Folksonomy Based Socially-Aware Recommendation of Scholarly Papers for Conference Participants

Feng Xia, Nana Yaw Asabere, Haifeng Liu, Nakema Deonauth, Fengqi Li
School of Software, Dalian University of Technology
Dalian 116620, China
f.xia@acm.org

ABSTRACT
Due to the significant proliferation of scholarly papers in both conferences and journals, recommending relevant papers to researchers for academic learning has become a substantial problem. Conferences, in comparison to journals have an aspect of social learning, which allows personal familiarization through various interactions among researchers. In this paper, we improve the social awareness of participants of smart conferences by proposing an innovative folksonomy-based paper recommendation algorithm, namely, Socially-Aware Recommendation of Scholarly Papers (SARSP). Our proposed algorithm recommends scholarly papers, issued by Active Participants (APs), to other Group Profile participants at the same smart conference based on similarity of their research interests. Furthermore, through computation of social ties, SARSP generates effective recommendations of scholarly papers to participants who have strong social ties with an AP. Through a relevant real-world dataset, we evaluate our proposed algorithm. Our experimental results verify that SARSP has encouraging improvements over other existing methods.

Categories and Subject Descriptors
H.3.3 [**Information Storage and Retrieval**]: Information Search and Retrieval – *Information Filtering, Retrieval Models, Selection Process.*

Keywords
Group Profile, Folksonomies, Paper Recommendation, Social Awareness, Smart Conference

1. INTRODUCTION
Since the 1990s, recommender systems have been extensively investigated and deployed comprehensively in various domains and applications such as mobile commerce, electronic health and mobile learning. Various recommendation algorithms and techniques such as Collaborative Filtering (CF), Content-Based Filtering (CBF), Hybrid and Context-Aware are widely discussed in literature. Through the detection of suitable resources from a potentially overwhelming variety of choices, recommender systems provide a favorable approach to facilitate both teaching and learning tasks. Recommender systems for learning environments such as e-learning try to address the challenges of finding relevant resources and people for learning by attempting to filter contents for different learning settings [1].

There is the need for researchers and academicians to retrieve relevant information with a greater degree of efficiency. Currently, researchers and academicians find it difficult to connect with the right people (e.g. people with similar research interests and educational goals) and find the right content (e.g. specific learning purpose, context and pedagogy) [2]. In recent years, social behavioral data has been exponentially expanding due to the tremendous success of various outlets on social websites in different forms and purposes. This has paved the way for social computing/intelligence research, aimed to analyze, discover and model human social behavior. Furthermore, tagging systems have emerged as significant mechanisms that enable users in social networks to know themselves and understand each other well. Consequently, the innovative development of algorithms that combine recommenders and tags are likely to deliver both the flexibility and conceptual clarity inherent in tagging systems as well as the automation inherent in recommenders [3].

The high magnitude and vast growth of publications in both conferences and journals makes it difficult for researchers to survey or find all relevant and needed research papers in their specific fields [4][5]. Research Paper Recommender Systems are therefore developed to meet the demands of researchers who are seeking relevant papers to read for their research. Conferences create a greater sense of social awareness, familiarization and interactions of participants or attendees in comparison to journals. There is often a high possibility that a reader of a paper(s) in a particular journal does not personally know the author(s)/researcher(s) of the paper he/she is reading. Nevertheless, this assertion does not essentially imply that, all attendees of conferences, have the opportunity to socialize with their relevant participants. This is primarily because conference sessions and workshops are time-constrained and the participants are usually too many. A particular conference participant's research interest may qualify him/her to attend multiple conference sessions but it is not possible for such participants to attend all available sessions of a conference that meets their research interests.

As a result of such scenarios at conferences, the improvement of social awareness of conference participants through mobile multimedia recommendation has become increasingly necessary and vital. Conference participants should be able to advertise their research papers to other participants at a conference, who are likely to be interested in their research areas/disciplines.

