A Hybrid Trust-Based Recommender System for Online Communities of Practice

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Abstract—The needs for life-long learning and the rapid development of information technologies promote the development of various types of online Community of Practices (CoPs). In online CoPs, bounded rationality and metacognition are two major issues, especially when learners face information overload and there is no knowledge authority within the learning environment. This study proposes a hybrid, trust-based recommender system to mitigate above learning issues in online CoPs. A case study was conducted using Stack Overflow data to test the recommender system. Important findings include: (1) comparing with other social community platforms, learners in online CoPs have stronger social relations and tend to interact with a smaller group of people only; (2) the hybrid algorithm can provide more accurate recommendations than celebrity-based and content-based algorithm and; (3) the proposed recommender system can facilitate the formation of personalized learning communities.

Index Terms—Educational recommender, CoP, Collaborative filtering, trust-based algorithm, stack overflow

1 Introduction

Life-long learning means that learners use both formal and informal learning opportunities throughout their lives to foster a continuous development, knowledge, and skills needed for employment and personal fulfillment [1]. Informal learning represents a learner's intentions to continue his or her professional development by participating in activities which are not specifically designed for achieving formal certifications [2]. For adult learners, joining a Community of Practice (CoP, hereafter) is a very common approach for informal learning. A CoP consists of a group of friends or a network of connections between people who have a shared domain of interest [3]. In the past, practitioners usually participate in joint activities and discussions (such as conferences or symposiums) of CoPs in order to interact with other professionals, help each other, and share information.

Due to the rapid development of information technologies, nowadays online CoPs are getting popular as they are highly flexible (anytime) and expandable (anywhere).

Based on Connnectivism, knowledge is distributed across an information network and can be stored in a variety of digital formats. Learning and knowledge are said to "*rest in diversity of opinions*" [4]. Compared to traditional learning, CoPs emphasize the importance of collaborations and interactions in the process of knowledge construction. Learners are no longer considered as passive information consumers; instead, they need to contribute their own experiences, knowledge, and resources while they learn, connect, and collaborate with other contributors.

Therefore, a learner must play a more active role in managing and organizing his/her own learning to achieve expected learning goals [5], [6]. The characteristics of CoP, such as mutual engagement, joint enterprise, and shared repertoire [7], can sustain a learner's engagement level and thus foster effective, informal, and life-long learning [8].

Although online CoP expands the possible number of participants and connections by information technologies, it also generates the following issues: bounded rationality and metacognition [9]. In online CoP, a learner often receives a large amount of information, such as learning resources, personal comments, and solutions contributed by other professionals. However, the learner might not have sufficient knowledge, ability, and/or time to filter useful information. This well-known phenomenon in today's digital society is called "information overload" [10]. This phenomenon is especially noticeable in novice learners. To deal with information overload, a typical learner's approach is to take just as much information as needed. This approach has been described as both a common adjustment in overload situations and an exemplar of bounded rationality [11].

The other issue (i.e., metacognition) is defined as the awareness of one's cognitive states, processes, and knowledge as well as the ability to consciously monitor and adjust these cognitive states, processes, and knowledge [12]. Learners reply on the ability of metacognition to evaluate all the received information and then determine the best answer to a question or the most useful information for learning.

The issue of metacognition is even more serious in online CoPs because there is no instructor to facilitate a learner's

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metacognition process. Rubens et al. [13] suggested that the new generation of e-learning is the combination of Connectivism-based environment and artificial intelligence tools. Therefore, the issues of bounded rationality and metacognition might be alleviated by incorporating artificial intelligence tools as supportive means in online learning environments. Multiple studies have been conducted in traditional higher education institutions (e.g., [14], [15], [16]). However, in formal educational environments (e.g., degree or certificate programs), the instructor is usually the only authority and the ultimate expert in the classroom [17], [18], [19]. In addition, various instructional strategies can be applied to facilitate a learner's metacognitive and decision-making process. The instructor-moderated approach sacrifices elements of personalized learning but mitigates issues of metacognition and bounded rationality.

In informal learning environments, although learners can take full control of their own learning and some knowledgeable experts can be identified via interactions, not all learners are able to overcome the barriers of metacognition and bounded rationality [20], [21]. This implies that the development of artificial intelligence tools should be more focused on informal learning environments. However, only few studies have been carried out on the above topics [22]. Therefore, the purpose of this study is to develop a trust-based recommender system for learning facilitation.

Based on the definition of Luhman (1979), trust is defined as "a cognitive and social device can reduce complexity enabling people to cope with the different levels of uncertainty and risks" [57]. In online learning environments, learners encounter more uncertain situations than regular classrooms. Engaging trust can reduce the number of decisions involved and facilitate the decision-making process. From social perspectives, trust is necessary in knowledge sharing delegation and cooperative actions [58]. The proposed recommender system has the following advantages. First, in the learning process, learning takes place at two levels—the objective and the meta-levels (metacognition) [23], [24]. Learners need to plan, monitor, and evaluate learning goals and outcomes [24]. A recommender system can lower a learner's cognitive load at the objective level by reducing the amount of received information [25] and at the meta-level by lowering the burden of information monitoring and evaluation [24]. In addition, learner's self-reflection (an important step of metacognition) can be stimulated during the process of evaluating correctness of the recommendations [23].

Second, because novice learners are the major population to use the recommender system and data sparsity is a major issue that influences recommender systems' performance on novice users [26], this article also discusses how the hybrid approach deals with the issue of data sparsity by incorporating two trust relationships into algorithm computation. Third, one major function of CoP is to help individuals establish relationships with other professionals who are trustable and have common professional interests. This article also examines whether the recommender system can facilitate the formation of personalized learning community.

