Towards Human-centric Personalized Expertise Ranking in Community-based Question Answering

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ABSTRACT

Search engine has been the major source for discovering user-generated content with authority, not only on content-centric multimedia but also on human-centric social networks. Many studies have demonstrated the power of graph-based ranking algorithms to propagate reputation and expertise along social graph composed of users' links for information search, to promote experts and demote spams. However, these existing works shed little light on personalized expertise ranking algorithm from view of the topic-relevance between users' interests. In this study, we demonstrated the existence of *homophily* in users' interests measured by social annotations using *AskMeFi*, a large scale community-driven question and answering (CQA) system. We discovered that best answers as rated by questioners (users posting questions), are inclined to arrive promptly from co-interest users with authority and topic-relevance after the questions are posted. We proposed *Human-centric Personalized Expertise Ranking*, a graph-based algorithm which takes the topic-relevance and authority among co-interest users and time traits into the computation of the expertise level of users. The experimental results revealed that our proposed algorithm significantly outperforms other non-personalized expertise ranking algorithms.

Categories and Subject Descriptors: H.3.3 [Information Search and Retrieval]: Information filtering

Keywords: Community-based Question Answering, topic-relevance, social annotation, *homophily*, expertise ranking.

1. INTRODUCTION

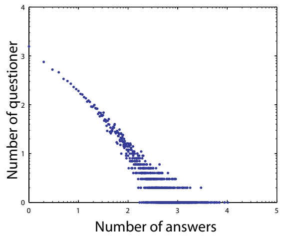
Online community-based question answering (CQA) service have emerged as one of the most popular platforms for people to seek help or share knowledge. The motivation for most users to ask questions through CQA are different and diverse. On one hand, people are seeking correct answers which are suitable for users who have similar questions acquire knowledge through information retrieval. On the other aspect, an amount of users expect to harvest various responses or personal experience which constitute a full investigation of the original and related questions through arousing the deeper discussions. For same or similar questions, it is entirely possible that users from different social circles might to give different and even conflicting answers because of the discrepancy rooted in interested topics and social cultures. In addition, the trust and quality of these answers are uneven, among which good answers mingled with spams, gossips or commercial advertisements that can not be easily differentiated and qualified. Hence, for improving social users' efficacy and experience of surfing CQA, it is increasingly important to help specific users to identify apropos experts and boost CQA's efficient communication among different users through promoting special experts and demoting malicious users and junk spams for each specific user. Pawel and Eugene have shown that graph-based methods are successful in the context of evaluating authority users and contents of CQA by demonstrating that "good questions attract good answers" and "good answers are given to good questions" [9]. Link analysis based methods, however, suffer from drawback for social context since it does not take the similarity of users' interest into consideration of screening out unrelated topic information for specific users.

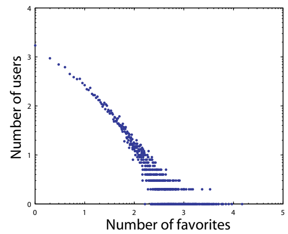
To overcome the challenge, this paper will make three contributions. First, this paper leverages the authority value propagated through mutual reinforcement relationship between questioners and answerers, as well as the topic-relevance measured by users' annotation tags. Second, by analyzing best answers' time traits, this paper revealed that most excellent answerers are inclined to respond to their interested questions in first several arrival time ranks of these questions and we incorporate this feature into personalized ranking algorithm design.

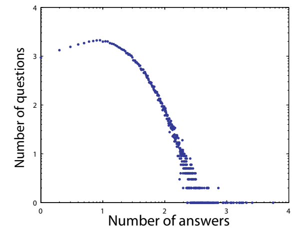
2. RELATED WORK

CQA has been studied from several different perspective. Su et al. [13] reported that the quality and trust of answers for specific questions are very uneven though overall quality of answers is good on average. Therefore, identification of high-quality contents and experts with authority through analyzing and using users' social features and their rich interaction relationships have a meaningful value on driving better service for future human-centric social media.

FhMN'13, August 16, 2013, Hong Kong, China.







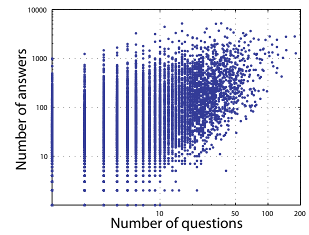


Figure 1: Distribution of users and their questions frequency.

