# Knowledge heterogeneity and social network analysis – Towards conceptual and measurement clarifications

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## Abstract

This literature review highlights some Social Network Analysis (SNA) concepts applicable to the study of organizational knowledge and, more particularly, to knowledge heterogeneity. Knowledge being all at the same time decentralized and distributed, knowing up to what point knowledge can be heterogeneous or homogeneous across organizational units becomes as important as the question of knowing how to structure the organization. SNA applied to knowledge management thus seems a stimulant for future research in the fields of management.

**Keywords:** Knowledge heterogeneity, knowledge sharing, social network analysis, knowledge communities, communities of practice, measurement

## Introduction

Organizations have always had to face a dilemma. Productivity grows due to the division of labour and specialization but as unit specialization increases, so does the cost of coordination and communication due to the interdependence of certain tasks (Kogut and Zander 1996, Tushman and Katz 1980). The organization's division in functional units each specializing in a sphere of activities did not prevent tasks from becoming increasingly interdependent. Oftentimes, the result is that an increasingly significant proportion of the necessary knowledge to achieve these tasks is distributed and disseminated across units (Argyres 1996, Argote and Ingram 2000). Today, with the new ways of doing business and advances in information technology (IT), other forms of structures appear and new configurations emerge with new units. These new units are more and more specialized and often constitute what Postrel (2002) calls small islands of knowledge.

The interest in the study of knowledge management is driven by (1) the increase in the informational and cognitive contents of products and services, (2) the shrinking of knowledge usefulness over time, (3) technological breakthroughs, particularly IT's (4) the increasing pressures of worldwide competition, and (5) the increasing focus of organization on their growth (Xerox 2002).

Research in this field relates to several disciplines. However past research has channelled its focus at the individual level while organization design is based on the assumption that it is the group and the relations within the group that are the basis for the processing, diffusion, and storage of knowledge.

Knowledge management is also, and especially, about people and groups of people. Knowledge is created within a social and relational context giving more truth to the old saying that it is not *what* we know that counts more but *whom* we know.

Division of labour and specialization still prevail in our society and in today's organizations (Müller-Prothmann 2005). All knowledge needed in an organization cannot possibly be held by just one person nor can it be held by every individual. Knowledge has to be broken down into smaller and more specialized units. Today, while the professional division of knowledge still exists, disciplines are becoming less distinct (Liebowitz 2007) and specialized knowledge, which Moorman and Miner (1997) would view as fragmented organizational knowledge, as well as general knowledge co-exist, albeit in unknown proportions. The almost parallel event of increasing diversity of the workforce and the popularity of teamwork led to the challenge of better understanding the advantages and drawbacks, if any, confronting heterogeneous work groups in organizations (Mayo and Pastor 2005).

As Ancona and Caldwell (1992) once put it, the question is still how do we form teams and groups? Should they be formed of specialists or should they incorporate generalists? Should they be formed completely of engineers or should they also include some scientists? These questions are central as a mismatch between existing organizational structures and organizational knowledge heterogeneity among organizational units, may negatively affect organization performance as a whole.

Knowledge heterogeneity is therefore important for two reasons: (1) understanding the best fitting work group compositions given a structural configuration and type of knowledge possessed by an organization and (2) its hypothesized relationship with important organizational variables such as product development (Batjargal 2005), innovation (Sandström 2004, Rodan and Galunic 2004), work group effectiveness (Mello and Ruckes 2006), and organizational performance (Kogut and Zander 1996). See Table 1.

**Table 1.** Selected literature on knowledge heterogeneity and related concepts and their implications.

| Studies | Main comments and/or results |
|---|---|
| Ancona and Caldwell (1992): Group (functional) diversity | Functional diversity is directly associated with lower performance, particularly for innovation and for team overall performance.<br>Group diversity was measured by a diversity index taking into account the proportion of project group members from each functional area (chemistry, engineering, manufacturing, marketing) |
| Klimoski and Mohammed (1994): Mental model homogeneity | Homogeneous teams with completely overlapping mental models can be dysfunctional because complex tasks performed by teams may have to be divided among several individuals, each responsible for a distinct subtask, thus affecting coordination and performance |
| Moorman and Miner (1997): Memory dispersion | In the presence of high technological turbulence, high levels of shared understanding and homogeneous knowledge detract from creativity. This implies that organizations may be better off with internal heterogeneity under conditions of high turbulence.<br>Memory dispersion was measured by a 7-point Likert scale rating the degree of consensus or shared knowledge among new product participants. |
| Rulke and Galaskiewicz (2000): Distribution of knowledge | Groups that have knowledge broadly distributed across group members (generalists) outperform groups that have unique knowledge concentrated in different group members (specialists).<br>To measure distribution of knowledge, each subject was rated a specialist, a generalist, or neither depending on their response to a Likert scale measure. |
| Espinosa et al. | Task knowledge similarity has beneficial effects on coordination and |

| | |
|---|---|
| (2002): Task knowledge similarity | performance. These effects can be complemented (or offset) with effective (or ineffective) knowledge distribution patterns within the team.<br>Task knowledge similarity was derived from peer ratings of each other's knowledge in three specific task areas: finance, production and marketing. |
| Rodan and Galunic (2004): Knowledge heterogeneity | Knowledge heterogeneity is a significant predictor of both managerial and innovation performance.<br>Knowledge heterogeneity was calculated using Rodan and Galunic's formula. |
| Bonner and Walker (2004): Customer knowledge heterogeneity | There is a significant and opposite relationship between customer knowledge heterogeneity and new product advantage.<br>Customer knowledge heterogeneity was measured by a combination of a similarity score and a concentration index similar to the Herfindahl (1950) industry concentration index. |
| Sandström (2004): Network heterogeneity | Innovation rises with the level of network heterogeneity. It is therefore important for organizations to encourage collaboration between individuals from different scientific backgrounds and organizational units. |
| Batjargal (2005): Knowledge heterogeneity | Knowledge homogeneity accelerates product development. Knowledge heterogeneity was measured by the Index of Qualitative Variation (IQV, Agresti and Agresti 1978). |
| Mello and Ruckes (2006): Team homogeneity | Heterogeneous teams generally have an advantage over homogeneous ones in highly uncertain situations and when the stakes in the decisions are high. Heterogeneous groups also display higher personnel turnover. |

## From formal structures to networks

Formal structures are typically reflected by organization charts showing who does what, which work is being done, where and who reports to whom. But generally, organization charts are seldom more than control and planning instruments. From the knowledge management vantage point, the organization also needs to know who knows what and who knows who (Krebs 1998). The emphasis is therefore on relations, social capital and communities, hence the distinction between formal structures and emergent structures often made in the literature. As in the words of Chan and Liebowitz (2006): "Formal structures underpinning organizational charts may not really reflect the actual knowledge flows." (p. 20).

