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IKNOW: A Tool to Assist and Study the Creation, Maintenance, and Dissolution of Knowledge Networks[1]

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Abstract

The introduction of new communication and information technologies in work communities has primarily been used to create new channels of communication and/or reduce the cost of communication among members in the workplace. Ironically, the pervasiveness of electronic communication media in virtual work communities make it increasingly difficult for individuals to discern social structures. Fortunately. information technologies that are responsible for triggering this problem can also be used to overcome these obstacles. Bccausc information transacted over electronic media such as the Web can be stored in digital form, a new generation of software called "collaborative filters" or "communityware" (Contractor, O'Keefe, & Jones, 1997; Kautz, Selman. & Shah, 1997) can be used to make visible the work communities' virtual social structure. One such tool, IKNOW (Inquiring Knowledge Networks On the Web; http://iknow.spcomm.uiuc.edu/), has been designed by a team of UIUC researchers to assist individuals to search the organization's databases to automatically answer questions about the organization's knowledge network, that is, "Who knows what?" as well as questions about the organization's cognitive knowledge networks, that is, "Who knows who knows what?" within the organization. Unlike traditional web search engines that help an individual search for content on the web, tools such as IKNOW search for content and contacts (direct and indirect). In addition to being instantly beneficial to users, they also provide the researcher with an opportunity to unobtrusively and reliably study the influence of communityware on the co-evolution of knowledge networks.

Introduction

More than at any other time in human history, advances in the 21st century will be based on knowledge networks. What it is, how it is represented, how it is distributed and to whom, are all pressing questions with significant economic, social, and political impact. Communities that generate and control the distribution of knowledge will have considerable competitive economic advantage over those who do not. Communityware is a new generation of tools that can help these human advances occur. This paper seeks to examine the role of communityware tools to identify the factors that lead to the creation, maintenance and dissolution of dynamically linked knowledge networks, The core research question is: How does communityware

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influence the co-evolution of social networks, cognitive social networks, knowledge networks and cognitive knowledge networks?

Conceptual Frameworks for Representing Knowledge and Knowledge Networks

Definitions of Knowledge

A number of definitions exist for the concepts of knowledge and intelligence, each reflecting the disciplinary context in which they are used. A common hierarchy offered in computer science is that data (bits, bytes, pixels, voxels) when combined with content (e.g. mctadata, often implicit) leads to information. The integration, analysis, and synthesis of information leads to knowledge. In artificial intelligence, the knowledge level is one in a hierarchy of many representational schemes. These formalisms imply that knowledge can only be defined and understood within a network of other knowledge concepts (Carley & Newell, 1994). In organizational and management theory, knowledge is also defined in reference to networks. However, in this case the links are between "actors," a term that will be used throughout this paper to refer to individuals, groups, or organizations.

Definitions of Knowledge Networks

From the standpoint of studying work communities, it is valuable to define knowledge networks that map on to the network of actors. The location of knowledge within this network of actors can vary along a continuum from centralized, where knowledge resides with only one actor, to distributed, where knowledge exists among many actors (Farace, Monge, & Russell, 1977). Further, distributed knowledge may refer to the flow or diffusion of knowledge, which increases the level of knowledge among all actors, Altemativcly, it may refer to the parts of a larger knowledge base, each possessed by separate actors within the network. In this form of distributed knowledge, actors bring relatively unique, non-redundant knowledge which enable a collective to accomplish complex tasks (Gore, 1996). Distributed knowledge occurs at many levels in the empirical world, including work groups, large scale project teams, and interorganizational strategic alliances, to name but a few. The figure below represents a knowledge network. The nodes in this network are individuals; included (in parenthesis) within the nodes are the knowledge items each individual reports possessing. The links between the nodes represent knowledge items shared by individuals.