Figure 2: Distribution of users and their favorites frequency.

Figure 3: Distribution of questions and obtained answers frequency.

Figure 4: Number of questions and number of answers for each user.

The first attempt of graph-based algorithm in the context of CQA is to apply HITS algorithm over question-answering relationships created by users in Yahoo! Answer [9] and this study demonstrated the effectiveness of HITS algorithm in finding experts and/or good answers. Zhang et al. [16] proposed ExpersiseRank corresponds to PageRank algorithms to identify users with high expertise and their results showed high correlation between link-based metrics and authentic human ratings in study of question answering forums. Insights from such studies informed the design of graph-based ranking algorithms for discovering experts and their contents with authority.

Aditya et al. [2] presented a temporal study of the evolution dynamics of experts in CQA and applied supervised classification model to distinguish experts from ordinary users by using users' temporal evolution feature. This line of investigation has also explored social network analysis to benefit CQA service. For example, Katrina et al. [12] presented a study relating tie strength to answer quality for questions asked on social network sites and they found that stronger ties actually provided better answers for some measures of answer quality.

Damon and Sepandar [8] presented a social search engine named *Aardvark* to route the question to the right persons who most likely to be able to answer that question in the user's extended social network through exploiting intimacy between users. Lada et al. [1] presented a study of combining both user attributes and answer characteristics to predict whether a particular answer will be chosen as the best answer by the asker within a given topic category.

Ashton et al. [3] investigated the dynamics of the community activity and observed significant assortativity in the reputations of co-answerers, relationships between reputation and answer speed in study of Stack Overflow. Inspired by this study, we also analyzed the time traits of good answers marked as best ones in the case of *AskMeFi*. Similarly, we found that good answerers promptly responded to their interested questions and took this feature into the design of Human-centric Personalized Expertise Ranking algorithm.

3. *ASKMEFI* DATASET

Our analysis was performed on *AskMeFi* data[1], which collected all QA records on *AskMeFi* from Jul 1999 to Jan 2009. In *AskMeFi*, when a user post a question, this user could annotate this question with several tags to describe and categorize it. Different from other collaborative tagging systems, question posted on *AskMeFi* only can be annotated by its questioner. A total of 40K users, 71K questions, 1M answers, 1M favorites and 0.3M tags (79K unique tags) comprise this dataset. Figure 1 to 3 respectively shows the distribution of questions posted and favorites produced by users, and answers responding to questions in the dataset. The long tail of these distributions in the log-log scale indicates that most users receive few answers after posting questions while some geek experts contributed amount of answers to others. This observation is consistent with the Zipf-like distribution of web contents popularity. Figure 4 shows number of questions and number of answers for each user in the dataset. From that, we cannot identify clear boundary of the role of questioners and answerers, which observation is consistent with [5].

[1]http://mssv.net/wiki/index.php/Infodump

3.1 Temporal Analysis of Good Answers

In Figure 5 we examine how long best answers do emerge after its related question posted. We find that 95% questions have received best answers no more than 12 hours after posting in which almost 50% of best were done no more than 30 minutes. From the comparison of several key timeslot, 10-30 minutes and 1-12 hours after question posted are two peak period for "best" answerers' actions. Additionally, in Figure 6 we examine the arrival time orders of all best answers. The distribution of the arrival time-rank of best answers follows the power law distribution and beyond 65% best answers occurred among top-five rank. This suggests that most good answerers are inclined to respond to their interesting questions quickly and then presumably gain best marks in advance, which is consistent with the conclusion presented in investigation of Stack Overflow [3]. In Figure 7 we examine how the ratio of the number of favorites of answers corresponding to different types of questions varies with respect to different arrival time-rank in further. We find that the earlier arrival answers of questions do usually received relative more favorites by masses. For short-threads(thread length:1-25), questioners and masses are inclined to favorite earlier answers in question threads. For long-threads(thread length:beyond 25), almost all answers harvest equal number of favorites though earlier answers were rendered relative less more favorites. This observation might to be because that most short-thread questions belong to *factual question* while lengthy-thread questions belong to *conversational question* which cannot be targeted clearly and perfectly with one or a few deterministic answers, instead, which need more responses from diverse perspective.

4. MEASURING SIMILARITY OF USERS

In this section we study the similarity between users through extraction of their interested topics measured by their social annotations.

