Novel personal and group-based trust models in collaborative filtering for 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 in order to improve recommendation quality. Some researchers have proposed rating-based trust models to derive trust values based on users' past ratings of items, or based on explicitly specified relations (e.g. friends) or trust relationships; however, 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; thus, users' preferences may be affected by group members. Accordingly, group trust can enhance personal trust to support recommendations from the group perspective. We then propose a recommendation method based on a hybrid model of personal and group trust to improve recommendation performance. The experimental results show that the proposed models can improve the prediction accuracy of other trust-based recommender systems.

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1. Introduction

Recommender systems have been, and continue to be applied in various applications to support item (e.g. movies or music) recommendation [19,30,34,46,47,52], and to solve the information-overload problem by suggesting items of possible interest to users. Even in a knowledge-intensive environment, recommender systems are able to support knowledge workers as they perform tasks, by recommending appropriate documents to suit their task needs. Of the various available recommendation methods, collaborative filtering (CF) [24] has been the most widely and successfully used method in various 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 [28,31,42] have incorporated the trustworthiness of users into CF techniques in order to improve the recommendation quality. These trust computation models [16,21,42] are used in trust-based recommender systems to derive trust values based on users' past ratings of items. Such trust computation models can be classified into two categories: reputation trust and relationship trust [26].

Reputation trust is a quantitative assessment that allocates a trust score to a specific person by accumulating other users' or a group of users' trust scores on that person [9,21,42]. Some researchers call this global trust [9,22,42]. On the other hand,

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relationship trust is the trust between two users. One user trusts another based on past interactions or explicitly specified relationships [15,16,25,28]. Some researchers call this personal trust, or local trust [13,16,40], whose value is limited between two users and diversified with different user pairs.

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 [42], 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 [14]. Users need to specify explicitly whom they trust and how much they trust each other.

O'Donovan and Smyth [42] suggest that if a user has usually delivered accurate predictions in the past, then s/he merits being called reliable and trustworthy. The accuracy of a prediction indicates whether the difference between a predicted rating given by a user (producer) and the real rating given by a target user is within a predefined error bound. A user is more trustworthy if s/he has contributed more accurate predictions than other users did; this trust model is reputation trust, and includes item level and profile level. The item-level/profile-level trust metric of a given user is derived by computing the ratio of accurate predictions that s/he has made to other users over a particular item/all items that user has rated in the past.

Massa et al. [37–40] propose a relationship-trust recommender system based on a user's Web of trust, which explicitly specifies the friends that s/he trusts. Their work, however, relies on the user's explicit assignment of trust values, which are not easy to collect, and may create a heavy burden on users. In addition, Hwang and Chen [16] propose a relationship trust metric to derive the trust value between two users by calculating the ratio of accurate predictions over all co-rated items, i.e. those items that have been rated by both users. Their proposed relationship trust metric is personal trust, and is more personalized than the reputation trust metric.

The rating-based trust model derives trust values between users based on their co-rated items. If two users have very few co-rated items, the trust value derived from the ratings of their co-rated items may yield misleading trustworthiness between those users. The rating-based trust model, therefore, may not be effective in CF recommendations due to unreliable trust values derived from insufficient past rating records.

Although conventional trust-based CF systems have proposed rating-based trust models, or explicitly specified trust metrics to derive the trustworthiness of users, they do not investigate the combination of 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 on their explicitly specified role relations. Such explicit relationship trust can complement the traditional rating-based trust model in improving the reliability of trust values. The proposed model adaptively adjusts the relative importance of rating-based trust and the explicit relationship trust based on the number of co-rated documents between two users.

Moreover, users with similar preferences usually form a group to share items (knowledge) with each other; thus, users' preferences may be affected by group members. Accordingly, group trust can enhance personal trust to support recommendations from the 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 in order to improve the performance of collaborative filtering. From the group-based trust metric we can obtain recommenders that are trustworthy from the group's point of view. 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. In the group-based trust, we define a role-weight for each user to represent his/her degree of importance within 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, compared with other trust-based recommender systems.

This paper is organized as follows: We present 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 discussed in Section 4. Conclusions and suggested future work are presented in Section 5.

2. Related work

2.1. Recommender systems

Recommender systems (RSs) can be classified into three categories: content-based recommender systems (CB) [45], collaborative filtering systems (CF) [5,24,47] and hybrid recommender systems [6,11,29]. CB identifies items of special interest through analyzing item descriptions, while CF filters or evaluates items by users' opinions. Hybrid recommender systems combine content-based filtering and collaborative filtering to improve the accuracy of recommendations. Details are given below.

A number of recommender systems apply a content-based technique to various domains, such as Web pages [44], blog articles [33], news articles [57] and TV programs [2,4]. Content-based recommender systems recommend interesting items to users by analyzing their content descriptions. The content features are used to establish a characteristic profile. Most content-based recommender systems adopt information retrieval to analyze item content, and build a profile for an item or user. The content-based approach recommends items with similar attributes to customer profiles according to their past preferences.

The collaborative filtering (CF) method predicts users' preferences by considering the opinions (in the form of preference ratings) of other "liked-minded" users [7,24,32,47]. In general, CF methods can be roughly classified as user-based and item-based CF methods. User-based CF exploits historical data expressing preferences to form user neighbors and to make recommendations based on those similar users' opinions. On the other hand, item-based CF determines recommendations by relying on items' associations, which are based on user's ratings among items. Sarwar et al. [51] built a user-item matrix to identify relationships between different items and then find other similar products that users might like.

To provide useful recommendations, the user-based CF approach involves two steps: neighborhood selection and target user's rating prediction on items. The purpose of neighborhood selection is to select users who have similar interests to the target user. Several metrics have been proposed for similarity computing, e.g., Pearson correlation coefficient [47]. Eq. (1) is used to evaluate the Pearson correlation between target user c and recommender p:

$$w_{c,p}^{Pearson} = \frac{\sum_{j \in (S_c^l \cap S_p^l)} (r_{c,j} - \bar{r}_c)(r_{p,j} - \bar{r}_p)}{\sqrt{\sum_{j \in (S_c^l \cap S_p^l)} (r_{c,j} - \bar{r}_c)^2} \sqrt{\sum_{j \in (S_c^l \cap S_p^l)} (r_{p,j} - \bar{r}_p)^2}}, \tag{1}$$

where S_c^l and S_p^l represent a document set rated by users c and p, respectively; $r_{c,j}$ is target user c's rating of item j; and $\bar{r}_c$ is user c's average rating of items in the set $(S_c^l \cap S_p^l)$.

In the prediction phase, Eq. (2), Resnick's prediction formula [47] is used to make predications. The predicted rating score is derived from the target user's average rating and his/her neighbors' relative opinions on the common rated items, as shown below:

$$\hat{p}_{c,j} = \bar{r}_c + \frac{\sum_{p \in NS} w_{c,p}^{Pearson}(r_{p,j} - \bar{r}_p)}{\sum_{p \in NS} |w_{c,p}^{Pearson}|}, \tag{2}$$

where $\hat{p}_{c,j}$ represents the predicted rating that target user c may provide for item j; $\bar{r}_p$ is the target user's average rating; $w_{c,p}^{Pearson}$ is the user similarity score between target user c and his/her neighbor p; and NS is the set of neighbors that have been selected to provide their relative interests.

In general, the effectiveness of the CF recommendation approach mostly depends on the set of historical data. There are still potential limitations, such as sparsity and cold start issues [1,53]. Then the sparsity issue entails low-quality recommendation results being obtained because the system has very few rating records of users to measure the similarity between users or items. The cold start issue involves new items or new users, for which the system will exhibit weak prediction performance because of the lack of active records viewed by users.

For the hybrid recommender systems, the weighted model and the meta-level model use different strategies to combine content-based filtering and collaborative filtering [6,29]. The weighted model uses linear combinations of the prediction results. For example, the method was applied to recommend news in an on-line newspaper [11]. The meta-level model employs a sequential combination of collaborative and content-based filtering, whereby the output generated by content-based filtering is used as the input for collaborative filtering [6]. Melville et al. [41] propose a content-boosted collaborative filtering (CBCF) approach for movie recommendations, where pseudo user-ratings are derived by combining users' actual ratings and content-based predictions on unrated items. Then, the method applies collaborative filtering based on this dense matrix. RAAP [12] is an example of a hybrid system that can classify and recommend a user's newly classified bookmark retrieved from the Web to other users with similar interests.