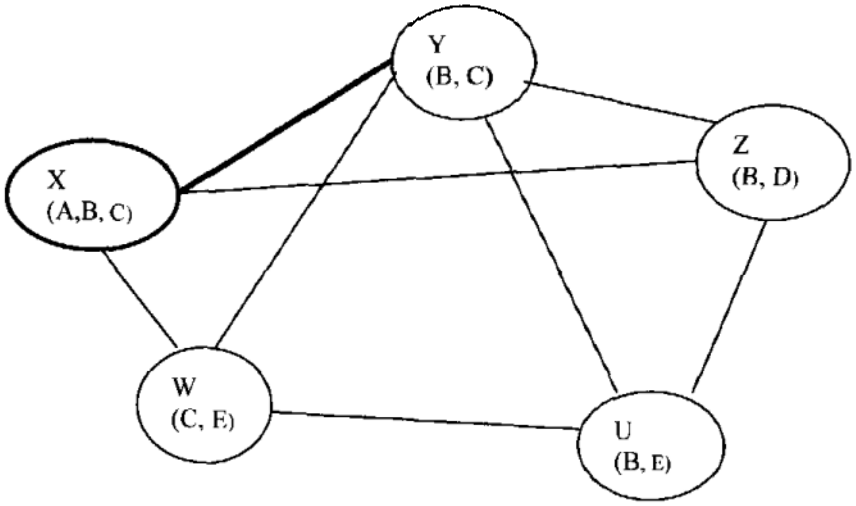

Figure 1. Knowledge network among members in a work community

In addition to these characteristics of the observable knowledge networks, actors have their own "cognitive" perceptions of the knowledge network -- that is, their perceptions of the knowledge possessed by each actor in the network. An idealized analogy often used is that of a set of networked computers, in which knowledge about a given domain is available on one of the hard disks (i.e. one of the actors), while the directory of information on all of the other hard disks (i.e., the entire knowledge network) is available to all actors (Wegner, 1995). In reality, the directory of information possessed by each of the actors (i.e., each actor's perception of "who knows what?") may be incomplete and/or inaccurate. Hence, all actors within an observable knowledge network, have their own cognitive knowledee networks describing their (potentially incomplete and/or inaccurate) perceptions of the overall observable knowledge network. The set of cognitive knowledge networks among the actors collectively constitute a transactive memory system. A transactive memory system begins when actors learn something about one another's domains of knowledge (Hollingshead, 1998; Wegner, 1987). Through self-disclosure and shared experiences, actors learn who is the expert across knowledge domains,

The accuracy of actors' cognitive knowledge networks (i.e., the extent to which their perceptions accurately reflect the observable knowledge network) reduces the amount of knowledge for which each actor is responsible, while providing each actor access to a larger pool of knowledge across domains. For instance, consider a work community as a knowledge network. The cognitive knowledge networks of individual participants within this knowledge network may be incomplete or inaccurate. That is, individual participants may not know about the areas of expertise of their colleagues. However, the cognitive knowledge network of a manager may be more accurate. That is, she is more likely to have a better understanding of the various areas of expertise represented within the work community. In responding to new information received by the group, the accuracy in her cognitive knowledge network gives her the ability to identify participants who could lead new projects and/or offer expert analysis of ongoing projects. The figure below represents Individual X's cognitive knowledge network. The nodes in this network are individuals; included (in parenthesis) within the node are the knowledge items that X perceives are possessed by each of the individuals in the network. The links between the nodes represent X's perceptions of common knowledge items shared by individuals. Note that according to the knowledge network defined above (Fiure 1), individuals Z and U share knowledge item B in common. However, X is unaware of this shared knowledge and hence X's cognitive knowledge network has no link between individuals Z and U.

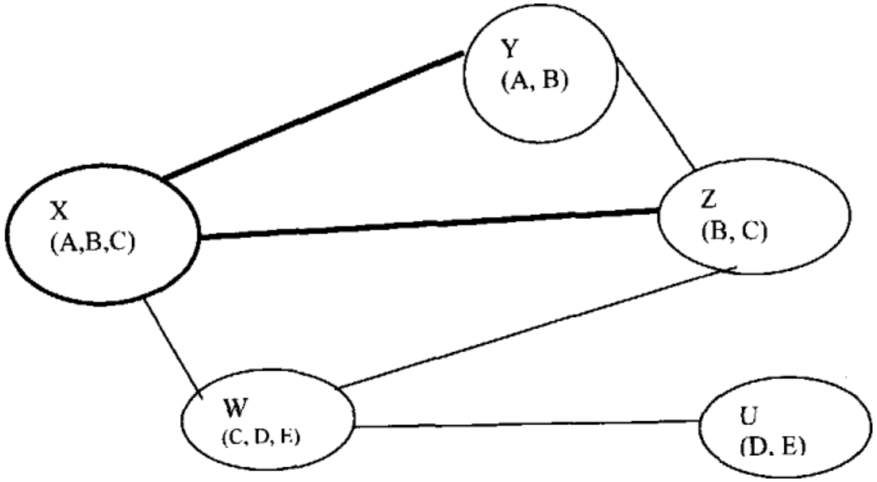

Figure 2. Individual X's cognitive knowledge network of the work community

To summarize, the work community can be represented in terms of two types of networks. Knowledge networks represent the extent to which the same or disparate knowledge is distributed among the various members of the group. Cognitive knowledge networks represent individuals' cognitive perceptions of "who knows what" within the group.

A final defining characteristic of knowledge networks is their fluidity, both in terms of actors and linkages. The actors join or leave a knowledge network on the basis of tasks to be accomplished, and their levels of interests, resuurces, and commitments. The links within the knowledge network are also likely to change on the basis of evolving tasks, the distribution of knowledge within the network, or changes in the actors' cognitive knowledge networks. Next we turn to the field of network analysis to provide a framework to analyze the state and co-evolution of knowledge networks

Knowledge Network Analysis

The conceptualizations of knowledge networks discussed in the previous section can be represented and analyzed exceptionally well using techniques developed within the field of social network analysis (Wasserman & Faust, 1994). Network analysis consists of applying a set of relations to an identified set of entities.

