In this *macro approach*, we can make networks grow or shrink by adding or omitting an entire mode of objects or an entire type of relation. For example, we could delete over time one of the two modes represented in the figures in this section, people or technologies, or we could add an entirely new mode of objects, say, robots or avatars. Similarly, we could shrink networks by deleting one or more types of relationship. In our example, this could be the "friendship," "provides information to," or "retrieves information from" types of relation. And, we could allow networks to grow by adding new types of relations, such as "provides directions to."

Microlevel multidimensional network dynamics. Figure 6 presents a very simplified representation of a dynamic microlevel multidimensional network. The types of nodes and the types of relations have not changed from Time 1 to Time 2. This network is composed of people and technologies, and it is linked by four types of relations. However, which nodes are linked, and by what relationship, have changed. Some people who were originally linked at Time 1 are no longer linked at Time 2 (N1 and N5). And some who were not linked at Time 1 are now linked at Time 2 (N1 and N2). Similarly, one of the nodes that existed at Time 1 is no longer a member of the network at Time 2 (Documents), and a new node that did not exist in Time 1 has joined the network at Time 2 (New Tech).

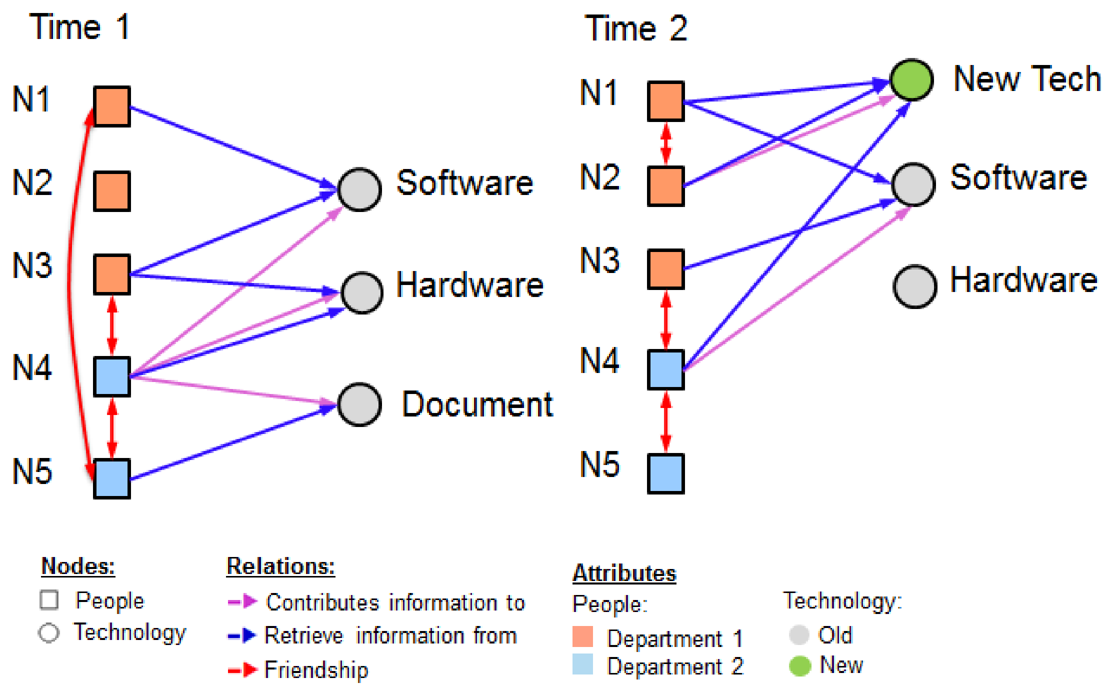


Figure 6. Dynamic Microlevel Multidimensional Network: Adding and Deleting Individual Instances of Nodes and Relations Over Time.

Macrolevel multidimensional network dynamics. Figure 7 provides an example of a dynamic macrolevel multidimensional network. Here, a new mode (or type) of object, avatars, has been added to the network at Time 2. And a new type of embodiment relation between individuals and avatars has been added to the network. Figure 7 also depicts that a type of node (chemicals) and a type of relation between individuals and chemical ("tests with") disappears from the network between Time 1 and Time 2.

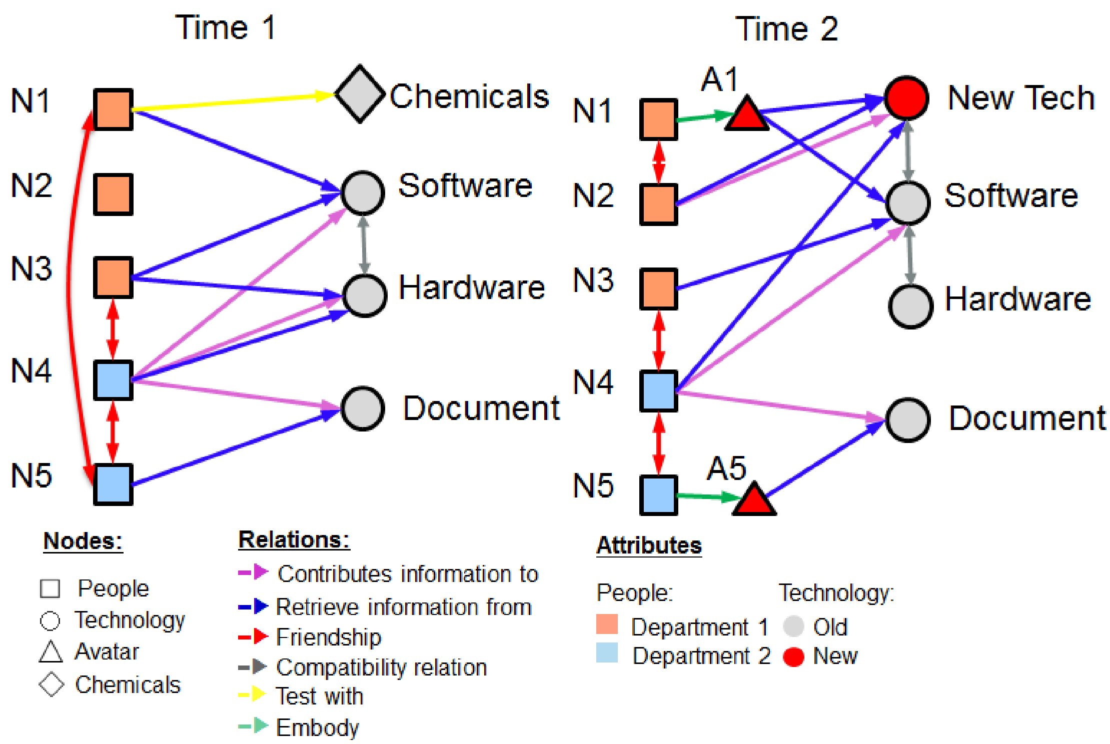


Figure 7. Dynamic Macrolevel Multidimensional Network: Adding and Deleting Entire Sets of Nodes and Relations Over Time.

Summary

In summary, unimodal networks comprise nodes that are all of the same type, while multimodal networks have nodes of different types. Likewise, uniplex networks are comprised of only one type of relationship among the nodes, while a multiplex network includes multiple types of relationships. A multidimensional network is one that is both multimodal and multiplex. Further, dynamic microlevel multidimensional networks are those where nodes or relations of existing types are added or eliminated over time. Dynamic macrolevel multidimensional networks are those where entire classes (or types) of nodes and relations might appear or disappear over time. It is important to point out that all seven cases in this typology can be studied as dynamic, rather than static, networks. We have illustrated the possible dynamic changes for the microlevel and macrolevel multidimensional cases in order to articulate the specifics of these more complex networks. Table 1 summarizes our framework for multidimensional networks. In the following section, we apply this framework to describe and understand a specific empirical example.

