Applying P2P-based Social Network to Collaboration Support for Knowledge Sharing

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Abstract

One of the essential goals of knowledge sharing is to enable collaboration among the participants (or collaborators) to share relevant knowledge. By collaborators, here we refer to other Web-based workers who either possess related knowledge or can help to discover and obtain the knowledge through communications and discussions. The performance of knowledge sharing is fundamentally based on how collaborators and relevant knowledge can be effectively found. In this paper, we establish a peer-to-peer-based social network to facilitate and enhance Web-based knowledge sharing by finding knowledgeable and trustworthy collaborators who are willing to share their knowledge. Results of this research demonstrate that applying such mechanism do improve the quality of collaboration in knowledge sharing.

Keywords: knowledge sharing, social network, P2P network

1: Introduction

Social network is built upon an idea that there existing a determinable structure of how people know each other. In such a network, people are connected through common association either directly or indirectly [1]. Researchers have recognized that a broader sense of social network is a self-organized structure of people, information, and communities of practices [2,3,4]. In such sense of social network, a composite contextual variable, social capital, which is derived from the social capital theory [5] has been widely considered as an important enabler of creation, exchange and combination of knowledge. Researchers have addressed the importance of various components of social capital, such as trust and social interaction [6]. They also discovered that trust and identification influence knowledge contribution to electronic knowledge repository. The aforementioned researches have brought two fundamental issues in knowledge sharing: how to find knowledgeable collaborator to interact with, and how to ensure the found collaborators are trustworthy.

Trustworthiness in a social network can be classified into three levels- infrastructure, understanding and policy. Infrastructure is the first level, which focuses on keeping a trusted infrastructure. For example, the underlying software and hardware of a Web-based system must be trustworthy. The network should guarantee that network transmission is reliable and secure. Understanding is the second level. Huhns and Buell [7] pointed out that we are more likely to trust something if we understand it. An approach is to calculate degree of confidence based on past experiences, such as rating service, reputation mechanism, and referral network [8]. Policy is the third level, which is used to describe requirements of trust, security, privacy and societal conventions to reach high-level trustworthy objectives [7]. In general, the policy provides many specific description-methods for requesting party to define what states and situations could accept. In other words, policy works like a rule set used to decide what behaviors and states could acquire authorizations.

The objective of this paper is to address issues of finding knowledgeable and trustworthy collaborators in a P2P-based environment. P2P provides a metaphor as a peer can be both knowledge consumer and producer in knowledge collaboration [9,10]. Throughout the paper, we will use the terms user and peer interchangeably. The contribution of this research is applying P2P-based social network with the consideration of trustworthiness. Our approach is to identify two types of association-knowledge association, and trustworthy social association, which are used to represent the social relationship between each pair of peers on the P2P-based social network. Results of this research demonstrate that applying such mechanism do improve the quality of collaboration in knowledge sharing.

2: P2P-Based Social Network

The key idea of our P2P-based social network is illustrated in Figure 1. Based on information retrieved from the P2P network, a social network containing trustworthy collaborators with right knowledge is dynamically constructed; then an IM-equipped collaboration tool helps the selected collaborators in sharing knowledge with each other.

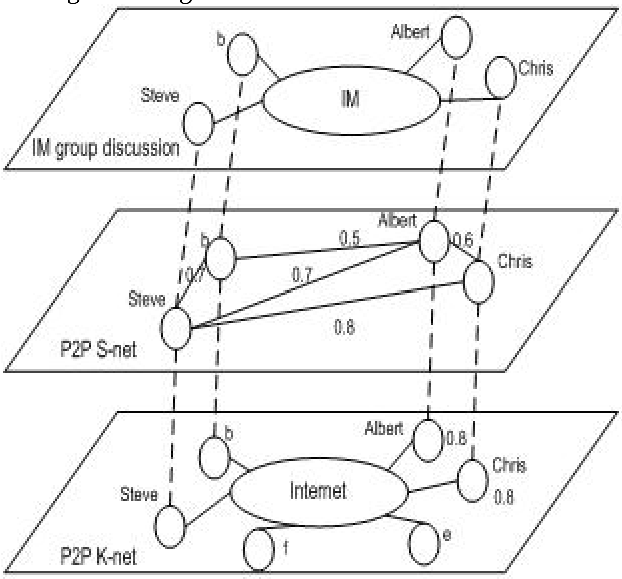

Figure 1. P2P-based social network for knowledge sharing

As shown in Figure 1, a P2P K-net is established to connect active users into a pool of active peers, i.e., the peers that are online and available from the Web. The pool can be either an entire P2P network or a specific local area network. Each peer appeared in Figure 1 represent a knowledge repository or a knowledgeable individual.