The growing interest in social network analysis can be attributed to its focus on relationships among social entities, and on the patterns and implications of these relationships. It is based on an assumption of the importance of relationship among interacting units (Wasserman & Faust, 1994). This focus stands in sharp contrast to other areas of the social sciences, which have tended to study "attributes," the characteristics of people, groups, and organizations rather than the relations between them (Monge & Contractor, 1988, in press). Hence, "(T)o an extent perhaps unequalled in most other social science disciplines, social network methods have developed over the past fifty years as an integral part of advances in social theory, empirical research, and formal mathematics and statistics" (Wasserman & Faust, 1994, p. 3).

The three major network mathematical foundations of network analysis have been graph theory, statistical and probability theory, and algebraic models. These foundations have been used to develop a suite of metrics that capture network properties of individual actors (e.g., actor connectedness, range, prominence, betweenness, isolation, popularity, and centrality), dyads (e.g., reciprocity, symmetry), triads (e.g., transitivity) as well as the global characteristics of the overall network (e.g., network density, heterogeneity, and centralization). The substantive interpretations of these metrics depend on the types of actors and relations being analyzed.

In the context of knowledge networks, the entities are actors (individuals, groups, organizations, etc.) and the relations between the entities represent the knowledge they share in common. The metrics developed in network analysis can easily be extended to the study of knowledge networks. For instance, an actor with high "betweenness" is defined as one who shares knowledge with several other actors in the network who do not share knowledge with one another. As such, this actor serves as a "knowledge broker" in the network. Likewise, the density of the knowledge network would index the extent to which the knowledge is distributed in the network. Network analysis can also he used to measure cognitive knowledge networks. For instance, an actor whose cognitive knowledge network accurately maps on to the observable knowledge network is more likely to be identified as the one "who knows who knows what." In general, network analysis offers the ability to measure the evolving characteristics of knowledge networks with a degree of precision that might otherwise be defined only in metaphorical terms.

While developing formal metrics of knowledge networks is an important contribution, it is only a means towards the substantively more challenging goal of understanding the theoretical processes by which these networks co-evolve across the various levels and over time. Before examining these theoretical mechanisms it is helpful to overview the technological infrastructures that are enabling knowledge networks in twenty-first century organizational forms.

Technical Infrastructure for Knowledge Networks in Work Communities

The diffusion of Internet-bascd networking technologies has accelerated the emergence of novel forms of work communities. The resulting Intranets, Extranets, and communityware support the co-evolution *of* knowledge networks. First, **Intranets** allow work communities to implement on a unified network platform a wide set of knowledge distribution activities that support teams and networks of teams within work communities. Second, because the underlying Internet standards are open and public, organizations can seamlessly interconnect their lntranet with those of clients, partners, suppliers or sub-contractors, via secure "Extranets". Third, while the pervasiveness of Internet technologies has enabled the creation of network work communities, they also make it increasingly difficult for actors to discern the scope and range of their "virtual" knowledge networks. Communitvware technologies are especially beneficial for actors assembling cross-skills teams to address specific tasks or projects by helping them accurately determine: "Who knows who?" "Who knows who knows who?" "Who knows what?" and "Who knows who knows what'?" IKNOW (Inquiring Knowledge Networks On the Web), is one example of "communityware" (Contractor, O'Keefe, & Jones, 1997).

Intervention of Infrastructure Technologies on the Co-evolution of Knowledge Networks

An important research focus is to explore the relation between knowledge networks and the technological infrastructures that work communities use to support them. Network analysis, described earlier, offers a framework to conceptualize and measure the various co-evolving networks. Communityware technologies described in the previous section influence how these networks co-evolve. The current deployment of Intranets, Extranets, and communityware provides an excellent opportunity **to** explore this recursive relationship. The evolving configurations of these technologies shape, and are in turn shaped by, the evolving knowledge networks (Contractor & Eisenberg, 1990).

Based on a review of the extant empirical literature on organizational networks, Monge and Contractor (in press) explicate several theoretical perspectives that describe various aspects of network evolution, including their formation, maintenance, transformation, and dissolution. These include: (a) theories of self-interest (social capital theory and transaction cost economics), (b) theories of mutual self-interest and collective action, (c) exchange and dependency theories (social exchange, resource dependency, and network organizational forms), (d) contagion theories, (social information processing, social cognitive theory, institutional theory, structural theory of action), (e) cognitive theories (semantic networks, knowledge structures, cognitive social structures, Cognitive consistency), (f) theories of homophily (social comparison theory, social identity theory), (g) theories **of** proximity (physical and electronic propinquity), (h) uncertainty reduction and contingency theories, (i) social support theories, and (j) evolutionary theories. Some of these perspectives are particularly relevant because they focus on co-evolution across multiple levels, including individual cognitions, dyads, groups, and organizations. We are therefore interested in making theoretical predictions about the impacts of communityware technologies on the co-evolution of knowledge networks in general and, more specifically, the social capital of actors within this network (Burt, 1997).

