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A social recommendation method based on the integration of social relationship and product popularity

Chin-Hui Lai[a], Shin-Jye Lee[b,*], Hung-Ling Huang[a]

[a] Department of Information Management, Chung Yuan Christian University, Taiwan
[b] Institute of Technology Management, National Chiao Tung University, Taiwan

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ABSTRACT

Web 2.0 technology fosters the flourishing growth and development of social networks. More and more people are participating in the activities on social networks to interact and share information with each other. Thus, consumers are often making their purchasing decisions based on information from the Internet such as reviews, ratings, and comments on products, especially from their trusted friends. However, a great amount of available information may cause the problem of information overload for consumers. In seeking to attain a good recommendation performance by taking the high-potential factors into account as far as possible, this paper proposes a novel social recommendation method on the basis of the integration of interactions, trust relationships and product popularity to predict user preferences, and recommend relevant products in social networks. In addition, the proposed method mainly focuses on analyzing user interactions to infer their latent interactions in accordance with the user ratings and corresponding reviews. Additionally, users may be affected by the popularity of products, so this factor has also been taken into consideration in this work. The experimental results show that the proposed recommendation method has a better recommendation performance in comparisons to other methods because the proposed method can accurately analyze user preferences and further recommend high-potential products to target users in social networks to support their purchase decision making. Furthermore, the proposed method can not only reduce the time and effort users spend on querying information, but also positively relieve the problem of information overload.

1. Introduction

Due to the significant development of Web 2.0, users are able to generate or share information on webs and engage in various interactions with other users (Tanaka, 2009). For example, when consumers purchase products via e-commerce sites or physical stores, they can share information about their experiences with other consumers via reviews on webs. In other words, this tendency enables users to easily acquire relevant information on products via the Internet; it also makes users more dependent on online information regarding purchasing decision making. However, the problem of information overload arises as the mountain of data generated in the Internet do not necessary fit the requirements of consumers. In recent years, the services provided by social networks attracts huge amounts of people to frequently communicate as well as interact on social networking sites based on a variety of human relations. Social networking sites provide the venue for establishing different relationships as well as information sharing (Boyd and Ellison, 2007). For example: *Flickr.com* allows users to record their personal life through photos and to share them with friends or other users on the website; their friends can comment on the photos as well. *Facebook.com* allows users to maintain easy relationships and instantly interact with their friends, including the publishing of comments and responding to topics. Due to the discussions above, numerous kinds of information are rapidly and constantly generated, so the problem of information overload is undoubtedly becoming a more serious in-depth issue.

In addition, several works have proposed a variety of recommender systems to solve the problem of information overload (Crespo et al., 2011; Fan et al., 2009; Golbeck, 2006; Goldberg et al., 1992; Jamali and Ester, 2009; Mislove et al., 2007). The basic mechanism of a recommender system involves determining user preferences by analyzing a large amount of raw data, by filtering out unnecessary information to find the valuable information related to potential user preferences. Generally, the recommender systems work through the collaborative filtering approach and content-based filtering approach. The collaborative filtering approach (CF) is the most used method in many domains; it can be classified as user-based CF (Herlocker et al., 1999) and item-based CF (Sarwar et al., 2001).

The traditional recommendation methods only focus on finding the connections between users and products based on similarity measure-

* Corresponding author.
E-mail address: hero@nctu.edu.tw (S.-J. Lee).

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ments. As the number of users and products increase, the computation overhead also increases and the scalability becomes very poor. To resolve these problems, it is necessary to analyze the relationships of users and products via recommendation methods. For example, by integrating similarity, both trust and reputation in the CF method can increase the connectivity of users and improve the recommendation quality (Than and Han, 2014). Davoudi and Chatterjee (2016) proposed a social trust model based on users' centrality and similarity; it uses the probabilistic matrix factorization method to predict users' preference. Additionally, the CF method has difficulty in computing the similarity of users who have small scales of user profiles or unique preferences. Exploiting users' new information in CF will cause the problem of data latency and increase the waiting time for generating the recommendation result (Chen and McLeod, 2009); using interrelatedness of the social networking structure may resolve this problem. In this study, we particularly present a complete design of a recommender method by analyzing both user interaction and user behavior in a social network.

