Applying Personal and Group-based Trust Models in Document Recommendation

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Abstract: Collaborative filtering (CF) recommender systems have been used in various application domains to solve the information-overload problem. Recently, trust-based recommender systems have incorporated the trustworthiness of users into CF techniques to improve the quality of recommendation. Some researchers have proposed rating-based trust models to derive the trust values based on users' past ratings of items, or based on explicitly specified relations (e.g. friends) or trust relationships. The rating-based trust model may not be effective in CF recommendations, due to unreliable trust values derived from very few past rating records. In this work, we propose a hybrid personal trust model which adaptively combines the rating-based trust model and explicit trust metric to resolve the drawback caused by insufficient past rating records. Moreover, users with similar preferences usually form a group to share items (knowledge) with each other, and thus users' preferences may be affected by group members. Accordingly, group trust can enhance personal trust to support recommendation from the group perspective. Eventually, we propose a recommendation method based on a hybrid model of personal and group trust to improve recommendation performance. The experiment result shows that the proposed models can improve the prediction accuracy of other trust-based recommender systems.

1 INTRODUCTION

Recommender systems have been, and are currently applied in various applications to support item (e.g. movies or music) recommendation (Resnick et al., 1994); (Schafer et al., 2007), solving the information-overload problem by suggesting items of interest to users. In the various recommendation methods, collaborative filtering (CF) (Konstan et al., 1997) is the most widely and successfully used method in diverse applications. It predicts user preferences for items by considering the opinions (in the form of preference ratings) of other similar (e.g. "like-minded") users. Thus, personalized recommendations are made according to the preferences of similar users.

Recently, trust-based recommender systems (Lathia et al., 2008); (O'Donovan and Smyth, 2005); (Liu et al., 2011) have incorporated the trustworthiness of users into CF techniques to improve the quality of recommendation. There are two categories of calculating trust scores (trustworthiness) between users. One category of trust-based system computes the trust scores based on users' past ratings on items (O'Donovan and Smyth, 2005), while the other uses an explicitly specified trust metric to derive the trust values based on explicitly specified relations (e.g. friends) or trust relationships. Users need to specify explicitly whom they trust and how much they trust each other.

Although conventional trust-based CF systems have proposed rating-based trust models (Hwang and Chen, 2007, O'Donovan and Smyth, 2005) or explicitly specified trust metrics (Massa and Avesani, 2004); (Massa and Avesani, 2007a); (Massa and Avesani, 2007b); (Massa and Bhattacharjee, 2004) to derive the trustworthiness of users, they do not investigate how to combine the rating-based trust model with an explicit trust metric. In this work, we propose a personal trust model that adaptively combines the rating-based trust model and explicit trust metric to resolve the drawback caused by insufficient past rating records. We derive the trust values between two users based

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on their explicitly specified role relations. Such explicit relationship trust can complement the traditional rating-based trust model for improving the reliability of trust values.

Moreover, users with similar preferences usually form a group to share items (knowledge) with each other, and thus users' preferences may be affected by group members. Accordingly, group trust can enhance personal trust to support recommendations from group perspective. Nevertheless, conventional trust-based CF systems do not address trust computation by considering both personal and group trust. Therefore, we propose a hybrid trust model, which integrates personal and group trust to improve the performance of collaborative filtering. From the group-based trust metric we can find trustworthy recommenders from the group's point of view. Such a group perspective may be important because it can complement the trustworthiness of personal perspective, in particular, when an individual is not sure who to trust. In the group-based trust, we define a role-weight for each user to represent the importance degree in the group. By adopting the role-weight value, the group-based trust can be aggregated from group members' trust values. On the other hand, the group-based trust focuses on the majority of the group's opinions, which might ignore the personal perspective. Accordingly, our proposed hybrid trust model combines personal trust and group-based trust models to integrate the merits of both perspectives. The trust values derived from our trust models are regarded as weightings in the collaborative filtering (CF) method to identify the trustworthy recommenders for predicting document ratings. Our experiment results show that the proposed trust model can improve the prediction accuracy of the CF method in comparison with other trust-based recommender systems.

This paper is organized as follows: We present the related work in Section 2. An overview of our trust computation models from the personal and group perspectives and recommendations based on these trust models are presented in Section 3. The experiment results and evaluations are presented in Section 4. Conclusions are presented in Section 5.

2 RELATED WORK

This section introduces the related works of trust-based CF recommender systems.