2.2. Relationship trust and reputation trust

The purpose of designing a trust metric is to quantify the degree of trust between users [58]. A trust value can be classified into either direct or indirect trust, depending on whether or not a user actively indicates trust [43]. The meaning of direct trust is that a user expresses their opinion in value or opinion format to another person during their interaction. The "friend" lists in *Epinions*, *Facebook*, or the feedback from *eBay* exemplify direct trust [37,38,40]. Conversely, indirect trust is derived through computation. Marsh [36] claims that trust can be viewed as a function of reputation, which can be computed over historical data.

With regard to the procedure of deriving the trust metric, two dimensions of trust metrics are defined: relationship and reputation [26]. Relationship trust relies on qualitative measurements dependent on social network connections. A user decides his/her trust of another based on some private knowledge gained through past interactions, or explicitly specified relationships. Some researchers call this personal trust, or local trust [13,16,40], whose value is limited between two users, and diversified with different user pairs. Several examples, such as *Facebook* and *Epinions*, by which the user includes a friend in his/her list, are of this type. If the relationship trust is not explicitly indicated, it can be inferred from the rating data or other

indirect information [16,23,28,58]. On the other hand, 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 of a community. A famous example is *eBay*, on which each seller attains a trust value through several buyers' comments. Some researchers call this global trust, or expert degree, with similar concepts [9,22,42].

As trust is applied in social networks, it provides more functions for the expansion of Internet intelligence. For example, users enjoy sharing documents with their friends, or reading articles written by a credible writer. These behaviors on the Internet form a so-called Web of trust (WoT). The main concept of a WoT is that even though two users are unknown to each other, their friendship is still able to be inferred through other trust relationships which are known and related to the two users [13,14,17,25,56]. People are linked through this relationship, and a social network is constructed. Since the advent of mass social media, trust relationships have attracted increasing attention [48]. Lately, several social network applications [60] on the Web have become mature, such as *MySpace* and *Facebook* [27]. Numbers of active users on such social network applications are growing rapidly. Thus, the trust issue is increasingly important in terms of social networking.

2.3. Trust-based CF recommender systems

Trust-based recommender systems mainly combine trust models with user-based CF to design hybrid techniques, i.e. trust-based CF methods to enhance the recommendation quality of CF systems [14,16,39,42,55]. The trust values are obtained by using different trust computation models for selecting neighbors of a target user. Moreover, the trust values may be combined with user similarity measures (Pearson correlation coefficient) as weightings to predict a target user's rating by a weighted average of neighbors' ratings. Conventional trust-based CF methods use different approaches to derive trust values, and combine with user similarity to make predictions. Victor et al. [55] have compared several well-known trust-enhanced techniques to evaluate their effectiveness in personalizing the recommendations for *controversial items* (CIs) that have a variety of high and low rating scores. According to the trust characteristic presented above, trust-based recommender systems can be classified into two categories: reputation trust and relationship trust.

2.3.1. Reputation trust-based recommender system

Several researchers propose reputation trust as an auxiliary factor in the recommendation phase. Reputation trust is referred to as "expert" or "professional degree" by some researchers [8–10,21]. Cho et al. [9] and Kim et al. [21] judge whether someone is qualified as an expert by adopting Riggs's model [49], which assigns scores to reviewers based on how close their ratings are to the average ratings. For example, Kim et al. [21] 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. O'Donovan and Smyth [42] claim that accurate recommendation in the past is important and reliable, and they propose profile-level trust and item-level trust derived from users' rating data. They use a simple version of Resnick's prediction formula [47] to calculate a target user c's predicted rating on an item i_k from a recommender p's rating on i_k, as defined in the following equation:

$$\widehat{P}^p_{c,i_k} = \bar{r}_c + (r_{p,i_k} - \bar{r}_p), \tag{3}$$

where $\widehat{P}^p_{c,i_k}$ is a predicted rating of target user c on item i_k by a recommender p; $\bar{r}_c$ and $\bar{r}_p$ refer to the mean ratings of target user c and recommender p, respectively; and r_{p,i_k} is p's rating on i_k. The rating prediction, by recommender p for target user c, is correct if the predicted rating is within an error bound of c's actual rating, as shown in the following equation:

$$Correct(i_k, p, c) \Longleftrightarrow |\widehat{P}^p_{c,i_k} - r_{c,i_k}| < \varepsilon, \tag{4}$$

where r_{c,i_k} is the actual rating of the item i_k given by target user c, and ε is an error bound measuring the closeness.

According to this equation, recommender p is regarded as trustworthy if his/her prediction on item i_k in target user c's view is close to c's actual rating. A user is viewed as trustworthy if s/he always contributes precise predictions. Let (p, c_x, i_k) denote a recommendation that both user c_x and recommender p have rated item i_k with, and can be used to derive p's trustworthiness. Let U be the set of users, and I be the set of items. All the recommendations that p has contributed form a set called p's *RecSet*, as shown in Eq. (5). For each recommendation in *RecSet(p)*, the trustworthiness of p on a specific item i_k for user c_x is measured, as in Eq. (4). *CorrSet(p)*, defined in Eq. (6), stores all recommendations that recommender p has made approximate predictions for, on some item i_k for some user c_x:

$$RecSet(p) = \{(p, c_x, i_k) | c_x \in U, \ i_k \in I; \ \text{both} \ p \ \text{and} \ c_x \ \text{have rated} \ i_k\}, \tag{5}$$

$$CorrSet(p) = \{(p, c_x, i_k) | (p, c_x, i_k) \in RecSet(p) \ \text{and} \ Correct(i_k, p, c_x)\}. \tag{6}$$

The profile-level trust, $Trust^{PL}(p)$, is calculated as the percentage of correct predictions that recommender p has made; while the concept of item-level trust, $Trust^{IL}(p, i)$, is similar, but focuses on a specific item i, as defined in the following equation:

$$Trust^{PL}(p) = \frac{|CorrSet(p)|}{|RecSet(p)|}; \quad Trust^{IL}(p, i) = \frac{|\{(p, c_x, i) | (p, c_x, i) \in CorrSet(p)\}|}{|\{(p, c_x, i) | (p, c_x, i) \in RecSet(p)\}|}. \tag{7}$$

Both profile-level trust and item-level trust can be used in the recommendation phase. The neighbors of target users are selected by filtering out users whose profile-level trust values are lower than a specified threshold. The weight between user p and target user c is derived by combining the value of profile-level trust with user *Pearson similarity* (Eq. (1)) in a harmonic mean. Then, these user weights are applied in a modified version of Resnick's formula for prediction. The item-level trust can be applied similarly in the recommendation phase. Please refer to O'Donovan and Smyth [42] for details.

2.3.2. Relationship trust-based recommender system

Relationship trust metrics consider the trusters' 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 [39] call this kind of trust opinion local trust (relationship trust), and take advantage of the Web of Trust in *Epinions.com* to balance the collaborative recommender system's defects [37,38,40].