In the past, some works improved the existing recommendation methods by integrating the factors of interpersonal relationships and corresponding interactions. Generally, the social network-based recommendation methods (Tang et al., 2013) primarily comprise the following influential factors: interpersonal interactions (e.g., online user interaction (Mei et al., 2007) and click behavior (Jiang et al., 2012), etc.), and social relations derived from user interaction (e.g. trust relationship (Borzymek et al., 2009; Jamali and Ester, 2009; Victor et al., 2009), relationships with friends (Chen et al., 2009; Yang et al., 2012), followers' relationships (Hajian and White, 2011; Hao et al., 2012), and members relationships (Cha et al., 2010; Yuan et al., 2009)). The social interaction information can improve the recommendation accuracy (Nie et al., 2014). Therefore, user relationships and interactions on a social network will be further explored herein for predicting user preferences. A friend recommendation method which utilizes the interaction intensity and adaptive user similarity on a social network is helpful in dealing with the problem of data sparsity (Agarwal and Bharadwaj, 2013). Zheng et al. (2011) proposed a hybrid system to recommend unvisited locations to users by analyzing the attributes of social networking and the popularity of locations. Because users' social relationships and interactions may influence the predictions of users' needs; these require further exploration.

For the above reasons, this paper proposes a recommendation method which combines user interaction and trust relationship to make predictions for users in the social networking environment. The user interactions among a target user and his/her social friends can be identified by mining the social interactions, including rating, sharing and posting behavior on a social network (Nie et al., 2014; Preece et al., 2015). In this paper, user interaction is derived from the combination of direct and indirect interactions by analyzing users' rating behavior. In the analysis of direct interaction, the ratings of products and reviews, the time weights of giving ratings, and the number of user interaction are considered. In the analysis of indirect interaction, we take into account the time weights of the ratings on common items, the rating difference of common items among users, as well as the number of ratings.

The trust relationship and its corresponding degree among users can be inferred by the products ratings and comments given by users on social networking sites. In addition, users are not only affected by online comments or suggestions, but also the compelling effect of popular products, so the products' popularity has been especially taken into consideration. The user interaction, trust relationship and products' popularity are then integrated in the recommendation method to make predictions for users on social networking sites. The proposed recommendation method aims to accurately analyze the preferences of users in social networks for the purpose of improving the prediction accuracy and its applicability in social networks. It also can reduce the time and effort users spend on querying information, and positively ameliorate the problem of information overload.

The rest of this paper is structured as follows. Section 2 introduces related works, including social network, collaborative filtering, and recommendation methods, based on trust and social networks. The proposed recommendation method, which integrates the interaction, trust relationship, and product popularity, is described in Section 3. In Section 4, several experiments are conducted for validating the performance of the proposed methods. The experimental results are compared and briefly discussed. Finally, the conclusion and the future directions are illustrated in Section 5.

2. Related works

The related works are described in this section, including social networks, recommender systems, trust-based recommendation methods, and recommendation methods, based on social networks.

2.1. Social network

Since social networking sites emerged and proliferated this century, people are interacting more closely and frequently in social networking environments. Generally, the key factor of social networks is promoting users to make persistent interactions usually through interactive discussions on popular topics. Basically, the structure of social networks consists of a large number of nodes and links. A link connects each two nodes in the structure; it represents its connection among nodes (Watts, 1999). Watts and Strogatz (1998) found that a connection between two unknown people is achieved through six other people. These six are related to one another, as a path between the two people. As such, social networking allows for different groups to be influenced by their interrelatedness. Because the links among people in a social network are based on proximity relations and extensive connections, the relationships among people are complicated and diversified. Thus, the social networks can not only handle a variety of relations among people, but also information exchanges. Nettleton (2013) proposed that the node relationships of social networks can be evaluated by a variety of factors, including a variety of people's behaviors and their intersections in different times and places. Also, He and Chu (2010) consider that people are affected by their social friends, both immediate and distant, when making decisions.

