Spinning Multiple Social Networks for Semantic Web*

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Abstract

Social networks are important for the Semantic Web. Several means can be used to obtain social networks: using social networking services, aggregating Friend-of-a-Friend (FOAF) documents, mining text information on the Web or in e-mail messages, and observing face-to-face communication using sensors. Integrating multiple social networks is a key issue for further utilization of social networks in the Semantic Web. This paper describes our attempt to extract, analyze and integrate multiple social networks from the same community: user-registered *knows* networks, web-mined *collaborator* networks, and face-to-face *meets* networks. We operated a social network-based community support system called *Polyphonet* at the 17th, 18th and 19th Annual Conferences of the Japan Society of Artificial Intelligence (JSAI2003, JSAI2004, and JSAI2005) and at The International Conference on Ubiquitous Computing (UbiComp 2005). Multiple social networks were obtained and analyzed. We discuss the integration of multiple networks based on the analyses.

Introduction

Social networks are important in various AI research areas, especially for the Semantic Web. Our lives are strongly influenced by social networks without our knowledge of their implications, and many applications are relevant to social networks (Staab *et al.* 2005). In the context of the Semantic Web, social networks are crucial to realize a web of trust that enables the estimation of information credibility and trustworthiness (Golbeck & Hendler 2005; Massa & Avesani 2005). Ontology construction is also related to social networks (Mika 2005b): for example, if numerous people share the same two concepts, the two concepts might be related. Conflict of Interest (COI) detection (Aleman-Meza *et al.* 2006) and information exchange (Mori *et al.* 2005) on social networks are other applications in the Semantic Web.

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Several means of obtaining social networks exist: Recently, social networking services (SNSs) have received much attention on the Web (Tenenbaum 2005). Friendster and Orkut are among the earliest and most successful SNSs. Users register their friends and acquaintances on SNSs. Friend-of-a-Friend (FOAF) is vocabulary to describe information about a person and their relation to others[1]. We can collect FOAF documents and obtain a FOAF network (Finin, Ding, & Zou 2005; Mika 2005a). Both SNS data and FOAF data are created by the users themselves though FOAF data is open to public while SNS data is often not.

On the other hand, automatic detection of a relation is also possible from various sources of online information such as e-mail archives, schedule data, and Web citation information (Adamic & Adar 2003; Tyler, Wikinson, & Huberman 2003; Miki, Nomura, & Ishida 2005). Especially in some studies, social networks are extracted by measuring the co-occurrence of names on the Web using a search engine (Mika 2005a; Matsuo *et al.* 2006).

Another stream of work exists to obtain social networks observing individuals' behaviors with ubiquitous and wearable devices (Pentland 2005). If we consider the famous sociological study in the 1930s by Mayo and Warner at the Hawthorne electrical factory (Wasserman & Faust 1994), it seems natural to obtain a social network by observing behavioral information of persons using recently developed devices. Quantifying face-to-face interactions is interesting because informal conversations are sometimes considerably important within an organization and a community.

Any method that we might use for obtaining a social network would be hindered by some flaw. For example, SNS data and FOAF data, which are based on self-report surveys, suffer from data bias and sparsity. Users might name some of their work acquaintances, but would not include private friends. Others might name hundreds of friends, while others would name only a few. Automatically obtained networks, e.g. web-mined social networks, would provide a good view of prominent persons, but would not work well for novices, students, and other "normal" people. Social networks observed using wearable devices are constrained by their device-specific characteristics; they might have detection errors, limited detection scopes, and bias according

[1] http://www.foaf-project.org/

to their usage.

This paper describes our attempt to obtain multiple social networks, i.e. *multi-plex* network in a sociological term, in an academic community. We operated our system, called *Polyphonet* at the 17th, 18th and 19th Annual Conferences of the Japan Society of Artificial Intelligence (JSAI2003, JSAI2004, and JSAI2005) and at The International Conference on Ubiquitous Computing (UbiComp 2005). More than 500 participants attended each conference; about 200 people actually used the system. Three types of social networks were obtained and analyzed: *knows* networks by users' registration of acquaintances, *collaborator* networks by Web mining, and *meets* networks obtained through observation of face-to-face communication.

The contributions of this study are summarized as follows:

- We introduce our three-year project of community support in Japan, which specifically addresses social networks; we provide an overview of *Polpyhonet*.
- We compare and analyze the three obtained social networks. Based on our attempts and other studies, we discuss integration of multiple social networks.