The article is organized as follows: Section 2 reviews important literature related to this study. Section 3 introduces algorithms of the hybrid trust-based recommender system. Sections 4 and 5 present a case study of Stack Overflow to examine expected advantages of the recommender system. Finally, discussion and future work are included in Sections of 6 and 7.

2 Related Work

The theoretical foundation of the trust-based recommender system is Connectivism. Hence, literatures of Connectivism and recommender systems in e-learning are discussed in this section.

2.1 Connectivism and CoP

Nowadays, knowledge is ubiquitous, constantly changing, and growing exponentially. In addition, the rapid development of internet technologies plays an important role in transforming how people learn, interact, and communicate with each other. Connectivism, a learning theory proposed by George Siemens, aims to explain how people learn in today's network-based society [27]. According to Connectivism, "*knowledge does not only reside in the mind of an individual, knowledge resides in a distributed manner across a network ... learning is the act of recognizing patterns shaped by complex networks [28].*" Connectivism regards each learner as a "node" in the networked structure similar to neural network. Under the assumptions of Connectivism, the following trends in learning were summarized: [27]:

- Comparing with formal education, informal learning comprises the majority of our learning experience. Learning can occur in a variety of ways through communities of practice, personal networks, and through completion of work-related tasks.
- Learning is a continual process, lasting for a lifetime. Learning and work-related activities are no longer separate. In many situations, they are the same.
- Technology is altering (rewiring) our brains and shaping our thinking.
- The organization and the individual are both learning organisms. Increased attention to knowledge management highlights the need for a theory that attempts to explain the link between individual and organizational learning.
- Many of the processes previously handled by learning theories (especially in cognitive information processing) can now be off-loaded to, or supported by, technology.
- Know-how and know-what is being supplemented with know-where (the understanding of where to find knowledge needed).

Siemens [27] further explained how learning occurs within the network:

"*The starting point of Connectivism is the individual. Personal knowledge is comprised of a network, which feeds into organizations and institutions, which in turn feed back into the network, and then continue to provide learning to individual. This cycle of knowledge development (personal to network to organization) allows learners to remain current in their field through the connections they have formed [27]*".

Since knowledge is distributed across information networks and stored in a variety of digital formats, learning and knowledge are said to "*rest in diversity of opinions*" [4];

the ability to search for information (know-where) and the ability to filter required information (know-how and know-what, i.e. metacognition) is crucial for effective learning in Connectivism-based learning environments [4]. In addition, learners can easily feel overwhelmed while processing a huge amount of information. Therefore, metacognition and knowledge overload are two major issues in network-based learning environments.

From the perspective of life-long learning, connections from CoP networks might play a more important role than those formed via formal education. Traditionally, CoPs exist among people who work in closer geographic locations [29]. However, the development of information technologies allows CoPs to be created and maintained online [29]. These technology tools offer convenience and flexibility for learners to obtain information and interact with others. However, learners need to spend more time and efforts in managing information and dealing with the issue of information overload [29].

2.2 Recommender Systems in E-Learning

2.2.1 Recommender Systems in e-Learning

Burke [30] defined a recommender system as "...*any system that produces individualized recommendations as output or has the effect of guiding the user in a personalized way to interesting or useful objects in a large space of possible options*." In the digital era, learners are exposed to a large amount of learning resources from various formal or informal settings. Potentially learners need some effective mechanisms which help them identify suitable resources from an overwhelming variety of choices. As a result, educational recommender systems attract lots of research efforts in recent years. The evidence can be found in conferences (e.g., SIRTEL 2007-2009; RecSysTEL 2010 and 2012), journal special issues (e.g., [31], [32]), and books (e.g., [33], [34]).

The authors of this article did an extensive literature survey on Google Scholar with the keyword "educational recommender system" and retrieved 52 refereed articles. Sixteen articles were filtered out because they are irrelevant to the development of recommender systems. The research purposes of the remaining 36 articles can be classified into four types: (1) Recommending learning resources to learners (18 articles, e.g., [35]); (2) Recommending peers who have similar learning interests (nine articles, e.g., [36]); (3) Recommending personalized learning path (six articles, e.g., [38]); and (4) Predicting student performance (three articles, e.g., [45]). Fourteen of the 36 articles adopted collaborative filtering (CF) as the recommendation technique (e.g., [35]), six of them adopted content-based technique (e.g., [36]), nine of them adopted hybrid technique (e.g., [37]), and seven of them adopted ontology technique (e.g., [38]).

The above review shows that the major purpose of educational recommender systems is to provide personalized guidance in order to meet learning needs of individual learners. Although CF [48] is the most popular educational recommendation algorithm, like content-based technique [47], data sparsity is the major issue for both CF and content-based recommenders [39]. That explains why the hybrid approach is getting popular in recent publications because it is not sensitive to the above issues [40].

Scholars emphasize the importance of considering social and educational requirements when developing educational recommender systems. For example, [41] discussed that some non-technical factors should be considered in order to improve personalized recommender systems, particularly when systems are designed for non-standard learning environments. Drachsler et al. [42] also suggested that recommender systems in informal learning are different from recommender systems in well-structured domains, such as e-commerce or formal learning. Therefore, the authors suggested that more research efforts are required in informal learning environments. In addition, developers should consider the roles that the users are expected to play while selecting recommendation strategies.