***Table 1. A Framework for Multidimensional Networks*.**

Unidimensional networks

1. Unimodal, uniplex (single sets of nodes, single sets of relations)
    a. Static (single points in time)
    b. Dynamic (two or more points in time, nodes and links may be added or deleted)

Partially multidimensional networks (multiple sets of nodes or multiple sets of relations, or both, but relations *only between* different sets of nodes)

2. Multimodal, uniplex (multiple sets of nodes, single relations)
    a. Static
    b. Dynamic (two or more points in time, individual nodes or relations may be added or deleted)
3. Unimodal, multiplex (a single set of nodes, multiple relations)
    a. Static
    b. Dynamic (two or more points in time, individual nodes or relations may be added or deleted)
4. Multimodal, multiplex (two or more sets of nodes, two or more sets of relations)
    a. Microlevel
        i. Static
        ii. Dynamic (elements of sets of nodes and/or relations are added or deleted with relations only *between* different sets of nodes)
    b. Macrolevel
        i. Static
        ii. Dynamic (entire sets of nodes and/or relations are added or deleted with relations only between different sets of nodes)

Fully multidimensional networks (multiple sets of nodes and multiple sets of relations with relations both *within* sets of nodes and *among* sets of nodes)

5. Fully multidimensional networks (multimodal, multiplex nodes and relations with connections both *within* and *among* all sets of nodes)
    a. Microlevel
        i. Static
        ii. Dynamic (elements of sets of nodes and/or relations are added or deleted *within* and *among* all sets of nodes)
    b. Macrolevel
        i. Static
        ii. Dynamic (entire sets of nodes and/or relations are added or deleted *within* and *among* all sets of nodes)

Empirical Example: How Multidimensional Networks Aid in the Explanation of Sociomaterial Dynamics

Autoworks (a pseudonym) is a large automobile manufacturer. The company designs vehicle systems, like body structures, fuel systems, and powertrains, and it analyzes the interactions among them on a number of parameters. One of the most important of these is how well these systems work together to protect the vehicle's occupants during a collision. The idea behind "crashworthiness engineering" is that the best chance occupants have of surviving a crash with little or no injury is for the vehicle to absorb the energy of a collision (DuBois, 2004).

Crashworthiness is assessed both prospectively, using finite element (FE) analysis techniques on virtual simulations, and retrospectively, by analyzing the results of physical crash test data. Finite element analysis is a computational technique that divides the actual geometry of a part into a large but bounded (hence, finite) collection of small, discrete triangular or rectangular-shaped areas called finite elements. The elements are joined together at shared points.[2] Analysts transform geometrical drawings of the vehicle's systems into FE simulations by using pre-processing software. Pre-processors depict geometrical drawings in three dimensions and allow users to convert those drawings into an FE mesh. After the mesh is created, analysts select specific points in it that they would like to analyze. Then, computer solver technology is used to compare the location of this point before and after the collision. The solver gives the analyst a "displacement" calculation—a reading of how much change occurred as a result of the crash (Hughes, 2000). After the equations have been solved, analysts use post-processing software to, again, render the solution in three dimensions and obtain information on the performance, either of the vehicle as a whole, or of particular assemblies.

Crashworthiness analysts are dependent upon other analysts for information and advice on vehicle design. Analysts are also dependent upon numerous software programs (e.g., pre-processors, solvers, post-processors) to do their work, and those software programs also have computational interdependencies. Given the great number of social and technological interdependencies in crashworthiness engineering work, one would suspect that a small change in one set of relationships would quickly reverberate throughout the work system. This was the case when a relatively junior crashworthiness analyst named Jerry created a new software program to make his job easier. In the remainder of this section, we describe how this new software program became part of the crashworthiness engineers' social networks, and we demonstrate that a multidimensional network approach is superior to the other approaches discussed above. Details of the data collection and analysis procedures for this two year ethnographic study can be found in Leonardi's work (2009b, 2010, 2011, in press).

In their analyses of how well a vehicle faired in a crash, Jerry and his colleagues were often asked by management to determine how much various sections of the vehicle intruded into the occupant compartment. To make these "intrusion calculations," analysts would pick some set of points and measure

[2] The actual terminology that engineers use is that elements are joined together at "nodes," not points. But, because we write so often about nodes of networks in this paper, we have changed the term to "points" to avoid confusion.

how much they moved inward toward the occupant during the crash. To conduct an intrusion calculation, the analysts would open their post-processing software and choose the desired points in the mesh of the vehicle before the crash occurred. They would then advance the simulation to a post-crash condition, choose those same points, and calculate the distance between them. This analysis caused Jerry and his colleagues a good deal of consternation, because no one was sure which points to select. How were analysts to know which selections would result in the most robust and reliable depictions of intrusion?

In late 2006, Jerry finished development work on a small piece of software that he hoped would make this work much easier. The program, which he named "Intruder," (see Figure 8) was a simple script. After the solver completed its calculations of the simulation model, analysts would now send information from the solver directly to Intruder to render it for analysis without using the pre-processor to make their intrusion calculations. Analysts could choose from one of five common analysis scenarios in Intruder. Analysts would then move down the screen to the "Selections" box, which included the locations on the vehicle at which managers often wanted to see intrusion calculations (e.g., in Figure 8, the "B-Pillar Plane," the column separating the front and back doors of a car) and the program would suggest the points that were likely to provide the most robust results (e.g., in Figure 8, Intruder suggests points 111–113). Jerry hoped that Intruder would reduce the time to complete a job from an hour to less than 10 minutes.

To determine which points to include as recommendations to the user in Intruder, Jerry consulted Balaji, another analyst who worked in the same department at Autoworks. Balaji was a senior analyst to whom Jerry often went for advice. In addition to consulting with Balaji, Jerry consulted a number of internal documents created by Autoworks that summarized best practices for analysis, as well as a number of government documents that detailed crashworthiness regulations at the federal level. After he felt Intruder was ready for use, Jerry asked Balaji to test it.

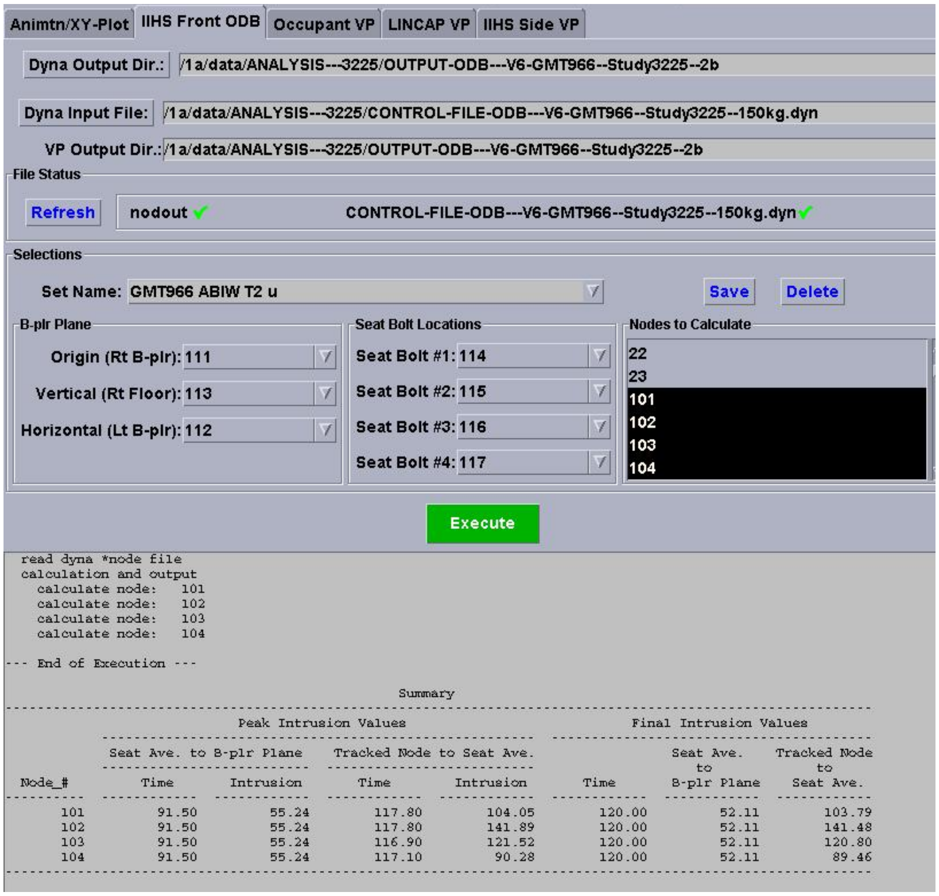


Figure 8. Screen Shot of Intruder Technology.