2.1 Reputation Trust based Recommender System

Reputation trust is a more quantitative assessment, which allocates a score to a specific object or person within a particular context. An individual's reputation trust is collected from the members in the community. Thus, reputation trust is referred to as "expert" or "professional degree". Cho *et al*. (Cho et al., 2007) and Kim et al. (Kim et al., 2008) judge whether someone is qualified as an expert by adopting Riggs's model (Riggs and Wilensky, 2001), which assigns scores to reviewers based on how close their ratings are to the average ratings. For example, Kim *et al*. (Kim et al., 2008) use *Epinion.com* data to derive the degree of trust based on users' expertise in categories, which is derived based on the quality of reviews and reputations of review raters/writers.

Several researchers propose reputation trust as an auxiliary factor in the recommendation phase. O'Donovan and Smyth (O'Donovan and Smyth, 2005) claim that accurate recommendation in the past is important and reliable, and they propose profile-level trust and item-level trust derived from user rating data. Both profile-level trust and item-level trust can be used in the recommendation phase.

2.2 Relationship Trust based Recommender System

Relationship trust relies on qualitative measurements dependent on social network connections. A user decides his/her trust of another based on some private knowledge which was gained through past interactions, or explicitly specified relationships. Thus, relationship trust metrics consider the truster's subjective opinions when predicting the trust value which s/he places on the trustee. *Epinions.com* allows users to express their trust opinions by adding a reviewer into their Web of Trust list or Block list, according to whether the reviewer's reviews are valuable. Massa and Avesani (Massa and Avesani, 2007b) call this kind of trust opinion as local trust (relationship trust), and take advantage of the Web of Trust in *Epinions.com* to balance the collaborative recommender system's defects (Massa and Avesani, 2004); (Massa and Avesani, 2007a); (Massa and Bhattacharjee, 2004).

Even though relationship trust presents an improvement on traditional CF recommender systems, the direct relationship trust data is not usual in most recommender systems, and it is difficult to collect. Besides this, the quality of a reviewer's

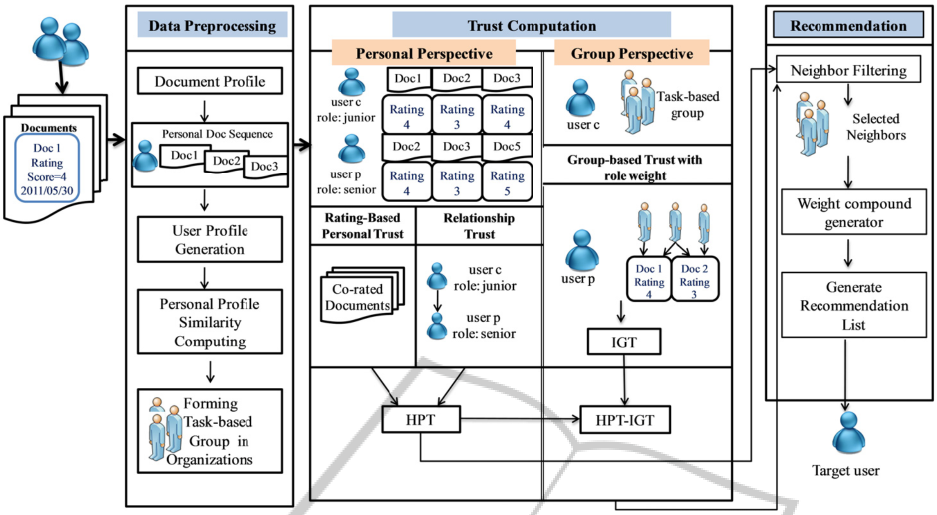

Figure 1: The framework of hybrid personal and group trust model for recommendation.

review cannot always maintain consistency, and the relationship trust may vary according to the reviewer's quality and the user's interest. Hwang and Chen (Hwang and Chen, 2007) consider the truster's subjective opinions to obtain more personalization effects when predicting the trust value which s/he places on the trustee. In their research, the experiment evaluation shows that the personal (local) trust-based CF method performs better than the global trust-based CF method. In this work, we also apply such relationship trust in our proposed method for making recommendations.

3 HYBRID TRUST MODELS AND DOCUMENT RECOMMENDATIONS

3.1 The Framework of Hybrid Trust Models for Recommendation

In this work, we propose hybrid trust models by combining personal and group trusts. Then, to improve the recommendation quality, these trust models are used in our recommendation methods to select trustworthy neighbors for target users. Figure 1 shows the framework of our proposed hybrid trust model and the CF recommendation methods, based on the proposed model. There are three phases in our framework:

Data Preprocessing: Documents are preprocessed by *tf-idf* approach (Salton and Buckley, 1988) to generate document profiles describing the key contents of documents. According to users' access behavior and document profiles, user profiles are generated to represent users' information needs. Users with similar user profiles are clustered into a task-based group.