Based on the sociocultural conception of cognition development, learning occurs through conversions representing a connection between the interactive and cognitive dimensions of collaborative learning. Guided by Connectivism [28], [43], [44], this study selects trust-based recommendation as the major algorithm because cultivating interactions among users is a major function of online CoPs.

2.2.2 Trust-Based Recommender Systems in e-Learning

Several recommendation algorithms, such as celebrity recommendation approach [46], content-based filtering [47], CF [48], knowledge-based filtering [49], and hybrid approaches [50], have been widely discussed in the literature.

However, all of the above approaches assume that users are independent and identically distributed. The assumption neglects an important facet (social relationship) in the process of information evaluation. For example, learners with similar learning preferences might give different evaluation weightings on a message due to their social relationships with the message provider. Since CoP is a Connectivism-based environment, learner's social associations, connections, or affiliations should be considered in the recommender system [52].

In studies related to social relationship formation and regulation, trust is regarded as a mechanism to quantify social relations since it has been recognized as a major influential factor on the strength of friendship [53], [54], [55], [56], [63]. Trust is defined as a cognitive and social device that is able to reduce complexity and enable people to cope with different levels of uncertainty and risks [57]. Without trust, a learner would be hesitant to make any decision because it is almost impossible to calculate all possible outcomes of a situation. In this study, trust is regarded as an indicator and an outcome of learner interactions and was used as the basis of recommendation algorithm [59].

This study adopts Massa's classification which classifies trust into local and global trust metrics [60]. Local trust metrics consider the personal and subjective views of a learner and predict different trust values in other learners for every single learner. Meanwhile, global trust metrics predict a global "reputation" value that estimates how the community as a whole considers a certain user [62].

There are some studies incorporating trust as the major algorithm in the development of educational recommender systems [43], [61]. However, most of them only consider local

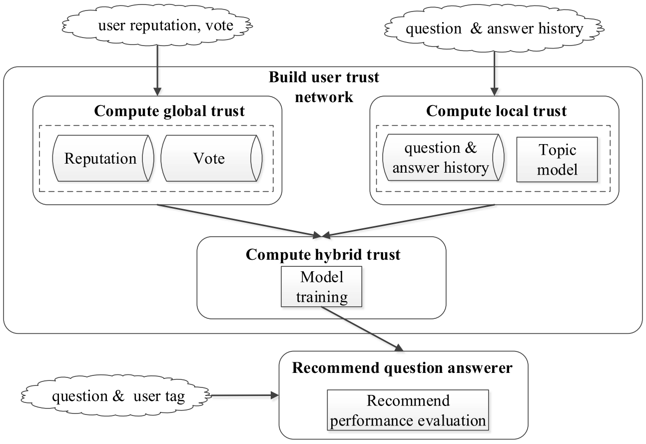

Fig. 1. The framework of question answerer recommendation on Stack Overflow.

trust [43], [61]. For example, Dwivedi and Bharadwaj [61] proposed a learning resource recommender system which recommends trustworthy answerers with similar learning styles and higher knowledge levels. The recommendation algorithm combines collaborative filtering and local trust. However, the approach cannot effectively alleviate the issue of data sparsity [26]. To deal with the issue of data sparsity, this study proposes a hybrid algorithm which combines both local and global trust metrics.

3 The Hybrid Trust-Based Recommender

For a novice learner with limited interactions with other professionals in the same CoP, the hybrid trust-based recommender offers the following functions: (1) recommending expert professionals who are trustable based on their professionals' historical records; and (2) ensuring that these recommended experts have common learning interests with the novice learner so interactions between experts and the novice learner can be enhanced through the recommender system. For an experienced learner in the CoP, the recommender system simplifies the decision making process by recommending experts who are trusted by the experienced learner. In addition, interactions within his or her personal community can also be promoted by the recommender system. Two types of trust networks—global and local trust networks, are used to construct the hybrid recommender system [62]. Global trust network refers to the trust weights computed by existed trust relations tracked by CoPs. For example, when a learner received votes from other learners on his/her post, the voting actions reflect learners' attitudes toward the post (agree/trust or disagree/distrust) [64]. Therefore, the range of received vote value is from $-\infty$ to $+\infty$ (one positive vote = +1 and one negative vote = -1)

Local trust network is inferred from a learner's learning preferences which can be revealed by mining his or her posted textual contents in the CoP [67]. If two learners have more common learning preferences, then these two learners are more likely to trust each other.

Fig. 1 shows the basic framework of the hybrid trust-based recommender system which consists of four major steps:

Step 1. Compute learner's global trust based on learner reputation scores and received vote values.

Step 2. Compute learner's local trust based on learning preferences from his/her own Q&A histories.

Step 3. Compute learner's hybrid trust based on learner's global and local trusts.

Step 4. Recommend the best question answerers based on the asker's hybrid trust network and tags of both the target question and potential answerers.

The details of the individual steps are described below:

3.1 Compute Learner's Global Trust

Individual learners' global trust values are computed through personal trust records tracked by CoPs. Therefore, each learner only has one global trust value (i.e., the global trust network is a one-to-many relation). Previous studies showed that a user's reputation score is highly related to his or her trustworthiness [65], [66]. In addition, a user's received vote value reflects other users' attitudes toward his or her posts. Because both reputation score and received vote value are common attributes tracked by CoPs (such as Stack Overflow, Sap Community Network, and Sermo for physicians), these two indicators were adopted in the computations of the global trust.