Balaji liked Intruder immensely. Analysts at Autoworks shared large cubicles with one another, and Balaji's cube-mate, Damen, saw him working with Intruder on multiple occasions. After some conversation about its features, Damen asked Balaji if he might be able to secure a copy. Balaji told Damen to ask Jerry if he could try a copy, and Jerry agreed. Damen quickly became a fervent Intruder user.

One day, Damen began to discuss Intruder with Cate, an analyst who worked in a different department and building, describing how much he liked using it. Cate asked Damen if she could obtain a copy. After securing permission from Jerry, Damen passed the software along to Cate. After a few weeks, Cate showed Intruder to her departmental colleague, Sebastian. Sebastian and Cate had a close working relationship. Sebastian liked what he saw in the software and eventually procured a copy for himself.

Up to this point, this case reads like a fairly common diffusion of technology story: Intruder's use spreads across a social network, and this diffusion is lubricated by various social forces. The technology moves from Jerry to Balaji due to a logic of exchange—Balaji will give feedback to Jerry in exchange for permission to use Intruder. The technology moves from Balaji to Damen based on a logic of proximity—Balaji and Damen sit no more than two meters from each other and thus share common stimuli. The technology then moves from Damen to Cate based on a logic of friendship—though the two analysts do not work together, their bond is based on a relationship forged outside of the workplace. It is because of this friendship relation that Intruder diffuses out of the department in which it was initially created. Finally, the technology moves from Cate to Sebastian, based on a logic of reciprocity, given that they often exchange ideas and information.

Moving past a simple story of diffusion, scholars might ask how the new technology became enmeshed in the existing sociomaterial dynamics that constituted crashworthiness work. To do so, scholars would first have to select which types of communicative behaviors are of most consequence for this work. Researchers have shown that, in technical and engineering work, advice seeking behaviors play a key role in people's ability to do their jobs effectively (Barley, 1990; Constant, Sproull, & Kiesler, 1996; Leonardi, 2007; Rice, Collins-Jarvis, & Zydney-Walker, 1999). In crashworthiness engineering work, analysts typically seek advice from one another. Although seemingly a banal type of consultation, research has shown that even basic advice-seeking behaviors—such as asking about what FE points to select—construct status hierarchies that have important implications for interpersonal and organizational communication (Blau, 1955; Gould, 2002; Scott, 2004).

Of course, not all advice-seeking about a given issue is of the same type. At Autoworks, analysts who sought advice sometimes went looking for a simple answer, and at other times, they went looking for an explanation about why certain points were preferred over others. In other words, analysts could be seeking advice about *what points to select* and *why to select those points.* Analysts were not restricted from seeking advice exclusively from people. They could, as Jerry did above, seek advice from documents. After its implementation, Intruder was also a possible indirect locus of advice.

Before analysts began using Intruder, junior analysts often sought advice about *what* points to select and *why* it was appropriate for them to select those points from senior colleagues. Most junior analysts viewed the need to answer the *what* question as a good excuse to learn from the senior analyst about *why* those points were important. These advice-seeking behaviors were highly correlated with proximity and friendship. Junior analysts almost never consulted internal documents or external government documents for either *what* or *why* questions. Senior analysts, by contrast, almost never sought advice about *what* points to select or *why* to select them from junior people. Instead, they often consulted internal and external documents or asked others who held their same level of seniority. Senior analysts' advice seeking about *what* and *why* practices were also highly correlated with each other, as well as with proximity and friendship.

Perceptions of expertise were based predominantly on advice-seeking behaviors. Because the departments were relatively small, people knew who received requests for advice and who did not. Analysts who were often sought for advice on *what* and *why* questions were revered as experts in crashworthiness analysis by their colleagues. Being considered an expert conferred numerous advantages at Autoworks, such as awards, sizeable salary increases, and the opportunity to work on prestigious projects.

After analysts had used Intruder for two years, many changes were evident in the structure of their advice networks. Advice-seeking about *what* points to select became decoupled from advice about *why* one should select those points. Analysts who were both junior and senior stopped asking their colleagues for advice about *what* and turned their queries toward Intruder. Although Intruder was helpful at aiding analysts in deciding *what* points to select, it was of no help in instructing analysts as to *why* those were the correct points in the first place. For such an answer, analysts could turn to either colleagues or internal or government documents. Before Intruder was implemented, these consultations would have been made of senior colleagues. But because people were using Intruder and knew that Jerry (who was junior) created the software, they began to go to him for advice about *why* questions. The logic of this shift in advice-seeking behaviors was simple: If someone relied on the technology to tell them *what* points to select, the software's developer must know *why* those were the appropriate points.

The dynamics of this case, simple though they may be, are actually fairly difficult to capture with traditional network models. Consider, for example, the unimodal uniplex network most often used by network researchers. If we would take a cross-section of advice network relations at two points in time—Time 1 = before Intruder is implemented, and Time 2 = two years after Intruder—we would only be able to map one set of relationships for nodes of one type. For the case presented above, we can render a network comprised of nodes representing our five analysts and edges representing advice seeking about *what* points to select (see Figure 9). At Time 1, Balaji occupies a fairly central role. We also see an information retrieval relationship across departments (between Damen and Cate) that is difficult to explain. Why are these two connected? The network dynamics following the implementation of Intruder are even harder to decipher. The graph for Time 2 shows only Sebastian seeking advice from Cate, but all other relations have disappeared. An observer of this longitudinal, unidimensional (unimodal, uniplex) network analysis would likely conclude that Intruder disturbed the existing fabric of social relationships in crashworthiness engineering at Autoworks, perhaps supplanting analysts as a source of information.

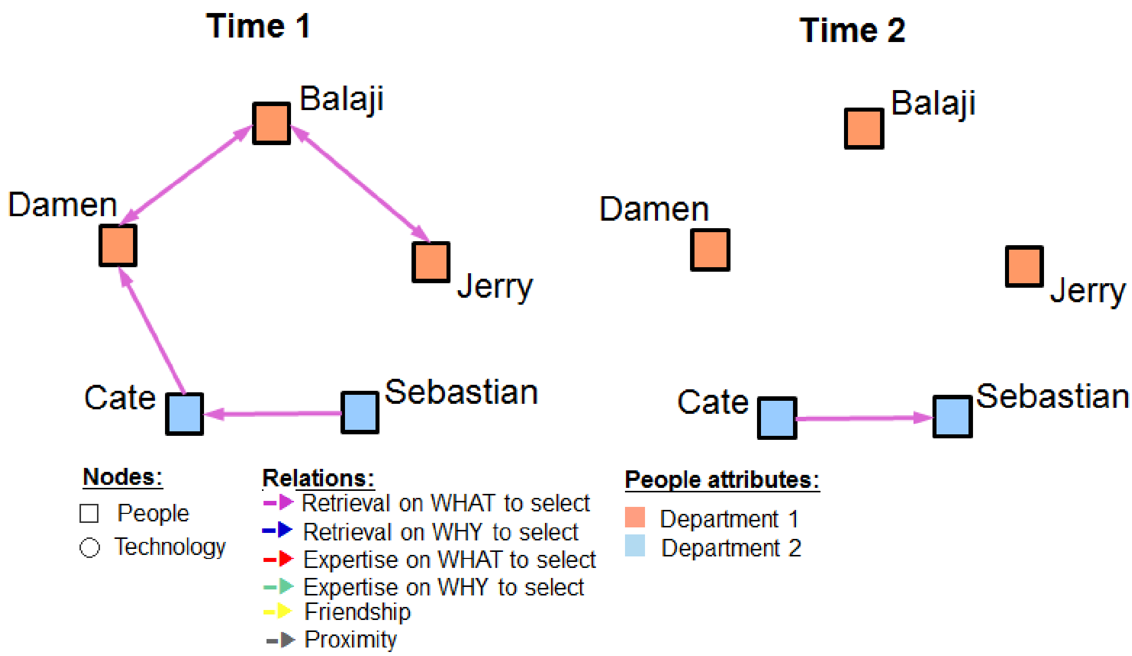


Figure 9. Explaining Sociomaterial Change Over Time by Using a Unidimensional Network.