In this paper, we propose an algorithm called Socially-Aware Recommendation of Scholarly Papers (*SARSP*). *SARSP* is designed to have a main aim of allowing and assisting active

WWW'14 Companion, April 7–11, 2014, Seoul, Korea.
ACM 978-1-4503-2745-9/14/04.
http://dx.doi.org/10.1145/2567948.2579239

conference participants' (i.e. users') advertise and recommend their research papers of interest to other participants of common social ties and similar preferences at the same conference. This will improve the social awareness of participants. Initially our proposed *SARSP* explicitly obtains information concerning contact durations, contact frequencies and research/academic paper interests of individual conference participants in order to determine the strength of their social ties as well as their preference similarities of research papers.

A beneficial feature of *SASRP* involves the generation of group profiles. Group profiles involve the combination of individual user profiles of conference participants into different groups according to similar research and academic paper interests. After the group profiles are generated, an active conference participant who wants to make a recommendation pertaining to his/her research paper will advertise/post his/her academic paper tag (title and author list) to the group profile of similar research/academic paper interests using his/her smartphone through a Near Field Communication (NFC) Mechanism.

Our contributions in this work include the following:

- In order to generate social recommendations, we propose and develop methods and procedures to create group profiles from individual conference participants through folksonomies. Furthermore, we develop methods to compute the social ties between the active conference participant (user) and other participants of a smart conference.
- Through a relevant dataset, we conduct experiments in order to obtain results and compare with other existing state-of-the art techniques and methods.

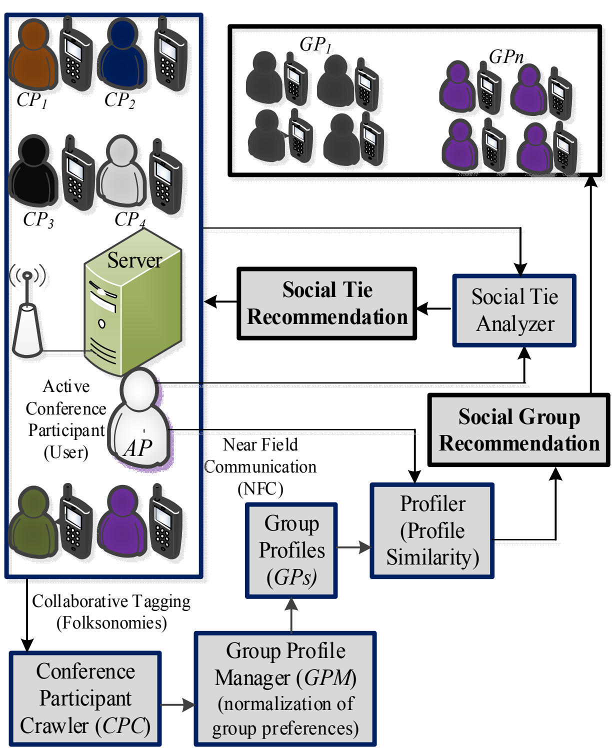


Figure 1. SARSP Framework

2. RELATED WORK

Several scholarly/research paper recommender systems and algorithms have been presented and discussed by various researchers in recent years. A significant number of them were proposed to recommend papers based on citation relations [4][5], while others such as [6-11] were proposed to recommend papers based on similarity of users or papers, reading purposes of users and folksonomies/collaborative tagging by users.

Liang et al. [4] proposed a novel method to address the problem of too many available research papers. This was done by incorporating various citation relations for a proper set of papers, which are more relevant but with a very limited size. Similarly, in relation to citations, Huynh et al. [5] also presented a recommender module that suggests papers to users based on the seed paper's citation network. Their work took into account the combination of the co-citation and co-reference factors to improve their algorithm's effectiveness.

To deal with the tri-relation of user-resource-tag in folksonomies and the data sparsity problem in personalized recommendation, Wu et al. [6] proposed a user taste diffusion model based on the tripartite hypergraph to recommend research paper resources for users. Similar to [6], Jomsri et al. [7] proposed a framework for a tag-based research paper recommender system. Their proposed approach exploits the use of a set of tags for recommending research papers to each user.

Pan et al. [8] proposed that by using topic model techniques to make topic analysis on research papers, they could introduce a thematic similarity measurement into a modified version of item-based recommendation approach. In the same vein, Jiang et al. [9] proposed a method of recommending the most problem-related papers or solution-related papers to users separately, in order to satisfy user-specific reading purposes.