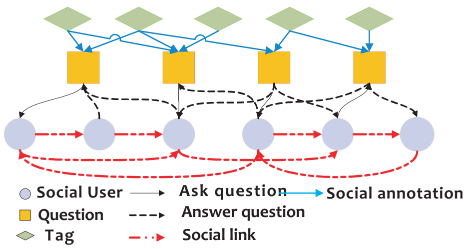


Figure 8: Illustration of a social network of CQA with six users and four questions and five tags.

4.1 Social Network Structure

Given the social graph of CQA shown in Figure 8, in which the entities occur in social network and their mutual relationship are represented. Three types of entities of CQA are to be casted into nodes as shown: (i) *User:* People either post questions and annotate them with tags or answer others' questions. (ii) *Questions:* Questions are asked for help or advice. (iii) *Tags:* Keywords are used by questioners for describing and categorizing questions. In further, social networks exhibit various relationships within the nodes of same type and between nodes of different types that are depicted by edges in this graph: (i) *Linkage(question, answers):* Good questions often draw many answers while poor questions usually received few or even no answers. (ii) *Linkage(questioner, answerer):* Users answering many questions from good users will naturally obtain high expertise scores. This mutual reinforcement relationship suggests that nodes representing questioners act as authorities while nodes representing answerers correspond to hub as claimed in [5]. (iii) *Linkage(user, question, tags):* Tags are associated with the user who associates them with its annotated question, also as a way to describe which topic the user may likely be interested in.

4.2 Homophily by Topics

Homophily is the tendency of individuals in social network to link to others who are similar to them and many interesting applications for personalization and social recommendation are benefited from better understanding of homophily [11]. In the context of CQA, *homophily* implies that users who share similar occupation, eduction background, and interested topics are inclined to post, to answer and to favorite similar and even same questions. The data related to users' personal profile such as occupation are sparse and incomplete since most users refused to publish their personal privacy on social system. Nevertheless, we investigated users' topic similarity through exploring their rich history of social annotations. To extract interested topics from users' tags related to questions, we directly choose **Latent Dirichlet Allocation (LDA)** model used in previous topic extraction works [4][15]. LDA views documents as mixtures of topics represented as a K dimensional random variable θ. Each topic is represented as a probability distribution over words. Given a collection of documents, it is possible to learn the latent topics that explain the words observed in the documents. In this model, a document is generated by first picking a topic distribution θ from the Dirichlet prior, and then using the document topic distribution θ to sample latent topic variables z_i. LDA makes the assumption that each word is generated from one topic, where z_i is a latent variable indicating the hidden topic assignment for word w_i. Probability of choosing a word w_i under topic z_i, $p(w_i|z_i;\beta)$, is different for all documents.

We employed LDA to explore the latent topic space of corpus of tags. Each *AskMeFi* user is viewed as a document while his or her history of tags usage are archived into collections of tags (a collection of tags used by this user) as documents are archived into bag of words in information retrieval. In our assumption, each user's bag of tags is represented as a mixture over $K = 300$ topics, and topics as distribution over tags. We performed experiments to target the question "are more topic similar users more likely to co-answer or co-favorite on same questions?" We study this question using user's tag usage as evidence to measure topic-relevance. Specifically, we present the similarity between two users using *Jensen-Shannon divergence* of their extracted topic vectors.

We screened raw data by filtering out the tags used less than 20 times, the users who annotate less than 20 times. The experiment data contains 6596 users and 2405 tags. We analyzed the correlation of the topic similarity between pairs of users and the likelihood of their co-answer on same questions. For each user, we calculated pair-wise similarity with all remaining users. Note that each pair either co-answer on same questions or not with certain similarity value. We used five different similarity threshold values (0.2, 0.4, 0.6, 0.8 and 1.0) to bin pairs of users. Next, we calculated the likelihood of co-answer in each bin. Figure 9(a) shows that the average likelihood of co-answer increases steadily with the rising of similarity threshold. It is obvious that topic similar users are more likely to be interested on same questions. To demonstrate that the observed correlation are not caused by assortativity (a preference of active users to form rich club), we divided users into two categories according to their cumulative answering records during timeframe: active users and fallow users. Active users have no less than 50 cumulative answering records while fallow users have less than 50 cumulative ones. Repeating above calculations, we divided pairs of users into bins based on similarity threshold and computing average likelihood of co-answer within each bin. As shown in Figure 9(a), the average likelihood of a co-answer increase from 0.08 to 0.25, while for fallow users, the likelihood of co-answer increase from 0.06 to 0.19. The difference in the likelihood of co-answer in the two category might be due to varying login-time and login-timeslot. Figure 9(b) show that the likelihood of pair-wise users' co-favorite increase monotonically with increasing of their topic similarity, though this trend is not clear below the similarity threshold of 0.5. Positive evidence shown in this experiment verified the existence of *homophily* in the context of CQA though we have not thoroughly exploited the causality of this phenomenon, which is beyond of the scope of this study and need to be investigated in future.