If we analyze this case using a unimodal multiplex network, we would uncover a very different story than what we saw in a unimodal uniplex network. Figure 10 shows the addition of other types of correlated relations at Time 1. Analysts who seek advice from a colleague about *what* points to select are also likely to seek advice about *why* they should select those points. Analysts tend to consider the people from whom they seek advice about *what* and *why* to also be experts about both topics. Moreover, advice-seeking and expertise-conferring behaviors are correlated with friendship or proximity. One might infer here that friendship and proximity are drivers of who people consider to be experts. The depiction of network dynamics at Time 2 is strikingly different from that shown by the unimodal uniplex network. Whereas the unidimensional network suggests that the technology brings a near-complete halt to inter-collegial advice seeking, the graph at Time 2 in Figure 10 shows Jerry becoming a very central actor on three sets of relations: (1) advice about *why* to select certain points, (2) expertise about *what* points to select, and (3) expertise about *why* one would select certain points. Further, many of the relations among the others (e.g., Balaji and Damen) have dropped away. Alone, the unimodal multiplex network might lead the observer to conclude that the technology shifts status and power toward its creator, Jerry. But the observer would have trouble explaining what happened to advice-seeking on *what* points to select. Did Intruder simply teach analysts how to select points, and now, they no longer need to seek advice on this behavior? The answer is unclear because technologies are not represented in the model.

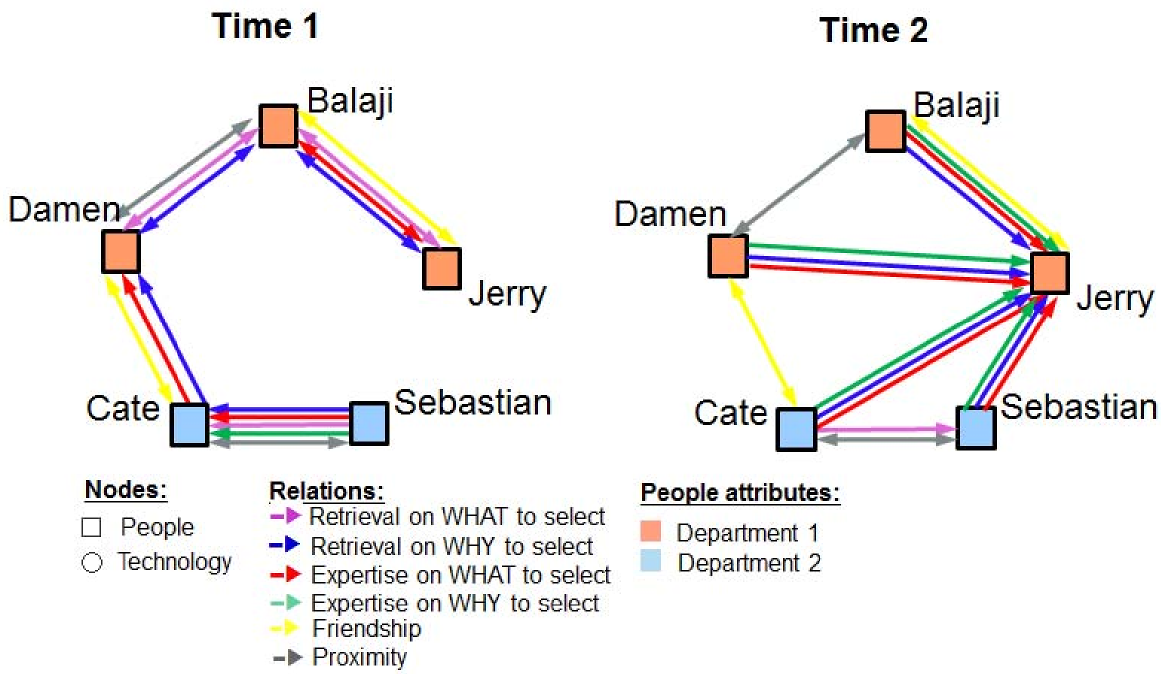


Figure 10. Explaining Sociomaterial Change Over Time by Using a Unimodal Multiplex Network.

An analysis of this case using a multimodal uniplex network (Figure 11) would help to more clearly explain the specific role that Intruder played at Autoworks. Focusing on advice seeking about *what* points to select, at Time 1, we would see that a few of the analysts consulted internal documents to make determinations about where to select points for intrusion calculations. At Time 2, we would learn that all of the analysts in the case have shifted their advice seeking patterns, and that they now consult Intruder when needing to determine what points to select. The story an observer of these networks might tell is one of deterministic technological change—a newer technology replacing an older technology. Due to the uniplex nature of the network, the observer would not know who of the analysts, if any, sought advice from each other about *what* points to select. We also would not know whether the technology had changed perceptions of expertise and status, or whether it had simply transferred people's practices from one technology to another.

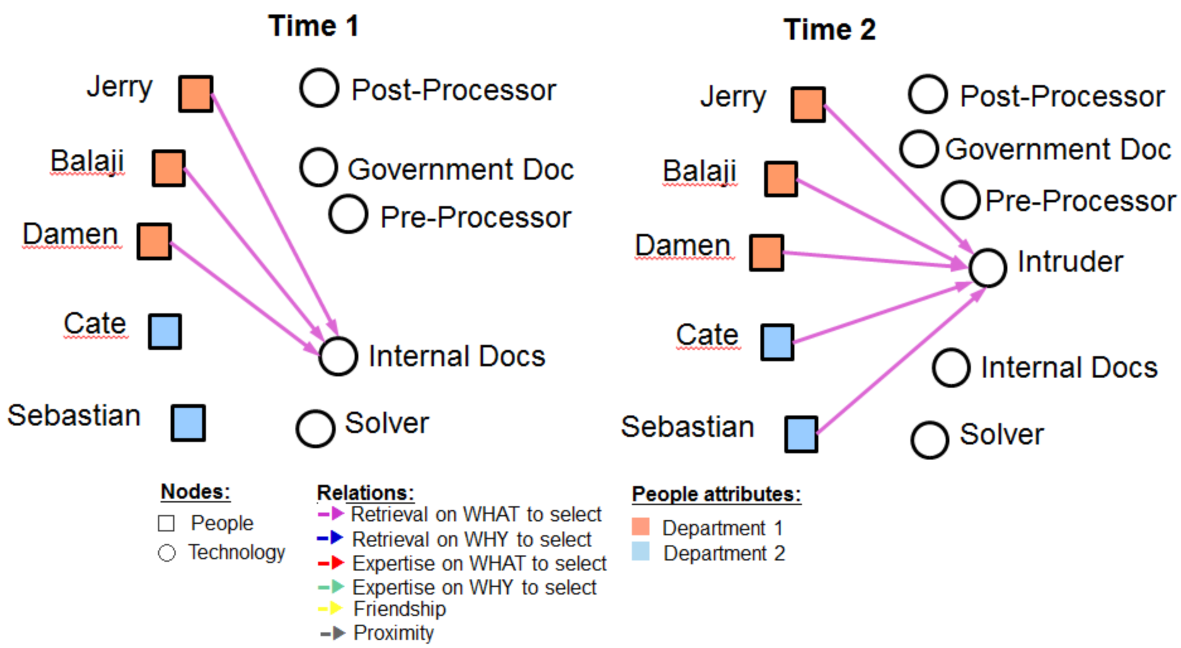


Figure 11. Explaining Sociomaterial Change Over Time by Using a Multimodal Uniplex Network.