Unlike knowledge capital, which refers to the knowledge possessed by an actor (i.e. who knows what?), social capital refers to an actor's knowledge ahout the knowledge possessed by other actors (i.e., who knows who knows what?). Enhancing social capital is an especially important resource for actors in work communities because communityware makes it possible to broaden actors' knowledge networks, thereby increasing their ability to exercise their social capital for a competitive advantage. However, the "virtuality" of this knowledge network sometimes makes it more difficult to identify the appropriate network links within this extended network. To the extent that communityware tools make the knowledge networks more visible to the actors, they can enhance the social capital of all the actors in the network by making their cognitive knowledge networks more accurate. **A** key research question here **is** the extent to which the introduction of communityware tools increases or reduces the gap between the social capital "haves" and the social capital "have-nots." Examining the influence of communityware on social and knowledge capital, encompasses the following set of research questions:

1. What effect does commuuityware, such **as** IKNOW, have on the community's power structures? Does it undermine the perceived centrality of those individuals in the community who are viewed **as** important resources about the community's social and knowledge networks.
2. What configurations of knowledge networks are more appropriate to specific types of tasks (such as brainstorming, design, buying-selling, execution, etc.) To what extent are knowledge networks reconfigurable to accommodate the team's changing tasks?
3. How can the use of Communitware such as IKNOW (Inquiring Knowledge Networks On the Web) alter the structures and growth of Knowledge Networks by making the virtual network more visible to the members?
4. What theoretical mechanisms are most influential in "growing" a Knowledge Network (in terms of its size as well **as** the density of connections)? To what extent does the initial configuration of the network influence the speed and characteristics of its growth patterns?
5. How do exchange and trust mechanisms explain the likelihood that individuals will remain members (or drop out) of a knowledge network?
6. How can credentialling (where knowledge network members anonymously rate the quality of contributions by fellow network members) serve **as** communityware, while not violating an individual's privacy.

This section has described research questions that can be addressed by studying the co-evolution of communication, knowledge, and cognitive knowledge networks. The schematic in the following figure describes a comprehensive analytic methodology to computationally model, empirically assess, and statistically validate the effect of communityware on the co-evolution of knowledge networks.

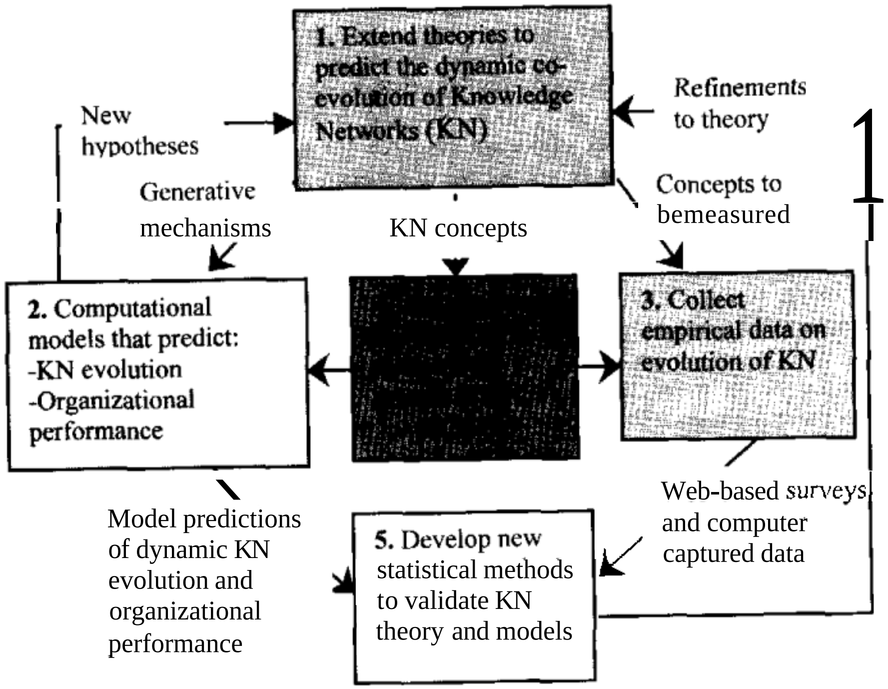

Figure 3. Methodology to study the influence of communityware on co-evolution of knowledge networks.

It shows the relationship among the key elements of the research approach: (1) theory building/hypothesis formulation about mechanisms of KN co-evolution; (2) computational modeling/simulation of those mechanisms and how they produce emergent behavior: **(3)** collection and analysis of empirical data, **(4)** development and deployment of "community-ware" tools to enable and study knowledge networks, and *(5)* statistical techniques for modeling, validating, and analyzing dynamic knowledge network data (Contractor et al., 1998). The next two sections describe how modeling and empirical field studies can be used to better understand the effect of communityware on the co-evolution of knowledge networks.

Modeling

Computational models offer a "virtual test-bed to articulate and examine the theoretical effects of communityware on the co-evolution of knowledge networks. Previous research has led to an increasing number of computational models that can be used to theorize about networks within and among work communities. Recently there has been a surge of interest in the creation **of** computational models (Carley, 1990; Carley, 1991; Carley & Prietula, 1994; Young, 1998) that can be used to capture and examine the dynamics of knowledge networks. These models serve **as** computational aids for theory construction by generating non-linear, empirically testable, dynamic hypotheses.