If a peer in such a P2P K-net (e.g., peer *Steve*) requests a specific piece of knowledge, the social network will dynamically generate a P2P S-net based upon the requestor's social relationships with other peers that own the requested knowledge. As shown in Figure 1, peers that do not know about the relevant knowledge are filtered out and will not appear on the P2P S-net (e.g., peers *e* and *f*). Weighted edges in the generated S-net are called social association (SA) to represent the levels that the peers can help the requestor (i.e., peer *Steve*) with the expected knowledge. Using the example shown in Figure 1, peer *Chris* can be more helpful than peer *Albert* because the SA between peers *Steve* and *Chris* is 0.8, which is greater than the SA between peers *Steve* and *Albert* that is 0.7. Based upon the generated S-net, an IM-equipped group discussion is created to help the requestor discuss with the other peers in real time. The essential challenge in this approach is how to construct such a social network. Our solution is through calculations of knowledge association and trustworthy social association.

3: Calculation Of Knowledge Association

A peer's knowledge association can be described by the peer's domain of knowledge and its proficiency to this domain. We use ACM Computing Classification System (http://www.acm.org/class/1998/) to classify domain of knowledge, and use Bloom taxonomy matrix [11] to classify user's proficiency in the domain. As shown in Figure 2 (a) and (b), a Bloom taxonomy matrix consists of two dimensions: Knowledge dimension and Cognitive Process dimension. The Cognitive Process dimension is divided into different levels. Each cell in the matrix is associated with a value ranging between 0 and 1, indicating the level of proficiency. For example, the Bloom taxonomy matrix shown in Figure 2(a) indicates that a peer is good at memorizing and understanding factual and procedural knowledge pertaining to the corresponding domain; the Bloom taxonomy matrix shown in Figure 2(b) indicates that the user is good at conceptual knowledge and especially good at applying the conceptual knowledge to the corresponding domain.

	Cognitive Process Dimensions					
Knowledge dimension	Level 1 Remember	Level 2 Understand	Level 3 Apply	Level 4 Analyze	Level 5 Evaluate	Level 6 Create
A. Factual knowledge	0.9	0.8	0.4	0.4	0	0
B. Conceptual knowledge	0.3	0.3	0.3	0.1	0	0
C. Procedural knowledge	0.6	0.5	0.3	0.2	0	0
D. Metacognitive knowledge	0	0	0	0	0	0

Figure 2(a). Example 1 of Bloom taxonomy matrix

	Cognitive Process Dimensions					
Knowledge dimension	Level 1 Remember	Level 2 Understand	Level 3 Apply	Level 4 Analyze	Level 5 Evaluate	Level 6 Create
A. Factual knowledge	0.2	0.7	0.7	0.7	0.8	0.8
B. Conceptual knowledge	0.8	0.7	1	0.8	0.7	0.7
C. Procedural knowledge	0.2	0.2	0.3	0.2	0	0
D. Metacognitive knowledge	0	0	0	0	0	0

Figure 2(b). Example 2 of Bloom taxonomy matrix

Definition

Consider a peer *i*, in a P2P K-net requests for a specific piece of knowledge *k* with proficiency, denoted by $BT_{(k)}$. To decide whether a peer *j* conforms to the request is computed by:

$$KA_k(i,j) = KP_k(j) \bullet (BT_{(k)}(i))$$

where

$KA_k(i,j)$: indicate the knowledge association from peer *i* to peer *j*, with respect to a certain domain of knowledge *k*. The higher the value is, the more strong association it is.

$KA_k(i,j)$ is a Bloom taxonomy matrix.

$KP_k(j)$: The knowledge proficiency of peer *j* with respect to a certain domain of knowledge *k*.

$KP_k(j)$ is a Bloom taxonomy matrix.

$BT_{(k)}(i)$: Peer *i* requesting for a specific piece of knowledge *k* with proficiency $BT_{(k)}$.

$BT_{(k)}(i)$ is a Bloom taxonomy matrix.