Trust Computation: We propose trust models from both the personal and group perspective. From the personal perspective, the rating-based personal trust and relationship trust are considered in the trust computation. The rating-based personal trust is derived from users' ratings on co-rated documents, while the relationship trust is explicitly assigned by experts according to the role relation between users. These two kinds of trust are adaptively combined as a hybrid personal trust (HPT) based on the number of co-rated items between two users. With a greater number of co-rated documents, the rating-based personal trust is more reliable, and thus more weight is assigned to it. Moreover, from the group perspective, the item-level group trust (IGT) is derived by aggregating the opinions of the target user's group members with the consideration of users' role weights. In addition, we also propose a hybrid trust model, i.e., HPT-IGT, which combines both personal and group trust models to derive a trust value from the personal and group perspectives. These trust models will be discussed in Section 3.3.

A user's rating of a document usually reflects the user's perception of the relevance or usefulness of the document content to his/her information needs. However, the proposed personal trust model ignores the opinions of other group members. From the group perspective, group trust, i.e., IGT, mainly focuses on the majority of the opinions of group users rather than an individual user. However, it may ignore personal information in computing trust.

Conventional trust-based recommendation systems have not addressed how to take both personal and group aspects into account to derive a reliable trust prediction. Accordingly, the hybrid model of personal and group trusts is proposed for trust computation.

Recommendation: According to the trust models in the previous phase, the obtained trust values are incorporated into our recommendation methods to discover the trustworthy recommenders, in order to enhance the performance of recommendations, and facilitate knowledge sharing. Users with high trust values are identified as trustworthy recommenders, and then they are selected as neighbors for our target users. The proposed CF methods derive the predictions of document ratings for the target user based on the trust values and the document ratings of neighbors. Documents with high predicted ratings are used to compile a recommendation list.

3.2 Document Profiling and User Clustering

In order to group similar users as a task-based group, we analyze users' information needed to generate document profiles and user profiles first. Then, similar users can be clustered into a group by measuring the similarities of user profiles. Two profiles, a document profile and a user profile, are used to represent a document and a user's preference, respectively.

A document profile can be represented as an *n*-dimensional vector composed of terms and their respective weights derived by the normalized *tf-idf* approach(Salton and Buckley, 1988). Based on the term weights, terms with higher values are selected as discriminative terms to describe the characteristics of a document. The document profile of d_j is comprised of these discriminative terms. Let the document profile be $DP_j = < dt_{1j} : dtw_{1j}, dt_{2j} : dtw_{2j}, \cdots, dt_{nj} : dtw_{nj} >$, where dt_{ij} is the term i in d_j, and dtw_{ij} is the degree of importance of a term i to the document d_j, which is derived by the normalized *tf-idf* approach. The document profiles are used to generate a user's profile.

Similarly, a user profile is generated by aggregating the profiles of documents that the user has accessed. Let $UP_x = < ut_{1x}:utw_{1x}, ut_{2x}:utw_{2x}, \ldots, ut_{nx}:utw_{nx} >$ be the profile of a user x, where ut_{ix} is a term in the user profile, and utw_{ix} is the weight of the term. These terms are chosen from all document profiles of the user, according to their term weights. Additionally, we adopt the *K*-means clustering algorithm (Jain et al., 1999) to group users with similar profiles into clusters by using the *cosine* measurement. Note that a cluster is a task-based group where users have similar task-related knowledge and preferences.

3.3 The Hybrid Trust Models

We will elaborate on the proposed hybrid of trust models, which take both the personal and group perspectives into account, in this section. In this work, "target user" indicates the user who is recommended, while "recommender" denotes the user who recommends items to the target user.

3.3.1 The Rating-based Personal Trust

The rating-based personal trust is derived from two users' past ratings on co-rated documents by adopting Hwang and Chen's (Hwang and Chen, 2007) trust computation method. Note that the document rating, which is given by a user on a scale of 1 to 5, indicates whether a document is perceived as useful and relevant to the user's task. In the conventional trust model (Hwang and Chen, 2007); (O'Donovan and Smyth, 2005), it calculates the ratio of accurate predictions made according to past ratings when counting how much the target user may trust the recommender. Generally, a recommender is more trustworthy if s/he has contributed more precise predictions than other users. Similar to the conventional trust computation model, we also use a simple version of Resnick's prediction formula (Resnick et al., 1994) to calculate a target user c's predicted rating of a document d_k, $\hat{p}^{p}_{c,d}$, which is derived from a recommender p's rating of d_k, as defined in Eq. (1):

$$\hat{p}^{p}_{c,d_k} = \overline{r_c} + \left(r_{p,d_k} - \overline{r_p} \right), \tag{1}$$