The paper is organized as follows: After describing related works in the next section, we provide an overview of Polyphonet and three kinds of social networks. The analysis is shown in Section 4 and discussion on the integration of social networks is made in Section 5.

Related Work

In the mid-1990s, Kautz and Selman developed a social network extraction system from the Web, called *Referral Web* (Kautz, Selman, & Shah 1997). It estimates the strength of relevance of two persons X and Y by putting a query "X and Y" to a search engine: If X and Y share a strong relation, we can usually find much evidence on the Web. Recently, P. Mika developed a system for extraction, aggregation and visualization of online social networks for a Semantic Web community, called Flink (Mika 2005a). Social networks are obtained using analyses of Web pages, e-mail messages, and publications and self-created FOAF profiles. The Web mining component of Flink, similarly to that in Kautz's work, employs a co-occurrence analysis.

A. McCallum and his group have presented an end-to-end system that extracts a user's social network (Culotta, Bekkerman, & McCallum 2004; Bekkerman & McCallum 2005). That system identifies unique people according to e-mail messages, finds their homepages, and fills the fields of a contact address book along with the other person's name. Links are placed in the social network between the owner of the Web page and persons on that page.

Some particular relations on the Web have been investigated in detail: L. Adamic has classified social networks of Stanford and MIT students, and has collected relations among students from Web link structures and text information (Adamic & Adar 2003). Cimiano and co-workers developed a system called (PANKOW), which puts a named entity into several linguistic patterns that convey semantic meanings (Cimiano, Ladwig, & Staab 2005). Ontological relations among instances and concepts are identified by sending queries to a Google API.

Analyses of FOAF networks is a new research topic. To date, only a couple of interesting studies have analyzed FOAF networks (Finin, Ding, & Zou 2005; Mika 2005a). Aleman-Meza et al. proposed the integration of two social networks: "knows" from FOAF documents and "co-author" from the DBLP bibliography (Aleman-Meza *et al.* 2006). They integrate the two networks by weighting each relationship to determine the degree of COI among scientific researchers.

Within the ubiquitous computing and wearable infrastructure, A. Pentland and his group have undertaken numerous studies to understand social signaling and social context, namely social network computing (Eagle & Pentland 2003; Pentland 2005). For example, the Laibowitz and Paradiso UbER-Badge is a badge-like platform that allows social context sensing using IR, audio, and motion so that wearers can automatically bookmark interesting people and demonstrations. Such a system helps a person build a social network (Gips & Pentland 2006) as social capital. They mention that it can be used to create, verify, and better characterize relationships in SNSs.

Numerous studies have targeted academic conferences. Recent works include IntelliBadge(Cox, Kindratenko, & Pointer 2003), which as used at the IEEE SC2002 Conference to track conference attendees, provide several functions such as to locating friends or searching for interesting events. A Personal Digital Assistant (PDA) (Sumi & Mase 2001) can be used to show networks among exhibits and participants. Using a PDA, participants can register their preferences on presentations, and receive recommendations. Many other studies have targeted academic conferences such as projects using Active Badge, Hummingbird and Meme Tags.

Three Social Networks in Polyphonet

Three kinds of social networks are addressed in this paper: user-registered, web-mined, and face-to-face social networks. In this section, we explain the technical points of Web mining, social networking function, and real-world interface of *Polyphonet*[2]. We encourage the reader to visit the website for UbiComp2005[3], and for JSAI2005[4]. Please refer to (Matsuo *et al.* 2006) for further technical details of Web mining.

Web mining

A social network is extracted through two steps. First, we collect authors and co-authors at the JSAI conference; we then posit them as nodes. Next, edges between nodes are added using a search engine. For example, assume that we are to measure the strength of relations between two names: Yutaka Matsuo and Peter Mika. We put a query *Yutaka Matsuo* AND *Peter Mika* to a search engine. The number of hits estimates the strength of their relation by co-occurrence of

[2]Polyphonet is a coined term from *polyphony* + *network*.

[3]http://www.ubicomp-support.org/ubicomp2005/.

[4]http://jsai-support-wg.org/polysuke2005/.

Table 1: Error rate of relation types, precision and recall.

class	error rate	precision	recall
Co-author	4.1%	91.8% (90/98)	97.8% (90/92)
Lab	25.7%	70.9% (73/103)	86.9% (73/84)
Proj	5.8%	74.4% (67/90)	91.8% (67/73)
Conf	11.2%	89.7% (87/97)	67.4% (87/129)

their two names. We add an edge between the two corresponding nodes if the strength of relations is greater than a certain threshold.