Blanche is one such object-oriented environment for computationally modeling network systems. It models networks as a set of actors characterized by some collection of attributes and related by one or more network links (Hyatt, Contractor, & Jones, 1997). In addition, it requires specification of **a** set oftheoretical mechanisms to examine the evolution of networks. **A** discrete set of thcorctical mechanisms provides tlexibility and expressiveness such that dependencies among actors' attributes and links over time are modeled **as a** function of values at previous time steps. The theoretical mechanisms are implemented **as** nonlinear difference equations. The suite of mathematical and logical operators implemented within Blanche make it **a** general purpose computational modeling environment for a variety of network theories. For instance, the dynamic theoretical mechanisms among the actors' attributes (e.g., their levels of resources, interests, skills) and actors' networks (e.g., density, heterogeneity of observable and cognitive knowledge networks) proposed by various theories can be specified and executed using ***Blanche.*** The dynamic hypotheses generated by computational modeling provide theoretical predictions about the co-evolution of knowledge networks. These predictions must then be empirically validated in test-beds.

Test-beds

Versions of IKNOW are currently being designed for use in the (i) National Computational Science Alliance **(NCSA)** at the University of Illinois at Urbana-Champaign, (ii) Faculty Summer Institute on Collaborative Learning, (iii) a ten-week Summer Workshop at the Engineering Research Center for Collaborative Manufacturing at Purdue University, (iv) the Public Works Division of a U.S. military installation, (v) the Global Information Systems Project at the Office of International Programs at Purdue University (IPPU), (vi) a PrairieNet Community Networking Project in Champaign-Urhana,. (vii) and several graduate and undergraduate courses taught at the University of Illinois at Urbana-Champaign.

These work communities represent diverse characteristics in terms of (i) their size (30-300), *(ii)* unit of analysis (individuals versus organizations) *(iii)* geographical dispersion of members (co-located to world-wide), (iv) content of social interaction (e.g., computational science, voluntary non-profit communities, manufacturing, education), (v) current use of Intranet-based technologies (no prior use to high performance computing environments), (vi) past history as a community (start up communities to 10 years old), and (vi) life cycle of the community (1 week to projected five year life cycles).

Data Collected from Testbeds

In addition to serving the user community, IKNOW also serves as an effective data collection instrument for researchers. Unlike most network based research in work communities, the data provided by users are generated as part of their ongoing use of communityware. Since users have a vested interest in the information provided being accurate and current, the large corpus of longitudinal data has a greater likelihood of being reliable.

Five types of network data are captured by IKNOW: (i) a communication network of actors based on existing task and projects links between them; (ii) a knowledge network based on actors providing an inventory of their skills and expertise, (iii) a knowledge network of actors based on the links between their web sites, (iv) a knowledge network of actors based on common links from their web sites to third party web-sites and (v) a knowledge network based on similarity in content (vocabulary) between different actors' web sites. The data from these networks are automatically captured longitudinally and serves as empirical data to validate the networks generated from computational modeling tools such as *Blanche.*

Benefits to the Community

As discussed in this paper, IKNOW serves as a Communitware tool that has benefits for the researcher as well as for the community. It is this synergy that makes it a particularly useful tool to study the co-evolution of knowledge networks.

There are at least three ways in which IKNOW can assist user communities create, sustain, and grow their knowledge networks:

1. First, it provides all members of the community the ability to efficiently and effectively identify others within the community who share common and complementary interests, and how they may he directly or indirectly connected to them. This is especially beneticial for members assembling ad-hoc cross-skills teams to address specific project concerns.
2. Second, it provides members with a set of visual tools to inspect, identify, and critically analyze the existing and potential collaborations (both in terms of membership and topics) among the members of the community.
3. Third, it offers members the ability to track over time the growth characteristics of the knowledge network (in terms of the size of the network, the density of inter-connections, and the content areas).

Below are four current examples of he use of communityware:

I. PrairieNet Communityware

The PrairieNet communityware (http://iknow.spcomm.uiuc.edu/prairienet login/password: guest/guest) consists of 285 organizations in Central Illinois with public web pages. Each organization's set of web pages were scanned to create a list of links on those pages and a list of words that occurred on those pages. From this information we can view networks of web page links between these organizations, how many outside links these organizations have in common, as well as similarity in the content of their web site. For instance, the Danville Public Library shares a tie with the Urbana Free Library, and the Urbana Free Library shares a tie with the Friends of the Urbana Free Library. Boy scout troops, religious organizations, bands, clubs, and political groups all share similar ties. Thus IKNOW communityware is especially useful to community organizations that are trying to use their resources efficiently and effectively to mobilize for joint collective action.

II. NCSA Alliance Communityware

The NCSA Alliance communityware (secured web site) consists of 291 members in over 200 organizations. As part of their registration on the Alliance Intranet they were required to enter information about their interests by choosing items from a list. The similarity of these lists are used to create network visualizations similar to the ones described for Prairienet. Thus IKNOW communityware is especially useful to members in the Alliance who want to identify others within the distributed community who share common and/or complementary interests.

III. Faculty Summer Institute Communityware

The Faculty Summer Institute on Collaborative Learning communityware (http://iknow.spcomm.uiuc.edu/fsi login/password: guest/guest) was used by twelve faculty members from state universities in Illinois participating in a week long workshop on the use of technologies to support collaborative learning. Communityware was used by the group as a quick and effective "ice-breaker" to identify common and complementary interests among the participants, as well as to choose partners to work on group projects during and after the workshop.