The matrix notation of KA can be further serialized into a single value by

$$KA_k(i,j) = \sum_{m=1}^{4}\left(\sum_{n=1}^{6} KA_{(m,n)}\right)$$

Example

The value of *$KA_k(i,j)$* indicates the knowledge association from peer *i* to peer *j*, the higher the value is, the more strong the association it is. For example, consider a peer, *Steve*, requests for peers with the knowledge proficiency to apply conceptual knowledge of *Software Engineering* to solve problems. Based on the aforementioned equation, we found there are two peers, *Albert* and *Chris*, whose $KA_{SE}(Steve, Albert)$ and $KA_{SE}(Steve, Chris)$ are non-zero, respectively, which means both *Albert* and *Chris* conform to Steve's request in terms of knowledge association. Nevertheless, since $KA_{SE}(Steve, Chris)$ is greater than $KA_{SE}(Steve, Albert)$, that is Chris is more knowledgeable than Albert in terms of helping Steve to apply conceptual knowledge of *Software Engineering* to solve problems.

Let $BT_{SE}(Steve) = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$

Let $KP_{SE}(Albert)$ is the matrix as shown in Figure 2(a) and $KP_{SE}(Chris)$ is the matrix as shown in Figure 2(b)

$$KA_{SE}(Steve, Albert) = KP_{SE}(Albert) \bullet (BT_{(SE)}(Steve))$$

$$KA_{SE}(Steve, Albert) =$$

$$\begin{bmatrix} 0.9 & 0.8 & 0.4 & 0.4 & 0 & 0 \\ 0.3 & 0.3 & 0.2 & 0.1 & 0 & 0 \\ 0.6 & 0.5 & 0.3 & 0.2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \bullet \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$KA_{SE}(Steve, Albert) = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

After the serialization, $KA_{SE}(Steve, Albert) = 0.2$. Similarly, we can compute that $KA_{SE}(Steve, Albert) = 1$, as show in the following.

$$KA_{SE}(Steve, Chris) =$$

$$\begin{bmatrix} 0.2 & 0.7 & 0.7 & 0.7 & 0.8 & 0.8 \\ 0.8 & 0.7 & 0.1 & 0.8 & 0.7 & 0.7 \\ 0.2 & 0.2 & 0.3 & 0.2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \bullet \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$KA_{SE}(Steve, Chris) = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

4: Calculation Of Trustworthy Social Association

The social association indicates how a peer is associated with another peer directly connected to it on the S-net. For a pair of peers, as denoted by peer *i* and peer *j*, the trustworthy social association between them is the product of the social relationship tie and the social reputation of peer *j*.

$SA(i,j) = SRT(i,j) \times SR(i,j)$

where

SA: social association between peer *i* and peer *j*.

SRT: social relationship tie indicates how a pair of peers on the social network treats each other.

SR: social reputation is a confidence indicating the degree of trust from peer *i* to peer *j*.

Calculation of Social Relationship Tie

Social relationship tie (SRT) indicates how a pair of peers on the S-net treats each other. Each peer needs to specify its SRT with other peers on the S-net by filling forms and answering questionnaires. For those peers not specified explicitly, the default value of SRT is zero, meaning that there is no relationship between the two peers. SRT can exhibit different levels of social relationship, such as friend, team member, organization member, or community member. Meanwhile, SRT can be positive or negative values ranging between [-1,1], indicating the relationship is good or bad. To perform quantitative analysis, we define SRT between peers *i* and *j* as follows:

SRT(i,j) = 0, if there is no relationship between peer i and peer j.
SRT(i,j) = 0.8~1.0, if peer i treats peer j as a friend with positive relationship
SRT(i,j) = 0.5~0.7, if peer i treats peer j as a team member with positive relationship
SRT(i,j) = 0.3~0.4, if peer i treats peer j as an organization member with positive relationship
SRT(i,j) = 0~0.2, if peer i treats peer j as a virtual community member with positive relationship
SRT(i,j) = -0.8~-1.0, if peer i treats peer j as a friend with negative relationship
SRT(i,j) = -0.5~-0.7, if peer i treats peer j as a team member with negative relationship
SRT(i,j) = -0.3~-0.4, if peer i treats peer j as an organization member with negative relationship
SRT(i,j) = 0~-0.2, if peer i treats peer j as a virtual community member with negative relationship

Calculation of Social Reputation

For a pair of peers who are on the S-net and socially related, as denoted by the requesting peer *i* and the requested peer *j*, the social reputation between the two peers is denoted by SR(i,j). SR(i,j) is a confidence indicating the degree of trust of the requesting peer *i* to the requested peer *j*. SR(i,j) is used to determine whether the requested peer conforms to the requesting peer's requirements of trust. The value of SR(i,j) is a percentage, the higher the percentage is, the higher the confidence is. For example, if the value of SR(Steve, Albert) is 78%, which means the requesting peer Steve has 78% confidence that the requested peer Albert is trustworthy.