where $\overline{r}_c$ and $\overline{r}_p$ refer to the mean ratings of target user c and recommender p; and r_{p,d_k} is p's rating of document d_k. If $\hat{P}^{p}_{c,d_k}$ is close to the real rating score of user c on d_k, i.e., r_{c,d_k}, we conclude that both the target user c and the recommender p have a similar perspective on document d_k. The more similar the perspective, the more trust they have, as illustrated in Eq.(2):

$$T^{d_k}_{c,p} = 1 - \frac{\left| \hat{P}^{p}_{c,d_k} - r_{c,d_k} \right|}{M}, \tag{2}$$

where $T^{d_k}_{c,p}$ is the pure trust value between target user c and recommender p pertaining to document d_k that is derived from the rating data, and M is the range of the rating score, which equals the difference of the maximum and minimum rating scores.

We adopt Hwang and Chen's (Hwang and Chen, 2007) trust model to calculate the rating-based personal trust by considering all items that are co-rated by recommender p and target user c, as defined in Eq.(3):

$$PT_{c,p}^{ra} = \frac{1}{\left|I_c^d \cap I_p^d\right|} \sum_{d_k \in \left(I_c^d \cap I_p^d\right)} \left(1 - \frac{\left|\hat{P}_{c,d_k}^{p} - r_{c,d_k}\right|}{M}\right), \tag{3}$$

where $PT_{c,p}^{ra}$ is a trust degree of the rating-based personal trust that represents how much a target user c trusts the recommender p; I_c^d / I_p^d is a document set of target user c / recommender p; M is the range of the rating score, which equals the difference of the maximum and minimum rating scores; $\hat{p}_{c,d}^{p}$ is a predicted rating on a document d_k of target user c, which is derived from a recommender p's rating of d_k; and r_{c,d_k} is the actual rating score of user c on d_k. By counting $PT_{c,p}^{d_k}$ from the co-rated document set, we derive the average trust value. With more co-rated documents, the trust degree of the rating-based personal trust is more reliable.

However, if two users have no co-rated documents, the result is no direct relationships between them; the rating-based personal trust is unreliable to represent the trust relation between these two users. Thus, to enhance the prediction ability for the personal trust model, we consider the relationship trust based on two user's roles in computing personal trust. The detail is illustrated in Section 3.3.2.

3.3.2 The Hybrid Personal Trust (HPT)

To resolve the limitation in the rating-based personal trust, we propose the hybrid personal trust (HPT) model, which adaptively combines rating-based personal trust and relationship trust based on the number of co-rated documents between two users. The rating-based personal trust is derived from users' ratings on the co-rated documents by adopting Hwang and Chen's (Hwang and Chen, 2007) trust computation method, illustrated in Section 3.3.1. The relationship trust is measured according to the role relationship between two users. A user is usually assigned a specific role when he/ she participates in an organization or group. Because there are various roles, the relationships and trust reliability among these roles may differ. For example, a junior user generally trusts a senior user more than they would another junior, since senior users have more knowledge and experiences of tasks. Thus, the value of the relationship trust between these two roles, i.e., junior-to-senior, should be higher than that of senior-to-junior.

Because of the relationship trust, HPT can adaptively provide a precise prediction of trust based not only on co-rated documents, but also on users' role relationships. It also can resolve the problem that insufficient co-rated documents could cause an unreliable prediction of rating-based personal trust. The model which adaptively integrates the rating-based personal trust and the relationship trust is proposed and defined in Eq.(4):

$$HPT_{c,p} = \alpha \times PT_{c,p}^{ra} + (1-\alpha) \times PT_{c,p}^{rel}, \tag{4}$$

where $HPT_{c,p}$ is a hybrid personal trust for the target user c with respect to recommender p; $PT_{c,p}^{ra}$ is the rating-based personal trust for the user c, derived from the co-rated documents between user c and p; $PT_{c,p}^{rel}$ is the relationship trust for the target user c based on the role relation between user c and p; and α, which ranges from 0 and 1, is used to adaptively adjust the relative importance of the rating-based personal trust (i.e., $PT_{c,p}^{ra}$), with respect to the relationship trust (i.e., $PT_{c,p}^{rel}$).

The value of α is adaptively computed based on the number of co-rated documents between two users. It is defined as $\alpha = m/N$ if $m < N$, and $\alpha = 1$ if $m \geq N$, where m is the number of co-rated documents between target user c and recommender p; and N is a pre-specified value, and is an appropriate number of co-rated documents which is used to determine the reliability of rating-based personal trust. The more documents the target user c and recommender p have accessed and given ratings, the more reliable the rating-based personal trust is. That is, with more co-rated documents, the rating-based personal trust is more capable of inferring the personal trust for the target user c.