Several indices can measure co-occurrence (Manning & Schütze 2002): matching coefficient, mutual information, Dice coefficient, Jaccard coefficient, overlap coefficient, and cosine. Depending on the co-occurrence measure that is used, the resultant social network varies. Through comparison of the indices with co-authorship relation, among them we conclude that the overlap coefficient is best for our purposes (Matsuo *et al.* 2004; 2005).

To date, several studies have produced attempts at personal name disambiguation (Bekkerman & McCallum 2005; Lloyd *et al.* 2005; Li, Morie, & Roth 2005). These works identify a person from their appearance in the text when a set of documents is given. However, to use a search engine for social network mining, a good keyphrase to identify a person is useful because it can be added to a query. In the UbiComp case, we develop a name-disambiguation module (Bollegala, Matsuo, & Ishizuka 2006). Its concept is this: no words need to be added for a person whose name is not common such as *Yutaka Matsuo*; for a person whose name is common, we should add a couple of words that best distinguish that person from others. In an extreme case, for a person whose name is very common, such as *John Smith*, many words must be added. The module then uses text similarity to cluster the Web pages that are retrieved by each name into several groups. It then outputs characteristic keyphrases that are suitable for adding to a query.

Not only the strength of the tie, but also the type of relation is detected in Polyphonet. Inferring the class of relationship is thereby reduced to a text categorization problem that can be addressed using a machine learning approach. We first fetch the several top pages retrieved by the "X and Y" queries. Then we extract features from the contents of each page to classify pages into classes of relations. Especially, four kinds of relations are selected: Co-author, Lab (members of the same laboratory or research institute), Proj (members of the same project or committee), and Conf (participants in the same conference or workshop). Table 1 shows error rates of five-fold cross validation. Although the error rate for Lab is high, others have about a 10% error rate or less. Precision and recall are measured by manually labeling an additional 200 Web pages.

Polyphonet also addresses scalability: The number of queries to a search engine becomes a problem when we apply extraction of a social network to a large-scale community: a network with 1000 nodes requires half a million queries and grows at $O(n^2)$, where n is the number of persons. Considering that the Google API limits the number of queries to one thousand per day, that number is huge. One

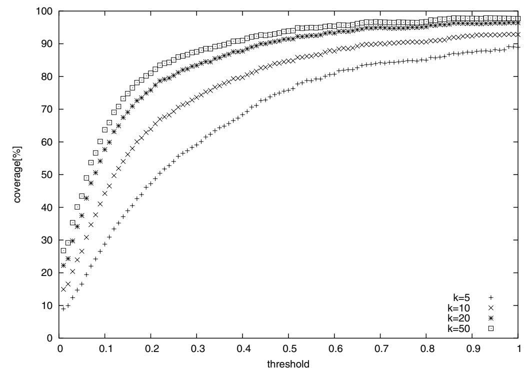

Figure 1: Coverage versus overlap coefficient by scalable network extraction.

solution might be found in the fact that social networks are often very sparse. For example, the network density of a web-mined network for JSAI2003 is 0.0196, which means that only 2% of possible edges actually exist. Our idea is to filter out pairs of persons that apparently have no relation. We first put a query with the person's name, get k documents, and filter out names which does not appear in the documents. For 503 persons who participated in JSAI2003, ${}_{503}C_2 = 126253$ queries are necessary. However, our scalable module requires only 19182 queries in case $k = 20$ empirically ($O(n)$ queries theoretically), which is about 15%. How correctly the algorithm filters out names is shown in Fig. 1. For example, in case $k = 20$, 90% or more of the relations with an overlap coefficient of 0.4 are detected correctly.

Social networking on Polyphonet

We call web-mined social networks *collaborator* networks and web-mined relation as *collaborator* links. In Polyphonet, a *collaborator* network is shown from the initial use of a user. Users can register their friends and acquaintances, as they can with other SNSs. We call this network a *knows* network and their relations *knows* links. *Collaborator* networks and *knows* networks are managed separately, but can be represented in the same network figure. Few people have FOAF files so far (at least in academic societies in Japan). Therefore, we do not collect the FOAF files of participants. Instead, users can get their FOAF files instantly in a similar manner to that of FOAF-a-Matic.