"Interaction" is the mode whereby the information receiver can either respond or revise the content of messages, to gradually establish effective two-way communication via this iterative process (Preece et al., 2015). In addition, Hoffman and Novak (1996) proposed the concept of machine interaction, indicating that people interact with websites to engage individually in interactions in websites, such as reading and responding to information provided in websites. As for human to human interactions, it allows people to partake in multi-discussions by sending messages online, further simulating the communication scenarios of the real world (Steuer, 1992). Massey and Levy (1999) also discuss how people are able to exchange information via instant messaging, chat room or public forum by the human to human interaction in the Internet. In this regard, the interactions among people in the Internet have become more frequent and intensive by online multimedia applications; it also highlights the importance of people's interactions.

In the research domain of recommender systems, some methods resolve the problem of data sparsity by incorporating social information in their recommendations. Van Lierde and Chow (2017) proposed a recommendation method which combines rating information and friendship ties as different types of interactions in a single user network. Zhang et al. (2014) utilized user clustering and implicit trust among users to construct a small-world implicit trust network, and then made adaptive recommendations based on the topology of such trust network. These proposed methods have proven effective in both the dense and sparse contexts.

2.2. Collaborative filtering

The development of web 2.0 allows ever increasing numbers of people to share information and their experiences on the web, resulting in a huge amount of data growing rapidly and exponentially. People may have difficulty in finding the information they need. Various recommender systems have been developed and applied for the purpose of solving the information overload problem. They can analyze various preferences of users from the numerous data, and then recommend the items of interest which may satisfy the needs of users. The traditional recommendation methods can be classified as collaborative filtering (CF), content-based filtering (CBF), and hybrid recommendation (Burke, 2002) which combines two or more techniques to improve the performance. Among these methods, CF is the most widely used method in a variety of fields, especially in daily life, in seeking information on movies, music, and news. Therefore, the design of the method proposed herein is based on the CF method. Basically, the CF method aims to analyze the historical data of users to find their possible preferences, such as the product rating given by users and the products they bought in the past (Sarwar et al., 2001). Generally, two steps are primarily applied in this method: similarity analysis and preference prediction, which are described below.

2.2.1. Similarity analysis

The method of similarity calculation is used to analyze the similarity degree between users and products to find similar neighbors of target users in order to make recommendations. The most commonly used methods are the *Pearson Correlation Coefficient* method (Shardanand and Maes, 1995) and the Cosine method (Ahmed et al., 1974; Nguyen and Bai, 2011). Basically, the Pearson Correlation Coefficient method is used to measure the preference similarity between two users by calculating the difference of rating given to the same products. Furthermore, the formula can be depicted as follows:

$$Sim_{a,b}^{Pearson} = \frac{\sum_{i\in(I_a\cap I_b)} (r_{a,i} - \bar{r}_a)(r_{b,i} - \bar{r}_b)}{\sqrt{\sum_{i\in(I_a\cap I_b)} (r_{a,i} - \bar{r}_a)^2}\sqrt{\sum_{i\in(I_a\cap I_b)} (r_{b,i} - \bar{r}_b)^2}} \tag{1}$$

where $Sim_{a,b}^{Pearson}$ is the Pearson similarity between user a and user b; I_a and I_b are the sets of products that user a and user b use respectively; $r_{a,i}$ and $r_{b,i}$ are the rating given to the product i by user a and user b, respectively; $\bar{r}_a$ and $\bar{r}_b$ are the mean values of ratings of user a and user b, respectively. Basically, the value of Pearson similarity is between [−1,1]. If the value is higher than 0, there is a positive correlation between the two users; otherwise, there is a negative correlation between the users. The Pearson similarity is not effective when users only have a few ratings (known as the cold-start problem). A new user similarity model which considers the local context information of user ratings and global preference of user behavior is proposed herein to improve the limitation of similarity computations (Liu et al., 2014).

2.2.2. Preference predictions

The preference prediction of a target user is based on his/her similar user preferences. Similar users of a target user are regarded as the neighbors of the target user, and their ratings given to products are used to make item predictions for the target user. The predicted ratings of items are measured by using Resnick's formula (Resnick et al., 1994), as follows:

$$\hat{P}_{a,i} = \overline{r_a} + \frac{\sum_{P\in NS} Sim_{a,b}^{Pearson} \times (r_{b,i} - \bar{r}_b)}{\sum_{P\in NS} \left|Sim_{a,b}^{Pearson}\right|} \tag{2}$$

where $\hat{P}_{a,i}$ represents the predicted rating of the target user a to item i; NS is the similar user set of user a. A higher predicted score indicates that the user might like this item in the future. Finally, the top-N items with higher predicted scores are recommended to the target users. The performance of a recommender system can be determined based on the result of evaluation by using accuracy metrics (Herlocker et al., 2004). Generally, accurate recommendations sometimes are not the recommendations that are most useful to users (McNee et al., 2006).