Even though relationship trust presents an improvement on traditional CF recommender systems, the direct relationship trust data has some defects. This kind of data is not usual in most recommender systems, and it is difficult to collect. Besides this, a reviewer's quality of review cannot always be consistent, and the relationship trust may vary according to the reviewer's quality and the user's interest. Hwang and Chen [16] consider the truster's subjective opinions in order to obtain more personalization effects when predicting the trust value which s/he places on the trustee. They calculate the personal (local) trust value of target user c with respect to recommender p, as shown in the following equation:

$$T_{c \to p} = \frac{1}{|(I_c \cap I_p)|} \sum_{i_k \in (I_c \cap I_p)} \left(1 - \frac{\left| \hat{p}^p_{c,i_k} - r_{c,i_k} \right|}{M} \right). \tag{8}$$

Recommender p predicting item i_k in target user c's view is denoted as $\hat{p}^p_{c,i_k}$. Instead of filtering with an error bound, they use all items that are co-rated by p and c to compute the personal trust. M is the range of the rating score between maximum and minimum rating scores. If two users have no co-rated items, which results in no direct trust relationships between them, trust propagation [17] can be used to infer their trust value through indirect relationships in the Web of trust. In addition, a user c's global trust can be derived as the average of the personal trust values given by neighbors directly connected to c in the Web of trust. Resnick's prediction formula (Eq. (2)) is then used to make predictions by replacing the similarity score with the trust value as the weight to compute the weighted mean of the ratings given by neighbors. 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 this 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

Most trust-based recommendation models [37,58,61,62] consider accurate predictions derived from past rating records to infer the trust value. A prediction on an item contributed from a recommender is accurate for a target user if the difference between their ratings on the item is small. Generally, a user is more trustworthy if s/he has contributed more precise predictions than other users. Trust-based recommender systems [16,42] compute the trust value based on users' ratings on co-rated items. However, such a trust value may not be accurate when the number of users' co-rated items is insufficient. It is difficult to identify trustworthy users using only a few co-rated items. In addition, users may work collaboratively to contribute their knowledge and experience when performing a task. In such task-based groups, users may have similar information needs, and each user may have a different role in representing the importance to the group. Based on users' roles, there are various relationships among users. From our point of view, the inference of trust value should not depend only on accurate predictions, but also on users' role relationships when the rating is made. To derive a reliable and accurate trust value, the trust model should also consider the personal and group perspectives in trust computation.

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. Fig. 1 shows the framework of our proposed hybrid trust models and the CF recommendation methods, based on the proposed models, i.e. HPT, IGT and HPT–IGT. From the personal perspective, the hybrid personal trust (HPT), which adaptively integrates rating-based personal trust and relationship trust, is derived from users' personal rating information and role relationships to other users. Rating-based personal trust and relationship trust complement each other to resolve the problem of insufficient co-rated items. The proposed group trust method, i.e. item-level group trust (IGT), is obtained from the group perspective by aggregating the rating-based item level trust of group members for a trustee, according to their role weights. Conventional trust-based recommendation systems have, as yet, not addressed how to take both personal and group aspects into account to derive a reliable trust prediction. Accordingly, hybrid models of personal and group trusts (HPT–IGT) are proposed for trust computation. There are several phases in our framework.
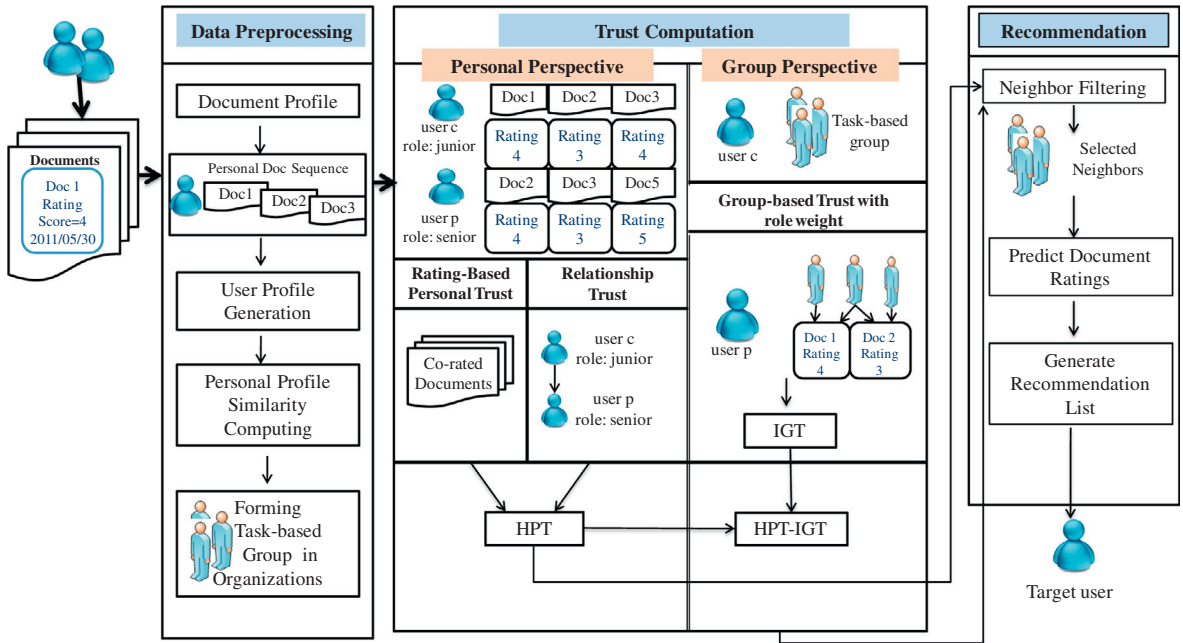
Fig. 1. The framework of hybrid personal and group trust model for recommendation.

3.1.1. Data preprocessing

Documents are preprocessed by *tf-idf* approach [3,50] to generate document profiles describing the key contents of documents. In addition, the system also records users' access behavior in regard to documents: uploaded, downloaded, browsed or rated documents, and ratings of documents. If a user does not rate a document, a default score is assigned according to the user's access behavior. In this work, uploading and downloading behavior are regarded as more important than browsing behavior. Therefore, a default score of 3 is given for browsing behavior, and 4 for uploading or downloading behavior. According to users' access behavior and document profiles, user profiles are generated to represent users' information needs [20,59]. Because each user has various information needs, the similarities among user profiles are measured by *cosine* measurement. Users with similar user profiles are clustered into a task-based group.

3.1.2. Trust computation

We propose trust models from both the personal and group perspectives. From the personal perspective, both rating-based personal trust and relationship trust are considered in the trust computation. Rating-based personal trust is derived from users' ratings of co-rated documents, while relationship trust is explicitly assigned by experts according to the role relationships between users. These two kinds of trust are adaptively combined as hybrid personal trust (HPT), based on the number of co-rated items between two users. With a greater number of co-rated documents, rating-based personal trust is more reliable, and thus more weight is assigned to it. However, this personal trust ignores the opinions of other group members. Moreover, from the group perspective, item-level group trust (IGT) is derived by aggregating the opinions of the target user's fellow group members with the consideration of users' role weights. However, group trust mainly focuses on the majority of the opinions of group users, rather than those of 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, we propose a hybrid trust model, HPT–IGT, which combines both personal and group trust models to derive a trust value from both the personal and group perspectives. These trust models will be discussed in Section 3.3.

3.1.3. Recommendation

According to the trust models in the previous phase, 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. Users with high trust values are identified as trustworthy recommenders, and are then 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. Moreover, the proposed methods further improve the prediction process by considering the neighbors' similarity to the target user based on user similarity.

3.2. Document profiling and user clustering

In order to group similar users as a task-based group, we first analyze the users' information required to generate document profiles and user profiles. 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. Generally, information retrieval (IR) can be used to transform text documents into a list of features, and filter out non-relevant ones by three phases: stop-word removing, stemming, and term weighting [3]. Each document is described by a term vector, which consists of representative terms and their term weights. Thus, 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 [50]. 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: $DP_j = \langle dt_{1j}$-$_j = \langle dt_{1j}{:}dtw_{1j}, dt_{2j}{:}dtw_{2j}, \ldots, dt_{nj}{:}dtw_{nj}\rangle$, where dt_{ij} is the term i in d_j, and dtw_{ij} is the degree of importance of a term i to 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 the documents positively accessed by that user. That is, documents with ratings greater than or equal to 3 are used to generate a user profile. Let $UP_x = \langle ut_{1x}{:}utw_{1x}, ut_{2x}{:}utw_{2x}, \ldots, ut_{nx}{:}utw_{nx}\rangle$ 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. Let D_x be the set of document profiles of user x. The term weight in the user profile is determined by:

$$utw_{ix} = \frac{\sum_{j \in D_x} dtw_{ij}}{|D_x|},$$

(9)

where dtw_{ij} is the weight of term i in document j, and $|D_x|$ is the number of documents that have been referenced by the user x. The term weight in the user profile is obtained by averaging the term weights in the document set.