Definition 1. *Let $Rp(u)$ denote the reputation score of learner u, $Vote(u)$ denote the received vote value of learner u, and $GT(u)$ denote the global trust value of learner u.*

Both $Rp(u)$ and $Vote(u)$ are transformed onto interval (0, 1) with the function $f(x) = (logistic(x/Rp_{avg}) - 0.5) \times 2$ and $f(x) = (logistic(x/Vote_{avg}) - 0.5) \times 2$, where Rp_{avg} represents the average reputation value of all learners, $Vote_{avg}$ represents the average received vote value of all learners, and the logistic function is equal to $logistic(x) = 1/(1+exp(-x))$.

It should be mentioned that a learner's reputation score is greater than or equal to zero and received vote value can be from $-\infty$ to $+\infty$. Finally, the global trust value is computed by

$$GT(u) = a \times Rp(u) + (1-a) \times Vote(u), 0 < a < 1. \tag{1}$$

The parameter a will be obtained from model training and it balances constitution ratios from learner's reputation scores and received user votes. $GT(u)$ is an interval (0, 1) as well and a larger $GT(u)$ means the learner u is more trustworthy by the whole community.

In fact, the global trust method is a celebrity recommendation approach [46] which recommends top learners trusted by other learners within the community.

3.2 Compute Learner's Local Trust

The local trust network is inferred based on the similarity of learners' learning preferences [67]. When a learner participated in discussions (asking or answering questions), his or her learning preferences are actually hidden in discussion contents. Therefore, a learner's learning preferences can be revealed by mining his or her historical Q&A contents.

Definition 2. *A learner's local trust network is constructed by computing learning preference similarities to the rest of individual learners within the CoP. $LT(u_1, u_2)$ is the local trust value between learner u_1 and learner u_2; it denotes the similarity of their interest allocation.*

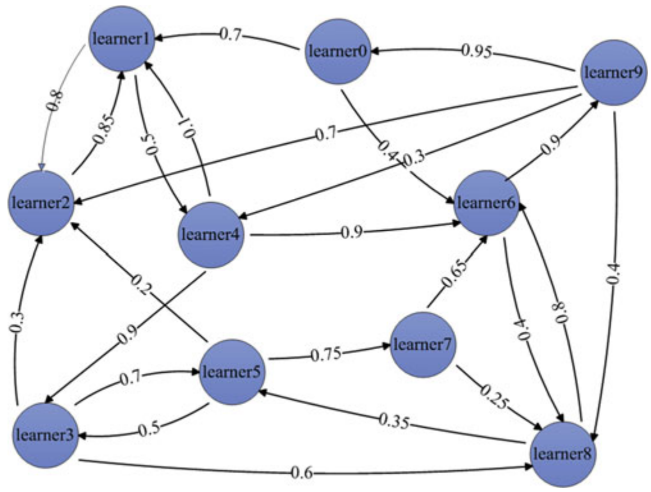

Fig. 2. Learners' hybrid trust network.

The local trust between two learners is bidirectional (a one-to-one relation). Latent Dirichlet Allocation (LDA) [68] is used to perform text mining analysis which consists of two steps. First, set a topic value (i.e. the dimensionality of a learner's learning preference) and obtain distributions of individual learners' learning preferences by mining learners' Q&A contents. Second, compute learning preference similarities between learners using cosine similarity [69]:

$$similarity = \cos(\theta) = \frac{A \bullet B}{||A||||B||} = \frac{\sum_{i=1}^{n} A_i \times B_i}{\sqrt{\sum_{i=1}^{n} {A_i}^2}\sqrt{\sum_{i=1}^{n} {B_i}^2}}. \tag{2}$$

It should be noticed that the proposed local trust method is actually a content-based recommendation approach [51]. LDA is used to mine the textual content formation (i.e., Q&A history) to reveal individual learners' learning preferences.

3.3 Compute Learner's Hybrid Trust

The hybrid trust combines both global and local trusts to depict individual learners' hybrid trust networks.

Definition 3. *$HT(u_1, u_2)$ is the hybrid trust value of learner u_1 with reference to learner u_2, with a possible value range of 0 to 1. 0 means learner u_1 totally distrusts learner u_2 and 1 means learner u_1 totally trusts u_2. The trust relationship is monodirectional (i.e., $HT(u_1, u_2)$ is not necessary equal to $HT(u_2, u_1)$)*

$$HT(u_1, u_2) = b \times GT(u_2) + (1 - b) \times LT(u_1, u_2), 0 < b < 1. \tag{3}$$

IThe parameter b will be obtained from model training by using the coordinate ascent method [70]; it determines constitution ratios of the global and the local trust values respectively.

Fig. 2 shows a hybrid trust network of 10 learners with 24 hybrid trust relations. Learner 9 has the highest hybrid trust value with learner 0 (0.95) and learner 4 has the lowest hybrid trust value with learner 1.

3.4 Recommendation and Model Evaluation

After the hybrid recommender algorithm was trained, the system can recommend a list of potential answerers based on the asker's hybrid trust network. To further improve recommendation performance, the recommender system examines both the asker's question and potential answerer's profile tags. The recommender system only recommends answerers whose profile tags match the asker's question tags.

Precision and recall are adopted to evaluate the system performance [71], [72].

Let M represent the total number of answerers obtained by an asker (i.e. the number of true positive and false negative answerers), L represent the number of all qualified answerers who can be recommended by the system (i.e. total number of positive answerers), and Nrepresent the number of positive answerers recommended to the asker (i.e., the number of true positive answerers). Then

$$Precision = N/L, Recall = N/M. \tag{4}$$

For example, there are 10 learners who answered a question from learner A and there are 20 positive answerers recommended by the recommender system. If eight of 10 learners are true positive answerers recommended by the system, then the system's precision is 40 percent and the recall is 80 percent.