One major problem of the traditional collaborative filtering is the cold-start problem. It is difficult to make recommendations for new users or users who have only rated a few items; user similarity may not be computable because of the little knowledge of user preferences. The other problem is scalability. Collaborative filtering usually depends on finding similar users in order to make recommendations. As the number of users increases, the computation overhead will also increase and the scalability will become poor. To resolve these problems, integrating similarity, trust and reputation in the collaborative filtering method can increase the connectivity of users and improve the recommendation quality (Than and Han, 2014). In addition, the CF method may provide inaccurate results because it cannot cover extreme cases, recommend new items which are not-yet-rated or not-yet-labeled, or deal with the data latency (Chen and McLeod, 2009). Therefore, using the information in social networks in the recommendation process may resolve these problems.

2.3. Trust-based recommendation

In society, trust is an important concept in human interactions. It has many basic characteristics, such as being context sensitive, subjective, unidirectional, intransitive, and so on (Yu et al., 2010). Such trust concept was extended to the field of computer science in the form of a computational trust model. The trust relationships among users in social networks can be inferred from the records of user interactions in the past, or as specified by users. It is also called personal trust (Golbeck and Kuter, 2009). Meanwhile, this trust value indicates the degree of trust between two users; different pairs produce different values as a whole. If users cannot explicitly specify their trust relationships, these values can be calculated and inferred by using rating information or other indirect information (Hwang and Chen, 2007; Lathia et al., 2008).

The trust relationship among users can be classified as direct trust and indirect trust. These two types of trust are established according to whether or not users directly give trust value (O'Donovan, 2009). Basically, direct trust means that the relationship can be explicitly specified between two users, such as users' "trust list" in *Epinions.com*, or "friends list" in Facebook (Massa and Avesani, 2004, 2007). Contrarily, indirect trust is calculated and inferred from common items or information between users. Additionally, trust is related to reputation, so that users' trust relationship can be measured by the combination of helpfulness-based reputation (HBR) scores and centrality-based reputation (CBR) scores (Meo et al., 2017). The HBR scores rely on the aggregation of users' feedback from the reaction to the comments/ratings posted by other users. The CBR score relies on the users' connections in a trust network, and quantifies the reputation of a user by evaluating his/ her centrality in such network. Kazai and Milic-Frayling (2008) proposed a hybrid trust network which combines reputation models and trust propagation mechanisms in order to distinguish between the authoritative and popular approval of an item.

O'Donovan and Smyth (2005) considered that the past ratings of trustworthy users can be effectively used to predict the preferences of other users and provide more accurate recommendations. The recommendation methods based on trust relationship, including profile-level trust and item-level trust, are hence proposed. These two types of trust are applied to find the recommenders with high trust values; the trust values are then combined with users' Pearson similarity by harmonic mean. Then, this combination is applied to Resnick's formula (Resnick et al., 1994) for predicting the ratings and making recommendations. In addition, Hwang and Chen (2007) propose a trust-based recommendation method which infers the trust relationships of users based on the ratings of common items given by users. Also, the trust degree replaced the user similarity in Resnick's formula, and then the collaborative filtering method was further applied to predict the ratings of items. Their experimental results showed that the collaborative filtering method based on individual trust can have a much better recommendation effect compared to traditional recommendation methods. To improve the accuracy of recommendations, the trust relationship is hence considered in the proposed recommendation method in this paper.

