# Expert Ranking using Reputation and Answer Quality of Co-existing Users

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**Abstract**: *Online discussion forums provide knowledge sharing facilities to online communities. Usage of online discussion forums has increased tremendously due to the variety of services and their ability of common users to ask question and provide answers. With the passage of time, these forums can accumulate huge contents. Some of these posted discussions may not contain quality contents and may reflect users' personal opinions about topic which may contradict with a relevant answer. These low quality discussions indicate the existence of unprofessional users. Therefore, it is imperative to rank an expert in online forums. Most of the existing expert-ranking techniques consider only user's social network authority and content relevancy features as parameters of evaluating user expertise. But user reputation as a group member of thread repliers is not considered. In this context a novel solution of expert ranking in online discussion forums is proposed. We proposed two expert ranking techniques: The first technique is based on user and their co-existing user's reputation in different threaded discussions, and the second technique is based on user answers' quality and their category specialty features. Furthermore, we extended a technique expertise rank with our proposed features sets. The experimental study based on real dataset shows that the following proposed techniques perform better than existing techniques.*

**Keywords**: *Co-existing user, expertise rank, ExpRank-CRF, ExpRank-COM, ExpRank-FB, ExpRank-AQCS.*

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## 1. Introduction

The World Wide Web (WWW) provides an immense kind of platform to online communities for searching topics and areas of interests. But due to present architecture of WWW it is difficult for users to find topics of their domain within a single web site. News aggregators and social media networks like Digg[1], Reddit[2] and Google news reader[3] are emerging services of web 2.0. These services facilitate users by sharing and recommending stories and news articles. But it is difficult for users to obtain a list of topic specific articles that are similar and relevant because the posted articles may not be chained or linked together in a logical sequence or may not be categorized. In these news aggregators there is no reliable criteria to evaluate the competencies of users whom provide ratings to articles. On the other hand an online discussion forum provides convenience to users whom are interested in thorough topic reading. Structural analysis and visualization of social networking communities yields a better understanding of user authorities in the network, like influential people finding etc. Community network structural properties gives insight about the dynamics of a community, evolving nature of it etc. Systematic and comprehensive analysis and visualization of social network community gives insight into the structural aspects of a social network [7]. Content quality is a major concern in online discussion communities. Due to the presence of poor quality content it is desirable to find topic specific experts so we may recommend a list of experts for user queries. Both document content and social network structures are used as the basic parameters for expert finding [18]. In an effort, a link analysis algorithm PageRank is adapted as expertise rank algorithm [20] for online help seeking or technical communities, the algorithm considers the reputation of users to whom a user answered in java discussion forum, if a user answers people who are also experts then his rank will be boosted. Z-score measure is recommended for finding experts who play active and cooperative roles by providing quality answers have been recommended [10]. Online forums possess a hierarchal structure which consists of a thread and their respective posts or replies. These forum structures possess social network characteristics which may help in expert finding. An expert ranking technique is presented in which topic specific threads and posts have been retrieved through Query likely hood method [15].

Online discussion forums have a thread/post structure, where the thread represents a question asked or topic shared by a question-asker whereas a post is a

[1]http://digg.com/
[2]http://reddit.com
[3]http://news.google.com/

reply/answer or comment to that question. Topics discussed in online forums are grouped and similar in nature due to the forum structure because all replies to a single question or all discussion opinions on a single topic follow a strict hierarchal structure. Therefore, it is easy to find a chain of relevant discussions on some topic. In most of research efforts in expert ranking domain, single user authority or prestige has been considered which include features like the number of answers provided by a user or social network features of a user etc. Users and their co-existing users' reputation has not been considered for ranking experts. User's answer quality and their answering behavior in different categories is also an effective parameter for expertise evaluation. We may achieve better expert rankings by incorporating these reputation and answer quality features. Our contributions are as follows:

- The primary objective of our work is to provide expert ranking techniques for online discussion forums. Initially, extraction of co-existing users (users who co-occur together in different threads as repliers) have been performed using priory algorithm. Details are given in section 5.
- Firstly, an expert ranking technique *ExpRank-CRF* has been proposed. According to this technique, a user will be an expert if theirs and their co-existing user's reputation is high. Content and link based attributes have been used to measure the reputation. Furthermore, we have extended *ExpertiseRank* [20] algorithm with our proposed *ExpRank-CRF*. We named it *ExpRank-COM*. Details are given in sections 6.1 and 6.2.
- Secondly, an expert ranking technique *ExpRank-FB* has been proposed. According to this technique, a user will be an expert if he provides quality answers in specific categories. Content relevancy and category specialty features have been used to measure user expertise. Furthermore, we extended *ExpertiseRank* [20] algorithm with our proposed *ExpRank-FB*. We named it *ExpRank-AQCS*. Details are given in sections 6.3 and 6.4.