We adopt the K-means clustering algorithm [18,35] to group users with similar profiles into clusters using the *cosine* measurement. The K-means algorithm [18,35] starts by creating singleton clusters around k randomly sampled points (i.e. user profiles), and then assigns each point with the closest centroid, based on the cosine similarities between the point and all centroids. It continues to re-assign points and shift centroids until the centroids no longer change. 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 trust models that 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. Rating-based personal trust

Rating-based personal trust is derived from two users' past ratings on co-rated documents by adopting Hwang and Chen's [16] trust computation method, illustrated in Section 2.3.2. Note that the document rating, which is given by a user on a scale of 1–5, indicates whether a document is considered useful and relevant to the user's task. In the conventional trust model [16,42], the ratio of accurate predictions made is calculated 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 do. As in the conventional trust computation model, we also use a simple version of Resnick's prediction formula [47] to calculate a target user c's predicted rating of a document d_k, $\hat{p}_{c,d}^{p}$, which is derived from a recommender p's rating of d_k, as defined in the following equation:

$$\hat{p}_{c,d_k}^{p} = \bar{r}_c + (r_{p,d_k} - \bar{r}_p),$$

(10)

where $\bar{r}_c$ and $\bar{r}_p$ 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 $\widehat{P}_{c,d_k}^{p}$ is close to the real rating score of user c on d_k, i.e., r_{c,d_k}, we conclude that both target user c and recommender p have a similar opinion of document d_k. The more similar the perspective, the more trust they have, as illustrated in the following equation:

$$T_{c,p}^{d_k} = 1 - \frac{\left| \widehat{P}_{c,d_k}^{p} - r_{c,d_k} \right|}{M},$$

(11)

where $T_{c,p}^{d_k}$ 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 [16] trust model to calculate rating-based personal trust by considering all items co-rated by recommender p and target user c, as defined in the following equation:
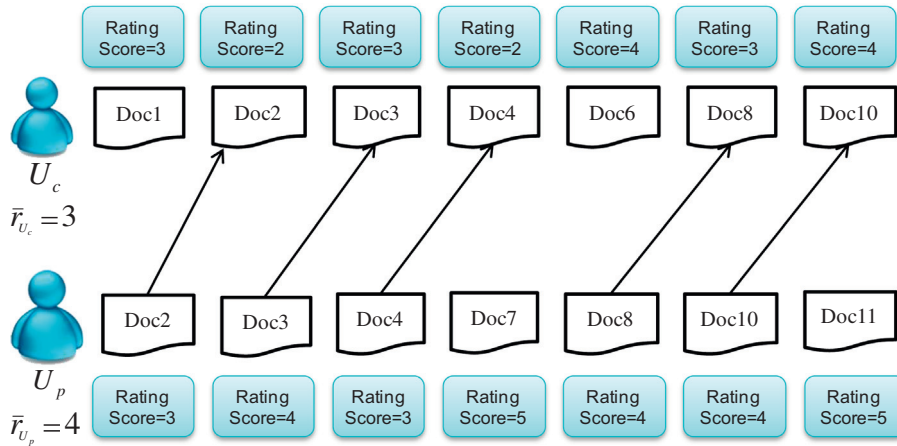
Fig. 2. Illustration of the rating-based personal trust.

$$PT_{c,p}^{ra} = \frac{1}{\left| I_c^d \cap I_p^d \right|} \sum_{d_k \in (I_c^d \cap I_p^d)} \left(1 - \frac{\left| \widehat{P}_{c,d_k}^p - r_{c,d_k} \right|}{M} \right), \tag{12}$$

where $PT_{c,p}^{ra}$ is a trust degree of the rating-based personal trust that represents how much a target user c trusts 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 $PT_{c,p}^{ra}$ from the co-rated document set, we derive the average trust value. With more co-rated documents, the trust degree of rating-based personal trust becomes more reliable.

Fig. 2 shows an example of the computation of the rating-based personal trust model. U_c is a target user with mean rating 3, while U_p is a recommender with mean rating 4. The co-rated documents that both user U_c and U_p have are Doc2, Doc3, Doc4, Doc8 and Doc10. We use U_p's opinions on these co-rated documents to predict U_c's score. According to Eq. (12), the weighted average on all co-rated documents is calculated, and then rating-based personal trust is derived as 0.96.

$$PT_{c,p}^{ra} = \frac{\left(1 - \frac{|2-2|}{5} \right) + \left(1 - \frac{|3-3|}{5} \right) + \left(1 - \frac{|2-2|}{5} \right) + \left(1 - \frac{|3-3|}{5} \right) + \left(1 - \frac{|3-4|}{5} \right)}{5} = 0.96.$$

However, if two users do not share any co-rated documents, the result is an absence of direct relationships between them; rating-based personal trust cannot represent the trust relation between these two users. Thus, to enhance the prediction ability for the personal trust model, we consider relationship trust based on two user's roles in computing personal trust. Details are given in Section 3.3.2.

3.3.2. Hybrid personal trust (HPT)

In order to address the above limitation of 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. Rating-based personal trust is derived from users' ratings of co-rated documents by adopting Hwang and Chen's [16] trust computation method, illustrated in Section 3.3.1. Relationship trust is measured according to the role relationship between two users. A user is usually assigned a specific role when s/he 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 experience 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. Therefore, we define the relationship trust to measure a user's trust based on the role level. This kind of trust is an explicitly specified trust, and its value, which ranges from 0 to 1, is usually assigned by experts.

In Fig. 3, target user c has relationship trust with four recommenders, based on their roles. For recommender P_1, the relationship between target user c and P_1 is a junior-senior one, and its relationship trust, i.e. $PT_{c,P_1}^{junior-senior}$, is assigned as 0.8 by experts. Therefore, we define the relationship trust to measure a user's trust based on the role level. This kind of trust is a directed trust, and its value, which ranges from 0 to 1, is usually assigned by experts.

With the inclusion of relationship trust, HPT can now 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 of insufficient co-rated documents causing 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 the following equation:
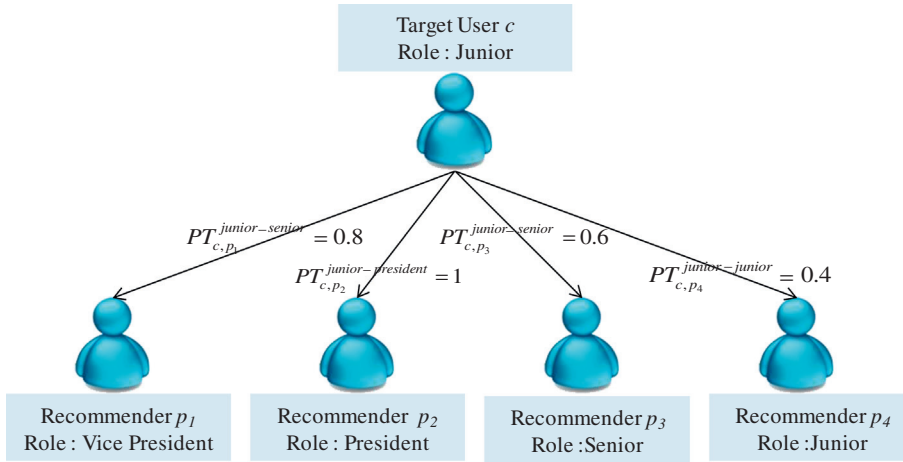
Fig. 3. Illustration of relationship trust based on user roles.

$$HPT_{c,p} = \alpha \times PT_{c,p}^{ra} + (1 - \alpha) \times PT_{c,p}^{rel}, \tag{13}$$

where $HPT_{c,p}$ is a hybrid personal trust for 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 target user c based on the role relation between user c and p; and α, which ranges from 0 to 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 $m \geqslant N$, 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 used to determine the reliability of rating-based personal trust. The value of α is larger if m is larger; thus the rating-based personal trust is more reliable, and more weight is assigned to $PT_{c,p}^{ra}$. When m is larger than N, the number of co-rated documents between target user c and recommender p is large enough to achieve the maximum reliability of rating-based personal trust, so that α is given as 1.