IV. Communityware for a course on Communication Technologies in the Workplace

During Spring 1998, IKNOW communityware (http://iknow.spcomm.uiuc.edu/class login/password: guest/guest) was used by *36* students in an undergraduate course on "Communication Technologies in the Workplace" at the University of Illinois. The students used IKNOW to form their own teams for semester projects. They were required to assemble teams that included individuals with some common skills (such as interest in aviation, advertising, etc.) and some complementary skills (such as at least one member with web-authoring skills).

V. Communityware for participants in the Kyoto meeting

A version of IKNOW (**http://iknow.spcomm.uiuc.edu/kyoto/** login, password: guest, guest) was developed to examine the knowledge networks among participants of the Kyoto meeting. After logging in, participants viewed the screen shown in Figure **4:**

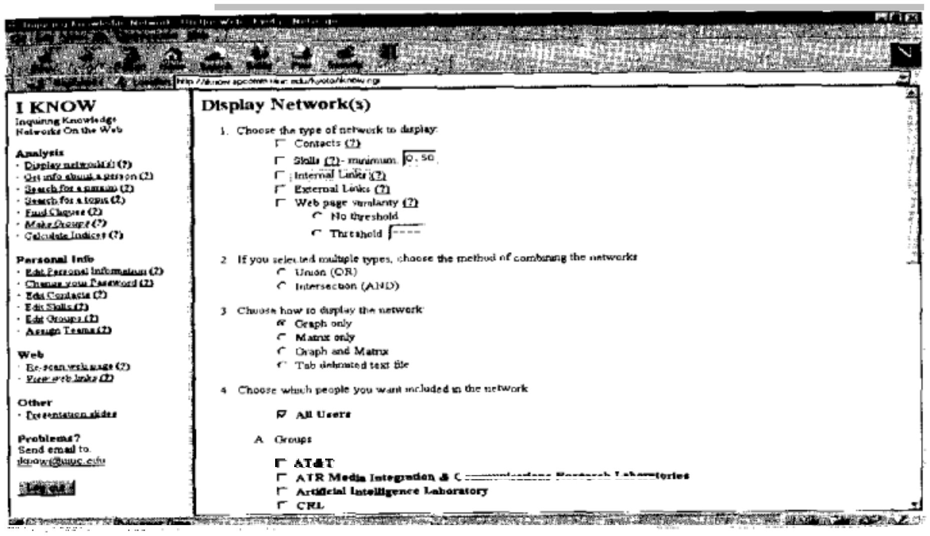

Figure 4. User interface for IKNOW

Figure 5 shows the knowledge network as indicated by web links between participants' web sites. For instance, Yoko Kubota (the node colored white) has links pointing to **his** web site from Yasuyuki Sumi and Toru Ishida (the nodes colored blue). Kubota has links from his web site pointing to the individuals whose nodes arc colored green.

Figure **6** shows the knowledge network as indicated by participants whose web sites point to the same external web sites. Unlike Figure **5**, where the nodes were arranged in a circle, here the network was annealed **so** that similar nodes appear clustered closer to one another. **As** a result several of the Japanese participants in the meeting were clustered together. Figure 7 shows the output of clicking on the link between Leonard Foner and Keiki Takadema. The two each have links from their web sites pointing to web pages at **NASA** and EFF.

Figure 8 shows the knowledge network **as** indicated by common vocabulary appearing on the participants' web sites, This annealed network indicates that many of the Japanese participants not only have similar vocabulary on their web pages. Further, they appear to share common terms with more of the non-Japanese participants than the latter do with one another. Finally, Figure **9,** shows a listing of the common terms found between the web sites of Geoffrey Bowker and Vijay Saraswat. The words are listed in descending order, ***so*** that words that are more