Figure 12 depicts the dynamics of the case using a multimodal, multiplex (or a partial multidimensional) network, in which multiple relations are represented *between* two types of nodes. The different types of nodes at Time 1 include people, technologies such as the Solver, Pre-Processor, Post-Processor, and the various documents that analysts used. At Time 2, it also includes Intruder. The different relations include people's perceptions of what expertise technologies possess about what points to select and why to select those points. It also includes relations that indicate from what technologies people choose to retrieve this information. This graph clearly shows that, at Time 1, only Jerry, Balaji, and Cate, the three senior analysts, sought advice from technologies and considered certain technologies as expert sources of knowledge. All three of the senior analysts sought advice about *what* points to select from internal documents, and all three considered those documents to be expert source of knowledge. Only Jerry consulted external government documents for advice on *why* certain points should be selected and came to view those documents as expert sources for this type of information. At Time 2, the graph shows that all three senior analysts have stopped consulting internal documents for *what* issues, and that they have shifted their queries to the new technology, Intruder. Additionally, junior analysts now consult Intruder for *what* questions as well. Jerry continues to consult government documents for *why* questions.

It is important to note that this multimodal, multiplex network contains only relations between the different types of nodes. It does not contain relations among the same types of nodes, like people or technologies. If observers used this partial multimodal, multiplex network to interpret the dynamics of the case, they would likely conclude that, before Intruder, junior people did not seek advice at all, from anyone or any technology.

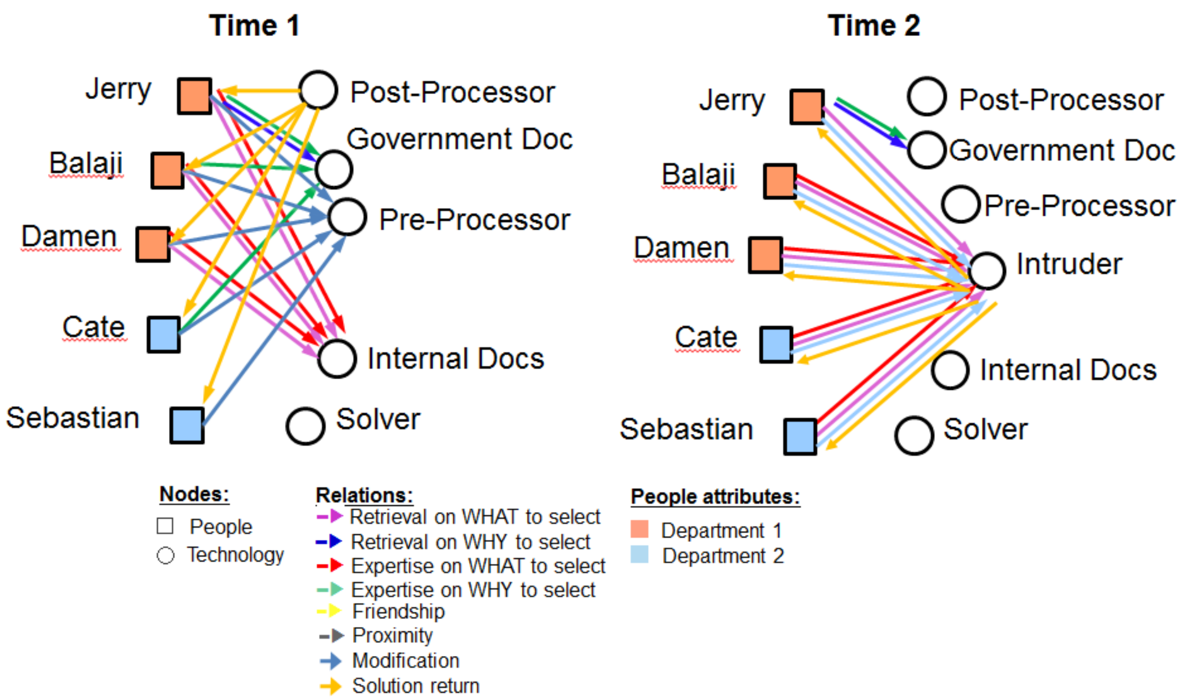


Figure 12. Explaining Sociomaterial Change Over Time by Using a Multimodal Multiplex Network.

As we have argued above, in order to more accurately reflect contemporary usage patterns, the most capable depiction of the dynamics of sociomaterial systems is generated through the use of a multidimensional network in which multiple relations are represented *between* and *within* different types of nodes.

Figure 13 provides an illustration of a full multidimensional network for this case. At Time 1, we can see a pattern of associations between advice-seeking about *what* points to select and *why* one should select those points. We see that these two advice-seeking practices vary with perceptions of who (person) or what (artifact) is perceived to have expertise about these two topics. We also see that friendship and proximity are social forces integral to advice-seeking from, and expertise-construal for, people, but that they are not so for technologies. This is because friendship is a logic of attachment that is appropriate for relations among people, but not between people and technologies or among technologies. Proximity is a meaningful construct when applied to people, but it cannot drive the formation of relationships between people and technologies. We also see that there is a submission relation between the pre-processor and the solver, as well as a rendering relation between the solver and the post-processor. Both of these types of relations are inappropriate for characterizing the communicative patterns among people.

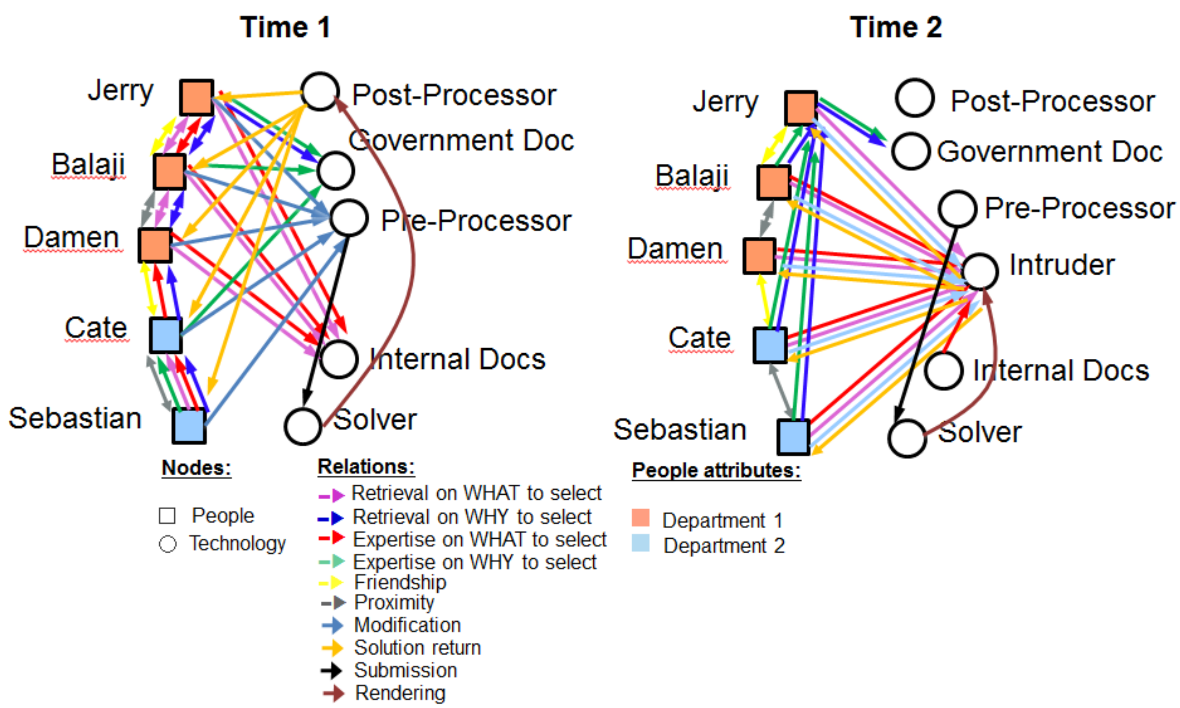


Figure 13. Explaining Sociomaterial Change Over Time by Using a Fully Multidimensional Network.