In terms of conference related issues, Pham et al. [10] presented Context-Aware Mobile Recommendation Services (*CAMRS*), which generates social recommendations based on the current context (whereabouts at the venue, popularity and activities of talks and presentations) sensed at the conference venue. Conry et al. [11] also presented a recommender system approach to conference paper assignment problems i.e. the task of assigning paper submissions to reviewers.

Our *SARSP* approach seeks to utilize not only the tag rating preference similarities of conference participants, but also their social ties computed through contact durations and contact frequencies. This is done to obtain a wider and effective coverage for recommending scholarly papers to conference participants by an active user. To the best of our knowledge, scholarly paper recommendation research using a combination of social ties and folksonomies is quite rare. This motivates us to embark on such a research direction.

3. DESIGN OF SARSP

This section presents the basic idea and framework of *SASRP*. Figure 1 shows that our *SARSP* framework generates both social tie recommendations through the social ties and social group recommendations through profile similarity (folksonomies) of the conference participants. Referring to Figure 1, the *Conference Participant Crawler (CPC)* gathers and sends the collaborative tag ratings (folksonomies) of the individual conference participants to *the Group Profile Manager (GPM)* for normalization into Group Profiles in accordance to tagged rating levels and interests. After the Group Profiles are formed, the

Profiler computes the level of preference similarity between the active conference participant *(AP)* and the Group Profiles *(GPs)* in order to make an effective, reliable and efficient social recommendation of scholarly/research papers belonging to *AP*.

The *Social Tie Analyzer* computes the contact durations and contact frequencies between *AP* and the other conference participants so that a wider coverage of reliable and efficient recommendations can be generated by *AP* to other participants according to their tie strengths. We elaborate further on our *SARSP* framework below.

3.1 User Interests

Usually, user interests are specified through explicit and implicit feedback techniques. Explicit feedback involves the user specifying his/her interests and implicit feedback involves the recommender algorithm observing the usage behavior of the user such as browsing habits and keyword inputs to determine the interests of the user.

We propose an explicit approach involving conference participants specifying their research paper interests by using their mobile devices to input specific keywords in the form of tags to denote interest in some specific topics/research disciplines. We also propose an explicit approach to determine the contact durations and contact frequencies between an *AP* and the other participants. The strength of the social ties between an *AP* and the other participants is determined by the *Social Tie Analyzer* through (1) using (2) as a threshold. In our proposed algorithm, a tag is a relevant keyword assigned to one or more scholarly/research papers by a conference participant, which describes an academic research paper and enables it to be classified.

3.2 Social Ties

The social interactions between individuals are usually called social ties. Ties usually represent the presence or non-presence of a significant relationship between two individuals, for example friendship, research familiarities etc. [12]. We measure and evaluate the tie strength between *AP* and another conference participant CP_i using (1).

$$SocTie_{AP,CP_i}(t) = (\lambda_{AP,CP_i} \times d_{AP,CP_i}(t)) / T \qquad (1)$$

In (1), $d_{AP,CPi}(t)$ is the contact duration between an *AP* and another conference participant, CP_i in the time frame T and $\lambda_{AP,CPi}$ is their contact frequency (i.e. the number of times *AP* and CP_i have been in contact within the time frame T). To determine the tie strength between *AP* and CP_i, we set a threshold, γ for (1) using (2) below. The social tie values between *AP* and the other conference participants has to fall within the determined threshold before social tie recommendations can be generated for them in accordance to their tie strengths.

$$SocTie_{AP,CP_i}(t) \geq \gamma \qquad (2)$$

3.3 Group Profile Generation

As mentioned in Section 1, the generation of a group profile involves the combination of individual user profiles of common research interests into different groups. The profile of a conference participant describes his/her interests related to research papers. These interests include various keywords regarding research papers. Group profiles therefore describe common attributes used by individual conference participants.

To generate group profiles consisting of individual conference participants, we adopted the approach used in [13] and initially combined the profiles of individual participants based on interests expressed from research papers through collaborative tagging (folksonomies). We also adopted the user-resource-tag relational model in [6] to create folksonomies among the conference participants through academic paper resources and tags. Folksonomies, also known as collaborative tagging systems, enable users to annotate, manage and share their resources/attributes through tags.