Companies such as American Management Systems (AMS) and the World Bank, mentioned by Wenger and Snyder (2000, pp. 144-145), have made communities of practice the foundation of their knowledge management strategy. Others, such as Chevron, Halliburton and Whirlpool, routinely analyze relationships among people, teams, departments or even entire organizations to stimulate innovation and to generalize best practices. They map relationships between leaders of opinion (SME-Subject Matter Experts), particularly innovating individuals, and those with specialized knowledge about the organization, its activities or the entire industry in which it operates. Some organizations go to the extent of constituting directories identifying key employees along with their areas of expertise to solve problems, to increase productivity by not reinventing the wheel and to boost knowledge sharing across the company (Laseter and Cross 2007).

Researchers such as Parise et al. (2006) and Laseter and Cross (2007) made it a point to show the usefulness of Social Network Analysis (SNA) and Organizational Network Analysis (ONA) in the identification of people who, if they leave the organization, would create a true cognitive deficit. Before them, SNA and ONA had promising prospects for Krackhardt and Hanson (1993), Zack (2000) and Monge and Contractor (2000), among others.

Thus, if organization charts offer a single and formal view, social networks can offer more whether we aim to study friendship networks, advice networks, communication networks, or any other type of relationships (Krackhardt 1990, Krackhardt and Porter 1985) whether at the group or at the organizational level. Other types of networks can be found in the literature such as information networks, knowledge networks, and cognitive knowledge networks (Morrison and Rabellotti 2005).

## Social Network Analysis

As early as in the 1940s, Radcliffe-Brown viewed SNA as a tool to study the interaction patterns that describe social structures. More recently, Cross et al. (2001) defined SNA as a set of methods and techniques that “provides a rich and systematic means of assessing informal networks by mapping and analyzing relationships among people, teams, departments or even entire organizations” (p. 103). For Liebowitz (2007) SNA is a technique useful in mapping relationships between ‘actors’ in order to determine their strengths.

Freeman (2000) considers social network analysis as an interdisciplinary field founded on the idea that social members are interdependent and that the ties between them have significant consequences for each one of them. Just as they present opportunities, these ties can also impose constraints on members’ behaviour.

Historically, it was Radcliffe-Brown and Malinowski who were the first to promote the social approach of networks of individuals by studying communities, villages and organizations and it was Radcliffe-Brown (1940) who was the first to use the term "network" as a metaphor for social groups. But it was probably Barnes (1954) who was the first to use social networks in an empirical study. Before him, Moreno (1934) coined the term "sociogram" to mean the charts used in SNA.

Social networks were used in sociology (see Everett and Borgatti 1999), ethnography (Turner 1957), anthropology (Barnes 1954), psychology (Shaw 1954), knowledge management (Zack 2000), computer science (Bonifacio et al. 2002), information systems (DeSanctis and Poole 1982), and marketing (Hutt et al. 1988), among others.

Social networks were also used in a multitude of fields of study. They were used in the study of discussion forums in the context of remote training (Allan 2004) where the author studied conversational events such as (1) who exchanged with whom, (2) on what occasion and (3) about what.

Social networks were used by Burkhardt and Brass (1990) through the concepts of centrality and influence to examine the organizational impacts of a new distributed information system. They could observe that the individuals who were first to adopt the technology had seen their centrality and their influence increase and that the structure of the social network had changed following the adoption of the technology. Rice and Aydin (1991) used social networks to conclude that the attitude towards an information system was influenced by the individuals on whom the users were socially dependent. Zack and McKenney (1995) had found that the pre-existent social structure affected the way in which an organization adopted an electronic messaging system.

Sarbaugh-Thompson and Feldman (1998) used SNA to show that an increase in the use of an electronic messaging system can be accompanied by a reduction in total communication between the users, including face-to-face, telephone, and fax communications.

Using the concepts of intensity of ties and degree centrality (see below), Rulke and Galaskiewicz (2000) had concluded that the structure of the work group conditions the relation between the distribution of knowledge in the group as well as its performance.

While studying knowledge, intersections or common areas are particularly attractive in social networks. The individuals who belong to groups whose borders are commonly defined (organizational units, communities of practice, associations, political parties, etc.) tend to be homogeneous in their thoughts, their code of conduct and their knowledge, to the extent that Boland and Tenkasi (1995) speak about "communities of knowing".

For Klimoski and Mohammed (1994), teams whose mental models are highly homogeneous are considered dysfunctional. To some extent, this joins Kao’s Law according to which the power of creativity of a network increases exponentially with the diversity and the divergence of its members (Kao 1996). A network’s capacity to innovate is more dependent on dissonant and complementary ways of thinking than on conformity and consensus (see also Mulgan 1998, p. 31). That is all the more true in industries where the knowledge required to manufacture a product spans multiple areas of expertise (Argyres 1996).

Having admitted that the networks are a potential source of learning facilitating the exchange of skills and expertise among individuals, scholars also admit that heterogeneous networks are particularly supportive of these exchanges. But with time, close and durable ties tend to minimize these exchanges if knowledge is not renewed; one does not exchange the same knowledge indefinitely and the differences, if any, grow blurred with time resulting in the homogenization of networks (Beckman and Haunschild 2002).

## Knowledge Heterogeneity

Rather than being monolithic, organizational knowledge is diverse, dynamic and made up of a multitude of knowledge systems localized in units and mobilized by the relationships which the individuals entertain socially or formally (Bonifacio et al. 2002).

Knowledge needed in the achievement of a task and available in a unit can be unavailable in another, and knowledge held by a group of people (a unit) is different from the knowledge held by these people taken individually (Walsh 1995, Wegner 1986). Hence, there is a difference between personal knowledge (the individual level) and shared knowledge (the group level) (Walsh 1995). Knowledge can be concentrated in the units and in the heads of individuals and it can be dispersed in the organization (Galunic and Rodan 1998, Müller-Prothmann 2005). Thus, the knowledge structure of the individuals is different from that of the unit. Blackler (1995) distinguishes among five types of knowledge: (1) embrained, (2) embodied, (3) embedded, (4) encultured, and (5) encoded knowledge. Embrained and embodied knowledge relate directly to the individual. Embedded, encultured, and encoded knowledge relate to the group or the entire organization. For Blackler, embrained knowledge is concerned with latent mental models whereas embodied knowledge concerns ways of acting based on historically developed routines. Embedded knowledge refers to organizational structures and processes whereas encultured knowledge refers to expectations about the intentions of others and encoded knowledge concerns the explicit and symbolic forms of knowledge.