At Time 2, the fully multidimensional network shows that the Intruder software and Jerry have become central nodes. By examining multiplex ties among and between nodes of different types, we can see that advice-seeking practices and attributions of expertise that were directed toward senior analysts before the implementation of Intruder are now split between Intruder and Jerry. Intruder has become the central actor in *what* advice consultations, and it is seen by analysts as an expert in *what* knowledge. Jerry has become the central actor in *why* advice consultations, and he is seen as an expert in *why* knowledge.

By examining this multidimensional network longitudinally, we can also begin to make inferences about how these shifts in network dynamics occurred. At Time 1, Jerry is the only analyst who actively consults the government documents to learn *why* one would select certain points. Intruder is able to serve as a source of advice to analysts about *what* points to select. But although the knowledge Jerry gained from the government documents about *why* certain points should be selected is inscribed in Intruder, it is not explicit, and it cannot be easily decoded by a user. Thus, the users who have begun to view Intruder as an expert on *what* points to select now go to Intruder's creator to learn *why* to select those points. In effect, Intruder acts as a gravitational force; as the technology comes to be viewed as an expert source for *what,* Jerry is pulled to the center of the network as an expert source for *why.* Finally, Intruder changes the relationship among the technologies. Solvers no longer render solutions to pre-processor in Time 2; instead, they render solutions directly to Intruder.

Summary

This illustration of the sociomaterial dynamics of crashworthiness engineering at Autoworks shows that many of the alternatives in the network typology presented in the previous section fail to capture the richness of these data. As we moved progressively through each analytic alternative, we sought to demonstrate how this narrative can be best understood when the new technology and other non-human artifacts are considered to be part of the multidimensional network, rather than as separate entities influencing and being influenced by the social network. We used the fully multidimensional network framework to understand the structure and dynamics of networks involving different types of nodes (people and technology) and different types of relations both among and between people and technologies. In particular, we demonstrated that examining the network from the unimodal and uniplex frameworks provided an inadequate and often misleading representation of the underlying structure and dynamics. The rich interplay between people and technology was progressively revealed as we considered a unimodal uniplex representation (Figure 9), a unimodal multiplex representation (Figure 10) or a multimodal uniplex representation (Figure 11), a multimodal multiplex representation (Figure 12) with relations only between nodes of different types (people and technologies), and finally, a multimodal multiplex "fully multidimensional" representation (Figure 13) with multiple types of relations among and between nodes of different types (people and technologies).

Although many authors recommend longitudinal, ethnographic approaches to capture the sociomaterial dynamics of organizing (e.g., Leonardi & Barley, 2010; Orlikowski & Scott, 2008), this type of study is not always possible. Some processes involve so many different types of actors that it would be nearly impossible to create an observation record capturing all of their interactions. Some organizing processes transpire over such a long period of time that field observation is not feasible. Nonetheless, we believe that including multiple types of relations within and between multiple types of actors will significantly increase our ability to analyze complex dynamic sociomaterial phenomena like those illustrated by these ethnographic data. However, when attempting to identify and explain sociomaterial dynamics at scale, it is helpful to have certain heuristics with which to be able to detect particular patterns within the data. In the next section, we explore these multidimensional representations.

Developing Multi-Theoretical Multilevel Models of Multidimensional Networks

In the past decade, social network scholarship has made a concerted effort to move from describing a network to developing techniques that explain the emergence and dynamics of the network. The development of analytic techniques to explain the emergence of networks is often motivated by multi-theoretical multilevel (MTML) models (Monge & Contractor, 2003). These models are multi-theoretical because of a growing recognition among social networks researchers that the emergence of a network can rarely be adequately explained by a single theory. Therefore, these models combine disparate theoretical generative mechanisms, such as self-interest, collective action, social exchange, balance, homophily, proximity, contagion, and co-evolution. These models are multilevel because the emergence of a network can be influenced, for instance, by theories of self-interest that refer to characteristics of actors (at the individual level), theories of social exchange that describe ties between pairs of actors (at the dyadic level), theories of balance that explain configuration of ties among three actors (at the triadic level), and theories of collective action that explain configurations among larger aggregates of actors (at the group or network level).

Of particular interest from an analytic perspective is that each of these theoretical generative mechanisms has a “structural signature” that is unique to that theory. Figure 14 shows the structural signatures associated with several theoretical mechanisms. Hence, in the case of social exchange given a network where the solid lines represent a set of relations among the actors, there is a greater likelihood of a tie from C to A because it reciprocates a tie from A to C. Likewise, there is a lower likelihood of a tie from F to D because of the absence of a relation from D to F. Recent statistical advances, such as exponential random graph models (also known as *p**, see Robins, Snijders, Wang, Handcock, & Pattison, [2007] for a recent review) are able to assess the degree to which these structural signatures are observed in a network, above and beyond what might be expected in comparable random networks. As such, these methods provide the means to test multi-theoretical multilevel hypotheses about mechanisms that explain the emergence of networks (Contractor, Wasserman, & Faust, 2006).

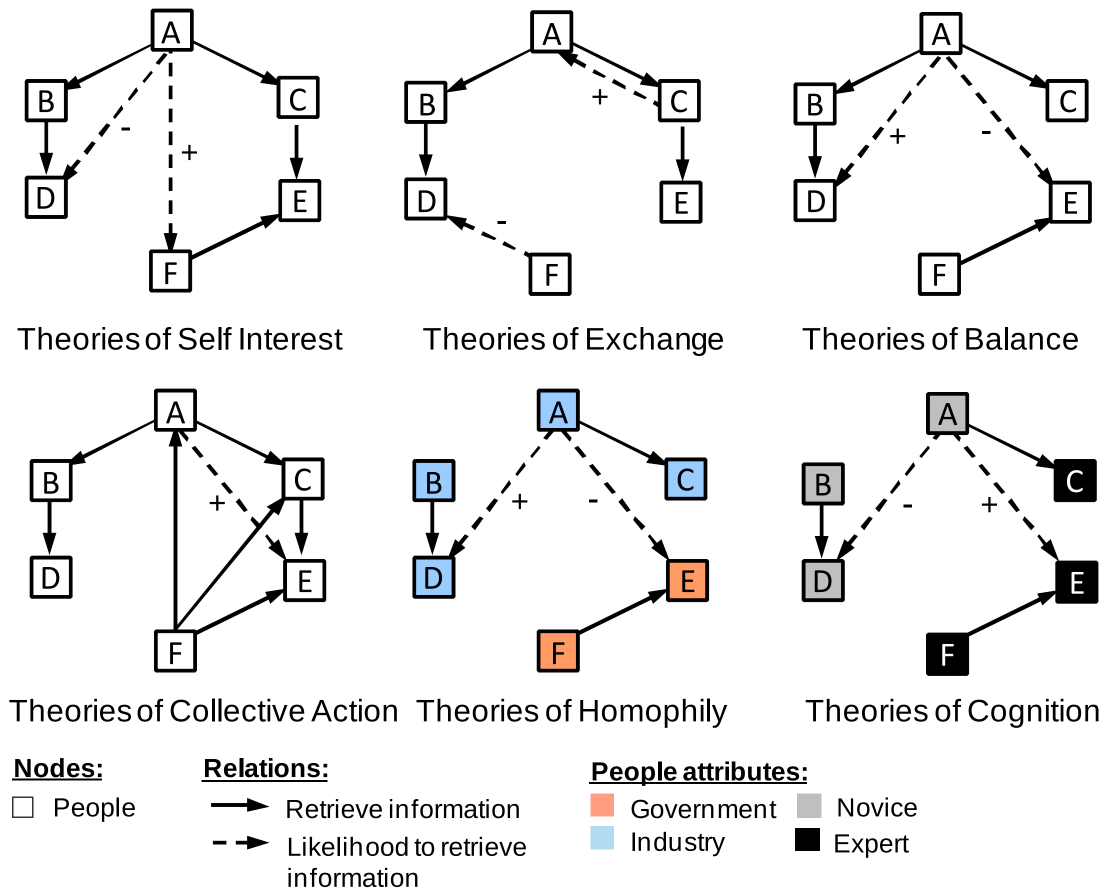


Figure 14. Examples of Structural Signatures Associated with Theories of Network Emergence.