The relative importance of rating-based personal trust and relationship trust depends on the number of co-rated documents between two users. The more documents that both 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, rating-based personal trust is more capable of inferring the personal trust for target user c. Thus, the hybrid personal trust, i.e. $HPT_{c,p}$, is influenced more by $PT_{c,p}^{ra}$. If $\alpha = 1$, the value of $HPT_{c,p}$ is derived from the rating-based personal trust without using the contribution of the relationship trust. Additionally, the rating-based personal trust is unreliable when the target user c and recommender p have insufficient co-rated documents. The value of α is smaller if m (i.e. the number of co-rated documents between two users) is smaller; thus the hybrid personal trust, i.e. $HPT_{c,p}$, is dominated more by $PT_{c,p}^{rel}$. If $\alpha = 0$, only the relationship trust based on users' roles is considered in computing the value of $HPT_{c,p}$. These two kinds of trust can complement each other to enhance the reliability of the personal trust computation.

Continuing the previous example in Fig. 2, we assume that the role relationship of target user U_c to recommender U_p is a junior-to-senior relationship and its relationship is given as 0.8. N is set to 20. Based on Eq. (13), the personal trust value of target user U_c to recommender U_p is $HPT_{c,p} = \frac{5}{20} * 0.96 + \left(1 - \frac{5}{20}\right) * 0.8 = 0.84$. This trust value is derived from both rating-based personal trust and relationship trust. Because there are insufficient co-rated documents, the relationship is given a higher weight in this trust computation.

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 those of their group members, such that a recommender trusted by the 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. In addition, users usually have different expertise in task-related knowledge, and may thus have different trust values for different items (documents). For example, a user who is trusted by other users for items related to "workflow management" may not be trustworthy for recommending items related to "recommendation technique".

Accordingly, item-level trust is more effective than profile-level trust in recommending items. However, traditional item-level trust [42] only computes the trust value of a recommender p from the perspective of all users for a specific item; it is a global trust and does not take the group perspective and user roles into account.

Since users have different task-related knowledge and experience, each user is assigned an appropriate role in performing a task. Each role has a weighting score, representing importance to the group. As with 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. For example, user A and user B are in the same group, and their roles are senior worker and junior worker, respectively. In the group, the senior worker has a greater influence than the junior worker. Thus, the role of user A can obtain a higher weight than that of user B. To compute a group trust, users in a group with higher role weights can contribute more to the trust value.

Accordingly, we modify O'Donovan and Smyth's [42] item-level trust in order to propose the computation model of IGT. However, our proposed IGT model differs from the item-level trust proposed by O'Donovan and Smyth in that it takes the group perspective and user role weights into account. The IGT model can infer a 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. More specifically, for a particular item (document), we aggregate the pure trust values between the recommender and group members on a specific document in order to derive the target group's trust value on the recommender. In addition, each user in a group is assigned an appropriate role with different role weight in performing a task. Thus, the IGT model takes not only the pure trust between two users on a specific document, but also users' role weights into account. This 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. (14), is used to predict a group trust value for a recommender on a specific document. 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 group U_g's group trust on recommender p for document d_k:

$$
IGT_{U_g,p}^{d_k} = \frac{\sum_{u \in U_g} \left(1 - \frac{\left| \widehat{P}_{u,d_k}^{p} - r_{u,d_k} \right|}{M} \right) \times W_{u,U_g}^{Role}}{\sum_{u \in U_g} W_{u,U_g}^{Role}},
\tag{14}
$$

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 group U_g. In this trust computation model, a user with a higher role weight can contribute more to the group trust value than can others with lower role weights. Moreover, compared to the opinions of other groups' members, a target user's opinion is generally more similar to those of his/her group's members. Accordingly, the trust value derived from the target user's group members is more reliable than that derived from other users in identifying trustworthy recommenders for the target user. The IGT model can be used to identify trustworthy recommenders 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.

For example, in Fig. 4, there are four persons with different roles in a task-based group. Their roles, W_{u_1,U_g}^{junior}, W_{c_2,U_g}^{senior}, W_{u_3,U_g}^{VP}, and $W_{u_4,U_g}^{President}$, are assigned role weights 0.3, 0.4, 0.6, and 1, respectively. The values of the pure trust between users and rec-
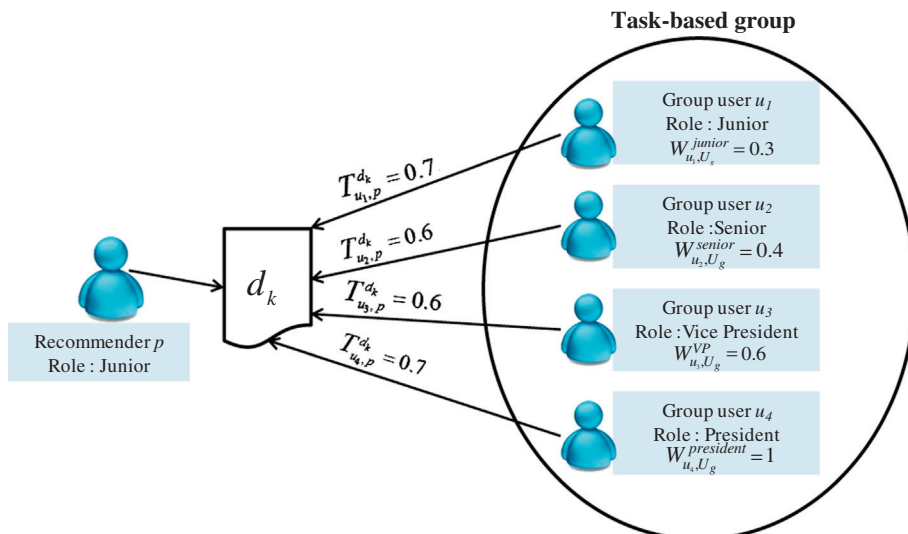

Fig. 4. Illustration of group trust based on item level.

ommender p are 0.7, 0.6, 0.6, and 0.7, respectively. Thus, the group trust of recommender p for document d_k is derived using Eq. (14), and its value is 0.6565. This value represents a trust degree of a specific document from the group perspective, i.e. considering the opinions of group users.

3.3.4. The hybrid of HPT and IGT (HPT–IGT)

In this section, we propose a hybrid trust model, HPT–IGT, which linearly combines hybrid personal trust (HPT) and item-level group trust (IGT). HPT, illustrated in Section 3.3.2, is used to derive a trust value from the personal perspective by considering the ratings of co-rated documents between two users and their relationship trust based on roles. IGT, as shown in Section 3.3.3, can be used to identify trustworthy recommenders of specific items from the group perspective. This model takes into account not only the pure trusts between users, but also the role weights.

However, HPT ignores other users' opinions because it mainly exploits the opinions of two users, i.e., the ratings of the co-rated documents, to obtain the personal trust value. In addition, 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 the 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.

To take advantage of the merits of both the HPT and IGT models, the hybrid of HPT and IGT (HPT–IGT) is proposed in order to predict a user's trust value from both personal and group perspectives. Let $HT_{c,p}^{H,d_k}$ be a trust value of target user c on recommender p for document d_k, which is derived by linearly integrating the HPT and IGT models, as defined in Eq. (15). This value represents a trust degree that a target user c trusts recommender p on document d_k:

$$HT_{c,p}^{H,d_k} = \beta \times HPT_{c,p} + (1 - \beta) \times IGT_{U_g,p}^{d_k}, \tag{15}$$

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 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 0–1. It is higher if the personal trust has a greater influence than the group trust. That is, the HPT model contributes more than the IGT model to the trust value of HPT–IGT. Conversely, the group trust has a greater influence if the value of β is smaller. From both personal and group perspectives, the trust value on a recommender is derived not only by the opinion of a target user, but also by those of the target user's group members. Therefore, such trustworthy recommenders could provide reliable predictions when making recommendations. 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 based on personal and group trust models

In the recommendation phase, the proposed trust models are used as filtering mechanisms to identify the highly trustworthy recommenders, i.e. trusted neighbors, for a target user. The trust values derived from these trust models are incorporated into recommendation methods to recommend documents for the target user. Moreover, the user similarity analysis is useful for selecting neighbors based on the similarity of document ratings, which reveal users' preferences on documents. The following sections describe the details.