## 2. Related Works

In this section, we introduce literature related to expert ranking problem in online forums. We provided details regarding expert ranking techniques based on link and content base features.

Authoritative user identification technique is presented by Bouguessa *et al*. [3] for Yahoo answers based on interactions between asker and answer providers. Several link analysis techniques like PageRank, HITS have been applied and analysed on this data. Crowd sourcing is the process of obtaining ideas, services from large people groups[4] and mostly from online communities. Using crowd sourcing companies may benefit from combined and collaborative efforts of experts. Schall [14] proposed a model DSARank for estimating the relative importance of persons based on reputation mechanisms in collaboration networks. It's a link intensity based ranking model for relevant user's recommendation. Expert finding problem in programming forums is need of community. By knowing experts, programming questions may be forwarded to them.

Li *et al*. [9] proposed an algorithm and a tool G-Finder which performs the question routing decisions to experts. In mapping threads to concepts thread's title, the source code and content has been used. Zhu *et al*. [23] proposed an expert finding framework to rank user's authority in extended-category link graphs. Initially relevance between categories is measured by KL-Divergence and topic model. Yang *et al*. [19] proposed probabilistic generative topic-expertise model for modelling discussion topics with expertise in an online QA services. Furthermore, based on this model a rank is proposed which combined textual and link features for deriving topic specific expertise. Kardan *et al*. [8] proposed a context based link analysis algorithm for expert finding. A user may be involved in online discussions in several contexts like sharing topics, answering questions or a user may ask some questions from experts. Venkataramani *et al*. [17] proposed an approach for expert finding in stack over flow programming forum. Technical programming terms in source code and tags associated with each query are used to mine user expertise. This model then captures expertise based on term and tag relationship. Super edge which is an adaptation of page rank algorithm is proposed. Several indexes have been suggested for super network modelling like index for finding influence during information dissemination, lexical overlap between terms etc.

Zhou *et al.* [22] addressed a problem of directing newly posted questions to relevant area experts in online forums. Three-model framework is proposed to accomplish the task of expert finding. Language models have been constructed based on experts profile and thread's conversation structure. Experts re-ranking has been performed using Page rank algorithm. According to Zhang *et al*. [21] response time for expert posted questions is higher than novice posted questions and if an expert asks a question then it is difficult for novice users to answer expert's questions which causes an expertise gap problem. This is due to fact that novice users have no experience in the specific area and their knowledge level is also very low. Several expertise ranking algorithms proposed including z-degree, in-degree, out-degree, HITS and an adaptation of PageRank algorithm. In a community question answering service, an expert answers a question which is relevant to his filed. Pal *et al*. [12] proposed a probabilistic model to evaluate the existing value of a question. Main attributes for evaluating

[4]http://en.wikipedia.org/wiki/Crowdsourcing

answers quality of a question are number of answers, votes received, answer status, author reputation and content quality. Shahzad *et al*. [16] have used Frequent Pattern (FP) growth and fuzzy for sanitizing sensitive sequential patterns. First, they find frequent patterns from sequential data using monotone and anti-monotone constraints. Then they fuzzily the frequent patterns and hide those patterns that are sensitive. Adhikari *et al*. [1] proposed a generalized approach for mining multiple databases using local pattern analysis. Daud *et al*. [6] presented a temporal and semantics based expert finding technique. Conference influence and time information used together as generalized topic modelling approach for expert finding problem. Zhu *et al*. [24] proposed an expert finding approach in which content and link similarities has been computed to measure the category relevance. Topic-Link based techniques used to measure the user authority across several categories. This has been done on extended category link graphs. Riahi *et al*. [13] recommended a profile based expert finding technique. These profiles are used to suggest experts for a given topic against a user query. Interests base user ranking has been done using Term Frequency and Inverse Document Frequency (tf-idf) and language model. Omidvar *et al.* [11] proposed a context based expert finding technique. Context is measured using WordNet and users ranking has been done using social network analysis techniques.