2.4. Recommendations based on social networks

Certain studies take behavioral theory into consideration in designing more effective recommendation methods compared to traditional ones. The relationships among people can be summed up as follows. (1) Trust relationship: users can assign the trust relationships between them (Victor et al., 2009), or infer the trust relationships based on the trust computation model (Borzymek et al., 2009). (2) Friendship: clear friendship between users can be established by the "join friends" function provided by social network websites (Yuan et al., 2009) or by the similarity degree of preferences between users (Chen et al., 2009). (3) Followership: users can follow other users' articles or items in which they are interested (Cha et al., 2010). (4) Group membership: the users who are members of the group participate in the discussions or share experiences (Yuan et al., 2009).

In recent years, numerous recommendation methods based on social networks have been developed to attain a good recommendation performance. Changchun et al. (2010) integrate traditional collaborative filtering method into their approach by considering user-related data and links in social networks, such as the degree of user-to-user contacts, the number of user contacts, and the importance of user roles; thereby, using the information derived from the social networks can effectively improve the predictions of recommendations. Arazy et al. (2009) integrated various information obtained from social networking websites, such as trust, reputation, user preference, and the frequency of interactions to predict user preferences and identify the items of interest for making recommendations. In addition, Li and Chen (2009) developed a blog-based recommendation method which combines trust relationships, semantic analysis, and user relationships in social networks; it infers the trust relationships among users by using the information in users' blogs, such as common comments and citations to enhance its recommendation performance.

Moreover, integrating similarity, trust and reputation in the CF method can increase the connectivity of users and improve the recommendation quality (Than and Han, 2014). Li et al., (2013) proposed a social recommendation method based on preference similarity, recommendation trust and social relations, to provide personalized product recommendations. Such social relationships and trust may influence the recommendations. However, most of above recommendation methods based on social networks only analyze the similarity between users with same items or users' indirect interaction. User behavior and interaction analysis in social networks are insufficient. In order to attain a better performance of recommendation methods, this work proposes an effective recommendation method integrating social networks and trust relationships.

3. Recommendation based on the combination of social relationships and product popularity

Many product recommendation methods proposed in previous researches used user interactions to make predictions. However, these methods do not explicitly define and analyze users' direct and indirect interactions based on users' interaction behavior. They also do not take both social interaction and trust relationships among users into account. On the basis of users' behavior in a social network, this paper analyzes user interaction and trust relationships for recognizing the connections among users. It also analyzes user preferences and product popularity. According to these analyses, the proposed methods can predict potential products that users may possibly prefer through the collaborative filtering method.

3.1. Preliminary phase

To make product predictions for users, we collected a dataset from a social networking website, including product ratings, product reviews, and users' trust lists. We propose a novel recommendation method herein based on the analysis of social interaction, trust relationships and product popularity to predict products for users in a social network. Our method considers not only users' preferences, but also their social relations. The proposed method is illustrated in Fig. 1. The proposed method is composed of four parts: interaction analysis, trust analysis, product popularity analysis, and product recommendation. Each part is briefly described below.

Interaction analysis

The interaction analysis is based on users' rating behavior. The ratings of products and product reviews are used in the computations of the direct and indirect interactions. The direct and indirect interactions are then integrated as the social interaction by giving weightings, and used in making recommendations.

Trust analysis

Because users' preferences usually are influenced by other trustworthy users, it is essential to determine the explicit and implicit trust relationships among users in a social network. The ratings of products, corresponding reviews given by users and the roles of users in a social network are utilized to infer the implicit direct and indirect trust relationships among users. Then, these two kinds of trust are integrated in the procedure to deduce the trust degree of users.

Product popularity analysis

The user preferences for the products are not only influenced by users' interactions and trust relationships, but also by product popularity. This study analyzes the product popularity based on how many users are interested in the specific products. Moreover, high-popularity products have a higher priority to be recommended to the target users.

Product recommendation

Based on the above analysis results, the users' social interactions and trust relationships are integrated into the procedure to establish the potential connections among users. The preferences of users who have strong connections with a target user are analyzed to predict the products of interest for the target user.

3.2. Interaction analysis

User interaction among a target user and his/her social friends can be identified by mining the social interactions, including rating, sharing and posting behavior on a social network (Nie et al., 2014). This study analyzes the direct and indirect interactions among users based on users' rating behavior and frequency of interactions with the corresponding priority in a social networking website. The proposed social network is constructed according to such analysis for the purpose of presenting the complex interactions among users. In the recommendation process, users with high interaction degrees will be selected as recommenders to provide recommendations for target users.