In this study, the average precision and recall are used to represent the system's recommendation performance.

4 Case Study

To test whether the recommender system can achieve expected outcomes, a case study was conducted to train and evaluate the recommender system. Stack Overflow,[1] one of the largest learning communities for computer programming professionals, was selected as the target CoP because of the following reasons: (1) Stack Overflow is a large online CoP for computer programming professionals; (2) as programming is a complex topic, many people encounter various difficulties and barriers when acquiring programming related knowledge. As a result, Stack Overflow aggregated a huge amount of Q&A records from a large number of registered learners; (3) on average, there were more than one million questions that did not get any up-voted answer daily. It indicates that users had difficulties in identifying appropriate answerers/experts for their questions due to a lack of a good recommender system.

4.1 An Overview of Stack Overflow

Stack Overflow, one of the largest professional learning communities worldwide, allows registered users to ask and answer computer programming questions. Each of the questions or answers might receive vote(s) from other learner(s) showing their attitudes. A learner's reputation scores can be earned by getting "up" votes, asking questions, providing answers, and suggesting edits [73]. Every posted question is required to attach at least one but no more than five tags. These tags are keywords or labels to group similar questions into categories (see Fig. 3) [74]. Fig. 4 shows the reputation score, tags, and Q&A history of a specific learner. For the purpose of privacy, personal information such as learner's name, website, email, and photo were replaced with unknown symbols (marked red in Fig. 4).

1. http://stackoverflow.com/, last accessed 25.08.2014.

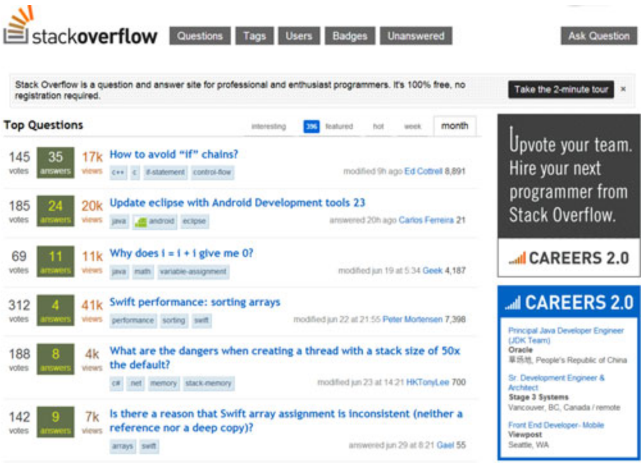

Fig. 3. Screenshot of Stack Overflow as of July 2014—top questions in a month with votes, answers, and views.

As of April 2014, Stack Overflow had over 2,700,000 registered users and more than 7,100,000 questions. The question tags show that the most popular discussion topics were: C#, Java, JavaScript, PHP, Android, jQuery, Python and C++ [75].

4.2 Data Collection

Variables, such as a learner's names, reputation scores, number of votes, tags, and question/answer descriptions were collected for the period of January 30, 2013 to March 3, 2013. To reduce data noise, questions with less than four answers were filtered out. The raw dataset contained 4,800 questions with 22,013 answers replied by 14,717 users. Eighty percent of data were randomly selected for model training and the rest 20 percent were used for model testing. Table 1 lists the basic statistics of training and testing datasets.

5 Results

5.1 Basic Network Statistics of Stack Overflow

The most important component of a CoP is user interactions. Table 2 examines user interactions by comparing Stack Overflow with other social communities in terms of social network statistics.

In social network analysis, each of the learners is represented by a node. The degree of a node [76] is the number of edges (links) incident to the node. The average degree of a network $<k>$ is the average degree [77] of all the nodes in the network. The clustering coefficient (C) [77] is a measure of the degree to which the nodes in a network tend to cluster together. The average path length (l) [77] is defined as the average number of steps along the shortest paths for all

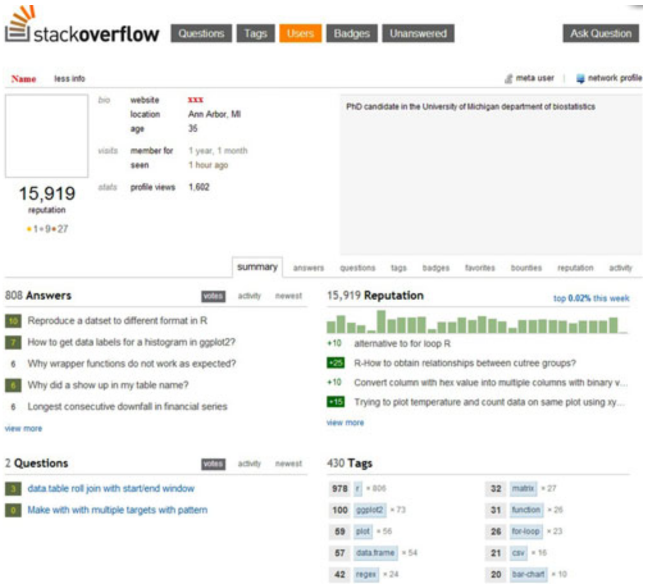

Fig. 4. Screenshot of Stack Overflow as of July 2014—learner reputation, tag, and question-answer history.

possible pairs of network nodes. It is a measure of the efficiency of information transmission in a network. Table 2 shows that Stack Overflow has an obviously higher average network degree, larger clustering coefficient, and lower average path length than the other social communities.