3.4.1. Recommendation 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 are then applied in the prediction formula as weightings to derive the predicted ratings for documents. The recommendation process based on the personal and group trust weightings is shown in Fig. 5. Let NS be a neighbor set, and TM be the proposed trust models to predict a trust degree of recommender p from the personal and group perspective. TM may be $HPT_{c,p}$, $IGT_{U_g,p}^{d_k}$, or $HT_{c,p}^{H,d_k}$, which represent one of our proposed trust models. $HPT_{c,p}$, which denotes the HPT model, adaptively combines the rating-based personal trust and the relationship trust to derive the hybrid personal trust between a target user c and a recommender p, as illustrated in Section 3.3.2. $IGT_{U_g,p}^{d_k}$, which denotes the IGT trust model, infers a user's trust value on a specific document by aggregating the opinions of the target user's group members, as discussed in Section 3.3.3. $HT_{c,p}^{H,d_k}$, which denotes the hybrid of HPT and IGT (HPT–IGT) models, obtains a trust value from both the personal and group perspectives, as described in Section 3.3.4. Based on these proposed trust models, different trustworthy users are selected as recommenders for a target user.

In this section, we propose the document recommendation methods 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, $\widehat{P}_{c,d_k}$ is calculated by:
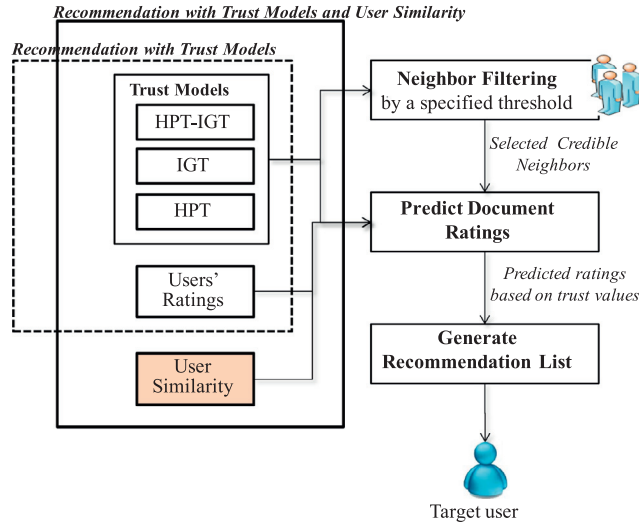
Fig. 5. The recommendation process based on the personal and group trust weightings.

$$\widehat{P}_{c,d_k} = \bar{r}_c + \frac{\sum_{p \in NS} TM \times (r_{p,d_k} - \bar{r}_p)}{\sum_{p \in NS} TM}, \tag{16}$$

where *NS* is a neighbor set for 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*; $\bar{r}_c/\bar{r}_p$ is the average rating of documents given by 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*, derived from one of our proposed trust models, including the HPT, IGT and HPT–IGT, as described in Sections 3.3.2–3.3.4, respectively. According to Eq. (16), documents with high predicted ratings are recommended to the target user.

3.4.2. Recommendation considering trust models and user similarity

In this section, we consider user similarity, and employ it in the recommendation phase to improve the prediction process, as shown in Fig. 5. The user similarity is measured by exploiting the Pearson correlation coefficient [47] to find users who have preferences similar to those of the target user. This similarity analysis is very useful for providing other preference information and revealing users' interests on documents in their history of document access. Therefore, when we judge whether a recommender is qualified to be a target user's neighbor, the user similarity offers another dimension to be explored.

Based on the collaborative filtering method, the document recommendation approach, including HPT-US-CF, IGT-US-CF and HPT–IGT-US-CF, is proposed. The HPT-US-CF/IGT-US-CF integrates the trust value obtained from the HPT/IGT model and user similarity by using a weighted arithmetic mean to derive the weightings for making predictions. Similarly, the HPT–IGT-US combines the trust value derived from the HPT–IGT model and user similarity (US) for making recommendations. In the recommendation step, the trust degrees derived from the HPT, IGT and HPT–IGT models are used to identify trustworthy recommenders. Nevertheless, some minor modification is made in the prediction of target user *c*'s ratings on document d_k, as shown in the following equation:

$$\widehat{P}_{c,d_k} = \bar{r}_c + \frac{\sum_{p \in NS} H(Psim(c,p), TM_{c,p}^H) \times (r_{p,d_k} - \bar{r}_p)}{\sum_{p \in NS} H(Psim(c,p), TM_{c,p}^H)}, \tag{17}$$

where $H(Psim(c,p), TM_{c,p}^H)$ is a weighted arithmetic mean of user similarity *Psim*(*c*, *p*) derived from the Pearson correlation coefficient and the hybrid trust degree $TM_{c,p}^H$, as defined in Eq. (18); *NS* is a neighbor set for target user *c* where each neighbor's trust value is greater than or equal to a specified threshold; user *p* belonging to *NS* is a neighbor of user *c*; $\bar{r}_c/\bar{r}_p$ is the average rating of documents given by target user *c*/recommender *p*; and r_{p,d_k} is the rating of document d_k given by user *p*. Note that $TM_{c,p}^H$ may be $PT_{c,p}^H$, $IGT_{U_g,p}^{d_k}$, or $HT_{c,p}^{H,d_k}$, which represent the trust value derived from one of our proposed trust models (i.e., HPT, IGT and HPT–IGT respectively) which take the personal perspective, group perspective and both into account, respectively:

$$H(Psim(c,p), TM_{c,p}^H) = \gamma \times TM_{c,p}^H + (1 - \gamma) \times Psim(c,p), \tag{18}$$

The advantage of using the weighted arithmetic mean is that it allows us to adjust the relative importance of user similarity *Psim*(*c*, *p*) and trust value $TM_{c,p}^H$. γ is a parameter determined by the best experiment result. Thus, users with trust values greater than a specified threshold are chosen as recommenders. Then, their document ratings are utilized in the

prediction process to compute the predicted ratings for documents. Note that an alternative is to derive the weightings using the harmonic mean of the trust value and user similarity. The harmonic mean is high when $TM_{c,p}^H$ and $Psim(c, p)$ are both high. Conversely, the harmonic mean tends to be small if one of the values is abnormally small.

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.

4.1. 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. We extract knowledge from these documents to derive the document profiles. Generally, each document profile consists of 800 distinct terms after information extraction by the *tf-idf* approach.

To share and retrieve the task-related knowledge, workers have four access behaviors in regard to documents: upload, download, browse or rate documents. These user behaviors are recorded in a log. For example, uploading behavior means that a worker "uploads" a document to the KMS to actively share the task-related knowledge, while downloading behavior means that a worker "downloads" a document relevant to his/her task from the KMS. Each user may access 45 documents on average, according to the log data. For the rating behavior, the user may give a document a rating on a scale of 1–5, to indicate how useful and relevant the document is perceived to be. In addition, if a user did not rate a document, a default score is assigned according to the user's access behavior. In this work, uploading and downloading behavior are regarded as more important than browsing behavior. Thus, a default score of 3 is given for browsing behavior, and 4 for uploading or downloading behavior. A high rating, i.e. 4 or 5, indicates that the document considered useful and relevant; while a low rating, i.e. 1 or 2, suggests that the document is deemed not to be useful.

In addition to the documents and document ratings, we also consider other user information, including users' roles and their weightings, in our proposed methods. Due to their various task-related knowledge and experiences, users in a group may be assigned different roles to execute the task. From the group perspective, we give each role a weighting value to represent its importance and influence for a group. Similarly, we also define explicit relationship trusts between users based on role relations. We set a value to the relationship trust for users based on the influence between their different roles. Note that this relationship trust is a direct trust. For two users, two different relationship trusts will be assigned. Additionally, users who conduct similar research tasks usually have similar information needs, i.e., similar interests in acquiring task-relevant documents. 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. We basically use a stratified sampling approach to select the target workers from each group of workers with approximately similar information needs. Some users accessed and rated less than the required threshold of 20 documents. These users were not used in the experimental analysis. Accordingly, 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. The data on target workers is further divided into 70% for training and 30% for testing, based on the access time of documents in those workers' document sequences. The training set is used to generate recommendation lists, while the test set is used to verify the quality of the recommendations. The training data is separated from the testing data. Accordingly, we evaluate the performances of our proposed methods and compare them with the traditional CF method, and other trust-based recommendation methods.