## 3. Problem Statement

In this section we first introduce definitions of basic elements used in online discussion forums and then formally define the problem for user-reputation based Expert ranking. In this paper, we define:

- Thread: Thread is a question asked by a user or it may be a topic initiated by a user for gaining insight on some topic in an online forum. A thread may consist of many posts.
- Post: Post is a reply or an answer provided by a user in a thread.
- Co-Existing User: Users who reply or co-occur together in two or more threads.
- Definition, (Users-reputation based Expert Ranking): Let $E=\{e_1, e_2, e_3, \ldots, e_n\}$ be the set of expert users. Let $T$ be the set of all threads in which user $U$ has participated, where $T=\{t_1, t_2, t_3, \ldots, t_m\}$ and $U=\{u_1, u_2, u_3, ..., u_n\}$. We say that a user $U_i$ is an expert if he has participated in thread $T_i$ as a $CE_i$ and whose *S-Rep*($U$, $T_c$, $FI_c$, $Cont_{sim}$) and *CE-Rep*(*S-Rep*, *SR*(*CR*)) is high. Where $CE_i$ represent *co-existence* of user with other users, *S-Rep represents self-reputation* score of a user, *CE-Rep* represents reputation score of members with whom he has co-existed in different threads, $T_c$ represents thread count and $Cont_{sim}$ represents content similarity

## 4. Baseline

PageRank [4] algorithm ranks a web page based on the quality of incoming links to that page. The more the number of incoming links to a web page the more will be the page rank of that page, further-more if incoming page has more number of out-going links then its impact will be decreased. PageRank value for a page *a* can be expressed as:

$$PR(a) = \sum k \in S_u \frac{PR(b)}{L(b)} \quad (1)$$

i.e., the PageRank value for a page *a* is dependent on the PageRank values for each page *b* contained in the set $S_u$(the set containing all pages linking to page *a*), divided by the number $L(b)$ of links from page *b*. Based on PageRank idea [4], Zhang [20] proposed an *Expertise Rank* algorithm for online community forum. According to this algorithm, if a user *A* provides answer to a user *B's* question who is a domain expert, than it means that user *A* has more expertise than user *B* because it answered an expert's question. Assume *UserX* has answered questions for users $U_1$, …, $U_n$, then the *Expertise Rank* of *User X* is given as follows:

$$ER(X) = (1-d) + d\left(\frac{ER(U_1)}{L(U_1)} + \ldots + \frac{ER(U_n)}{L(U_n)}\right) \quad (2)$$

Where $ER(X)$ is expertise rank for user $X$, $U_1$ is the user who is answered by $X$, $d$ is a damping factor which is set to .85 and $L(U_i)$ is defined as the total number of users who helped $U_1$, according to this idea, a user will have more expertise if he replies to the questions posted by expert users. User rank will be decreased if he puts too many questions in online forum.

Answer quality has not been considered as a parameter for evaluating user expertise in expertise rank [20]. Furthermore, users and their co-existing user's reputation have not been taken in to account. Both of these factors are effective in expert ranking. We have extended expertise rank [20] technique with our proposed methods. In our extended methods, we set damping factor *d's* value to .85 because we tried different values of *d* like .25 and .65 but it did not make a notable difference.

## 5. Co-existing Users Extraction

For expert ranking problem, first task is to extract co-existing users from threaded discussions. A general forum structure is represented as follows:

Let $F=\{t_1, t_2, t_3, ..., t_n\}$ be the forum containing a set of threads $T=\{t_1, t_2, t_3, ..., t_m\}$, where $T_i$ be the set containing posts $P=\{p_1, p_2, p_3, ..., p_n\}$ where $P_i$ be the post or reply posted by the user $U=\{u_1, u_2, u_3, ..., u_n\}$.

### 5.1. Co-Existing User Modelling

It is defined that co-existing users are group of users who reply together in several threads against user posted questions. Group of co-existing users is modelled as:

Let $R=\{r_1, r_2, r_3, ..., r_n\}$ be the group of users who replied in different threads $T=\{t_1, t_2, t_3, ..., t_n\}$. The group $R$ contains a set of *co-existing* users as $CE=\{r_1.r_2.t_1, r_1.r_2.t_2, r_1.r_2.t_3, ..., r_n.r_k.t_m\}$.