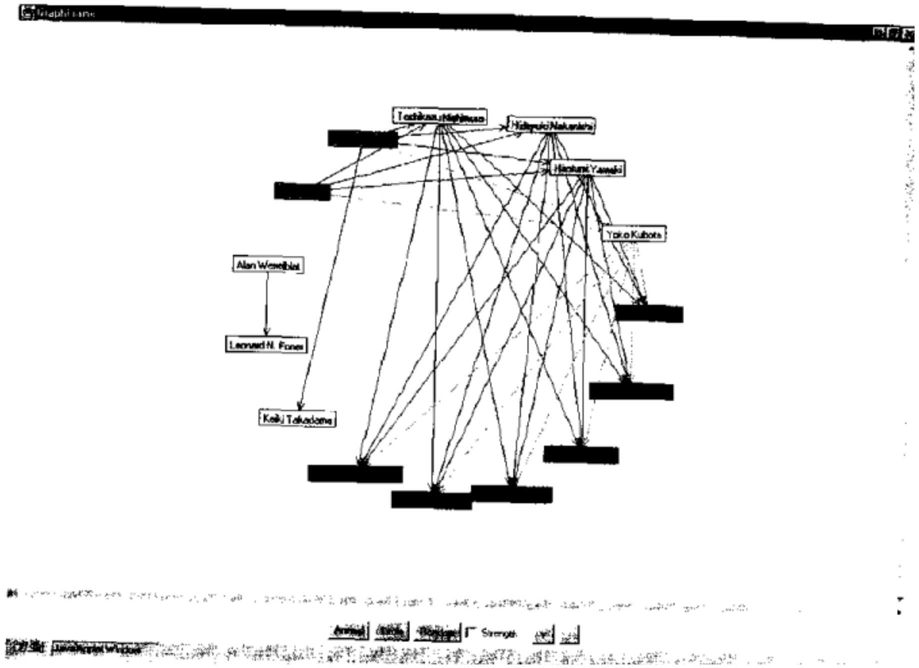

Figure 5. Network of web links behveen the web sites of participants

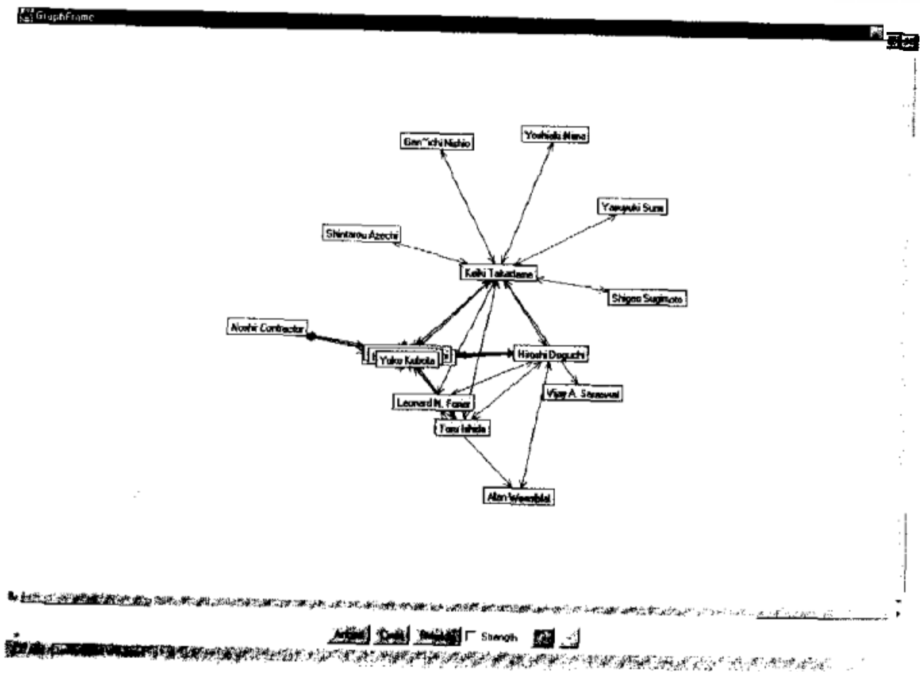

Figure 6. Annealed network of common external web links from participants' web sites

frequently used by the two participants, and less frequently used by any other participants are weighted higher. A quick inspection of the list iodicatcs that Vijay and Geoffrey both indicate an interest on their web sites in the following terms: computer science, John Seely Brown, teachers, participatory design, videotaping, and etiquette.