4.1.1. Evaluation metrics

The dataset used in our experiment includes users' rating behavior. 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 metric. The lower the MAE is, the more accurate the method will be. The MAE is defined in the following equation:

$$\text{MAE} = \frac{\sum_{k=1}^{N} |\widehat{P}_{d_k} - r_{d_k}|}{N}, \tag{19}$$

where N is the number of testing data, $\widehat{P}_{d_k}$ is the predicted rating of document d_k and r_{d_k} is the real rating of document d_k. Thus, the MAE metric is an appropriate evaluation metric in this work.

4.1.2. Methods compared in the experiment

In trust-based recommender systems, the trust values are obtained using different trust computation models for selecting neighbors of a target user. The trust values may be combined with user similarity measures (Pearson correlation coefficient) as weightings to predict a target user's rating. We have compared our proposed methods with other hybrid techniques presented in the literatures focused on trust-based CF systems. Conventional user-based CF and trust-based CF methods compared in our experiments are described as follows.

CF: the standard Resnick model in GroupLens [47]. The Pearson correlation coefficient (Eq. (1)) is used in filtering and making predictions [54].

Profile Trust-CF (ProfileT-US-CF): 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 [42], as described in Section 2.3.1.

Item Trust-CF (ItemT-US-CF): 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 [42], as described in Section 2.3.1.

Rating-based personal Trust CF (PersonalT-CF): Personal trust between two users is calculated by averaging the prediction error of their co-rated items [16], as described in Section 2.3.2.

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

Our proposed trust-based CF methods, which are developed based on the proposed hybrid personal trust and item-level group trust, are listed as follows.

Hybrid Personal Trust CF (HPT-CF): Recommendations with hybrid personal trust, which combines rating-based personal trust and relationship trust derived by Eq. (13), as described in Section 3.3.2.

HPT with User Similarity CF (HPT-US-CF): Recommendations with both HPT and user similarity (US) using Eq. (13) and Eq. (1), respectively. The weight in the prediction formula (Eq. (17)) is derived using the weighted arithmetic mean of the trust value and user similarity, as shown in Eq. (18).

Item-Level Group Trust CF (IGT-CF): Recommendations with the 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. (14)), as described in Section 3.3.3.

Hybrid of HPT and IGT CF (HPT–IGT-CF): Recommendations with the hybrid of HPT and IGT models, using Eqs. (13)–(15), as described in Section 3.3.4.

HPT–IGT with User Similarity CF (HPT–IGT-US-CF): Recommendations with the trust value of HPT–IGT and user similarity (US) using the weighted arithmetic mean (Eq. (18)), and the prediction formula (Eq. (17)), as described in Section 3.3.3.

4.2. Experiment results

In the experiment, we compare the performances of various recommendation methods from different aspects. There are 80 users in our data set. These users are clustered into 10 groups, as task-based groups, to acquire the groups' information for computing the trust value from the group perspective. According to the results of the trust computation, users whose trust values are greater than a threshold are regarded as a target user's neighbors for making recommendations. Then, we compare the MAE performances under different trust models and recommendation approaches.

HPT–IGT-CF uses a hybrid of HPT and IGT to compute trust degrees. To obtain a hybrid trust value, we adopt a parameter β which ranges from 0 to 1 to determine the relative importance of HPT and IGT. Because it is difficult to determine the optimal value for β, we conduct several experiments by systematically adjusting its value in increments of 0.1 in this work. Based on the experiment results, a suitable value for β is chosen if it leads to the best recommendation quality.

4.2.1. 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 a 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. It is difficult to determine the optimal value for the threshold. In this work, we conduct several experiments, trying different threshold values chosen based on the best MAE value of each recommendation method. According to our experiments, the most suitable threshold of trust value for the trust-based recommendation methods is 0.7.

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. (13)). The value of α is used to adaptively adjust the relative importance of the rating-based personal trust with respect to the relationship trust, based on the number of co-rated items between the two users. In Eq. (13), we set the value of N from 10 to 50 in our experiment in order to determine its appropriate value. From the experiment result, N is set as 20 for α to combine the two kinds of trust, because this achieved the lowest MAE.
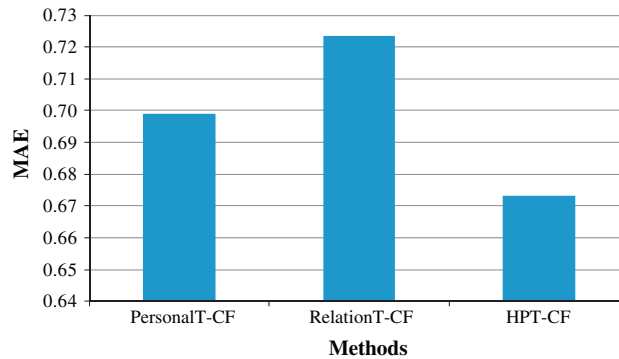
Fig. 6. The performance of hybrid personal trust.

The experiment result is shown in Fig. 6. 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. Moreover, we compare the performance of the PersonalT-CF and HPT-CF methods for target users with few past ratings. We selected one-third of target users as the target users with few past ratings by randomly removing their document ratings such that each of them had 7 document ratings in the training set. The MAEs of PersonalT-CF, RelationT-CF and HPT-CF methods for target users with few past ratings are 0.8747, 0.7998 and 0.7734, respectively. Compared with the result shown in Fig. 6, the recommendation quality of PersonalT-CF for target users with few past ratings becomes worse, since the personal trust values derived from these few past ratings are unreliable. The performances of RelationT-CF and HPT-CF also become worse, due to the lack of sufficient past ratings. However, the quality of HPT-CF is better than that of PersonalT-CF and RelationT-CF. The HPT-CF can resolve the drawback of PersonalT-CF under insufficient past rating records by considering both the rating-based personal trust and the relationship trust. The performance of HPT-CF is better than that of Personal-CF, whether the data has few past ratings or more past ratings.

4.2.2. 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 the 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 to systematically adjust the values of β in an increment of 0.1, as shown in Fig. 7. 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.

Fig. 7 also shows the performance of HPT-CF under $\beta = 1$, where the predicted rating of a document is derived totally by the HPT. When $\beta = 0$, 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. (15), 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. To predict document
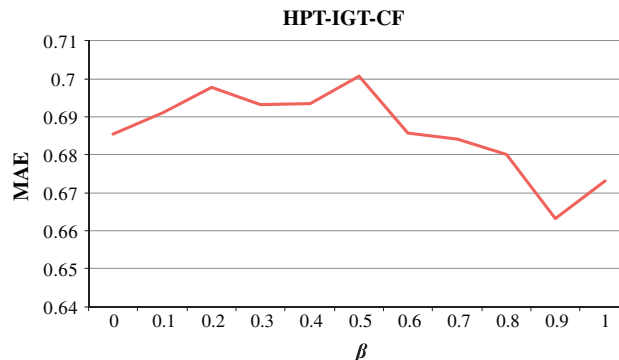

Fig. 7. The MAEs of HPT–IGT-CF method under different β.

Table 1
The MAEs of proposed methods without/with user similarity under different γ.

Weighted arithmetic mean	Methods		
	HPT-US-CF	IGT-US-CF	HPT–IGT-US-CF
$\gamma = 0.9$	0.67327	0.6856	0.6636
$\gamma = 0.7$	0.6740	0.6848	0.6645
$\gamma = 0.5$	0.6763	0.6832	0.6666
$\gamma = 0.3$	0.6807	0.6836	0.6708
$\gamma = 0.1$	0.6917	0.6892	0.6802
Harmonic Mean	0.6959	0.6971	0.6934
Trust-Methods	**HPT-CF**	**IGT-CF**	**HPT–IGT-CF**
$\gamma = 1$	0.6731	0.6853	0.6633

ratings based on trust models, the HPT only predicts users' trust value from the personal perspective, while IGT only predicts users' trust values from the group perspective, i.e. the opinions of a target user's group members. A target user usually has similar preferences 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.