Definition

We utilize binomial probability's sampling to calculate SR(i,j), based on a 95% confidence interval in terms of probability [12]. We here define the following terms

- S is a set of interaction instances representing samples of the requested peer's past interactions, $S = \{s_1, s_2, ...s_n\}$.
- Tr is a set of trust evaluation values containing past experience instance, and is denoted by $Tr = \{tr_1, tr_2, ...tr_n\}$.
- $Rating : S \rightarrow Tr \;\; Rating(s)$: The Rating function maps the interaction instance s to past experience instance, tr . In other words, the function associates past service instance with past experience instance, the experiences are collected by peers other than the requesting peer.
- $Accpet : Tr \rightarrow \{0,1\}$ A requirement hypothesis can be denoted as $Accpet$ function. The output of Accept function is 1 when past experience instance is accepted by the requesting peer, otherwise is 0.

$$\text{Accpet}(\text{tr}) \equiv \begin{cases} 1 & \text{Accept} \\ 0 & \text{otherwise} \end{cases}$$

Based on the usage of Large-Sample of Hypothesis for a Binomial Proportion to evaluate the simple error and true error of a hypothesis addressed in (Mitchell, 1997; Mendenhall, 1999), the result of the hypothesis assesses the sample is a Boolean value (true or false). Thus we can see that the hypothesis assesses the sample as a Bernoulli trial and the distribution of Bernoulli trial is a binomial distribution. The binomial distribution approximates the normal distribution when the number of sample is enough. Simple error is correct rate in samples and true error is correct rate in population. We will get a confidence interval according to the simple error and the area of confidence interval represents a probability which true error fall in the interval. In the normal distribution, the true error is 95% probabilities falling within the range of $mean \pm 1.96 \times SD$ (Standard Deviation) in compliance with the experience rule. In other words, we can utilize the confidence interval to evaluate lowest true error of the evaluating hypotheses.

Let $Accpet$ function be the hypothesis and then we can evaluate the possible true error of the hypothesis based on the past instances S according to the Evaluating Hypotheses theory (Mitchell, 1997). Whether the tr ($tr \in E$) is accepted by $Accpet$ is a binomial distribution which approximates the normal distribution when the number of samples is large enough. Thus we can utilize the normal distribution to calculate that the sample error closes with the true error. The true error is of 95% probabilities falling within a confidence interval, which will be approved as a trustworthy peer in the general application.

Example

Let Steve is the requesting peer, and let Albert is the requested peer. We define the confidence symbol as the lowest bound of the true error. The trust of service conforms to the request's requirement when the confidence is higher.

$$\hat{p}=\frac{1}{n}\sum_{s\in S}Accpet\left(Rating(s)\right),\ SD=\sqrt{\frac{\hat{p}\times\left(1-\hat{p}\right)}{n}},$$

$$z_{95\%}=1.96$$

$$Confidence\equiv\max\left\{\hat{p}-z_{95\%}\times SD,0\right\}$$

As the number of samples increases, the standard deviation decreases relatively and the confidence will be closer to the true error. For example, Albert's past instances is denoted as S, and let $|S|=256$. Steve proposes a Requirement Hypothesis $Accpet$. If the result of calculation is $\hat{p}=0.6$, the confidence can be calculated from the following equation.

$$\hat{p}=\frac{1}{256}\sum_{s\in S}Accpet\left(Rating(s)\right)=0.6,\ z_{95\%}=1.96$$

$$Confidence\equiv\hat{p}-z_{95\%}\times\sqrt{\frac{\hat{p}\times(1-\hat{p})}{256}}\cong 0.6-0.060012\cong 0.53998$$

The calculated confidence, i.e. SR(Steve,Albert) is 53.99%, which means Steve has 53.99% confidence that Albert can meet Steve's trustworthy requirement based on 95% confidence interval. In other words, we can assert that the Albert's degree of trust is 56.83% (53.99% over 95%) conforming to Steve's requirements.

5: EXPERIMENTS AND DISCUSSIONS

We have conducted quantitative and qualitative experiments to evaluate the method and environment presented in this paper. To evaluate the performance of the proposed social network, we measure two important indexes: *Precision* and *Recall*. Considering a request for peers with a specific knowledge, the search result contains a set of relevant peers, let $|R|$ be the number of peers in this set. Assume that a given search method generates a retrieved set of peers, and let $|A|$ be the number of peers in this retrieved set. Let $|Ra|$ be the number of peers in the intersection of the sets R and A. Precision and Recall are defined as

- *Precision* = $|Ra|$ / $|A|$, which is the fraction of the retrieved peers that are considered as relevant.
- *Recall* = $|Ra|$ / $|R|$, which is the fraction of the relevant peers that has been found.