Although MTML models have been used to understand the emergence of unidimensional networks among unimodal nodes (such as people or organizations), there is considerable potential for developing and testing new theories to explain the emergence of multidimensional networks. Software tools now exist to test multi-theoretical multilevel hypotheses for cross-sectional and longitudinal partially multidimensional networks—those that are multiplex or multimodal but without relations among different types of nodes (Seary & Richards, 2000; Huisman & Van Duijn, 2005;; Handcock, Butts, Goodreau, & Morris, 2008; Steglich, Snijders, & West, 2006).

While the structural signatures illustrated in Figure 14 capture the theoretical motivations to explain the emergence of relations among unidimensional networks, the previous section demonstrates that they are ill-equipped to unravel the structural signatures that might explain the structure and dynamics of multidimensional networks. For instance, one theoretical mechanism included within the

MTML model can explain why it is true that, if individual A knows B, and B knows C, then over time, based on theories of balance, there is a greater likelihood that A will know C. We can test that hypothesis by counting the number of times the structural signature implied by that logic (shown in Figure 14 as Theories of Balance) is more than one would expect in a commensurate random network. The assumption here is that A, B, and C are all nodes of the same type—they are all people. But in the multidimensional networks we are considering here, A and B might be people, but C might be a technology. This opens up the possibility of inscribing a vast number of new structural signatures that capture the dynamics of how multiple network relations among and between individuals and technologies will enable or constrain their dynamics.

The case study described in the previous section offers several provocative examples of structural signatures that might be particularly relevant in understanding the emergence of the multidimensional network depicted in Figure 13. Consider how extant theories of network emergence might be used in the present example. The theory of transactive memory systems developed by Moreland (1999) and Wegner (1995), for example, has been used extensively to explain the emergence of knowledge networks (Hollingshead, Fulk, & Monge, 2001; Su & Contractor, in press; Su, Huang, & Contractor, 2010; Yuan, Monge, & Contractor, 2010). This theory states, in part, that individuals are more likely to retrieve information from those they perceive to be experts in a particular area. As shown in Figure 14 (see Theories of Cognition), a novice (A) is both more likely to go to an expert (E) and less likely to go to another novice (D). If the network was driven by this mechanism, we would expect to find a pattern of association between a relationship where one individual considers the other as an expert and a relationship where that individual retrieves information from the expert. The simultaneous presence (or absence) of these two relations between individuals would therefore serve as the structural signature for the theory of transactive memory systems. A quick review of Figure 13 does, indeed, suggest that, at Time 1, individuals who consider others as having expertise on what points to select are also more likely to retrieve information from those with expertise on what points to select. For instance, Jerry rates Balaji's expertise highly on what points to select, and he also reports retrieving information on what points to select from Balaji. Continuing to examine Figure 13, there also appears to be an association at Time 1 between an individual's perceptions of those who have expertise on why to select a certain point and their likelihood of retrieving information from the same people. For instance, Cate considers Damen as having expertise on why to select a certain point, and she also reports retrieving information from Damen on this topic. The structural signature shown here is consistent with what has been developed for unimodal MTML models, and it is shown in Figure 15. If individual N1 perceives individual N2 as an expert, N1 is more likely to retrieve information from N2 and less likely to retrieve information from N3, who is not perceived an expert. This structural signature serves to validate a hypothesis offered by transactive memory theory in a multidimensional network.

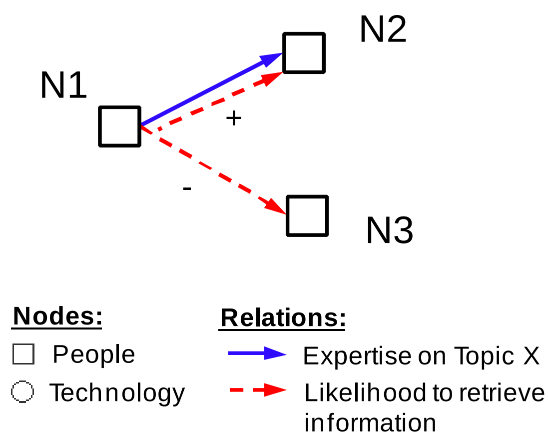


Figure 15. Structural Signature for Perceived Expertise and Information Retrieval Among People Based on Theories of Transactive Memory.

However, the above example based on the theory of transactive memory systems also illustrates the potential of extending existing theory from unidimensional to multidimensional networks. While the theory of transactive memory systems was developed to explain knowledge networks comprising individuals, the nodes in the Figure 13 network are individuals and technologies. An extension of the theory of transactive memory systems would suggest that the association between perceptions of expertise and retrieval should occur not only among people, but also between people and technologies. For instance, in Figure 13 at Time 1, Jerry (a person) reports a government document as having a high level of expertise, and he also reports retrieving information from the document. The structural signature for this tendency is shown in Figure 16.

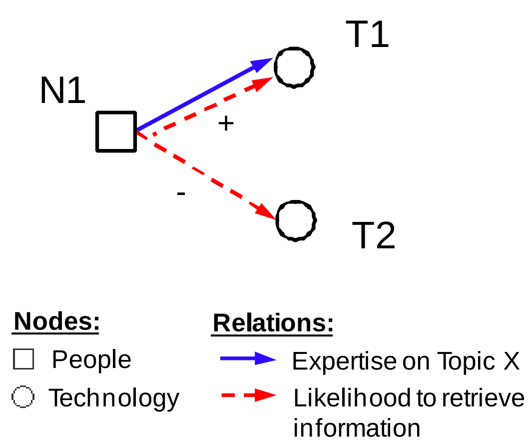


Figure 16. Structural Signature for Perceived Expertise and Information Retrieval Between People and Technologies Based on Extensions to Theories of Transactive Memory.

Here, the structural signature involves an individual N1 and two artifacts T1 and T2. If the individual N1 perceives technological artifact T1 as having expertise on a particular topic, N1 is more likely to retrieve information on that topic from T1, rather than from technological artifact T2, which is not perceived as having expertise on that topic. This structural signature invites consideration of what the theory might posit about links between humans and technological artifacts in a multidimensional network. It is interesting to note that this structural signature is not particularly prevalent. For instance, both Balaji and Cate consider the government document as having expertise on this topic, but they do not retrieve information from the government document. Given that the co-presence of an expertise relation and a retrieval relation might occasionally occur in any random network, the ERGM/p* analysis would likely prove to be statistically insignificant.

In fact, the network at Time 1 in Figure 13 suggests a novel structural signature with potentially interesting theoretical insights. Notice that, though Balaji recognizes the expertise embodied in the government document, he is more inclined to retrieve that information from Jerry, who retrieved that information from the document. This pattern might suggest a structural signature that, when given a choice to retrieve information from a technology or an individual, people are more likely to retrieve the information from other people who have already retrieved it from the document. The structural signature for this multidimensional configuration is shown in Figure 17, where, given that individuals N1 and N2 perceive that technology T1 has expertise on a topic and N1 retrieves information from T1, N2 is more likely to retrieve information from individual N1 than from technology T1. The structural signature discussed in this example illustrates how a multidimensional network framework can be used to extend transactive memory by simultaneously considering both interactions among people and those between people and technological artifacts.