3.3.3 Item-level Group Trust (IGT)

From the group perspective, the item-level group trust (IGT) method is proposed to predict a trust value of a user, i.e., a recommender, on a specific item. In task-based environments, users with similar preferences or information needs for task-related knowledge may form a group. In the same group, a target user usually has preferences similar to his group members', such that a recommender trusted by his group members may also be trusted by the user. Accordingly, a user trusted by the majority of the target user's group members is more likely to be a trustworthy recommender for providing reliable recommendations to the target user. Moreover, the preferences of users in different groups may be different; that is, the opinions of the target user's group may differ from those of other groups; thus the trust values derived from the opinions of the majority of all users without considering group perspective may not be appropriate for finding trustworthy recommenders for the target user. Traditional item-level trust does not take the group perspective into account.

Therefore, we propose the IGT model to infer the trust value of the target user's group on a recommender for a specific document by aggregating the opinions of the target user's group members. Additionally, since users have different task-related knowledge and experience, each user is assigned an appropriate role in performing a task. Similar to the relationship trust described in Section 3.3.2 , the role weight is also assigned by experts according to the role influence in the group. The trust value can be used to indicate how much a user is trusted by a target user's group members, from the group perspective.

IGT defined in Eq. (5) is used to predict a group trust value for a recommender on a specific document. We take not only the pure trust between two users on a specific document, but also users' role weights into account. The group trust of group U_g with respect to recommender p is derived by taking the weighted average of the pure trust values of predictions made for document d_k, and the role weights of users. Let $IGT_{U_g,p}^{d_k}$ be a group U_g's group trust on recommender p for document d_k:

$$IGT_{U_g,p}^{d_k} = \frac{\sum_{u \in U_g} \left(1 - \frac{\left|\hat{P}_{u,d_k}^{p} - \mathrm{r}_{u,d_k}\right|}{M}\right) \times W_{u,U_g}^{Role}}{\sum_{u \in U_g} W_{u,U_g}^{Role}}, \tag{5}$$

where U_g is a task-based group to which target user c belongs, and W_{u,U_g}^{Role} is the role weight of user u to the group U_g. The IGT model can be used to identify trustworthy recommenders, who have higher role weights in a group and similar opinions to a specific document, for a target user from the group perspective. Such a group perspective may be important, because it can complement the trustworthiness of the personal perspective, in particular, when an individual is not sure who to trust.

3.3.4 The Hybrid of HPT and IGT (HPT-IGT)

In this section, we propose a hybrid trust model of HPT and IGT (HPT-IGT), which linearly combines hybrid personal trust (HPT) and item-level group trust (IGT). It takes not only the pure trusts between users, but also the role weights into account. However, HPT ignores other users' opinions because it mainly exploits the opinions of two users, i.e., the ratings on the co-rated documents, to obtain the personal trust value. Besides, IGT computes a user's group trust value for a particular document from group users' opinions. That is, this kind of trust value is derived from the group perspective, which can complement the trustworthiness of personal perspective, especially when an individual has very few rating data and is not sure who to trust. However, it neglects the personal trust between users. Therefore, in order to obtain a reliable trust value, both HPT and IGT are integrated as a HPT-IGT model for trust computation.

Let $HT_{c,p}^{H,d_k}$ be a trust value of target user c on recommender p for the document d_k, which is derived by linearly integrating the HPT and IGT models, as defined in Eq. (6). This value represents a trust degree that a target user c trusts the recommender p on document d_k:

$$HT_{c,p}^{H,d_k} = \beta \times HPT_{c,p} + (1-\beta) \times IGT_{U_g,p}^{d_k}, \tag{6}$$

where $HPT_{c,p}$ is a hybrid personal trust derived from the HPT model to predict target user c's trust value on recommender p; $IGT_{U_g,p}^{d_k}$ is the trust value of target user c's group U_g on recommender p for document d_k, derived from the opinions of group U_g by using the IGT model; and β is the weighting to adjust the relative importance of the trust values of the HPT and IGT models. The value of β is on a scale of 0 to 1. From both personal and group perspectives, the trust value on a recommender is derived by not only the opinion of a target user, but also by those of the target user's group members. Therefore, we will apply the HPT-IGT model to our recommendation methods in determining the trustworthy recommenders for improving the quality of recommendations. The details will be discussed in the next section.