Where $r$ is replier, $t$ is thread and $R$ is the group, $CE$ is co-existing users in each group. Following co-existing user types have been found.

- Co-Existing User as an Answer Provider: These types of users are considered as expert users because they only provide answers and they did not posted any question. In our dataset there are few users who lies in this category.
- Co-Existing User as Asker as well as Answer Provider: These types of users give answers to posted questions but they also asks some questions. This type of users has been handled by our proposed techniques.
- Co-Existing User as Asker-Only: These types of users only post questions in forums. These may be novice people who want to get answers for their questions or to gain insight on some topic of their interest.

For expert ranking, we need to extract all co-existing users from threaded discussions. For extraction, we used apriori algorithm which has been used since long time for finding frequent item sets in transactional databases [2]. In our case apriori algorithm has been applied on a set of 10,000 threads and their respective posts. We obtained 450 forum users who have been found co-existing in different threaded discussions. *Support* measure has been used to check the existence frequency of users in different threads. Minimum obtained *support* was 2 and maximum-*support* was 22. *Support* and *confidence* measures[5] are defines as follows:

$$Support(X \rightarrow Y) = \frac{|X \cup Y|}{n} \tag{3}$$

$$Confidence(X \rightarrow Y) = \frac{Support(X \cup Y)}{Support(X)} \tag{4}$$

In some cases asker-only type users found in their own initiated threads as answer providers. Their appearance in the threads may be due to many reasons such as to clarify some point or they want to appreciate the answer of some expert. Their presence is also possible due to some controversy exist between their point of view and other users.

[5]http://en.wikipedia.org/wiki/Association_rule_learning

## 6. Proposed Expert Ranking Techniques

Two expert ranking techniques have been proposed. Furthermore, we have extended a technique expertise rank [20] with our proposed expert ranking techniques.

### 6.1. ExpRank-CRF

*ExpRank-CRF* is based on co-existing user reputation features; it is comprised of four distinct reputation features. Features are illustrated as follows:

#### 6.1.1. Threads Support Count for User

The motivation behind this feature is that the higher the user co-exists as a replier or answerer in different threads, the higher the chance that he will remain active overall. The support ($U$) of a user is defined as the percentage of threads which contain the user as co-existing.

Let $T_c$ be the thread support count of each user.

$$T_c = \sum_{i=1}^{n} T_i + \sum_{i=1}^{m} CE_i \tag{5}$$

Where $T_c$ is thread count, $CE_i$ *represents set of* co-existing users, Let $\psi$ be the support threshold. If $T_c >= \psi$ for a user $U=\{u_1, u_2, ..., u_n\}$ then $u_i$ is the active participant in thread $T=\{t_1, t_2, ..., t_m\}$, where $\psi=2$.

#### 6.1.2. Frequent Item-Sets in which User Co-Exist

The purpose of counting total frequent item-sets is to count the frequency of user's groupings or item-sets. Based on this feature, it is expected that higher the user appeared in different item-sets, the higher the chance that he will be an expert. It can be formulated as:

Let $F$ be the total frequent item-sets in which users have been co-existing. $F=\{Sup\ (U_i, T_i, CE_i)\}$, where $Sup\ (U_i, T_i, CE_i)$ is the support count of threads in which user has been co-existing, $U_i$ is the user set, $T_i$ *is* thread set, $CE_i$ is the set of *co-existing* users. Let $\alpha$ be the threshold value for $F$. If $Sup\ (U_i, T_i, CE_i) >= \alpha$ *then* $(T_i, CE_i)$ would be considered frequent. Here, we set $\alpha=2$ because only those users will be selected who found co-existing in 2 or more frequent item sets.

#### 6.1.3. Semantic Similarity Among Posts of Co-Existing Users for a Given Topic

Content quality is an effective way to evaluate a user expertise, therefore in our case content quality of posts for respective threads has been considered as a feature. It is expected for co-existing users that, if the content similarity between their post contents in different threads is similar or nearly equal, then those users may have common domain of interest and have expertise in that area. It is formulated as follows:

Let $S$ be the set of semantic similarity scores of *co-existing* users $C_r$*'s* post content in their respective threads. i.e., $S=\{S_1Cr_1, S_2Cr_2, S_3Cr_3, ..., S_nCr_m\}$. If $S_nCR_m>=\beta$ then the co-existing users have same area of expertise and have highly relevant content for a given question or topic.