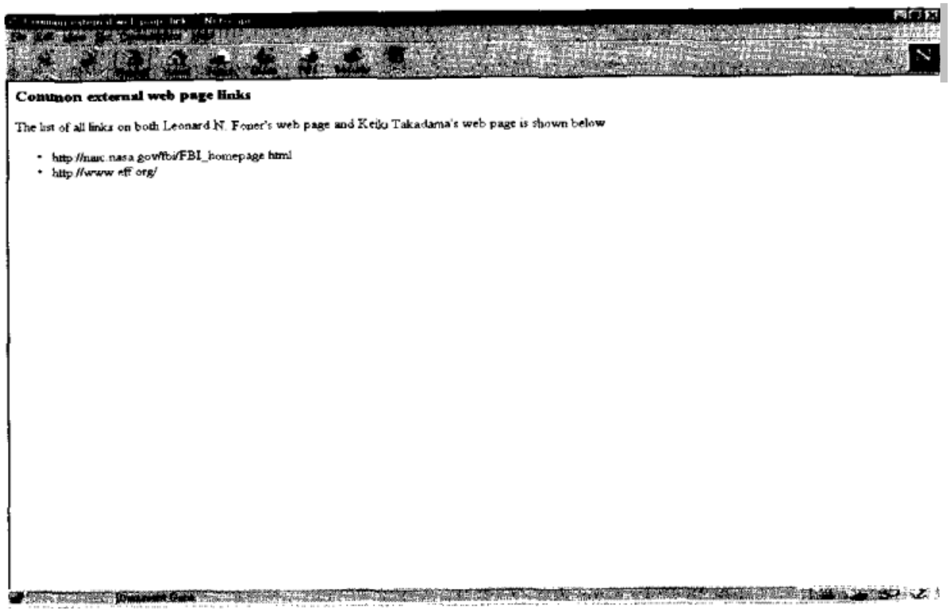

Figure 7. Display of common external web links between two participants

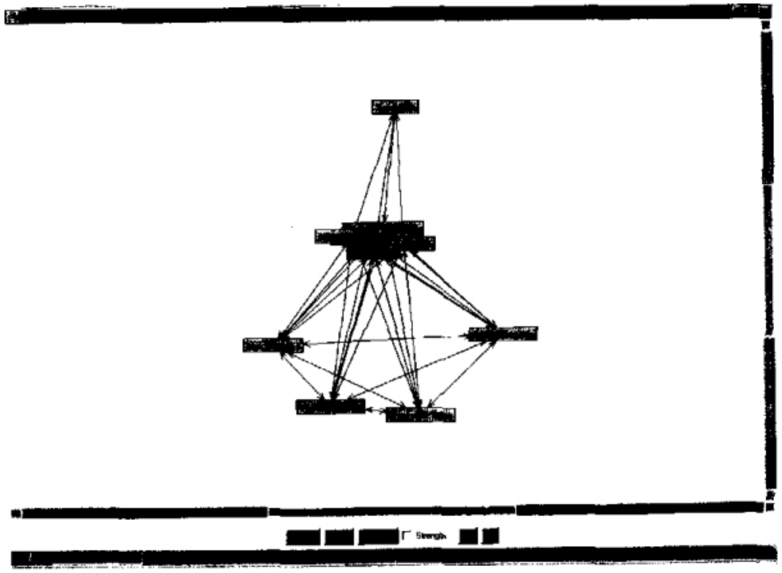

Figure 8. Annealed network of common vocabulary between participants' web sites

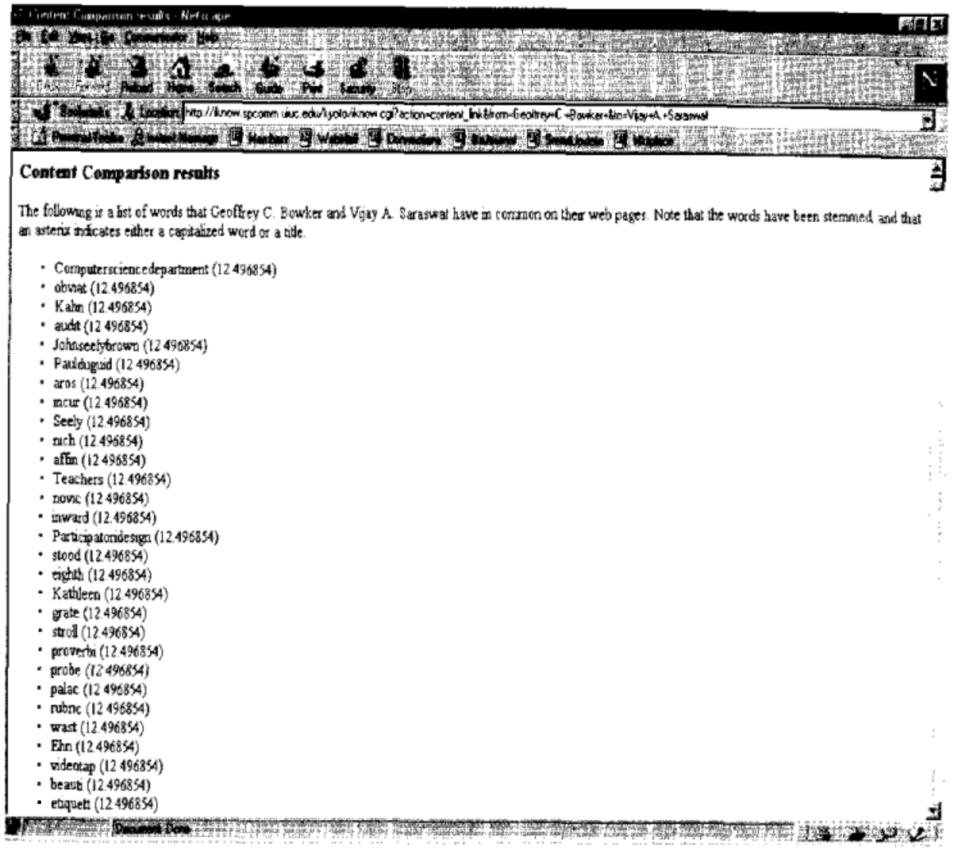

Figure 9. Display of common vocabulary between two participants' web sites

Conclusion

This paper has argued for the potentially important role of communityware in assisting the creation, maintenance, and dissolution of knowledge networks. Network analytic techniques offer an appropriate methodology to represent and analyze the evolution of knowledge networks and cognitive knowledge networks. Communityware tools, such as IKNOW, have the potential to assist in the evolution of these networks by making the virtual networks more visible to the actors and by adding contacts to the content of the knowledge network. The paper identified several theoretical mechanisms that can be used to study the effect of introducing communityware on the evolution of these networks. Computational models offer researchers the ability to simulate the long term non-linear implications of these theoretical mechanisms. The results of these simulations must be validated using the type of test-beds described in this paper.

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