For Van Wijk (2003), the distinction between knowledge communality and knowledge diversity is a derivation from the distinction between deep knowledge and broad knowledge. He associates deep knowledge with specialist knowledge and broad knowledge with generalist knowledge. For him, knowledge depth and breadth determine whether knowledge is common or diverse.

For Kitaygorodskaya (2006), it is necessary to distinguish between the differentiation of individual expertise and the awareness of who knows what. The former describes heterogeneity in task knowledge whereas the former describes homogeneity of team-related knowledge.

Available knowledge is thus either shared and largely diffused or scattered about individuals and groups (Stewart et al. 2003, Tortoriello 2005, Kitaygorodskaya 2006).

Thus interest in the concept of knowledge heterogeneity started to appear in the literature (Galunic and Rodan 1998, Cook et al. 2000, D'Adderio 2003, Espinosa et al. 2002, Kuhn and Corman 2003, Reagans and McEvily 2003, Stewart et al. 2003, Rodan and Galunic 2004). However, the concept of the knowledge heterogeneity had been identified relatively early. In a review of social research on innovation, Downs (1976) links knowledge heterogeneity (along with other structural attributes such as complexity, formalization, the impersonality of the relations, employee satisfaction, organizational structure, etc.) to the adoption of innovations.

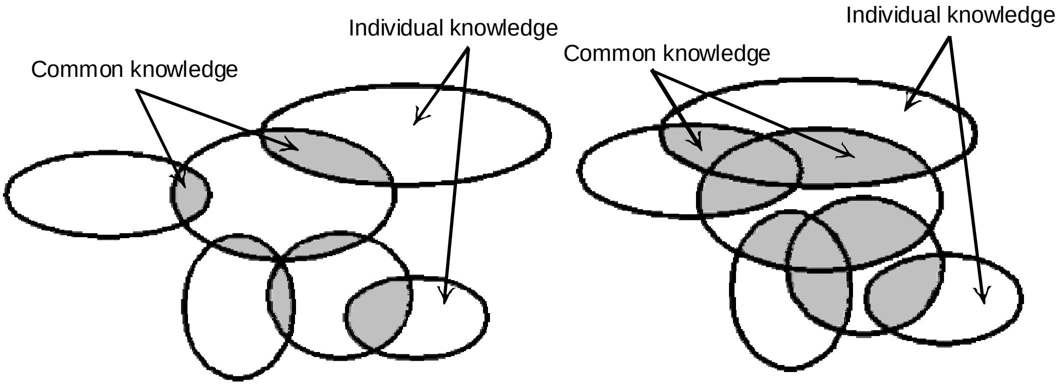
In marketing, Bonner and Walker (2004) define knowledge heterogeneity, applied to customers, as the degree of diversity of product-related information and competencies they hold on technical, market, strategy, and social dimensions. In strategy, Rodan and Galunic (2004) define knowledge heterogeneity as “the variety of knowledge, know-how, and expertise to which a manager has access through her network” (p. 545).

If, for Sandström (2004, Appendix B), network heterogeneity refers to the heterogeneity among the actors regarding some important attribute, our definition of knowledge heterogeneity considers background and functional specialization, as such an attribute. Our definition is closer to what Batjargal (2005) calls “knowledge heterophily”, defined as “the extent to which alters possess different knowledge in terms of content” (p. 7) and narrower than Mohammed and Dumville’s (2001, p.95) definition of “shared knowledge” which incorporates both the overlapping and complementary perspectives since we only consider the overlapping aspect of sharing.

In the literature on teams, authors have often used a variety of labels to refer to knowledge heterogeneity, including diversity (Prat 1996, Batjargal 2005), divergence (Levesque et al. 2001), heterophily (Batjargal 2005), or dispersion (Galunic and Rodan 1998). Its opposite, knowledge homogeneity, has been called similarity (Cook et al. 2000, Espinosa et al. 2002), redundancy (Tortoriello 2005), compatibility (Sperling 2005), overlap (Reagans 2005), dispersion (Galunic and Rodan 1998, Moorman and Miner 1997), shared cognition (Baba et al. 2004), division (Cross et al. 2001), communality (Reagans and McEvily 2003), shared knowledge (Mohammed and Dumville 2001),etc.

The heterogeneity/homogeneity distinction should remind us of the differences between the concepts of “common knowledge” and “specific knowledge” of Jensen and Meckling (1992) or the concepts of "specific competencies" and "general competencies" of Zuboff (1988). General knowledge is accessible to all and is independent of the particular tasks. Specific knowledge, or specialized knowledge, is the knowledge that is mobilized in general contexts, can be held by several individuals, and is, therefore, considered common.

If individual, different and specialized knowledge is more frequent than common knowledge, organizational knowledge tends to be heterogeneous. Conversely, if common knowledge is more frequent than individual knowledge, organizational knowledge tends to be homogeneous (Figure 1). For Stewart et al. (2003), organizational knowledge comprises a homogeneous proportion because it contains the information and the knowledge inevitably shared by all organizational members. It also comprises a heterogeneous proportion to make it possible for organizational members to break with organizational routines and their formalism, to sometimes question organizational processes, and to allow the organization to innovate and to move ahead.




(a) (b)

**Figure 1.** The homogeneity/heterogeneity concept of organizational knowledge. In the first case (a), knowledge is more heterogeneous than in the second case (b) where individually held, unshared, knowledge, is less significant.

It follows that heterogeneity increases as more and more members belong to an increasingly large number of communities of practice. The concept of communities of practice hence becomes particularly significant especially if we consider that their primary “output” is precisely knowledge (Wenger and Snyder 2000).

Obviously, one cannot plausibly design a purely heterogeneous or purely homogeneous organization. This is why we speak of degrees of heterogeneity or of homogeneity. Cohen and Levinthal (1990) and Prat (1996) recognize that the ideal structure of knowledge should be somewhere between heterogeneity and homogeneity; an excessive prevalence of one over the other may perhaps lead to dysfunction. The question is to know how much is too much and how to determine the optimal balance for a given organization.