Figure 2 depicts a portal page that is tailored to an individual user, called *my page*. The user's presentations, bookmarks of presentations, and registered acquaintances are shown along with the social network extracted from the Web. It helps users to register *knows* links easily by seeing the *collaborator* links. Various types of retrieval are possible on social networks: researchers can be sought according to their name, affiliation, keyword, and research field; related researchers to a retrieved researcher are listed; and a search for the shortest path between two researchers can be made.

Polyphonet is accessible via on-site information kiosks or via users' own portable computers. The numbers of participants and users are shown in Table 2. We conducted ques-

Table 2: Numbers of participants and users.

	JSAI03	JSAI04	JSAI05	UbiComp05
#presentations	259	288	297	122
#authors	510	544	579	355
#participants	558	639	about 600	about 500
#users	276	257	217	308
#*knows* users	99	94	94	376
#*meets* users	–	–	162	186

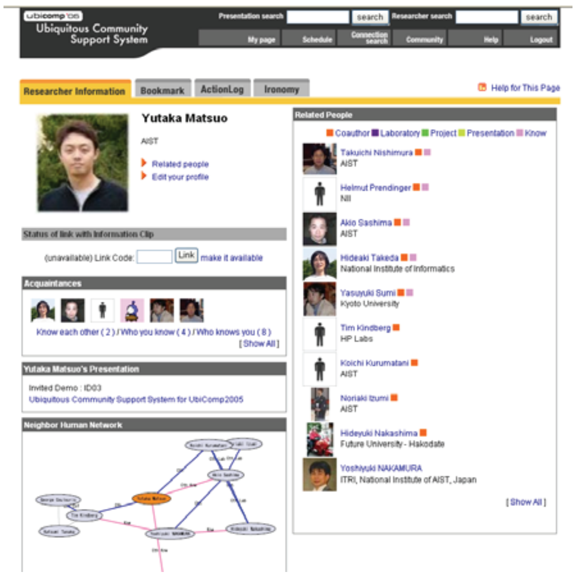

Figure 2: My page on Polyphonet.

Figure 3: Information kiosk and RFID badge.

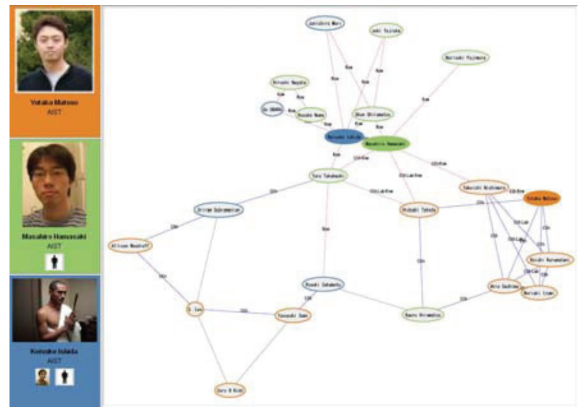

Figure 4: Social network among three persons on Polyphonet.

tionnaire surveys each year. The respondents' comments are almost entirely positive; they enjoyed using the system.

Face-to-face social networks

Several means are available to obtain a social network from users' behaviors: observing physical proximity, physical location, and communication. At JSAI2003 and JSAI2004, to track each participant and measure the proximity of persons, we installed about one hundred sensors at the conference sites. We provided infrared badges to participants (Nishimura *et al.* 2004). That method achieved fair precision, but low recall. Often people meet in places where sensors are not set (such as stairs, cafes, and outdoor restaurants). Some people felt uneasy about being tracked.

At JSAI2005 and UbiComp05 conferences, we employed another approach. We allowed users to make some simple action to inform the system that they met another person, similarly to the bookmark function of UbER-Badge (Gips & Pentland 2006): The method seemed to provide a good balance between privacy and effectiveness. We deliver each participant an RFID badge shown in Fig. 3. We set several information kiosks in and near the lobby and entrance. If two or three users put their cards on the readers, Polyphonet displayed the social networks that included two or three of them (Fig. 4). Therefore, it can serve as a real-world name-card exchange. We regard them as connected by a *meets* link, which consists of a *meets* social network, when users take this action.