3.2.1. Direct interaction analysis

In this paper, direct interaction is a user behavior whereby the user gives ratings to the products and product reviews written by other users. In analyzing the direct interaction between two users, the ratings of products and reviews, the time weights of giving ratings, and the number of user interactions are considered. Products and reviews with high

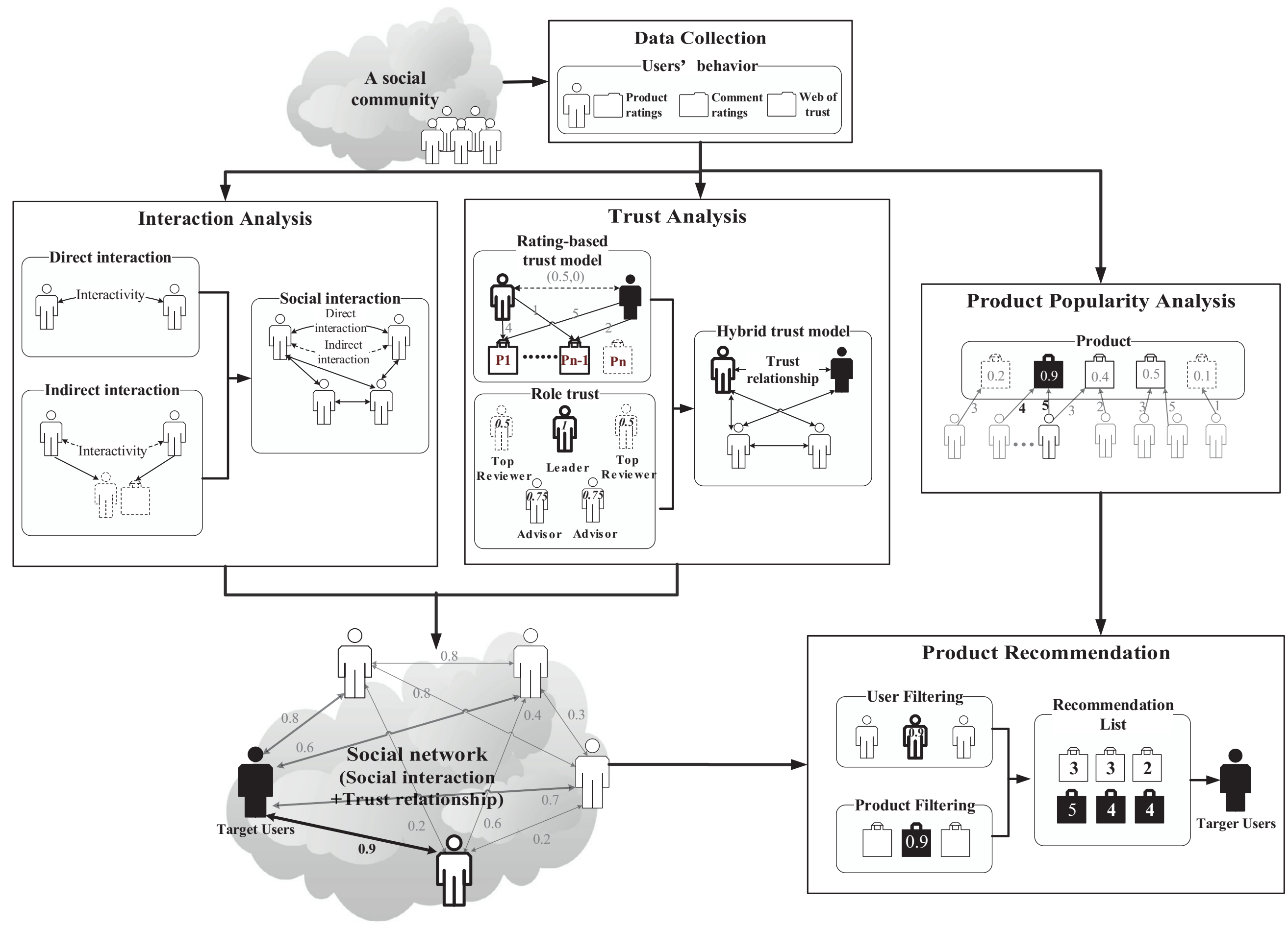

Fig. 1. An overview of the proposed recommendation method.