Based on this finding, the feature of topic-relevance should be considered into the design of personalized ranking algorithm in next section.

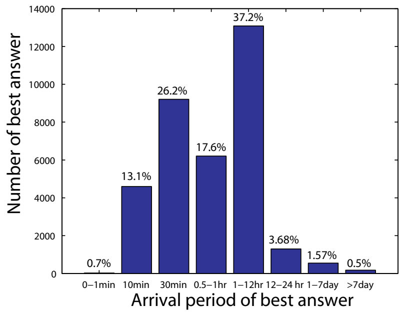


Figure 5: The distribution of best answers' arrival time

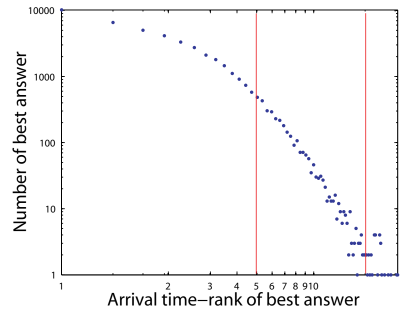


Figure 6: The distribution of best answers' arrival ordering

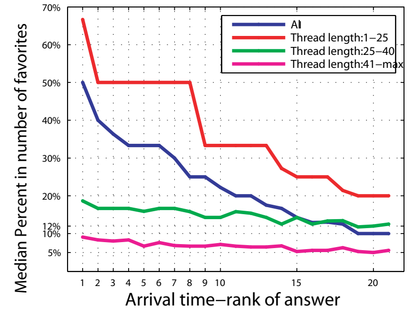
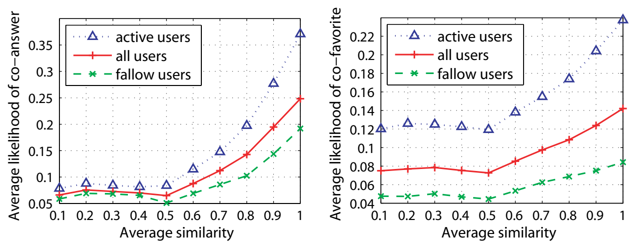


Figure 7: The number of favorites received varies with the different emerging order of answers



(a) (b)

Figure 9: Average likelihood of co-answer and co-favorite between pairwise users. Users are divided into two groups: active users & fallow users.

5. EXPERTISE RANKING ALGORITHMS

Intuitively, good questions attract good answers and good answers are given to good questions as demonstrated in [9][16][3]. This excellent assumption and its robust theoretical foundation motives the usage of graph-based algorithm presented in [10] for qualifying experts in the context of CQA. Nevertheless, different from web information retrieval, people prefer to use natural language to ask questions, answers are generated in real-time by anyone and trust is based on intimacy as investigated in [7]. Given these issues, a Human-centric Personalized Expertise Ranking algorithm is proposed to identify or approximate specific users' recognition of expertise list through taking social features into algorithm design.

5.1 Human-centric Personalized Expertise Ranking Algorithm Design

Personalization is the process of presenting the right experts and information to the right user at the right moment. To learn about a user's preference of experts and answers in the context of CQA, systems must collect personal information and social behaviors, analyze and store the results in a user profile. We take users' interest preference into consideration of Human-centric Personalized Expertise Ranking algorithm design.