For Hamilton (2002), knowledge heterogeneity is necessary for organizational learning because it implies the simultaneous use of old and new knowledge. On the other hand, heterogeneous organizational learning aims at connecting the individual and the organizational dimensions of knowledge, as well as at bridging between the experiences and competencies in the organization. This bridging tends to homogenize organizational knowledge by connecting the heterogeneous *know-how* and *who-knows-what* held by the individuals (Wexler 2002). This homogenization, a natural tendency according to Reagans (2005), facilitates inter-unit communication. Let us note, however, that this homogenization is not systematic as it was not detected empirically by Levesque et al. (2001) who showed that a team’s mental models do not necessarily become more similar over time. Studying the convergence/divergence of geographically dispersed teams (GDTs), a process by which cognitive structures of distributed team members gradually become more similar over time, Baba et al. (2004) obtained mixed results, but could conclude that shared cognition improves global team performance.

Having studied knowledge heterogeneity, Galunic and Rodan (1998) could determine that the setting up of rules and procedures reduced heterogeneity and diversity in the organizations. On the other hand, the existence of strong structural ties (a significant concept in SNA as we will see) between individuals tends to support information redundancy and, consequently, would make knowledge sharing easier. This, in turn, would result in a reduction of the heterogeneity of knowledge in the organization (Burt 2004).

For Mello and Ruckes (2006), culturally and cognitively heterogeneous groups have the advantage of having more sources of information and knowledge than homogeneous groups. It is apparently the position of the majority of the literature on groups and teams.

The degree of knowledge that is common to the individuals, whether at the group or at the organizational level, can be measured and determined using SNA. Just like organization charts, social networks can be represented graphically. In Figure 2, the circles (or nodes) represent the individuals working in three departments and the links (or ties) represent the relationships between them.

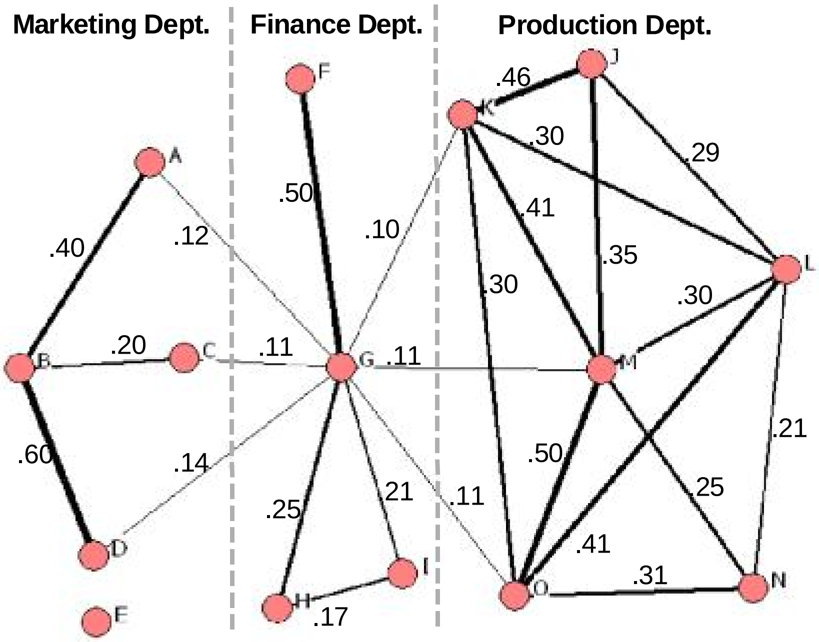



**Figure 2.** A network represented graphically illustrates not only the members of the network (above identified by name) but also the links between them and the type of the links while varying the features (solid, dashed, etc.) or by quantifying them (graphic inspired and adapted from Cross et al. 2002, p. 69).

If we consider that the links of Figure 2 measure the proportion of knowledge shared between the individuals whom they connect, a matrix can be deduced. For the Production department, the matrix takes the form given in Table 2. Each cell measures the proportion of knowledge, $d_{i,j}$, common to both individuals i and j.

**Table 2.** The Knowledge similarity matrix (S) between the Production department members of Figure 2.

| | *J* | *K* | *L* | *M* | *N* | *O* |
|---|---|---|---|---|---|---|
| *J* | 1 | .46 | .29 | .35 | 0 | 0 |
| *K* | .46 | 1 | .30 | .41 | 0 | .30 |
| *L* | .29 | 0 | 1 | .30 | .21 | .41 |
| *M* | .35 | .41 | .30 | 1 | .25 | .5 |
| *N* | 0 | 0 | .21 | .25 | 1 | .31 |
| *O* | 0 | .30 | .41 | .50 | .31 | 1 |

## The levels of analysis in SNA

What is the level of analysis? At which levels of the analysis can knowledge heterogeneity be evaluated? Can the concept of heterogeneity apply to the whole organization as much as to the units composing it?

In the literature on organizational memory, Anand et al. (1998) distinguish between systemic memory (memory when the organization is considered as the unit of analysis) and group memories (when organizational subunits are considered the units of analysis). The highest level of analysis is when groups of organizations (multinationals or joint-ventures) are examined. At the following level, one is interested in the entire organization. It follows almost naturally that heterogeneity at the workgroup level can be evaluated only according to the heterogeneity of the individuals composing it, though workgroups can be homogeneous on certain characteristics and heterogeneous on others. In Annica Sandström's (2004) doctoral dissertation, some departments gathered up to nine different disciplines. In Liang's (1994) study, groups composed of generalists (therefore homogeneous) functioned better than groups of specialists. She explained this result by suggesting that generalists had a high degree of similar knowledge whereas specialists had nonredundant knowledge which each member could tap into. The generalists did not have to spend much effort in the search of knowledge since they held it already. On the other hand, when members hold exclusive knowledge, they have more difficulties communicating and exchanging ideas.

In SNA language, one distinguishes three levels of analysis (Borgatti and Foster 2003):

(1) the micro or the ego, which is limited to the individuals and their relations,

(2) the meso, which is interested in groups extending until the organization and

(3) the macro, which is interested in the organizations or groups of organizations, communities, and all that Brown and Duguid (1991) would call the "communities of communities", and their interactions.

SNA thus makes it possible to consider several levels simultaneously (Hanneman and Riddle 2005), as well as their interrelations (micro-meso, micro-macro and meso-macro) (Marsden 1990), or, according to Krebs' (1998) expression, to see the tree and the forest at the same time. Thus, the studies concentrating on the individuals, for example, will be interested in them in the context of the group to which they belong (Klein et al. 1994).

That said, what is true for a given level is not necessarily true for the following level. The organization as a whole could have great quantities of knowledge but some of its units may be cognitively defective due to faulty or poorly developed technological, communication, or structural mechanisms. Conversely, knowledge at the organizational level can be evaluated poorly, but some groups could make exception and have great quantities of knowledge because of the presence of experts or specialists (Anand et al. 1998).