Although, cosine similarity has been extensively used in past research and gave better results but it only considers lexical overlap between documents. Due to this limitation, the context in discussion's content is totally ignored. It give rise to polysemy problem therefore semantic similarity techniques are preferred for evaluating content overlap between discussions. We computed semantic similarity between different post contents of different users. We used an algorithm proposed by Leacock-Chodorow [5]. This algorithm defines a similarity measure which is based on distance of the concepts in the WordNet IS-A hierarchy.

#### 6.1.4. Co-Existing User Reputation

Rank of users is boosted if their co-existing users have high reputation. Initially we compute the reputation of each user individually. Users reputation have been computed by adding their scores of thread support Equation 5, frequent item sets in which they co-exist section 6.1.2 and semantic similarity score of their posts section 6.1.3. It is illustrated as follows:

$$U-rep = Sup(Threads) + Count(Freq - itemsets) + Sim(Post) \tag{6}$$

Where *U_Rep* is user reputation score of each individual. *Sup* is thread support, *Count* is frequent item-sets count, and *Sim* is semantic content similarity score between co-existing users posts for each thread in which they appeared.

For computing user expertise based on their co-existing users reputation, *U_Rep* score Equation 6 for each user has been added to their co-existing users reputation score. It is illustrated as follows:

$$ExpRank_{CRF} = \sum_{i=1}^{n} U_{rep}(U_i, U_{ci}) + U - rep \tag{7}$$

*ExpRank-CRF* is user's expertise score based on the reputation of their co-existing users. Here, *U_Rep*is reputation score for each user which is computed in Equation 6 and $\sum_{i=1}^{n} U_{rep}(U_i, U_{ci})$ is the summed reputation score of all other users who co-exist with this user. This score is computed based on *U_Rep* score Equation 6. Where $U_i$ represent user who has participated in a thread *i* and $U_{ci}$ represents co-existing users for thread *i*.

### 6.2. ExpRank-COM

*ExpRank-COM* is a proposed extension of the *ExpertiseRank* [20] algorithm with our proposed *ExpRank-CRF* technique Equation 7. Notion behind the *ExpRank-COM* is to enrich *ExpertiseRank* [20] technique with our proposed *ExpRank-CRF* features Equation 7. According to this technique, user's expertise are not computed only based on the total number of question-askers to whom they answer but it also includes the reputation of question-askers who co-exists in different threads. If question-askers have high expertise and their co-existence reputation is also high then the rank of user will also be high who answers their questions. It is also assumed that such question-askers are of similar domain and they are actively participating in a collaborative way. So, both scores (*ExpRank-CRF* and *ExpertiseRank*) of a user have been combined by multiplying user reputation score (*rep*) with their *ExpertiseRank* score, we named it *ExpRank-COM*. It is illustrated as follows:

$$CR(A) = (1-d) + d\left(\frac{ER(U_1)}{C(U_1)} * rep_1 + ... + \frac{ER(U_n)}{C(U_n)} * rep_n\right) \tag{8}$$

Where *CR*(*A*) is *ExpRank-COM* score for user *A*, *ER* is *ExpertiseRank* score of user $U_1$ who is answered by user *A*, *rep* is *ExpRank-CRF* score of user $U_1$ computed in Equation 7, *C* is the total number of users who helped user *A*. and *d* is damping factor whose value is set to .85.

### 6.3. ExpRank-FB

According to this technique, a user is expert if he provides quality answers in topic specific categories. In this regard following features have been proposed:

- f1. Count User's Highly Similar Replies for each Thread: It is expected that, user expertise will be high if semantic similarity score between his post contents and thread titles is high. This feature is computed for all threads in which users exist using WordNet [5].
- f2. Mention Links: It is expected that, if users mention links in their post contents, their answer quality will be high as they provided an external source to support their answers.
- f3. Answer Count in each Category: It is expected that, if number of replies by a user in a specific category is high, he will be considered as an expert in that domain.
- f4. Mention Quotes: Existence of quotes in user's post contents shows that they provide quality answers.
- f5. Answer Count: The maximum the user will provide answers to questions. The higher the possibility of a user to be an expert.
- f6. Answer Length: It is expected that if a user provide answers with good length than it means he produces well explained answers.