Without loss of generality, we generate an interest preference for each user in the system. An user interest preference is represented as $\langle \vec{T}, \vec{W} \rangle$ in which $\vec{T} = (t_1, t_2, ...t_{\mathrm{K}})$ is a vector of interested topics extracted from this user's history of tags in Section 3, where K is the number of topics. $\vec{W} = (w_1, w_2, ...w_{\mathrm{K}})$ is a set of the corresponding interest strength. The first step of the algorithm is to extract an vector of interest score for each user from his or her history of tag usage. Our first assumption of personalization is that questions posted by users of similar interests engaged each other's attention and interest. Hence, we take similarity of users interest preference into re-weighting questioners' scores. As assumed in [5], the level of expertise of the answerers and the quality of the questioners mutually reinforce each other. The second step is to define a collection of answering expertise scores for users: $\mathcal{E} = (E_1, E_2, \ldots, E_{\mathrm{M}})$ and a collection of questioning quality scores for users: $\mathcal{Q} = (Q_1, Q_2, \ldots, Q_{\mathrm{M}})$,where M is the number of unique users for ranking. Mutual reinforcement means that the expertise score of a user depends on the quality scores of the questioners to which he answers, and the quality score of a user depends on the expertise scores of the users who answer his questions. To take time traits of good answerers into algorithm design, we prepare the adjacency matrix A adapted from SPEAR algorithm since the time traits of good answerers to good questioners in the context of CQA is similar to the case that discoverer tend to be faster than followers to bookmark high quality documents in *folksonomy* systems [6].

$$A_{i,j} := \sum_{\ell=1}^{\mathrm{N}} (|\{u|(u, u_j, q_{j_\ell}, t), (u_i, u_j, q_{j_\ell}, t_i) \wedge t_i < t\}| + 1) \tag{1}$$

The cell $A_{i,j}$ is calculated according to all QA records of user u_i to u_j: For u_j's ℓ_{th} question q_{j_ℓ}, u_i is assigned the score of 1 plus the number of users who have answered u_j's ℓ_{th} question q_{j_ℓ} after u_i, and then $A_{i,j}$ is set to sum over all QA scores for N questions posted by u_j. To overcome that the differences between scores are too big, we configured $A_{ij} := C(A_{ij})$ where $C := \sqrt{x}$ is a credit scoring function of A_{ij} in our experiment.

To personalizing the expertise ranking list of user u_i based on his or her topic of interest preference, we re-weight the quality score of user u_j with the similarity coefficient $sim\langle i, j \rangle$.

$$Q_j := sim\langle i, j \rangle \times \sum_{\ell=1}^{\mathrm{M}} E_\ell \tag{2}$$

$$sim\langle i, j \rangle := 1 - JSD(\vec{W}_i, \vec{W}_j) \tag{3}$$

$$E_\ell := \sum_{j=1}^{\mathrm{M}} Q_j \tag{4}$$

The idea behind this approach is to enable higher weight assignments to experts with closer similar interests of specific user u_j so as to make their quality scores and their corresponding answerers's expertise scores to be exemplified accordingly. By contrast, those topic dissimilar questioners' quality scores are shrunk by lower weights and then their corresponding answerer's expertise scores are shed with lower weights correspondingly. $JSD(\vec{W}_i, \vec{W}_j)$ is the Jensen-Shannon Divergence between the two users' interest vectors $\vec{W}_i$ and $\vec{W}_j$, which is defined as:

$$JSD(\vec{W}_i, \vec{W}_j) = \frac{1}{2}(D(\vec{W}_i \| \vec{M}) + D(\vec{W}_j \| \vec{M})) \tag{5}$$

where $\vec{M} = \frac{1}{2}\vec{W}_i + \frac{1}{2}\vec{W}_j$ and $D(\_\|\_)$ in Eq.(5) is the K-L Divergence which is defined as: $D(\vec{W}\|\vec{M}) = \sum_{\ell=1}^{\mathrm{K}} \vec{W}(\ell) \log \frac{\vec{W}(\ell)}{\vec{W}(\ell)}$.