4.2.3. The effect of user similarity

In this section, we evaluate the effect of including user similarity in our trust models, i.e., HPT, IGT, and HPT–IGT, on making recommendations. The HPT-US-CF, IGT-US-CF, and HPT–IGT-US-CF methods use the weighted arithmetic mean (Eq. (18)) of trust value and user similarity (US) as the weight to predict the rating (Eq. (17)), as described in Section 3.3.3. A parameter γ is used to adjust the relative importance of trust value and user similarity in the weighted arithmetic mean formula. Table 1 shows the MAEs of HPT-US-CF, IGT-US-CF, and HPT–IGT-US-CF under different values of γ. These methods integrate user similarity into their trust models, i.e. HPT, IGT, and HPT–IGT, by applying 0.9, 0.7, 0.5, and 0.3, respectively as weighting values in the weighted harmonic mean. According to this result, the appropriate value of γ for each method with user similarity is determined. HPT-US-CF with $\gamma = 0.9$, IGT-US-CF with $\gamma = 0.5$, and HPT–IGT-US-CF with $\gamma = 0.9$ have better performances. Therefore, giving different combination weights for the trust value and user similarity may slightly influence the recommendation quality. The result shows that trust value is generally more important than user similarity in deriving the weights for making predictions. Note that an alternative is to derive the weightings by using the harmonic mean of the trust value and user similarity. Our experiment result shows that the harmonic mean approach performs worse than the weighted arithmetic mean approach.

Table 1 also shows the MAEs of HPT-CF, IGT-CF, and HPT–IGT-CF without integrating user similarity. The IGT-US-CF performs slightly better than IGT-CF. However, the HPT-US-CF/HPT–IGT-US-CF does not perform better than HPT-CF/HPT–IGT-CF. This implies that considering the user similarity in HPT-US-CF and HPT–IGT-US-CF does not improve the recommendation quality for our data set. The user similarity derived from the Pearson correlation of rating data may not be reliable, since some users may not have enough rating data. Generally, our proposed trust model, combined with user similarity, does not significantly enhance the recommendation quality of the proposed methods.

4.2.4. 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 Fig. 8. The ItemT-US-CF/ProfileT-US-CF method predicts users' trust by computing the ratio of accurate predictions that s/he 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. Experiments are also conducted to evaluate the performance of ItemT-CF/ProfileT-CF, which uses the item-level/profile trust value as the weight to make predictions. For our data set, the result shows that the difference between the MAEs of ItemT-US-CF and ItemT-CF is very small (0.708086 vs. 0.708002). The MAEs of ProfileT-US-CF and ProfileT-CF are also very similar (0.7124361 vs. 0.7124360).

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 of 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. Generally, users in the same group may have more similar preferences on documents than other groups' users. The opinions of the target user's group may also be different from those of other groups. Thus the trust values derived from the opinions of the majority of all users, without considering group perspective,
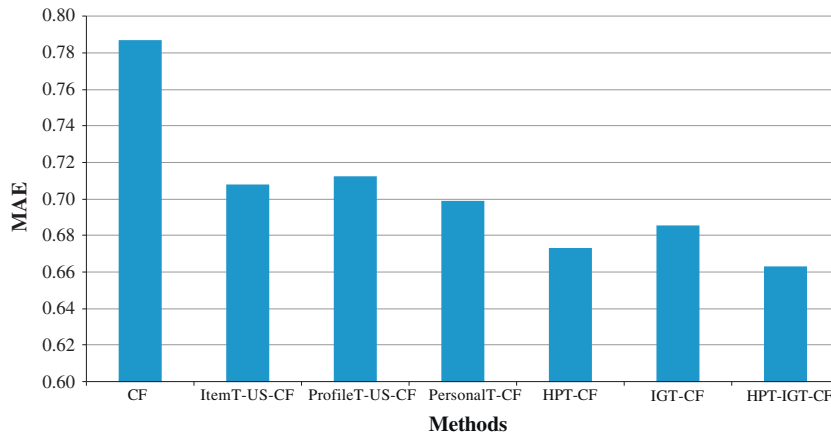
Fig. 8. Comparison of all methods.

may not be appropriate for finding trustworthy recommenders for the target user. Therefore, the group perspective can indeed improve the recommendation performance.

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, which adaptively combines rating-based personal trust and role-relationship trust, performs better than the traditional trust-based recommendation methods, including Personal-TCF, Item-US-CF, and Profile-US-CF. HPT-CF can resolve the problem of an insufficient number of co-rated documents between two users, which may result in unreliable trust prediction.

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, CF, has the worst recommendation quality because it does not consider trust between users. Therefore, the trust models do indeed contribute to improved recommendation quality. The result also shows that the HPT–IGT-CF method performs better than HPT-CF and IGT-CF methods. Note that the HPT–IGT-CF method uses the hybrid trust model, considering both personal trust (HPT) and item-level group trust (IGT), in order to make recommendations. The HPT and IGT complement each other, and contribute to derive more reliable trust predictions from both personal and group perspectives. Recommending documents from both personal and group perspectives results in better performance than making recommendations based on only one or the other. The hybrid trust model enhances the trust models in order to improve the recommendation quality. 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.

5. Conclusions and future work

This work focuses mainly on proposing novel personal and group trust models to enhance recommendation quality. We propose document recommendation methods based on hybrids of personal and group trust models. These 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) model, the item-level group trust (IGT) model and a hybrid of the HPT and IGT (HPT–IGT) models. From the personal perspective, HPT adaptively takes not only users' ratings on co-rated documents, but also the role relationship trust into account in trust computation. Existing trust-based recommender systems mainly combine trust models with user-based CF to design hybrid techniques, i.e., trust-based CF methods to enhance the recommendation quality of CF systems. However, conventional trust-based CF methods have not explored combining the rating-based trust model with an explicit trust metric. We propose a hybrid personal trust (HPT) model which can adaptively integrate rating-based personal trust and explicitly specified relationship trust. Additionally, role relationship trust is applied in order to address the drawbacks of rating-based personal trust, and resolve the unreliability of trust computation when two users only share a few co-rated documents. 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 of a specific item. In general, users in the same group have more similar preferences for documents than other groups' users. The preferences of users in different groups may also be different. Our proposed group-based trust model (IGT) performs better than the traditional non-group based trust models.

Moreover, existing trust-based CF systems do not consider both personal and group perspectives. To take advantage of the merits of both the 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 those of the members of their group, such that a recommender trusted by their group members may also be trusted by the user. The

experiment result shows that the trust value of IGT complements the trustworthiness of personal perspective. The experiment results show that the prediction accuracy of recommendation is 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 do other trust-based CF methods.

In future work, we will model user relationships as a social network structure, and use the social network analysis to analyze their relationships. Social networking is very popular, whether in academic or industrial environments. It is useful for identifying not only trustworthy users, but also other kinds of user relationships. The analysis of user relationships may enhance the accuracy of trust computation and recommendation quality. Additionally, we will investigate how to infer user's relationship trust and role weights from users' information, or past rating data, instead of deriving them by observation of domain experts. We will also apply our trust models and recommendation methods in other application domains to evaluate their effectiveness. Moreover, existing studies on trust-based recommendations also use the *Pearson* similarity integrated with the trust models to design trust-based CF methods. This work mainly focuses on proposing novel personal and group trust models to enhance the recommendation quality. Thus, we did not discuss and combine other similarity functions with our trust models, which we will undertake in future work. Furthermore, it is difficult to find a public dataset to evaluate our proposed methods because our trust computation models use a dataset which contains documents, document ratings, users' roles, user groups, users' access and rating behavior and so on. Therefore, we will try to develop other trust-based recommendation methods from different perspectives, and evaluate those methods using public datasets, e.g. *MovieLens* or *Epinions* datasets, in our future work.

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