This pooling of knowledge can be facilitated by the presence of IT such as computer networks connecting various units, Intranets providing common information directories of specialists and experts in the organization (*who knows what*). ERP, CRM, workflow systems, groupware, electronic messaging systems, and data warehouses, are often given as examples of technologies that facilitate knowledge sharing in organizations. IT has often been presented as a significant lever in organizational knowledge management for two essential reasons: (1) it allows fast and timely communication and (2) it has the capacity to create and maintain an organizational memory available for all (Goodman and Darr 1998).

These different levels of analysis have different SNA characteristics (Wasserman and Faust 1994), some of which will be re-examined in the next section:

1) At the level of the entire network (the organization): density, connectivity, centralization.

2) At the level of the sub-networks: distance, structural equivalence, cliques, cohesion, plexes, clans, clusters, dyads, triads, etc.

3) At the individual level: centrality (degree, proximity, and betweenness), structural holes, similarity of the members, etc.

## SNA Measures

SNA's three major mathematical foundations, graph theory, statistical and probability theory and algebraic models, provided a broad set of measures. Applied and interpreted judiciously, these measures can reveal essential characteristics of the studied systems (Contractor et al. 2000).

1) The *centrality* of certain members is an indication of their prominence and their importance in the network (Wellman et al. 2006). For example, in Figure 3, J has the greatest number of direct ties (6), which makes it the most active member in the network and confers it the statute of *centre* or *connector*. The centrality of a node in a network can be evaluated by (Freeman 1979):

   a) its *degree centrality*, or the number of connections it participates in in the network,

   b) its *closeness centrality*, or the distance which separates it from other members in the network. In this case, nodes C and G participate in fewer connections than node J but both enjoy better access since they can reach any part of the network more quickly than anybody else, or

   c) its *betweenness centrality*, or the extent to which a member mediates between any two members. A member with high *betweenness centrality* shares knowledge with other members who do not share knowledge one with the other (Contractor et al. 2000). In such a case, the member with a relatively high betweenness centrality will be used as a knowledge broker (Contractor et al. 2000).

   One also speaks of the direction of the centrality: received (*in-degree centrality*) or emitted (*out-degree centrality*). They are the number of links coming to a member from other members and the number of links going form a member to other members respectively.

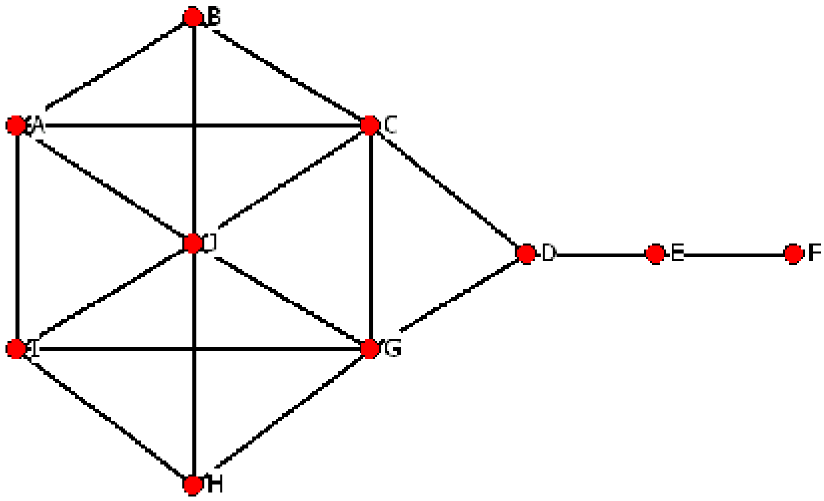



**Figure 3.** An example of network inspired by the kite network of Krackhardt (1990) as modified by Krebs (2007).

2) The *distance* between two members is measured by the number of members located between them. It showed to be a significant factor in the choice of communication modes (face-to-face discussions, telephone, written messages, etc). Conrath (1973) showed that until a distance of 100 feet, the probability that individuals choose the face-to-face mode over the telephone was 22 times higher. Moreover, more communication was established between the individuals who were in the immediate vicinity. Cross et al. (2001) mention a study in which engineers and scientists in search of assistance turned to a person five times more often than to a computerized data base. Finally, Hansen (2002) showed that project teams obtain the knowledge needed to complete their project more easily and more quickly if they address their questions to neighbouring units.

3) The *density* of the network is the number of ties present compared to the total number of possible ties (Borgatti and Everett 1997, Marsden 1990). A dense network generally indicates strong communications between network members whereas a sparse network reveals disconnections between its parts. A network in which all members are interconnected has a density equal to 1. Consequently, knowledge sharing is supposed to increase as the density of the network increases. Knowledge sharing is also more marked between similar specialties and interdisciplinary interactions take place between members who are in the centre of their group of discipline (Allen and Cohen 1969).

   Thus members of a dense network benefit from the access to knowledge facilitated by the multitude of ties. However, over time, the knowledge carried over these ties becomes increasingly redundant whereas members of a sparse network, rich in structural holes (see below), face less redundancies (Burt 1992). It follows that members of a dense and redundant network have access to similar knowledge whereas members of a sparse network have access to dissimilar and nonredundant knowledge.

4) *Structural holes*. A structural hole exists in a network when some of its parts are not interconnected (Burt 1992, Ahuja 2000).

   When a network is composed of members with dissimilar backgrounds or organizational identities, it can be taken to span several structural holes (Reagans and Zuckerman 2001, Sandström 2004). Conversely, by definition, a completely connected network does not contain any structural hole (Burt 1992); the existence of structural holes being an indication of lower redundancy. In addition, the scarcity of structural holes indicates the scarcity of bridges between disconnected network parts indicating the presence of heterogeneous knowledge sets (Burt 2004). The individuals filling structural holes establish a kind of "bridging" between disconnected groupings and are in a position to have access to diversified ideas and nonredundant information (Burt 1992). For example, in Figure 3, there would have been a structural hole between the group made up of nodes E and F if and the rest of the network had not there been node D. Node D is therefore said to fill a structural hole between nodes E and F on the one hand and nodes A, B, C, G, H, I, and J, on the other. For larger networks, the number of structural holes (i.e., of "disconnects") is computed by software packages such as UCINET, for example, with the menu command Network>Ego Networks>Structural Holes which provides a wealth of information on structural holes in a network.

   This should lead us to believe that the diversity of the slightly disconnected sub-networks encourages creativity. However, Burt (2004) found that creative ideas were seldom followed up upon because of a lack of coordination between groups. Similar results were obtained by Obstfeld (2005) who suggest that while supporting creativity, structural holes slow down innovation.