ratings indicate that these products and reviews are very helpful to the users. The ratings of products and reviews given by both two users are considered. Besides, a user's preference for products may change over time, so that the latest ratings given by the user reflect his/her current preferences. Therefore, we consider not only users' ratings but also the time weight of these ratings in analyzing the direct interaction. Additionally, the number of user interactions means the rating frequency of a user's reviews of a specific user. It also represents the frequency of the user's direct interactions. The interaction frequency is measured by using the proportions of the number of review ratings to the total number of ratings given by a specific user. High frequency interactions lead to a large degree of direct interactions. For measuring the degree of two users' direct interaction, the ratings of item, time weights, and the number of user interactions are integrated to infer the degree of direct interaction between users, as defined in the following equation:

$$DI_{u_i \to u_j} = \frac{\sum_{k \in CR_{u_i,u_j}} r_{u_i,k} \times T_{u_i}^k}{\sum_{k \in CR_{u_i,u_j}} T_{u_i}^k} \times \frac{\left|CR_{u_i,u_j}\right|}{\left|RR_{u_i}\right|} \tag{3}$$

where $DI_{u_i \to u_j}$ is the degree of direct interaction between users u_i and u_j. $r_{u_i,k}$ is the rating of user u_i on item k of user u_j. CR_{u_i,u_j} is a set of ratings given by user u_i to the review of user u_j. RR_{u_i} is the a set of ratings given by user u_i. $|CR_{u_i,u_j}|$ is the number of ratings given by user u_i to the review of user u_j and $|RR_{u_i}|$ is the number of ratings given by user u_i. When user u_i gives higher ratings to the reviews of user u_j or the rating frequency between user between u_i and u_j is high, the interaction degree between user u_i and u_j is also high.

$T_{u_i}^k$ is a time weight of the rating of item k given by the user u_i, as defined in Eq. (4). It is used to calculate the time weight of a rating of item k (i.e. a product or a product review) given by user u. For each user, the ratings on the products and reviews are assigned time indices and are ordered by the rating time as a time-order rating sequence. In such sequence, the time index of a rating is converted into a time weight. Higher time weights are given to ratings with a more recent time index:

$$T_u^k = \frac{\left(t_u^k - ts_u\right)}{\left(tf_u - ts_u\right)} \tag{4}$$

where t_u^k means the time index of the rating of item k by the user u; ts_u and tf_u are the starting time index and the latest time index in the sequence of the user u, respectively.

3.2.2. Indirect interaction analysis

There also certain implicit relationships among users in a social network, such as unfamiliar users giving ratings to the same products or corresponding comments; these are so-called indirect interaction relationships. If two users did not have direct interaction, their implicit relationships can be inferred from users' rating behavior on common items (i.e. products and product reviews). In the analysis of indirect interactions, we take the time weights of the ratings on common items, the rating difference of common items among users, as well as the number of ratings into account. Similar to the concept of time weighting mentioned in Section 3.2.1, users' item preferences may change over time. The ratings given by users at different time may have different time weight. Generally, the latest ratings given by the user reflect his/her current preferences, so that these ratings may have higher time weights. Such time weights of the ratings on common items are regarded as a factor in analyzing the indirect interaction.

Additionally, the rating difference of common items among users can represent the preference difference of users. Basically, the smaller the difference of ratings, the more similar the preferences of the two users! Moreover, the frequency of indirect interaction is measured by the proportions of the number of ratings given by both two users to the total number of ratings given by the specific user. If two users give ratings to many common items, it implies that their indirect interaction is very close. The calculation for measuring a degree of two users' indirect interaction is expressed in the following equation:

$$II_{u_i \to u_j} = \frac{\sum_{s \in I_{u_i} \cap I_{u_j}} \left(1 - \frac{|r_{u_j,s} - r_{u_i,s}|}{M}\right) \times TW^s_{u_i,u_j}}{\sum_{s \in I_{u_i} \cap I_{u_j}} TW^s_{u_i,u_j}} \times \frac{|I_{u_i} \cap I_{u_j}|}{|RR_{u_i}|} \tag{5}$$

where $II_{u_i \to u_j}$ is the degree of indirect interaction between user u_i and user u_j. $r_{u_i,s}$ and $r_{u_j,s}$ indicate the ratings of items (i.e. including products and corresponding reviews) given by user u_i and user u_j, respectively. M is the maximum rating among all item ratings. $|RR_{u_i}|$ is the total number of ratings given by user u_i; s is a set of common products and corresponding comments rated by user u_i and user u_j. $TW^s_{u_i,u_j}$ is a time weight derived from the rating of the common item s given by users u_i and u_j.