In order to rank experts, features scores have been added for all users, it is illustrated as:

$$ExpRank_{FB} = \sum_{i=1}^{n} (U_i, f_i) \tag{9}$$

Where *ExpRank-FB*: Is features based expert ranking which is computed by adding answer quality and user's category specialty features score for each user, $f_i$: Is the feature score for user $U_i$.

### 6.4. ExpRank-AQCS

*ExpRank-AQCS* is a proposed extension of *ExpertiseRank* [20] algorithm with our proposed *ExpRank-FB* technique Equations 9. Notion behind the *ExpRank-AQCS* is to enrich *ExpertiseRank* [20] by adding answer quality and category specialty features score of a user to his *ExpertiseRank* score. According to this technique, a user's expertises are not only based on the total number of question-askers to whom he answers but it also includes the question-asker's answer quality and their category specialty score. So both scores (*ExpRank-FB* and *ExpertiseRank*) of a user have been combined by multiplying user's answer quality and category speciality score with their *ExpertiseRank* score, we named it *ExpRank-AQCS*. It is illustrated as follows:

$$AQCS(A) = (1-d) + d\left(\frac{ER(U_1)}{C(U_1)} * f_1 + \dots\dots\dots + \frac{ER(U_n)}{C(U_n)} * f_n\right) \tag{10}$$

Where *AQCS*: Is *ExpRank-AQCS* score for user *A*, *ER*: Is *ExpertiseRank* of user $U_1$ who is answered by user *A*, *f*: Is a summed features (answer quality, category speciality) score for each user computed as *ExpRank-FB* in Equation 9, *C* is the total number of users who helped user *A*. *d* is damping factor whose value is set to .85.

## 7. Experiments

In this section we describe dataset, performance measures and results.

### 7.1. Dataset

We used a public BBC message board's discussions dataset from cyberemotions[6]. BBC data set consist of different categories including world news, UK news, media and religious topics. It was a four year data. There were 97,946 threads and 2,592,745 posts/comments. Total 18,000 users have been participated in these online discussions. For expert ranking problem, based on our requirement we selected forum users who provided maximum replies for questions or topics. Initially, we selected users who participated in 10,000 threads. There were 1500 users who participated in these threaded discussions. Out of 1500 users, there were 450 users who co-exist in different discussions. Labelling a big dataset was a major problem. Therefore, human judgments for labelling the dataset have been taken. For labelling purpose, Zhang [20] categorized users into five expertise levels. We have adapted their rating criteria for labelling users as experts in our dataset. Table 1 shows the details:

Table 1. Expertise rating levels.

| Level | Category | Description |
|---|---|---|
| 5 | Experts | Highly informative and can timely answer critical questions. |
| 4 | Professional | Can answer and discuss domain specific topics well. |
| 3 | User | Can answer general questions and have some basic concepts. |
| 1-2 | Beginner or Amateur | Just starting to know about general issues or want to gain insight on some topic. |

Because most of our data set was consist of world news and sports topics, therefore we take help from two human raters to label these 450 users. These raters were from Broadcast Journalism domain.

### 7.2. Performance Measures

Spearman's rho and Kendall's Tau are the common correlation measures[7]. However, weak ordering are not handled well by Spearman correlation (weak ordering means that ranking has multiple items and neither item in the list is preferred over other item). In our case we have weak ordering because multiple users have been assigned same rating score by human raters. On the other hand Kendall's Tau gives equal weight to any interchange of equal distance, regardless of where it occurs [20]. We selected Kendall's Tau which is a better metric. Upon receiving 450 users' ratings from human raters the human rater's reliability have been checked by intra-rater correlation. The Kendall's Tau distance between the two human raters was found 0.773, and the Spearman's rho correlation coefficient was 0.791 ($p$<0.01), which is sufficiently a high rate of inter-rater correlation.

### 7.3. Results and Discussion

In our case we computed both Kendall's Tau and Spearman's rho correlations for both proposed and extended methods. Top-50 and top-100 ranked users have been selected for measuring correlations. Figures 1, 2, 3 and 4 show the correlations scores for baseline, proposed and extended methods. It is evident from the Figures 1, 2, 3, and 4 that proposed and extended techniques have achieved a better and significant correlation score against human-assigned score. This shows the strength of proposed methods. Here, we discuss some main methods comparisons.