   Several researchers studied the relationship between structural holes and knowledge heterogeneity. Sandström (2004), for example, links heterogeneity with structural holes while advancing that a higher degree of heterogeneity indicates a greater number of structural holes.

   For Rodan and Galunic (2004), the interaction between the number of structural holes (*network sparseness*) and knowledge heterogeneity was significant. They posit that the advantages of knowledge heterogeneity should be more pronounced in the presence of structural holes partly because of the bridging opportunities than they offer.

   In the study of Batjargal (2005), structural holes and knowledge heterogeneity had a positive effect on product diversity; the interaction between structural holes and knowledge diversity makes it possible for the contractors to create new products, to derive new applications from existing technologies and to sell old products in new markets.

   Bridges are also called third parties -or *tertius*- playing several roles. Burt (1992) and Obstfeld (2005) borrow Simmel's notions of *tertius gaudens* and *tertius iungens*. According to Simmel (1950), individuals filling a structural hole can play one or the other of two roles: (1) occupying the position for their own advantage (*tertius gaudens*) or (2) making themselves useful while joining otherwise disconnected groupings (*tertius iungens*) (Obstfeld 2005).

At a more general level, Cross and Parker (2004, Chapter 5) had identified four roles likely to be played by organizational key members: (1) *central connectors*, (2) *boundary spanners*, (3) *information brokers*, and (4) *peripheral actors*.

A little later, Parise et al. (2006) eliminated the boundary spanners and replaced information brokers with knowledge brokers. The new categorization of the roles played by key knowledge members is thus: (1) *central connectors*, (2) *knowledge brokers* and (3) *peripheral actors*. Merging the boundary spanner and the information broker roles into one of knowledge broker seems logical if we accept that boundary spanners are intermediaries between various islands of knowledge, to use Postrel's (2002) metaphor. They play the role of translators and bridges between heterogeneous subsets, and are therefore comparable to knowledge brokers.

A greater number of structural holes in a network means that individuals are at the intersection of more knowledge fields. That creates more possibilities for new combinations and recombinations of ideas (Galunic and Rodan 1998).

In Figure 3, the group made up of nodes E and F would be disconnected from the rest of the members if D did not establish the bridge. In this case, D, acting as a bridge and a broker, fills the void which would have created a structural hole and thus enjoys a greater social capital than the other members. To preserve this, D would not find interest in connecting E with C or G, no more than E would appreciate F being directly connected with D, belying the old proverb which says that the friend of a friend is a friend.

The software package UCINET 6, version 6.164 (Borgatti et al. 2002) indicates that there is a structural hole between J and D (Figure 3). The analysis reveals that the tie between I and J is 75% redundant, meaning that 75% (6 out of 8, excluding nodes I and J from the 10 members of the network) of the other members have also ties with J.

5) *Structural ties*. There are two kinds of structural ties: strong and weak. Hansen (1999) had shown the importance of strong ties in the transfer of complex and tacit knowledge between organizational units and the role of weak ties in the search for simple knowledge in neighbouring units. Knowledge is transmitted more easily between individuals when they are connected by strong ties. However, Burt (1992, p. 25) recommends not to confound the weakness of ties with nonredundancy; the first is the correlate of the second and, in the context of knowledge, Hansen (1999) specifies (p. 86) the reasons for which strong ties between the units can be more constraining than weak ties.

   For some, novelty and innovation are common when weak ties dominate whereas strong ties can produce group think (Granovetter 1973), knowledge redundancy, and cognitive overload (Espinosa et al. 2002). Weak structural ties in sparse networks indicate more heterogeneity in the network (Galunic and Rodan 1998).

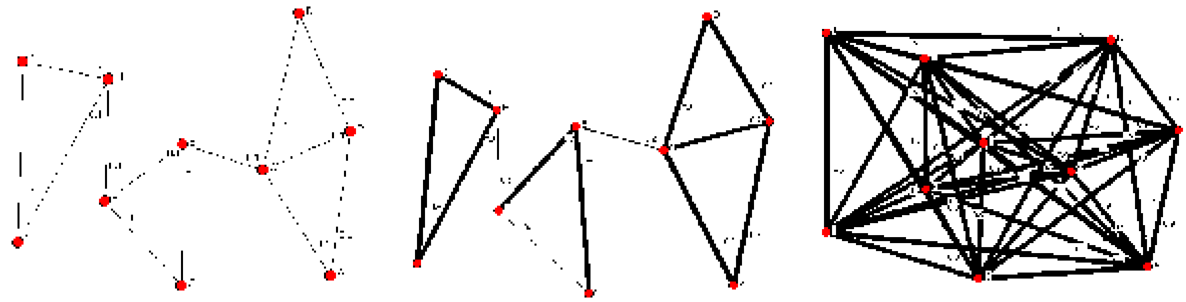
   Individuals connected by strong ties tend to develop common standards but they tend to close themselves off from others, a phenomenon that Uzzi (1997) calls the *paradox of embeddedness*.

6) *Cohesion* is defined as the number of ties within a network (Festinger et al. 1950). More precise, Wassermann and Faust (1994) define it as being the "subsets of actors among whom there are strong, direct, intense, frequent and positive ties" (p. 249).

   At the individual level (ego), members having the highest cohesion scores are those who tend to conform to the standards of their group and to reinforce its homogeneity. In this case, the cohesion of the group is the average of the cohesions of its members. Festinger et al. (1950) contend that communication between the members of a cohesive network tends to increase or to remain constant and high. Conversely, communication between the members of a low density network tends to decrease.

In terms of social networks, heterogeneity is thus revealed when the density of the ties varies across the network. Buskens (1998) used this measure to evaluate the heterogeneity of a trust network. But several other measures of heterogeneity are available in the literature. The most promising include, but are not limited to, the Jaccard coefficient (1901), the Index of Qualitative Variation (IQV, Agresti and Agresti 1978), the formula used by Rodan and Galunic (2004), the background heterogeneity formula used by Scholten (2006, p.193), Blau's index (1977), the measure of tie intensity (Rulke and Galaskiewicz 2000), the index of Herfindahl (1950), and the interdisciplinarity measure as applied in a citation analysis study undertaken by Leydesdorff (2007) focusing on the multidisciplinary and the interdisciplinary of scientific journals. Indeed, when the multidisciplinary and the interdisciplinary notions are transposed to knowledge, one can study the number of competencies held by an individual (as compared to the number of subjects covered in a journal in the study of Leydesdorff) and the intersection of the knowledge held by several individuals (as compared to the same subject covered by several journals in the same study). Other measures, such as idea diversity (the distribution of difference in idea sharing) and knowledge relative similarity (the degree of similarity between two agents based on shared knowledge) can be found in Carley and Reminga (2004).