A folksonomy can be described as a hypergraph $G =< CP, A, T, H >$, where $CP = \{cp_1, cp_2, ..., cp_n\}$ is the set of conference participants and $SP= \{sp_1, sp_2,...,sp_n\}$ is the set of scholarly papers. The interests of the individual conference participants in the hypergraph are associated with their scholarly/research papers. Additionally, in the hypergraph, $T = \{t_1, t_2, ..., t_n\}$ is the set of the tags (keywords with ratings from 1-5) that specifies the levels of interest for research paper resources and $H = \{h_1, h_2,..., h_n\}$ is the set of the hyperedges which only exist among the nodes in different sets [6].

Referring to Figure 2, if user cp_1 annotates scholarly paper sp_1 with tag t_1, these three nodes will be connected by hyperedge h_1. Additionally, if the same user cp_1 annotates scholarly paper sp_2 with tag t_2, these three nodes will be connected by hyperedge h_2. Therefore the annotations of tags t_1 and t_2 through connections of hyperedges h_1 and h_2 respectively, can be defined as the research paper interests of cp_1. Similarly, the annotations of scholarly paper sp_2 and sp_3 with tag t_3 by cp_2 and cp_3 connected to hyperedges h_3 and h_4 respectively, shows that the participants' cp_2 and cp_3 have a common research paper interest through tag t_3. After computing the folksonomies of the conference participants, their tagged ratings have to be arranged into groups by the *GPM* because they have different scales and ratings. It is therefore necessary to compute the average of the weights associated with each tag that is used to describe the preferences of the participants in order for the *GPM* to create a priority list of preferences for generating each group profile. Each preference of a participant, which is classified by a tagged rating, is denoted as an integer value ranging from 1 to 5,

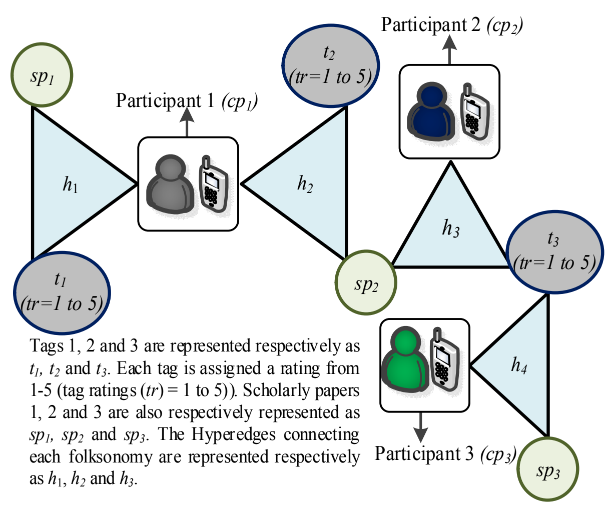


Figure 2. A Conference Participant-Scholarly Paper-Tag Relation Model

where 1 is for the lowest preference rating, while the highest preference rating is 5. Each participant may have multiple tag ratings for different scholarly papers. Let the preferences of each group profile be $GP = \{gp_1, gp_2, gp_3, ..., gp_n\}$. *GPM* further intersects common neighbors and predicts different groups of participants through a normalization procedure.

$$ncp_{i,j} = cp_{\min} + \frac{(cp_{\max} - cp_{\min}) \cdot cp_j}{TR\max - TR\min} \tag{3}$$

In (3) $ncp_{i,j}$ is used to compute the normalized (n) values for common tags that have been rated differently by conference participants. Furthermore, $cp_{i,j}$ represents the individual ratings of the participants for a particular tag, where i is the notation for a particular participant and j is his/her tagged rating for a particular scholarly paper. The specific maximum and minimum ratings of the participants for a particular tag are respectively represented as cp_{max} and cp_{min}. Additionally, $TRmax$ and $TRmin$ represent the overall maximum and minimum tagged ratings in the dataset. For example, in a scenario where the lowest and highest ratings of participants for a "cloud computing" tag in the dataset are 2 and 4 (cp_{min}=2 and cp_{max}=4), respectively. If a conference participant, cp_1 annotates a "cloud computing" tag with a rating of 4 (cp_j), the normalized value pertaining to the tag annotation of cp_1 is computed as:

$$ncp_{1,4} = 2 + \frac{(4-2) \cdot 4}{5-1} = 2 + \frac{2 \times 4}{4}$$

$$ncp_{1,4} = 2 + 2 = 4$$

It must be noted that, in the above computation, $TRmax$ and $TRmin$ are respectively equal to 5 and 1, representing the highest and lowest possible tagged ratings in the dataset.