Analysis of Social Networks

In this section, we show some results of analyses on obtained networks from JSAI2005. Figures 5, 6, and 7 respectively show *collaborator*, *knows*, and *meets* social networks. Generally, the *collaborator* network is well connected throughout the participants. In the JSAI case, several sub-communities exist, where nodes are especially densely connected. We can determine a group of central persons who initiate the research community. On the other hand, the *know* network tends to be more concentrated. Several participants have numerous (out-)edges. In the *meets* network, there is only a small dense part in the network. Users meet (i.e. use the information kiosk together) with several friends, but not exhaustively with their friends. These tendencies are identical to those of UbiComp2005.

Table 3 shows common link quantities and QAP (Pearson) correlations between two of the three networks. QAP correlation represents how similar the two networks are. *Knows* and *meets* are the most similar, which implies the effectiveness of automatically creating *knows* relations from face-to-face communications. Although the QAP correlation between *collaborator* and *knows* is not high, user log analy-

Table 3: Number of common links

Pair of links	#common links	QAP correlation
collaborator & *knows*	754	0.279
knows & *meets*	136	0.426
collaborator & *meets*	149	0.260

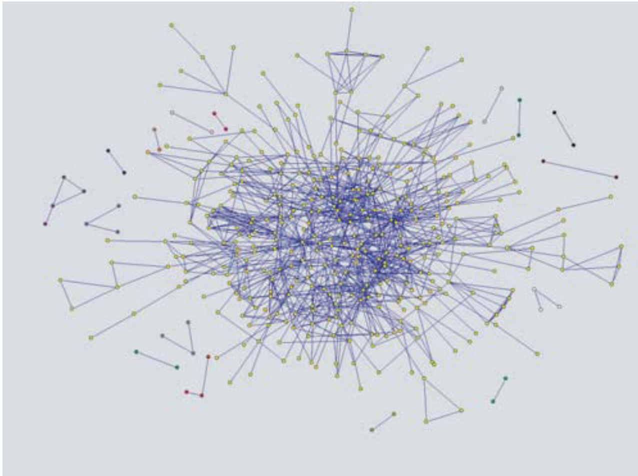

Figure 5: *Collaborator* network at JSAI2005 ($n = 415$, $m = 1049$). n denotes the number of nodes, and m denotes the number of edges. The threshold is tuned for clear visualization.

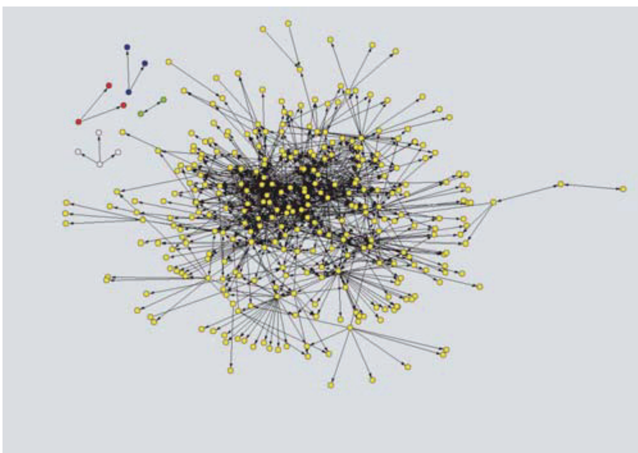

Figure 6: *Knows* network ($n = 308$, $m = 1005$). The network is directional; edges are from 94 persons.

ses show that 52% of the *knows* links are registered from a user's *collaborator* page. This fact suggests that, at least in Polyphonet, the *collaborator* link contributes to set *knows* links efficiently. On the other hand, *meets* and *collaborator* correlation is not high: participants talk and use information kiosks with others in proximity, not necessarily with collaborators.

We also analyzed path lengths, degree distributions, and so on. Some interesting findings are: We measure the authoritativeness of each person using several measures such as the number of Web hits and the number of publications. Then, authoritative people tend to have more *collaborator* links. However, most authoritative people do not use *knows* links the most; active middle-authoritative users do. They might know the community well and feel interested in it. Less-authoritative users use *meets* links more. Especially, persons with similar levels of authoritativeness are likely to have *meets* links. That situation seems natural because persons who have fewer acquaintances would probably seek more acquaintances. Furthermore, people are likely to meet people of a similar level in the community.