For illustrative purposes, Figure 4 presents three network configurations in which heterogeneity varies from high to low.



| (a) | (b) | (c) |
|---|---|---|
| Heterogeneity: | Heterogeneity: | Heterogeneity: |
| 1. .960 (formula 1) or | 1. .797 (formula 1) or | 1. .100 (formula 1) or |
| 2. .971 (formula 2). | 2. .817 (formula 2). | 2. .100 (formula 2). |

**Figure 4.** Graphical representations of three networks: (a) a heterogeneous network, (b) a fairly heterogeneous network and (c) a homogeneous network. Like all other network graphs in this paper, these representations were obtained using the NetDraw software version 2.055 (Borgatti 2002).

Because the matrix cells represent similarity between individuals, we first computed percentages of dissimilarity before applying the formulae. We obtained these percentages by subtracting the contents of each $d_{i,j}$ cell from 100.

In the network of the Figure 4a, the members, taken two-by-two when they are connected, share 10% of their knowledge. The network is thus relatively heterogeneous considering that its members have more unshared than shared knowledge. In this figure, we used two formulae; both are perfectly correlated in spite of the different values that they produce:

1) Formula 1 gives the average of the cohesion densities in the matrix as obtained using the UCINET 6 software (Borgatti et al. 2002) (using the routine *Network>Cohesion>Density*) and

2) Formula 2 gives the average of the intensity of the ties using Rulke and Galaskiewicz's (2000, p. 616) formula:

$$L = \left( \sum_{i=1}^{m} \sum_{j=1}^{m} d_{i,j} \right) / m(m-1)$$

where $i \neq j$ and m is the number of members in the network.

## Conclusion

The capacity of an organization to carry out its cognitive potential largely depends on the type and the quality of the relations linking its members. The new organizational forms permitted by IT, among other things, generate new structures and make new organizational and relational configurations possible, and, as in the words of Gibbons et al. (1994, p. 6), transdisciplinarity, heterogeneity, and transience are becoming quintessential organizational characteristics associated with knowledge management.

The increasing diversity of work and the need for team work is a further motivation to seek a better understanding of how teams work best and the best distribution of individuals based on their knowledge and their contribution to team knowledge. Knowledge heterogeneity within groups could be a means to optimize the arrangement of individuals across units. Consequently, research in management can only benefit from the methods and techniques offered by SNA (Cross et al. 2001, Zack 2000).

Even if research in social networks supports the idea that unique sources of knowledge have more value than shared (common) knowledge (Burt 1992, Granovetter 1973), our interest in knowledge heterogeneity does not necessarily plead for its advantages. The exclusive interaction between organizational members whose knowledge is homogeneous has also its advantages. These include facilitating tacit knowledge exchange, simplifying coordination and avoiding conflicts. Reducing the interactions between members whose knowledge is heterogeneous limits the advantages of diversity and encourages the creation of clans (Borgatti and Foster 2003). Answering the question as to what is the optimal proportioning between homogeneity and heterogeneity is however not simple (D'Adderio 2003).

One stream of literature suggests that greater knowledge heterogeneity leads to more creativity and better organizational performance. For example, for Klimoski and Mohammed (1994), homogeneous teams, with completely overlapping mental models, are dysfunctional because complex tasks performed by teams may have to be divided among several individuals, each responsible for a distinct subtask, thus affecting coordination and performance. Others, like Ancona and Caldwell (1992), found that team diversity could affect performance both positively and negatively and that, overall, the effect of diversity on performance was negative.

Marengo (1998) asserted that organization members who share a perfectly homogenous knowledge do not face any "cognitive" obstacles to effective coordination, “but are likely to present little scope for learning and adaptation, as mutual learning is not possible”. He adds that diversity of knowledge “allows such learning but makes coordination more problematic” (p. 227).

For Rulke and Galaskiewicz (2000), shared knowledge improves group performance because when information is held by group members and when these provide knowledge retrieval cues to each other, they improve decision making. Whereas for Reagans and Zuckerman (2001), heterogeneity in team member skills can lead to differences in team performance, Rodan and Galunic (2004), found knowledge heterogeneity to be a significant predictor of both managerial and innovation performance.

For Mello and Ruckes (2006), heterogeneous teams generally have an advantage over homogeneous ones in highly uncertain situations and when the stakes in the decisions are high. Heterogeneous groups also display higher personnel turnover. Mello and Ruckes (2006) add that homogeneous groups tend to be formed either by very knowledgeable or very incompetent leaders. Leaders who are in between prefer input from diverse sources and therefore prefer heterogeneous groups.

One way to reconcile these findings is to hypothesize a curvilinear relationship between knowledge heterogeneity and performance. Incidentally, Moorman and Miner (1997) suggested such a relationship between memory dispersion and new product creativity. Somewhat related, Earley and Mosakowski (2000) have also suggested a curvilinear relationship between team heterogeneity on nationality and performance and suggest an upright U relationship between team heterogeneity and effectiveness basing their reasoning on the idea that highly homogeneous and highly heterogeneous groups are more effective than moderately heterogeneous (resp. homogeneous) ones. They tested the U shaped relationship with mixed support.

In any event, knowledge diversity in an organization allows it to deal with complex situations requiring a broader range of competencies. Complex situations call on complex decisions which call on complex tasks which cannot be carried out with the knowledge of just one individual (Hayek 1937) and past research suggests that the heterogeneous nature of a task affects the heterogeneity of knowledge in a group (Wholey et al. 2007). If, as Van Wijk (2003) argued, investments in the breadth of knowledge determine the extent to which knowledge will be overlapping and investments in deep knowledge increase learning performance, organizations can alter the trade-off between commonality (homogeneity) and diversity (heterogeneity) of knowledge by investing in deep or broad knowledge.

SNA will help researchers to better study the problem of distribution of knowledge among employees, a problem that Kogut and Zander (1996, pp. 505-506) consider central to organizational performance supported in that by Moorman and Miner's (1997) finding that more dispersed organizational memory had an effect on short-term financial performance of product development activities by enhancing cross-functional understanding and cooperation.

SNA can also be used to diagnose organizations, to collect data on the relations between individuals and groups (Wellman 1983). Combined with knowledge management, SNA tools and techniques will make it possible to identify not only relationships between individuals and groups (Liebowitz 2007) but also to improve knowledge and information flows and to identify key knowledge keepers (Rulke and Galaskiewicz 2000).