$$gp_j = \frac{\sum_{i=1}^{cp} ncp_{i,j}}{Ncp} \tag{4}$$

In (4), the values obtained from (3) are summed up and divided by the number of conference participants (*Ncp*) who assigned ratings to a particular tag. Consequently, through (4), we compute and achieve an average normalized value that indicates the formation and allocation of a group profile for the *cps*. The *cps* are allocated into their respective group profiles if their rating for a particular tag is greater than or equal to (≥) their corresponding groups' average normalized value (gp_j).

$$Sim(a,b) = \frac{\sum_{i \in I}(r_{a,i} - \bar{r}_a)(r_{b,i} - \bar{r}_b)}{\sqrt{\sum_{i \in I}(r_{a,i} - \bar{r}_a)^2}\sqrt{\sum_{i \in I}(r_{b,i} - \bar{r}_b)^2}} \tag{5}$$

To determine the similarity between *AP* and gp_j, i.e. $Sim(AP,gp_j)$, our algorithm returns a Pearson Score between -1 and 1, where 1 signifies that *AP* and gp_j have exactly the same or quiet similar ratings and -1 signifies otherwise [14]. Due to the fact that there are multiple group profiles and different research/scholarly papers to be recommended by different *APs*, our algorithm loops through different *AP* and gp_j transactions for the entire smart conference, in order to calculate relevant Pearson Scores for each transaction by using (5). In (5) $r_{a,i}$ and $r_{b,i}$ denote the highest ratings of users *a* and *b* for item *i*. In our algorithm, *a*=*AP* and *b*= gp_j. The average ratings of users *a* and *b* are denoted by $\hat{r}_a$ and $\hat{r}_b$ respectively.

Algorithm: Pseudocode for the social tie and recommendations of *AP's* scholarly paper(s)

```
1: // Define Structure of conf_part to contain
2:     String User
3:     String Tag
4:     String Scholarly Paper
5:     Integer Rating
6: // Declare and initialize variables
7:     i and j                              // integer variables
8:     Sim_thresh and Soc_tie_thresh        // floating variables
9 : Identify unique tags and classify as group
10: //Calculate normalized values of groups
       using Eqs. (3) and (4)
11: //Allocate conf_part to respective groups
12:    for every conf_part i
13:        if (conf_part[i].Rating >=gp[j].val)
14:            Assign conf_part[i] into group gp[j];
15:        end if
16:    end for
17: //Compute Similarity between AP and gp_j using Eq. (5)
18:        if Sim(AP,gp_j) ≥ Sim_thresh then
19:            recommend AP's scholarly paper to gp_j;
20:        end if
21: //Calculate Social Tie using Eq. (1)
22:    for every CP_i
23:        if (SocTie_AP,CPi (t)≥Soc_tie_thresh) then
24:            recommend AP's scholarly paper to CP_i ;
25:        end if
26:    end for
```

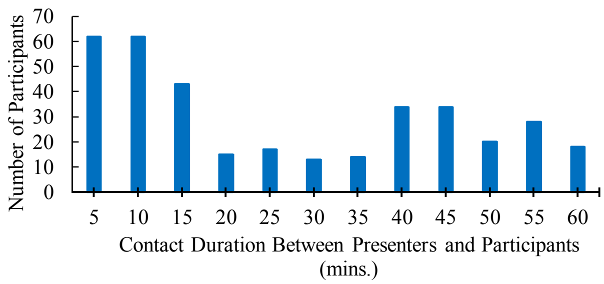
In our algorithm, for the group profile generation, we divide our procedures into structure transactions. Each transaction, which is similar to the hypergraph is made up of three strings; namely a conference participant, tag and research paper resource. These are depicted in steps 1-5. Variables are declared and initialized in steps 6-8. In step 9, unique groups are identified. In steps 10-15, our algorithm calculates the normalized values of identified groups and allocates conference participants to their respective groups. Steps 17-20 compute the similarity between the *AP* and the group profiles and recommends *AP's* scholarly paper based on a threshold value. Similarly, steps 21-25, calculate the social tie between *AP* and every conference participant and recommends *AP's* scholarly paper based on a threshold value.