6. EMPIRICAL EVALUATION

To evaluate the performance of Human-centric Personalized Expertise Ranking algorithm we use explicit human rates as "gold standard". By omitting those users posting questions and giving answers fewer than 50 times, we made sure that all sampled users had produced enough contents for ranking their expertise levels. We used each user's individual rates to verify the performance of Human-centric Personalized Expertise Ranking algorithm compared to other non-personalized ones for the corresponding specific user. Three quality metrics of *AskMeFi* used by our paper are shown as follows: (i)*Number of Answers:* The interactive proximity between an answerer and a questioner can be measured by the number of answers this answerer contributed to this specific questioner. In other words, few or no contributions of answers suggests little importance of this answerer for the specific user even if the expertise level of this answerer is very high for others. (ii)*Percent of Best Answers:* The trust of a questioner to an answerer can be roughly estimated by the percent of best answers that the answerer obtained from this questioner. (iii)*Number of Favorites:* Most users of CQA are inclined to favorite or bookmark their interest answers for future reference. In our experiment, we generate an expertise ranking list in which answerers are ranked as decreasing order by their *expertise scores* for each specific questioner, and compare with the ranking of these answerers by their corresponding records of *number of answers*, *number of best answers*, and *number of favorites*. We conducted our experiments of verifying the effectiveness of Human-centric Personalized Expertise Ranking algorithm compared against several authoritive ranking algorithm include: (i) **PageRank**, which propagates expertise scores the question answer network. (ii) **HITS**, which uses an interative approach to distinguish between authority node and hub node. (iii) **Topic-sensitive PageRank**, which performs a topic-specific random walk on linked graph adjusted by users' topic similarity. (iv) **SPEAR**, which uses time traits to identify authorities based on HITS algorithm. Figure 10 shows the statistical correlations between various ranking algorithms and the three quality metrics for 2446 specific users. One can see that SPEAR algorithm which takes time traits of answerers into design obviously outperforms the HITS algorithm in the context of CQA. This observation supports the assumption that good experts are inclined

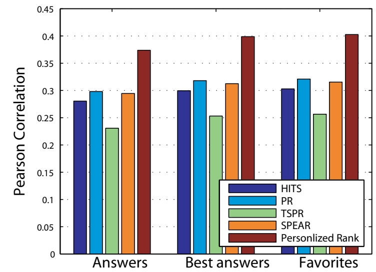
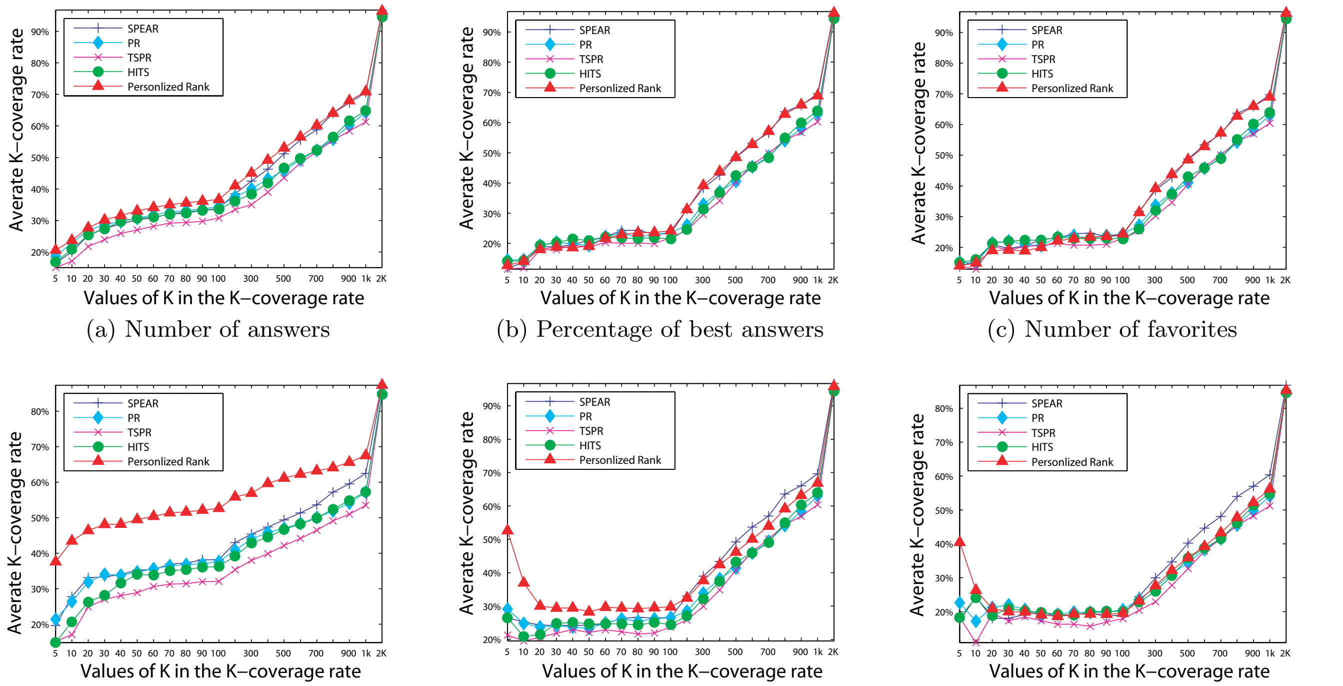