Using SNA tools and techniques, researchers could seek to explain why units are better equipped than others to share their knowledge (Hansen 1999) and why certain units are more successful than others in seeking and finding knowledge elsewhere in the organization (Hansen 2002).

If Zack and McKenney (1995) had been able to show that pre-existent social networks had influenced the adoption of IT, it would be interesting to know up to what point IT can affect the configuration of an existing social network. The study of Burkhardt and Brass (1990) presents an example going in this direction.

In studying team heterogeneity on nationality, Earley and Mosakowski (2000) showed that, over time, and after finding ways to interact and communicate, highly heterogeneous teams appeared to create a common identity. When transferred to the study of knowledge, do heterogeneous networks tend to remain so or do they evolve into more homogeneous networks (Beckman and Haunschild 2002, Reagans 2005), and if so, how and when? What organizational unit properties affect knowledge persistence or depreciation over time (Argote et al. 2003)?

Such can be research avenues to be explored using SNA tools and techniques.

However, SNA suffers from several limitations. Müller-Prothmann (2005, pp. 141-143) has identified five such limitations: (1) methodical weaknesses with regards data collection (accuracy, social desirability bias, etc.), (2) restriction to limited dimensions of interaction (one can study only one dimension at a time: friendship, trust, communication, etc.), (3) descriptive character (one can seldom come up with recommendations to improve what is revealed in SNA maps), (4) boundary specification problems (networks limited to organizational units overlook ties outside those preset limits), and (5) snapshot character (SNA rarely takes into account the causes and effects of why things are the way they are).

Added to these limitations, several conceptual issues remain open. Most relate to the semantics of the SNA literature. For example, literature on teams has often been concerned with knowledge sharing (Klimoski and Mohammed 1994). However, the verb “to share” can convey at least two meanings: (1) to have in common and/or (2) to divide (like dividing a task) (Klimoski and Mohammed 1994); it thus incorporates two notions: complementarily and overlapping (Mohammed and Dumville 2001).

Due to this confusion, Cook et al. (2000) avoided to use the term "shared" and use instead the expression “team knowledge” when they speak about division with overlapping of knowledge within a team. For Sperling (2005), shared models can refer to two concepts: (1) the mental models which are homogeneous between team members or (2) the mental models which are distributed among them without intersection. The questions of compatibility and complementarily attached to the division also arise.

Another caution relates to the very meaning of the word heterogeneity. Some authors define heterogeneity according to the individuals rather than to what they have. Blau (1977), for example, defines heterogeneity as being the distribution of the individuals among various groups. That could be extended to the heterogeneity of knowledge held by only one individual because even an individual, with a broad general knowledge, can be cognitively more heterogeneous than an expert or than a specialist in a given field of expertise.

In this paper, we proposed to use social networks to study knowledge heterogeneity at the group and organizational levels, therefore on the meso level of analysis, at least to avoid this last shortcoming.

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# Appendix

An illustrative example

We derived the knowledge heterogeneity measure from the knowledge distance matrix (D) obtained from the knowledge similarity matrix (S, Table 2). Like Rodan and Galunic (2004), we started by calculating the uniqueness of knowledge for each member.

The uniqueness of knowledge of a member i is some function of the uniqueness of each of his or her contacts. This is obtained by calculating, for each network member, the value $u_i$ given by formula (1):

$$\lambda u_i = \sum_{j=1}^{m} d_{i,j} \times u_j \qquad (1)$$

Equation (2) is the characteristic equation for extracting eigenvectors and eigenvalues. The uniqueness values at the level of the entire network was obtained by solving for equation (2) in which U is the mx1 eigenvector corresponding to the eigenvalue of the first principal component, λ, obtained on the basis of D (the largest eigenvalue of D) using the UCINET command, *Network>Centrality>Eigenvector*.

$$\lambda U = DU \qquad (2)$$

We solved this equation using the PopTools Excel *addin* (version 2.7) (Hood 2005). We should point out that the derivation of U and λ was based on the assumption of a symmetric matrix in which all entries are comprised between 0 and 1.

The vector U is the eigenvector composed of the uniqueness measures for each member. Thus, at the member's level, heterogeneity $h_i$ is given by formula (3):

$$h_i = \frac{1}{m} \sum_{j=1}^{m} d_{i,j} \times \lambda \times u_j \qquad (3)$$

The 1/m factor compensates for network size since the eigenvalue, λ, increases linearly with m (Rodan and Galunic 2004). At the network level, knowledge heterogeneity is obtained by summing the values given for each of its members. As an example, the network in Figure 2 and the similarity matrix of Table 2 where a number in row i and column j indicates the proportion of knowledge common to members i and j (obviously, the amount of knowledge common to a member and herself is 100%, or 1):

$$S = \begin{pmatrix} 1 & .46 & .29 & .35 & 0 & 0 \\ .46 & 1 & .30 & .41 & 0 & .30 \\ .29 & 0 & 1 & .30 & .21 & .41 \\ .35 & .41 & .30 & 1 & .25 & .5 \\ 0 & 0 & .21 & .25 & 1 & .31 \\ 0 & .30 & .41 & .50 & .31 & 1 \end{pmatrix} \quad \text{and} \quad D = \begin{pmatrix} 0 & .54 & .71 & .65 & 1 & 1 \\ .54 & 0 & .70 & .59 & 1 & .70 \\ .71 & 1 & 0 & .70 & .79 & .59 \\ .65 & .59 & .70 & 0 & .75 & .50 \\ 1 & 1 & .79 & .75 & 0 & .69 \\ 1 & .70 & .59 & .50 & .69 & 0 \end{pmatrix}$$

Since λ = 3.71, it follows that:

$$U = \begin{pmatrix} .428 \\ .394 \\ .415 \\ .361 \\ .455 \\ .389 \end{pmatrix} \quad \text{and} \quad D \times l \times U = \begin{pmatrix} .790 \\ 1.935 \\ 2.399 \\ 2.345 \\ 1.999 \\ 1.166 \end{pmatrix}$$

Thus, for the first member (i=1), $h_1$ is equal to: .79/6=.13. Applying the same formula to each and every member of the network and computing the average of $h_1$, $h_2$, $h_3$, $h_4$, $h_5$, and $h_6$, yields a network knowledge heterogeneity index of .295.

Using Rulke and Galaskiewicz's (2000, p. 616) formula, the knowledge heterogeneity index is equal to .7373 and using UCINET's average of the cohesion densities, it is equal to .7373 as well.

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