4. EXPERIMENTAL EVALUATION

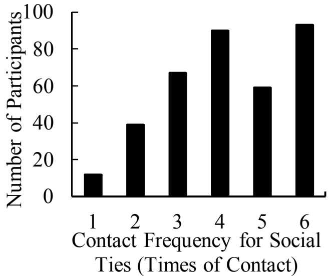
In this section, we evaluate the performance of our *SARSP* approach through benchmarking experiments. We initially discuss the experimental dataset followed by a description of the evaluation metrics that we employed to validate the performance of our algorithm. Finally, we present our experimental analysis and results.

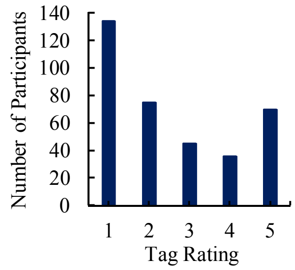
4.1 Dataset and Experiment Setup

In order to test our algorithm using relevant data, we simulated a "mock conference". There was difficulty in obtaining the relevant data parameters for our experiment. Therefore, we gathered our own dataset by collecting data from research students in the School of Software at Dalian University of Technology, China and named it SocRec dataset. The SocRec dataset consists of data covering title of paper (paper id), keywords and ratings which are



(a) Contact duration trends





(b) Contact frequency trends **(c) Tag rating trends**

Figure 3. Details and components of SocRec dataset

used to identify user interests through tagging. The SocRec dataset also includes data for estimating the social ties of users and is made up of a total number of 73 *APs* and 360 participants. We gathered tagged rating trends of participants and a summary of these details is shown in Figure 3(c). Additionally, we monitored the contact trends between the *APs* and participants, this information is illustrated in Figure 3(a) and Figure 3(b) which respectively shows the contact duration and frequency trends. We divided the SocRec dataset into two parts: training set (60%), test set (40%).

The simulated "mock conference" was scheduled to run for a total time frame T of 12 hours (720 minutes). We found the highest contact duration and contact frequency to be 60 minutes and 6 respectively i.e. $d_{AP,CPi}(t)$ = 60 and $\lambda_{AP,CPi}$= 6. Using (1), we computed the highest $SocTie_{AP,CPi}(t) = (6 \times 60)/720$ and obtained a result of 0.5 for the highest positive and effective recommendation based on strong social ties between AP and CP_i. Therefore, we set the range for recommendation based on the social ties as $0 \leq SocTie_{AP,CPi}(t) \leq 0.5$ and allocated a social tie threshold of 0.3 and above in accordance to the dataset. Usually, the Pearson Score (PS) between two users/products for the computation of their similarities is between -1 and 1 i.e. $-1 \leq PS \leq 1$. Therefore, the range for generating social group recommendations for gp_j by AP was based on the Pearson Scores achieved by our algorithm.

4.2 Evaluation Metrics

We focused on the quality of the set of recommendations regarding scholarly papers and employed two common classification metrics namely, precision and recall to evaluate our proposed recommendation method. These evaluation metrics are appropriate for evaluating proposed methods and algorithms that involve the binary preferences of users [15].

Precision is defined as the ratio of the number of relevant items/resources received to the total number of retrieved items/resources. Recall is defined as the ratio of the number of relevant items/resources which are retrieved to the total number of all relevant items/resources [15]. Using (6) and (7), we computed precision and recall for each social tie value and Pearson Score in accordance to the dataset.