5.2 Determination of Model Parameters

The learner's global trust was computed by formula (1) in Section 3.1, where the value of a balances constitution ratios of reputation scores and received votes. A larger a means that the reputation score contributes a larger portion toward the global trust. Similarly, the value of b balances constitution ratios of global and local trust values in the computation of the hybrid trust. A larger b means that the hybrid trust value consists of larger portion of global trust. If b is equal to zero, that means the hybrid trust value comes from the local trust only (i.e., content-based recommendation). On the contrary, if b is equal to one, then the hybrid trust is based on global trust only (i.e., celebrity recommendation). The hybrid trust between learner u_1 and u_2 is presented below by combining formulas (1) and (3):

$$HT(u_1, u_2) = b \times a \times GT(u_2) + b \times (1 - a) \times Vote(u_2) + (1 - b) \times LT(u_1, u_2). \tag{5}$$

Here, the coordinate ascent method [70] was used to determine parameters a and b in the training dataset. A detailed process of coordinate ascent is explained as follows:

TABLE 1
Information of Training and Test Data Set

	Training data set	Test data set
Number of learners	11,416	3,301
Number of questions	4,000	800
Number of answers	18,368	3,645
Average received answers per question	4.6	4.56
Average received votes per learner	1.94	1.26
Average number of tags per learner	152	197
Average number of posted words per learner	1,547	2,496

TABLE 2
Comparison of Basic Network Statistics

Network	Size	<k>	l	C	Reference
Silwood Park food web	154	4.75	3.40	0.15	Montoya & Sole', 2000
Math. co-authorship	70,975	3.9	9.5	0.59	Baraba'si et al., 2001
Sina blogging network	122,470	3.28	-	0.149	Fu, Liu & Wang, 2008
Xiaonei network	396,836	35.8	3.72	0.16	Fu, Liu & Wang, 2008
FIT Community	273	-	1.9	0.23	Hamulic & Bijedic, 2009
Epinions	6,902	4.146	5.086	0.012	Chen et al., 2013
Stack Overflow	**3,281**	**619.4**	**1.586**	**0.58**	**This study**

Step 1. Initializing a and b.

Step 2. Fixing b to initial value if it is the first iteration, otherwise fixing $b = b^{new}$; maximum recommendation precision or recall by updating a then get a^{new}.

Step 3. Fixing $a = a^{new}$; maximum recommendation precision or recall by updating b then get b^{new}.

Step 4. Evaluating recommendation precision or recall and check for convergence, return to step 2 until the recommend precision or recall performance remains unchanged.

5.3 Algorithm Performance Comparison

In this study, the number of potential positive answerers to an asker is equal to the number of learners whose hybrid trust values with the asker are higher than a threshold and whose profile tags match the asker's question tags. Via experiments, the threshold in this case study was set to 1.1 $\times HT(u_1, u)_{avg}$, where $HT(u_1, u)_{avg}$ represents the average hybrid trust value of the asker u_1 to the rest of learners. Because the number of positive answerers is very large on Stack Overflow, it can be expected that precision will be low in the algorithm evaluation.

Section 5.4 will explain why learners having high hybrid trust values with the asker can be regarded as true positive answers.

Figs. 5 and 6 compare precision and recall performances of the global trust (celebrity recommendation), the local trust (content-based recommendation), and the hybrid trust algorithms under different topic values. Topic values represent the numbers of topics used in mining learning preferences. The results show that the hybrid trust algorithm performs better than the other two methods on both recall and precision. On average, the proposed approach outperforms both the global and local trust algorithms by 192.39 and 91.99 percent respectively on precision, and 15.54 and 16.92 percent respectively on recall. In addition, the performance of hybrid algorithm is superior to the other two across all topic values. The results show that the combination of global and local trust values can generate better recommendations.

5.4 The Relationship between Hybrid Trust Values and Received Votes

As discussed in the previous section, the number of received votes reflects the learners' trust or distrust toward a specific answer. An answer with higher received "up" votes (one up vote = received vote value plus 1) indicates that the answer is trusted by more learners. Meanwhile, an answer with higher received "down" votes (one down vote = received vote value minus 1) means that the answer is distrusted by more learners. If the recommender system can generate good recommendations, recommended learners' hybrid trust values should be positively correlated with their received vote values. Fig. 7 examines the relationship between the average hybrid trust values and received votes values in the test dataset. Results show that the average hybrid trust value has a proportional relationship with the average value of received votes. In addition, the Spearman's correlation coefficient ($\rho = 0.96$) [79] indicates a very high positive correlation between the average hybrid trust values and the received votes. Thus, the results show that answerers with high hybrid trust values can be regarded as true positive answerers.

5.5 The Facilitation of Personalized Learning Communities

In order to test whether the proposed algorithm can facilitate the formation of personalized learning communities, 97 learners were randomly selected from learners with 0.85 or higher hybrid trust values in the training dataset. Fig. 9

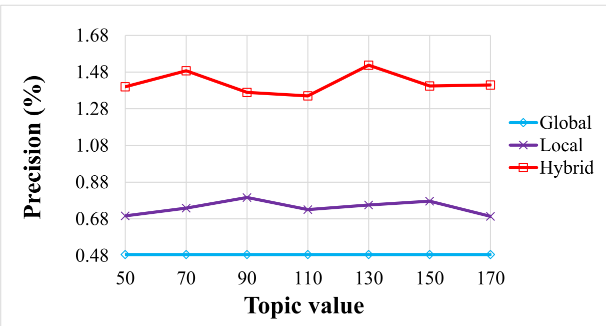

Fig. 5. Comparisons of recommendation precision among algorithms and topic number.