Figure 10: The performance of various algorithms by Pearson Correlation.

to give answers in a quick way. Human-centric Personalized Expertise Ranking algorithm performs the best in all scenarios. Furthermore, to examine that whether or not Human-centric Personalized Expertise Ranking algorithm can identify or approximate each specific users' recognition of the expertise level of his answerers, we further compared the k-coverage rate of various ranking algorithms with evaluation metrics used in [14]. The k-coverage rate between the reference list R and the ranking list E to be evaluated describes the percentage of the first k common elements of R and E. Apparently, the higher the k-coverage rate are for each k, the more close the ranking results E by algorithm is to the reference R by specific users.

$$CR_k = \frac{R_k \bigcap E_k}{R_k} = \frac{\{r_i | 1 \le i \le k\} \bigcap \{e_i | 1 \le i \le k\}}{k} \tag{6}$$

Figure 11(d)-11(f) show the k-coverage rate of various algorithms experimented over whole users by metrics of *number of answers*, *percent of best answers*, *number of favorites* respectively. From the three figures, it is difficult for us to distinguish the performance of various algorithms in sense of average. Hence, we filtered out some typical users producing rich contents to further examine results as follows: We filtered out all users posting more than 100 questions since inactive users posting few cannot draw many good experts to reply so that their preference are hard to be approximated. Figure 11(a) shows the k-coverage rate of various algorithms for active users (beyond 100 QA records). It is obvious that Human-centric Personalized Expertise Ranking algorithm outperforms in identification of active experts contributing many answers for each specific user compared to non-personalized expertise ranking algorithms. In addition, we filtered out active users to check the results for percent of best answers. Similarly, we only choose users giving more than 100 best answers to experiment because many inactive users marking too few don't have reliable experience or standard to justify which is best. In Figure 11(b), we observe that the coverage rate of Human-centric Personalized Expertise Ranking algorithm is higher than others for top-100 expertise ranking. Especially, for top-10, Human-centric Personalized Expertise Ranking algorithm almost identifies half of users' recognized expertise level whereas all non-personalized algorithms can only identify one or two. By contrast, we filtered out typical users who favorite less than 300 and more than 100 since most users have high frequency of favorites in which many users favorite some contents just due to that these contents have been favorite amount of



(a) Number of answers (b) Percentage of best answers (c) Number of favorites

(d) Number of answers (e) Percentage of best answers (f) Number of favorites

Figure 11: K-coverage rate of various ranking algorithms versus users' feedbacks.

times. As a result, too big number of favorites cannot represent the authentic preference of the corresponding users whose actions of favorite might to be just following majority. In figure 11(c), we observe that Human-centric Personalized Expertise Ranking algorithms can correctly identify half of experts for top-10 while the coverage rate of non-personalized results is lower than 0.2.

7. CONCLUSIONS AND FUTURE WORK

In this paper we implemented experiments on demonstrating the presence of homophily and the time traits of good answerers in CQA through exploring their social annotations to benefit future personalized algorithm and application. We presented out idea of Human-centric Personalized Expertise Ranking algorithm based on time traits, topic relevance and authority to readjust the weight of user relationship link graph of CQA, to identify experts and to approximate recognition of expertise level for each specific user. We have shown that our proposed algorithm significantly outperforms other non-personalized expertise ranking algorithms.

In future work, we would like to investigate social trust and reputation involved in friend relationships by various social structures and interactions. This would enable us to gain insights about trust and reputation of users in CQA and to develop reliable and accurate personalized expertise ranking algorithms and applications. We want to have profiling of users preference through integrating user information by connecting various personalized social service used by them. Since personalized social services rely on private and sensitive information about user preferences and personal activities that might allow for identification of the user and activities, it is important to propose distributed and efficient end-to-end privacy-preserving features to be incorporated into the personalized expertise ranking algorithm.

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