3.4 Recommendations with Personal and Group Trust Weighting

To provide accurate recommendations for a target user, the trust values between the target user and recommenders, as illustrated in Section 3.3, are used to select the trustworthy recommenders (or neighbors), and then applied in the prediction formula as weightings to derive the predicted ratings for documents. Let *NS* be a neighbor set; *TM* be the proposed trust models to predict a trust degree of recommender *p* from the personal and group perspective; *TM* may be $HPT_{c,p}$, $IGT^{d_k}_{U_g,p}$, and $HT^{H,d_k}_{c,p}$, which represents one of our proposed trust models. Based on these proposed trust models, different trustworthy users are selected as recommenders for a target user.

In this section, we propose a document recommendation method based on our proposed trust models. The recommendation methods utilize the personal/group/hybrid trust values as weightings. Users whose trust values are more than or equal to a specified threshold are selected as credible recommenders for a target user, and their document ratings are used to make recommendations. The predicted rating of a document *d* for a target user *c*, $\hat{P}_{c,d_k}$ is calculated by Eq. (7):

$$\hat{P}_{c,d_k} = \overline{r}_c + \frac{\sum_{p \in NS} TM \times \left(r_{p,d_k} - \overline{r}_p\right)}{\sum_{p \in NS} TM}, \tag{7}$$

where *NS* is a neighbor set for the target user *c* that each users' trust value is greater than or equal to a specified threshold; user *p* who belongs to *NS* is a neighbor of user *c*; $\overline{r}_c / \overline{r}_p$ is the average rating of documents given by the target user *c*/ recommender *p*; r_{p,d_k} is the rating of document d_k given by user *p*; and *TM* is the trust value between user *c* and *p*, which derived from one of our proposed trust models, including the HPT, IGT and HPT-IGT respectively. According to Eq. (7), documents with high predicted ratings are recommended to the target user.

4 EXPERIMENTS AND EVALUATIONS

In this chapter, we conduct experiments on our proposed trust models and recommendation methods, and compare them with other trust-based recommendation methods in order to evaluate their recommendation quality. We describe the experiment set-up in Section 4.1, and demonstrate the experiment results in Section 4.2, 4.3 and 4.4.

4.1 Experiment Set-up

In our experiment, we collect a data set from a research institute laboratory. We build a knowledge management system (KMS) to collect documents related to knowledge workers' tasks. The data set contains users' access and rating behaviors concerning documents over time in conducting research tasks. Workers' tasks are research-based tasks, and their research domains are recommender systems, data mining, information retrieval, workflow systems, knowledge management, etc. There are over 800 research-related documents, and about 80 users in the data set.

From the group perspective, a user's role also has different degree of importance to the group. Therefore, we give each role a weighting value to represent its importance and influence for a group. Similarity, we also define explicit relationship trusts between users based on role relations. In general, a user usually may trust other users who have great influence in a group. Therefore, we set a value to the relationship trust for users based on the influence between their different roles. For example, the trust value of "senior-junior" is higher than that of "junior-senior" in our dataset. Note that such relationship trust is a direct trust. For two users, two different relationship trusts will be assigned. Moreover, according to users' information needs, we cluster these users into 10 groups as task-based groups by utilizing the K-means clustering method. Each group may consist of 5-16 users with similar information needs.

In our experiment, the data set is divided into a training set and a testing set. The training set is used to generate recommendation lists, while the test set is used to verify the quality of the recommendations. 30% of the users in the data set were selected as the target workers. The data of non-target workers is included in the training set.

To measure the recommendation quality of our proposed methods, we use the Mean Absolute Error (MAE), which evaluates the average absolute deviation of a predicted rating, and the user's true rating, as an evaluation metrics. The lower the MAE is, the more accurate the method will be. The MAE is defined in Eq. (8).

$$MAE = \frac{\sum_{k=1}^{N} \left|\hat{P}_{d_k} - r_{d_k}\right|}{N}, \tag{8}$$

Here *N* is the number of testing data, $\hat{P}_{d_k}$ is the predicted rating of document d_k and r_{d_k} is the real rating of document d_k.

4.1.1 Methods Compared in the Experiment

In the trust-based recommender systems, the trust values are obtained by using different trust computation models for selecting neighbors for a target user. Thus, we use different trust computation models to make recommendations, and then analyze their recommendation quality. These recommendation methods are defined as follows:

CF: the standard Resnick model in GroupLens (Resnick et al., 1994). The Pearson correlation coefficient is used in filtering and making predictions.

Profile Trust-CF (ProfileT-US-CF): The profile-level trust is used in filtering, and the weight which combines both the profile-level trust and user similarity by harmonic mean is used to make predictions (O'Donovan and Smyth, 2005).