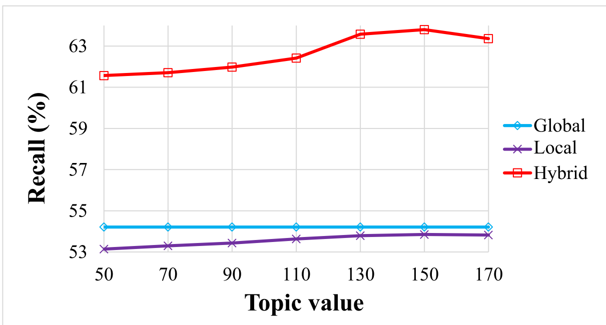

Fig. 6. Comparison of recommendation recall among algorithms and topic values.

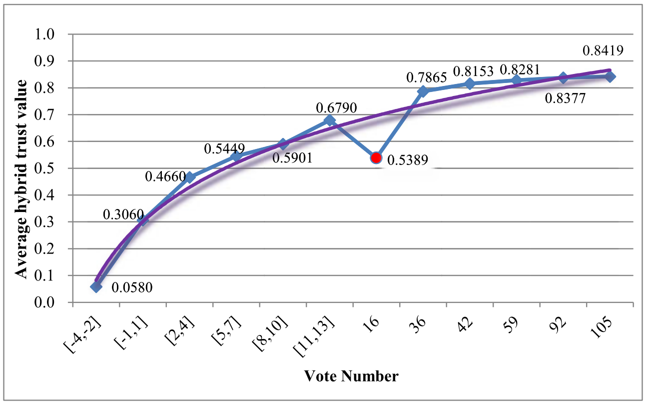

Fig. 7. Average trust values of different votes in the test dataset.

shows the results of the network analysis and community detection [78]. Fig. 8 shows that the 97 learners formed nine smaller communities. Each of the communities was marked in different colors and every community was given a theme based on the shared user tags. The size of node represents the number of hybrid trust connections with other learners. The direction of the connections represents the trust relations. For example, $A => B$ means the trust relation is from A to B. When a learner received many connections from others within the community, it indicates the learner is trusted by these connected learners so he or she can be considered as an expert in the community.

Fig. 8 shows that each community contains at least one expert. In addition, hot topics usually contain a lot of learners. Instead of forming a larger community (such as one large community in C and C++), the recommender system classified these learners into three smaller groups (C & C++, C++, and C++ & C). Note that learners in C & C++ community were more focused on C, while learners in C++ & C were more focused on C++. Learners within the groups have closer trust relations and more shared learning preferences than those between groups. Fig. 9 shows the number of learners in each of the groups. The largest community, Ruby and Java, consisted of 20 learners. The smallest community, iOS, consisted of three learners.

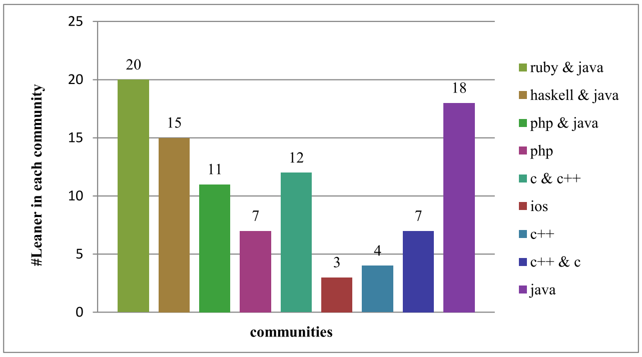

Fig. 9. Community detection result of the hybrid trust network.

6 Discussion

6.1 Expected Outcomes of the Hybrid Trust-Based Recommender System

Table 2 shows that Stack Overflow is a successful CoP because of the characteristics below. Comparing with other social communities, Stack Overflow's:

- relations between learners are closer (larger $<k>$);
- information is easier to disseminate (smaller l);
- learners are easier to group together (larger C).

Different from users in other social community platforms, learners in Stack Overflow have stronger motivations and tend to interact with a smaller group of people only. Therefore, an effective recommender system is necessary

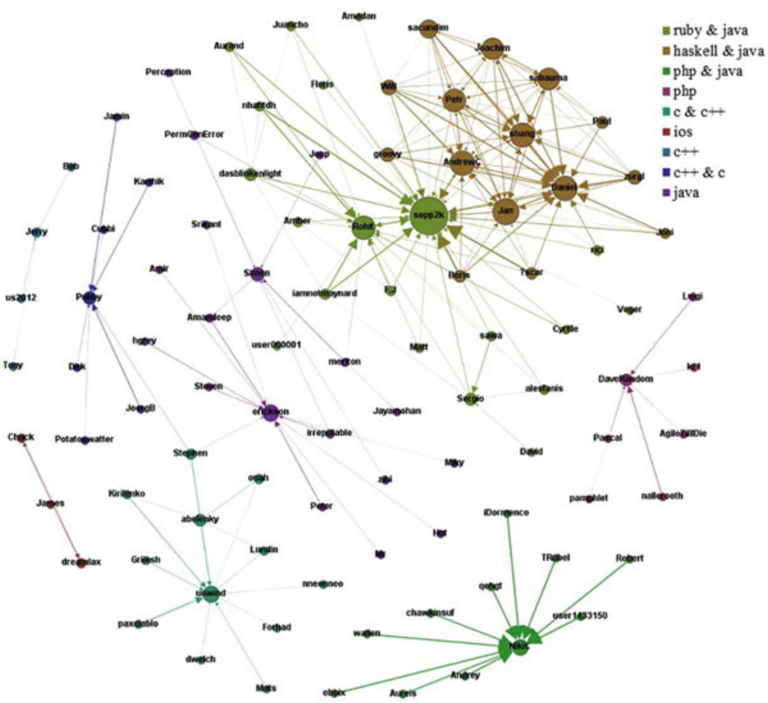

Fig. 8. A hybrid trust network of 97 learners in the training dataset.