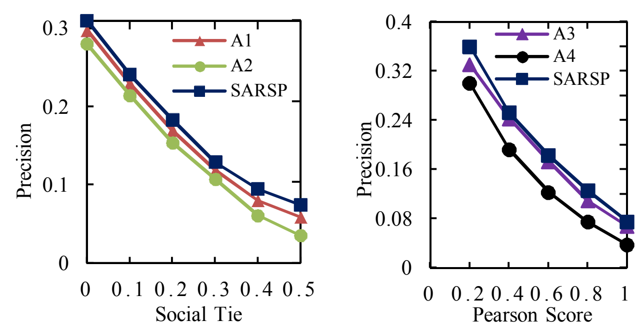
$$Precision = \frac{good\ papers\ recommended}{all\ recommendations} \qquad (6)$$

$$Recall = \frac{good\ papers\ recommended}{all\ good\ papers} \qquad (7)$$

4.3 Results and Analysis

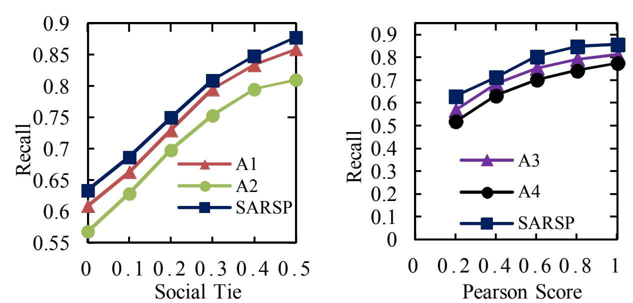
As elaborated above, we utilized the precision and recall of different social recommendations based on collaborative tagging of preference similarities (folksonomies) and social tie strengths of conference participants (users). We compared our proposed method with those of Ziberna and Vehovar [16] and Ye et al. [17] for social tie recommendation, respectively represented as A1 and A2 in our experiments. Similarly, the work by Gartrell et al. [18] and Peng et al. [19] were used as a comparison for social group recommendation and were likewise represented as A3 and A4 in our experiment.

The results obtained from computing the Pearson correlation and social tie values between the *APs* and participants in the dataset of our experiment corresponded to the efficiency of *APs* social recommendation. Therefore high computed values resulted in effective social recommendations. Figure 4(a) and Figure 4(b) of



(a) **(b)**

Figure 4. Precision Performance on SocRec Dataset: (a) Social Tie Recommendation and (b) Social Group Recommendation



(a) **(b)**

Figure 5. Recall Performance on SocRec Dataset: (a) Social Tie Recommendation and (b) Social Group Recommendation

our experimental analysis show that, at the maximum threshold value for social ties (0.5) and Pearson Score (1.0), *SARSP* attained the highest precision values (0.072 and 0.076) when compared to A1 (0.059), A2 (0.035), A3 (0.068) and A4 (0.038). Interestingly, *SARSP* had the lowest false positive error and generated more effective and good recommendations (high precision). Therefore, according to Figure 4, a continuous decrease in precision of the four methods will result in *SARSP* outperforming A1 and A2 in terms of social tie recommendation, and A3 and A4 in terms of social group recommendation.

According to Figure 5(a) and Figure 5(b), the recall values of *SARSP* are higher than those of A1, A2, A3 and A4. Furthermore, at the highest social tie maximum threshold value of 0.5, *SARSP* achieved a higher recall value (0.878) than A1 (0.859) and A2 (0.810). This scenario is repeated in the same way for the maximum Pearson Score of 1.0. Therefore *SARSP* outperformed A1, A2, A3 and A4 in terms of recall and generated more social tie and group recommendations. Our experiment also showed that there was a reduction in data sparsity and cold-start problems because most of scholarly papers in our dataset had been rated (high coverage) by the users (participants). It can be seen from Figures 4 and 5 that *SARSP* achieved better results reliably in all the utilized evaluation metrics. In particular, our approach is prominent on the dataset in terms of social tie evaluation.

5. CONCLUSION

This paper has proposed an algorithm (*SARSP*) that enlarges the coverage of mobile social recommendations for conference participants through the benefit of constructing relations in folksonomies and social ties. *SARSP* utilizes contact durations and frequencies as well as tagged ratings to advantageously raise its level of performance among others. Consequently, the comparative results illustrate that our proposed method outperformed the others in terms of precision and recall evaluation metrics. However, our proposed method does not include integration of context and clustering techniques for a more concise generation of group profiles in the recommendation procedure. We hope to tackle these research issues in the future.

6. ACKNOWLEDGMENTS

This work was partially supported by the Liaoning Provincial Natural Science Foundation of China under Grant No. 201202032.

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