Item Trust-CF (ItemT-US-CF): The item-level trust is used in filtering, and the weight which combines both the item-level trust with user similarity by harmonic mean is used to make predictions (O'Donovan and Smyth, 2005).

Rating-based Personal Trust CF (PersonalT-CF): Personal trust between two users is calculated by averaging the prediction error of their co-rated items (Hwang and Chen, 2007).

Relationship Trust CF (RelationT-CF): recommendations with relationship trust between two users, based on their role relationships, as described in Section 3.3.2.

Hybrid Personal Trust CF (HPT-CF): recommendations with hybrid personal trust, which combines rating-based personal trust and relationship trust derived by Eq.(4), as described in Section 3.3.2.

Item-Level Group Trust CF (IGT-CF): recommendations with IGT trust model, which infers a user's trust value on a specific document by aggregating the opinions of the members of a target user's group (Eq. (5)), as described in Section 3.3.3.

Hybrid of HPT and IGT CF (HPT-IGT-CF): recommendations with hybrid of HPT and IGT models, using Eqs.(4), (5), and (6), as described in Section 3.3.4.

4.2 The Effect of the Hybrid Personal Trust Model

In this section, we evaluate the effect of the hybrid personal trust model by comparing its recommendation quality to those of the PersonalT-CF, RelationT-CF, and HPT-CF methods. For the trust-based recommendation methods, recommenders with trust values greater than a threshold are selected as the neighbors of target user for making CF recommendations. The setting of the threshold for the trust value may affect the recommendation quality. A suitable threshold should be decided to select "trustworthy" recommenders in the trust models. According to our experiments, the most suitable threshold of trust value for the trust-based recommendation methods is 0.7.

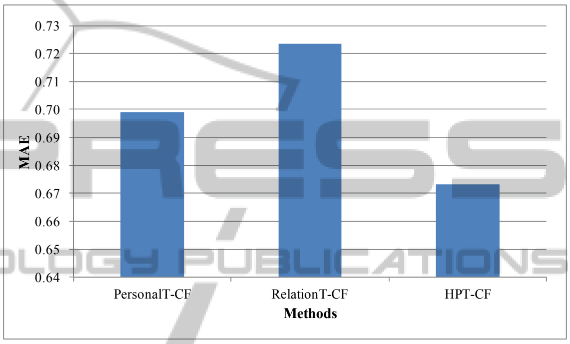

Figure 2: The performance of hybrid personal trust.

The PersonalT-CF derives personal trust from the ratings of co-rated items between two users. The HPT-CF adaptively integrates a user's rating-based personal trust and relationship trust to obtain a hybrid personal trust by adopting a parameter α (Eq. (4)). From the experimental result, N is set as 20 for α to combine the two kinds of trust, because this achieved the lowest MAE.

Figure 2 shows that HPT-CF performs better than PersonalT-CF and RelationT-CF. This implies that considering both the rating-based personal trust and the relationship trust in deriving the trust values can more effectively improve the recommendation quality than can the methods which consider only rating-based personal trust or relationship trust. HPT-CF resolves the drawback of insufficient past rating records, and improves the reliability of trust values.

4.3 The Effect of the Hybrid Personal and Group Trust Model

In this section, we evaluate the effect of the hybrid personal and group trust model by comparing the HPT-CF, IGT-CF and HPT-IGT-CF methods. To combine two trust values of HPT and IGT in HPT-IGT-CF, a parameter β is utilized to adjust the relative importance between the hybrid personal trust value (HPT) and item-level group trust (IGT). In order to determine the optimal value for β, we conduct several experiments for systematically adjusting the values of β in an increment of 0.1, as shown in Figure 3. According to the experiment results, HPT-IGT-CF has the lowest MAE when β is 0.9. This means that the relative importance for HPT and IGT is 0.9 and 0.1, respectively. The HPT-IGT-CF performs better when HPT is given a higher weight than IGT in computing the trust degree of HPT-IGT.

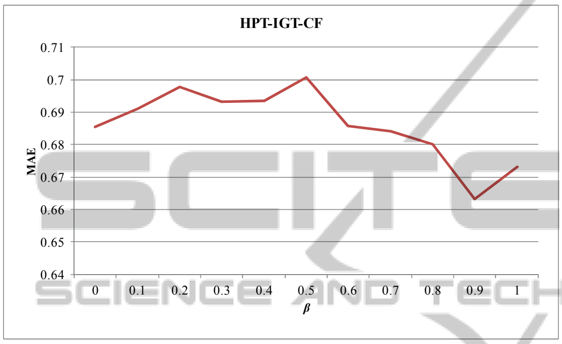

Figure 3: The MAEs of HPT-IGT-CF method under different β.