because it can assist learners to achieve the goal of personalized learning. Using the recommender system to identify potential experts for questions posted can benefit both learners and experts. Experts may improve their skills through the process of answering relevant questions. Thus, the recommender system is likely to improve the overall quality of participation in the community [80]. In addition, the recommender system allows learners to focus on learning contents because it saves time and effort in searching and filtering information.

Based on the results of the case study, the hybrid trust-based recommender system achieves the expected outcomes: (1) it alleviates issues of bounded-rationality and metacognition by recommending trusted experts. In addition, Fig. 7 shows the answerers with high hybrid trust values have high chances to provide correct answers to askers; (2) The recommender system addresses the issue of data sparity by incorporating global and local trust values. Even for a novice learner without Q&A history, the recommender system can still make recommendations based on the global trust and the novice learner's tags; (3) Fig. 8 and Fig. 9 show that the recommender system can facilitate the formation of personalized learning communities. In a large online CoP, each of those hot topics usually contain many learners. Figs. 8 and 9 show that the recommender system can further chunk a larger hot topic community into smaller groups. As discussed in the literature review, a learner's self-motivation is the key factor for successful life-long learning. Forming a smaller personal learning community can help sustain a learner's motivation and participation levels, because the recommender system can strengthen learners' relations within the study group. Pal et al. [80] suggested that a potential expert may not have enough motivation to help others. Forming a personal learning community may help increase potential experts' willingness as they may get recognized by other members within the community for their efforts in helping others. Our observations showed that some learners left and no longer used Stack Overflow because their questions were not answered at all. As active participation of both learners and potential experts are important for the learning community to function and grow, implementing a recommender system can be very useful.

6.2 The Hybrid Trust-Based Algorithm

The precision values of all the algorithms are small because the number of qualified answerers (users who meet the recommendation criteria) is very large on Stack Overflow.

Figs. 5 and 6 indicate that the hybrid trust algorithm can generate better recommendations than celebrity recommendation (global trust) or content-based recommendation (local trust) systems. However, Fig. 7 shows that there is a lower hybrid trust value (0.5389) at the point with 16 votes. After further examining the data point, it showed that there were two answers with 16 votes among 3,645 answers. Therefore, the sudden value drop might be attributed to the small sample size (two answers only).

6.3 Limitations

The proposed algorithm has the following limitations. First, learner reputation and received vote value were used to compute learner global trust, while both indicators may not exist in all online CoPs. Second, the local trust computation is based on the user's history of Q&A contents. For a novice learner without any Q&A history, the recommender system can still generate recommendations based on global trust and the novice learner's user tags. However, the system's recommendation performance might be poor for novice learners without Q&A histories.

6.4 Suggestions for Developers and Researchers

Although a promising recommender prototype has been elaborated, the authors encountered challenges in data collection because Stack Overflow does not provide Application Program Interface (API). Since online CoPs are getting popular, providing APIs or anonymized data can attract more researchers to conduct related research activities.

This study adopted reputation score and received vote value for global trust calculation because these two indicators are common built-in features in online CoPs such as: Stack Overflow, Sap Community Network, and Sermo for physicians. That means platform developers should consider adopting these indicators when construct online CoPs. Moreover, it does not mean reputation score and received vote are ultimate indicators for constructing global trust. More research efforts are needed to identify other variables for CoPs or other similar learning environments.

Finally, Stack Overflow was selected as the target CoP for the case study. However, Stack Overflow is a CoP for computer programming professionals. It somehow is easier to determine whether an answer is correct or not than other social science subjects. More studies are required to verify whether the proposed recommender system can be generalized for online social science CoPs.

7 Conclusions and Future Work

Based on the case study, the proposed recommender systems meets the following technical and educational requirements suggested in previous studies. First, the recommender adopts hybrid techniques to eliminate the issue of data sparsity. Second, the target users are professionals in informal learning environments. Third, accurate recommendations can be made based on professional's global and local social relations so that professionals can develop their own personal networks and get connected with experts in the same field. Finally, the recommender facilitates meta-cognitive activities by considering learner's attributes and learning preferences.

Future work can focus on the following directions. First, other techniques, such as community detection and trust propagation, can be incorporated to see whether these methods can further enhance recommendation performance. Second, an advantage of the proposed recommender system is to facilitate the formation of personalized learning community by promoting interactions among a smaller group of learners. However, the dynamics of the community formation process need further investigations. Third, investigating learners' perceptions in using the recommender system is a good topic for future research. Finally, verifying the proposed algorithm in other CoPs (especially in social science subjects) can help generalize findings.

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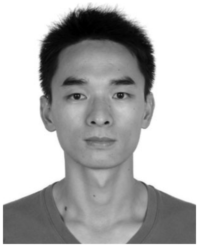

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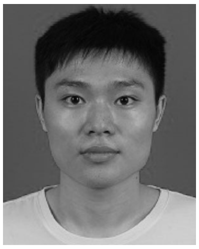

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