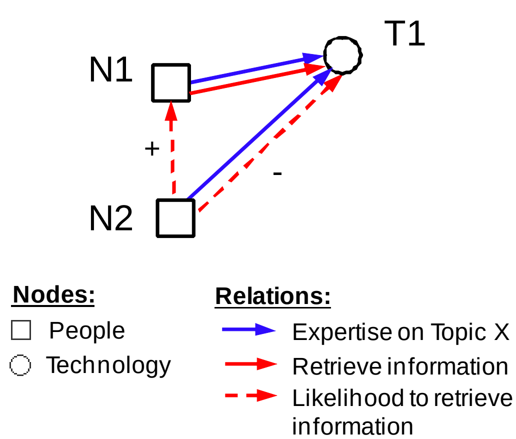


Figure 17. Structural Signature for Perceived Expertise and Information Retrieval Among and Between People and Technologies Based on Extensions to Theories of Transactive Memory.

Figure 13 also provides several illustrations of how structural signatures can be used to theorize the dynamics of networks—in this case, from Time 1 to Time 2. One focal point is the emergence of the new Intruder software as an important network node. The introduction of this new technology by Jerry resulted in several individuals within the network adopting the new technology based on contagion, social exchange, proximity, homophily, or friendship ties with Jerry and his colleagues. The adoption of this technology by an individual is represented by the presence of a retrieval link from the individual to the Intruder technology. A structural signature for this adoption based on contagion would suggest that a person would create a retrieval link to Intruder if the person had a friendship link to another person who already had a retrieval link to Intruder. For instance, Balaji should have a retrieval link to Intruder because Balaji has a friendship link with Jerry, who already has a retrieval link to the Intruder. This particular structural signature is shown in Figure 18.

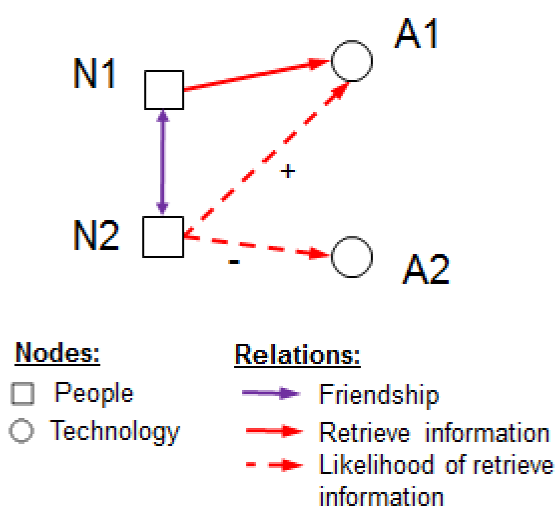


Figure 18. Structural Signature for Information Retrieval Between People and Technologies Based on Theories of Contagion.

A similar approach can be used to test the hypothesis that proximity leads to adoption of a new technology. In this case, the structural signature would suggest that a person is more likely to retrieve information from Intruder if they have a proximity tie to another individual who retrieves information from this same new technology. In Figure 13 at Time 2, this structural signature can be found between Balaji, Damen, and the Intruder technology. This structural signature is analogous to the one shown in Figure 18, with the friendship relation replaced by the proximity relation.

Finally, structural signatures can also be used to develop new theories about how the introduction of technology, a new node in a multidimensional network, can transform the structure of relations in that multidimensional network. The network in at Time 1 in Figure 13 indicates that individuals in the network identified several others who had expertise, from whom they then retrieved information about *what* points to select and *why*. The development of the Intruder software by Jerry resulted in the introduction of a new node (the software) at Time 2 and a "development" link from Jerry to this node. This appears to have resulted in a substantial restructuring of the networks. Individuals forged expertise and retrieval links to this new technology on issues related to deciding *what* points to select. Further, they maintained retrieval links to the developer of this technology (Jerry) on issues related to *why* to select these points while dissolving links with others. The structural signature that can be discerned is this: If an individual develops a link to a new node (i.e., develops a technology), individuals who previously went to others sources for information provided by the technology will create links to the technology on certain (automated or *what*) aspects of the task, but will create links with the developer of the technology for other (more intellectual or *why*) aspects of the task. This structural signature is shown in Figure 19.

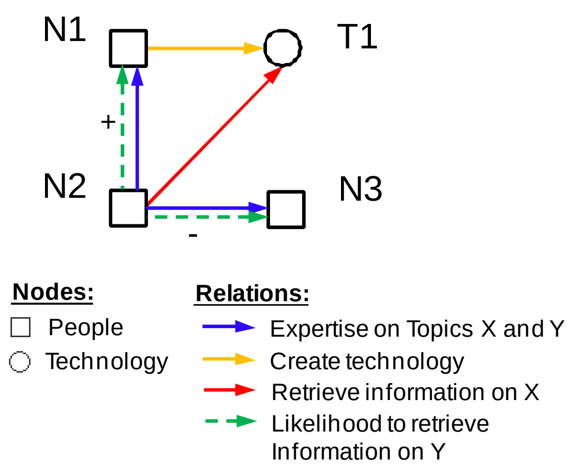


Figure 19. Structural Signature for Change in Information Retrieval Among People and Technologies Following Creation of a New Technological Artifact.

It shows that N1 develops a new technology T1, and that N2 perceives that both N1 and N3 have expertise on related topics X and Y. Given these conditions, if N2 now uses technology T1 to retrieve information on X, N2 is more likely to retrieve information on Y from N1 than from N3. A high prevalence of this structural signature will explain the transformation in the network, including significant changes in the prominence of some nodes. This example also shows multiple relations both within node types (people) and between node types (people and technologies), thus illustrating a fully multidimensional network.

This modest case study illustrates the distinctive structural signatures that emerge from an analysis of a multidimensional network. Our goal here has been to develop a multidimensional framework, and to demonstrate how it can be used to tease out novel structural signatures that capture the richness missed by unidimensional analyses. We have also shown how to incorporate new technologies and other non-human artifacts into social networks. The added value of the multidimensional approach emerges when we seek to unravel the dynamics of sociomateriality at scales that go beyond small case studies. Furthermore, the multidimensional network approach and methods will enable us to develop novel theories, and to more precisely test extensions to existing theories with a degree of inferential certitude that will benefit from, and contribute to, the careful case studies and in-depth ethnographies that have been the mainstay of scholarship based on actor-network theory and sociomateriality.

In summary, there are three reasons for the development of MTML models of multidimensional networks. First, articulation of new multidimensional structural signatures will enable us to examine unique network patterns. Second, it enables us to empirically investigate the extent to which multiple structural signatures (which, in turn, reflect multiple logics of attachment) might simultaneously be considered in understanding the emergence of the multidimensional networks. Third, it opens the possibility of attempting to understand the emergence of multidimensional networks where there is a large corpus of digital data tracing the network relations within and between human actors and technologies. In such cases, MTML models can be used to posit and detect structural signatures that have previously been proposed or tentatively identified using theory or ethnographies.

The promise of this approach is further accentuated by the potential of applying these frameworks to address interesting and intriguing questions about the emergence of multidimensional networks that are on the scale of the Web (Lazer et al., 2009). The increasingly easy access to large amounts of multidimensional network data from the Web within the past decade make this challenge eminently addressable. Specifically, the recent exponential growth in the development and utilization of the Semantic Web (especially the Linked Open Data initiative) offers considerable promise in capturing, collating, and reasoning about large-scale multidimensional networks (Berners-Lee et al., 2006; Hall, this special section; Shadbolt, Hall, & Berners-Lee, 2006). Engaging with these multidimensional networks at the scale of the Web will provide us with an unprecedented opportunity to understand the implications of technology becoming part of the networks from the perspective of theories of actor networks and sociomateriality.

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