Figure 3 also shows the performance of HPT-CF under β=1, where the predicted rating of a document is derived totally by the HPT. When β = 0, the HPT-IGT-CF becomes the IGT-CF, which derives the predicted rating according to the IGT. The experiment results show that the HPT-IGT-CF performs better than HPT-CF and IGT-CF, while HPT-CF performs better than IGT-CF. Thus, giving a large weight to the HPT method in computing the hybrid trust value of HPT-IGT, i.e. Eq. (6), is reasonable. This implies that considering both the personal and group perspectives in deriving the trust values can better improve recommendation quality than can the methods considering only personal trust or group trust.

4.4 Comparison of all Methods

We compare our proposed methods, i.e., HPT-CF, IGT-CF, and HPT-IGT-CF, with the CF method, and other traditional trust-based recommendation methods, i.e., ProfileT-US-CF and ItemT-US-CF, as shown in Figure 4. The ItemT-US-CF/ProfileT-US-CF method predicts users' trust by computing the ratio of accurate predictions that s/he has made to all other users over a particular item/all items rated in the past. The trust metrics of these two methods ignore the group perspective. The suitable threshold values for selecting trustworthy neighbors by ItemT-US-CF and ProfileT-US-CF are set to 0.7 and 0.5, respectively. Note that the two methods use the harmonic mean of item-level/profile trust value and user similarity as the weight to make predictions.

The group perspective can be considered in trust computation to derive a reliable trust value, and enhance the recommendation quality. The IGT-CF method aggregates the opinions of the target user's group members on a specific item to derive the trust value of a target user's group on a recommender. Both ItemT-US-CF and ProfileT-US-CF derive trust values without considering group perspective. The experiment result shows that IGT-CF has better recommendation quality than both the ItemT-US-CF and ProfileT-US-CF methods. In addition, the conventional trust-based CF methods do not address users' role relationships in the computation of trust values. For the trust models based on personal perspective, the HPT-CF performs better than the traditional trust-based recommendation methods, including Personal-TCF, Item-US-CF, and Profile-US-CF.

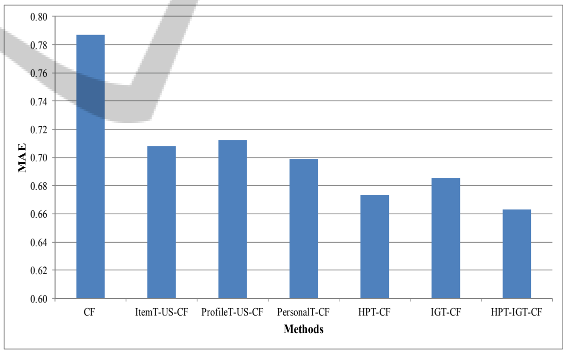

Figure 4: Comparison of all methods.

Moreover, our proposed trust methods, i.e., HPT-CF, IGT-CF, and HPT-IGT-CF, perform better than the conventional trust-based CF methods. The traditional recommendation method, i.e., CF, has the worst recommendation quality because it does not consider the issue of trust between users. Therefore, the trust models indeed contribute to improve the recommendation quality. The result also shows that the HPT-IGT-CF method performs better than HPT-CF and IGT-CF methods. Recommending documents from both personal and group perspectives results in better performance than one based on only one or the other. The hybrid trust model can indeed enhance the trust models in order to improve the recommendation quality.

5 CONCLUSIONS

In this work, we proposed document recommendation methods based on hybrids of personal and group trust models. Such hybrid models are used to compute users' trust values from the personal and group perspectives in order to discover reliable and trustworthy users in the recommendation process. In considering these two perspectives, three trust models are proposed, namely the hybrid personal trust (HPT), item-level group trust (IGT), and a hybrid of HPT and IGT (HPT-IGT). From the personal perspective, HPT adaptively not only takes users' ratings on co-rated documents, but also the role relationship trust into account in trust computation. From the group perspective, IGT derives the trust value of a target user's group on a recommender by using users' role weights to aggregate the opinions of the target user's group members on a specific item.

Moreover, to take advantage of the merits of both HPT and IGT models, we also propose a hybrid of HPT and IGT (HPT-IGT) models in order to obtain trust values by considering both the personal and group aspects. A target user usually has preferences similar to his group members', such that a recommender trusted by his group members may also be trusted by the user. The experiment result shows that the trust value of IGT can indeed complement the trustworthiness of personal perspective. Additionally, the prediction accuracy of recommendation is indeed improved using the HPT, IGT, and HPT-IGT models. Our proposed methods not only intensify the prediction accuracy of trust, but also offer better improvement of recommendation quality than other trust-based CF methods.

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