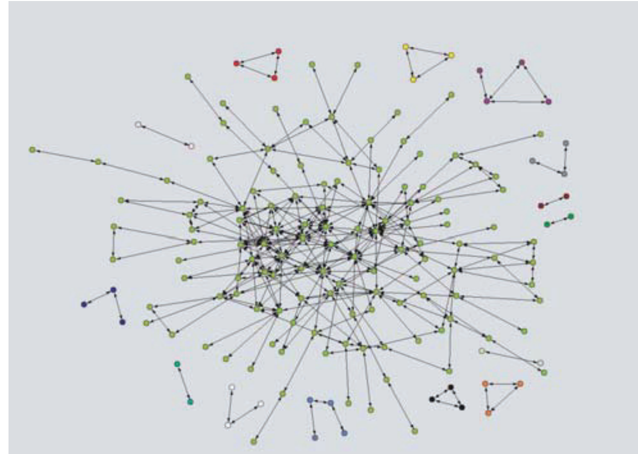

Figure 7: *Meets* network ($n = 162$, $m = 288$).

Integration of Multiple Social Networks

How can we integrate multiple social networks? In social network analysis, a network is called a *multi-plex* graph where actors are connected in multiple ways simultaneously (Hanneman & Riddle 2005). There are several ways to reduce the multiple network matrices into one; we can use sum, average, maximum, multiplication to each corresponding element of the matrices.

In typical social science studies, a social network is obtained according to survey purposes. Otherwise, a network is only a network that represents nothing. In the context of the Semantic Web, social networks are useful for several purposes:

- locating experts and authorities (Mika 2005a; Matsuo *et al.* 2004);
- calculating trustworthiness of a person (Golbeck & Hendler 2005; Golbeck & Parsia 2006; Massa & Avesani 2005);
- detecting relevance and relations among persons, e.g. COI detection (Aleman-Meza *et al.* 2006);
- promoting communication, information exchange and discussion (Matsuo *et al.* 2006); and
- ontology extraction by identifying communities (Mika 2005b).

To locate experts and authorities, it is useful to use a *collaborator* network and calculate centralities based on the network. Correlation to research performance, e.g. publication and citation, is used to measure whether the network is appropriate or not. To calculate trustworthiness and aggregate information, the *knows* relation works well because of the inherent nature of the explicit declaration. The *collaborator* and *meets* links might help to suggest the *knows* relation, as shown in the previous section.

For promoting communication and finding referrals, *knows* links and *meets* links are important: if a user explicitly declares knowing some friends, he is likely to introduce friends to others. The *meets* link is also a key because a person actually meets others on-site. The person feels easy talking again to introduce someone. Our analysis shows that *knows* and *meets* networks have high correlation. For that reason, gathering *meets* data at several conferences might create an appropriate *knows* network, e.g. for trust calculation.

For (light-weight) ontology extraction, it is important to detect the community precisely under consistent criteria. In that sense, the *collaborator* network is the best in an academic context. Integration of *collaborator* plus *knows* might improve the result because it increases the probability that the two are of the same community.

In social network analyses, network measures are sometimes compared to external data to judge whether the network is obtained well or not. We can extend this notion to integrating the multiple networks. Actually, some recent studies match this approach (Aleman-Meza *et al.* 2006; Massa & Avesani 2005; Matsuo *et al.* 2004). So far, we can only tune integration according to trial and error; (semi-)automatic tuning is an important future task. One rough sketch for that process is the following: Weight multiple networks $G_i (i = 1 \dots k)$ and obtain one network $G_{reduced}$. Then calculate some network measures of $f(G_{reduced})$, e.g., centrality value for each node. Next, prepare an external index p, which represents the survey purpose. Finally, tune the weight so that the correlation cor is maximized.

$$\max cor(f(G_{reduced}), p)$$
$$\text{s.t.} \quad G_{reduced} = \sum_{i=1}^{k} w_i G_i$$

An important issue of using the network measure is their robustness (Costenbader & Valente 2003): Some measures, such as eigenvector centrality, are robust for the sampled network. Others, such as betweenness centrality, are fragile. The implementation and evaluation of the method are now underway. We will report the results in a later publication.

Conclusion

This paper described extraction and analyses of three kinds of social networks that exist at academic conferences: user-registered *knows* networks, web-mined *collaborator* networks, and face-to-face *meets* networks. In Polyphonet, the advanced Web mining function demonstrably enhances communication in academic communities.

Social networks are important for the Semantic Web. Integration of multiple networks, or spinning social networks, is becoming increasingly necessary. We argue that integration of social networks should be done depending on its purposes. Further works will include execution of several case studies for different purposes using the multiple networks. We believe that our work contributes to other studies that focus on social networks, not only for the Semantic Web, but also for other research into artificial intelligence.

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