We compared the two types of association presented in this paper as the search criteria: knowledge association and social network. In this experiment, we adopt four domains of knowledge as the search domains: logic programming, predicate logic, fuzzy logic, and temporal logic. The experiemnt result is summarized in Table 1.

Table 1. Search criteria and search results corresponding to four domains of knowledge

	Knowledge association (KA)		Social association (SA)	
Domain	Precision	Recall	Precision	Recall
Logic programming	0.721	0.818	0.834	0.746
Predicate logic	0.553	0.783	0.726	0.532
Fuzzy logic	0.561	0.729	0.674	0.512
Temporal logic	0.542	0.751	0.713	0.565

Besides the quantitative performance analysis, to understand how the P2P-based social network can augment enhance knowledge sharing, we conducted an experiment at the Department of Computer Science and Information Engineering, National Central University in Taiwan. 56 undergraduate students (junior) who are in class "Introduction to Knowledge Engineering" participated in this experiment. Each student was required to individually complete a course project by exercising our P2P-based social network. We conducted with every student a questionnaire with 14 questions to verify their satisfaction rates regarding our system. For each question, we measure the item based on a five-point Likert scale ranging from *strongly disagree* (1) to *strongly agree* (5). Accumulating the students' answers, we calculated the mean value and standard deviation of each question item. The result of the survey is summarized in Table 2.

Table 2. Performance of P2P-based collaboration system and group formation

No.	Questionnaire	Mean	SD
1	Are you interested in finding collaborators by using this P2P-based social network?	4.45	1.34
2	Are you satisfied with the system performance in terms of connection time and searching time?	3.67	.80
3	Can you find the same results every time you use the P2P?	3.97	1.29
4	Do you keep your P2P on line for most of the time?	4.47	0.75
5	Are you always willing to share the resources obtained from the P2P network?	3.65	1.75
6	Do you think your group member chosen is knowledgeable?	4.24	1.13
7	Do you think your group member chosen is trustworthy?	4.01	0.78

8	Do you think you can form better group by yourself?	4.56	1.10
9	Are you satisfied with the user interface design of group collaboration?	3.95	0.94
10	Is it easy to form a group?	3.67	1.28
11	Are you satisfied with the group discussion performance in terms of communication and synchronization?	3.56	0.84
12	Do you think it is important to connect to other IMs?	4.23	0.62
13	Do you think it is important to have voice enabled discussion?	4.37	0.68
14	Do you think it is important to have e-whiteboard for synchronous file sharing?	4.18	0.61

The survey reveals students' doubts about the stability of the P2P search results. They cannot obtain the same search results in each trial even though they use the same search option. This is due to the decentralized nature of P2P network; it only searches for the peers currently on line. This doubt can be alleviated since the survey shows that most of the P2P users remain on line most of the time. The other reason of non-deterministic search results is due to the problem of free rider, as many users are not willing to share all the resources they obtained from the network. From the survey results, we found that most of the students are satisfied with the automatic group formation. Rather, they prefer to find their own collaborators even though they admit that the group members picked by our system are knowledgeable and trustworthy. This observation suggests that we take into account users' social relationships besides knowledge competence when we form groups. In addition, most of the students emphasize the importance of user interface design of group collaboration, and they expect better control of dynamic group formation. We also perceived that students desire powerful collaboration instruments, such as voice communication and e-whiteboard for synchronous discussion and file sharing.

Our experiment confirms the effectiveness of our P2P-based social network. Most students expressed their willingness to utilize the system for their daily studies.

6: Concluding Remarks

The contribution of this paper is applying P2P-based social network to augment knowledge sharing by overcoming the difficulty in finding knowledgeable and trustworthy collaborators to interact with. In this paper, we have demonstrated the new possibilities using social network for collaborative work and knowledge sharing that attempt to combine social and technical feasibility. These efforts assume the possibility of technical augmentation to the way community shares knowledge through social networks, but they attempt to do this augmentation in collaborative work's feasible ways.

We see several areas that deserve further research. First, it is a general problem for a social network to support the discovery, access, and sharing of knowledge. Peers and other collaborators may have their own needs when they access subjects and discuss with others. Further study is needed to investigate the special requirements from different social networks or social networking. Second, to take into account the context of collaboration, we plan to explore applied social networks to combine collaborative domain and collaborators' ontology.

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