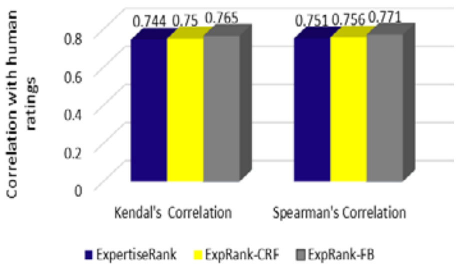


Figure 1. Correlations for top-50 users.

[6]http://www.cyberemotions.eu/data.html

[7]http://en.wikipedia.org/wiki/Rank_correlation

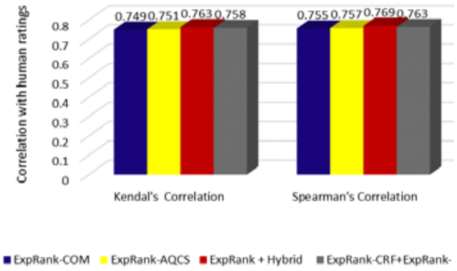


Figure 2. Correlations for top-50 users.

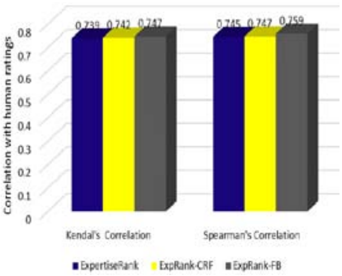


Figure 3. Correlations for top-100 users.

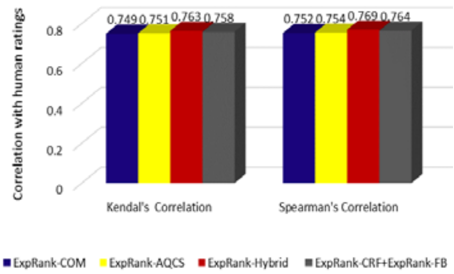


Figure 4. Correlations for top-100 users.

- *ExpertiseRank* vs. *ExpRank-FB*: Kendall's correlation between human experts is 0.773. From Figures 1 and 3, it is evident that for both top-50 and top-100 users, proposed method *ExpRank-FB* which is based on answer quality and category specialty features, outperformed both expertise rank and *ExpRank-CRF* methods. This shows that answer quality and category specialty features are very effective in expert ranking. User's high content overlap showed that these are from same domain and their point of view on given topic is also same. Additionally, answering in specific categories shows their domain specificity.
- *ExpertiseRank* vs. *ExpRank-CRF*: From Figures 1 and 3, it is evident that for both top-50 and top-100 users, proposed *ExpRank-CRF* method performed better than *ExpertiseRank*. This is due to the effect of adding user's co-existing reputation score to his self-reputation score.
- *ExpertiseRank* vs. *ExpRank-CRF+ExpRank-FB*: It is evident that for both top-50 and top-100 users, proposed hybrid method (*ExpRank-CRF +ExpRankCRF*) performed better and their correlation score with human rating is 0.758. Proposed features for these hybrid methods showed that user reputation, co-existing reputation and answer quality features are best for expert ranking problem.

*Hybrid method* (*ExpertiseRank + Hybrid*):

From Figures 2 and 4, it is evident that for both top-50 and top-100 user's proposed Hybrid method (*expertise rank+Hybrid*) outperformed all other methods. It is due to fact that characteristics of all proposed methods have been combined with baseline expertise rank method.

For all methods Spearman's rho shows relatively higher correlation scores than Kendall's, but for each result it shows approximately same ranking differences as Kendall's tau.

## 8. Conclusions and Future Work

This paper proposes expert ranking techniques for online discussion forums. These techniques considers users and theirs co-existing users reputation in different threads along with their answer quality and category speciality features. Although, proposed techniques show better performance, these techniques may be further improved by incorporating credibility of user's content through computing n-gram similarity between thread title and posts. Other features like counting nouns, verbs, stop words and non-stop words may also be significant and may be used in identifying quality answer providers. Currently, we proposed these techniques for online news discussion forum but these may be extended in future for ranking experts in online programming forums as well.

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