This time weighting method is presented in Eq. (6), which was extended from Eq. (4). The rating time of items given by a user is more recent, so that these items and ratings can reflect the users' current preferences. Because two users gave ratings to a common item at different times, the time weights of such item in the time-order rating sequences of these two users are combined as a harmonic mean:

$$TW^s_{u_i,u_j} = \frac{2 \times T^s_{u_i} \times T^s_{u_j}}{T^s_{u_i} + T^s_{u_j}}, s \in I_{u_i} \cap I_{u_j} \tag{6}$$

where $TW^s_{u_i,u_j}$ is a time weight of item s, which is rated by both user u_i and user u_j. I_{u_i} and I_{u_j} signify the set of ratings of products and corresponding comments given by users u_i and u_j, respectively. $T^s_{u_i}$ and $T^s_{u_j}$ signify the time weights of the common item s given by user u_i and user u_j, respectively. Furthermore, a greater value of $TW^s_{u_i,u_j}$ implies that the times of ratings given by the two users to the same items are much closer.

3.2.3. The combination of direct and indirect interactions

To evaluate the degree of user connection in a social network, the values derived from the direct and indirect interaction analysis are combined as an interaction degree by using following equation:

$$SL_{u_i \to u_j} = \alpha \times DI_{u_i \to u_j} + (1 - \alpha) \times II_{u_i \to u_j} \tag{7}$$

where $SL_{u_i \to u_j}$ is the interaction degree between users u_i and u_j. $DI_{u_i \to u_j}$ is the value of the direct interaction between users u_i and u_j (described in Section 3.2.1), while $II_{u_i \to u_j}$ is the value of the indirect interaction (described in Section 3.2.2). α is a weighting parameter for adjusting the relative importance between the direct and indirect interaction. Such parameter is calculated by using the number of common ratings of two users, as defined in the following equation:

$$\alpha = \frac{|CR_{u_i,u_j}|}{|CR_{u_i,u_j}| + |P_{u_i,u_j}|} \tag{8}$$

where $|CR_{u_i,u_j}|$ is the number of ratings that user u_i gives to the reviews of user u_j, and $|P_{u_i,u_j}|$ represents the rating set of users u_i and u_j on common products and product reviews. Also, a larger value of α indicates that the direct interaction between two users is higher; thereby, the social network based on user interaction can be created, as shown in Fig. 2. In this figure, nodes are represented as users, a link between two nodes is represented as user interaction between two users, and the values on the link are interaction degrees. Such social network is helpful to represent the potential interactions among users.

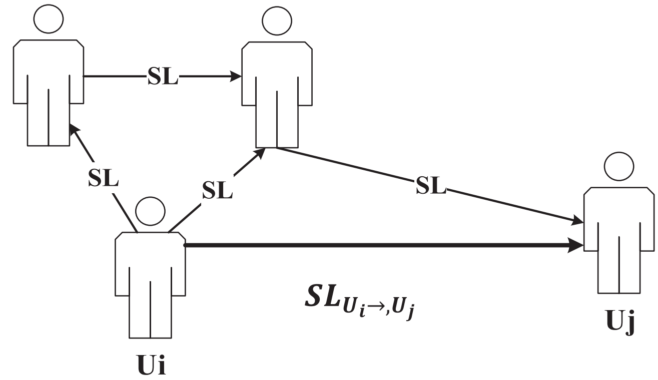

Fig. 2. The interaction degree among users in a social network.

3.3. The analysis of trust relationship

The trust relationship among users in a social network comprises direct and indirect trust relationships. The direct trust relationship is specified by users, while the indirect trust relationship is inferred by using users' rating behavior on common items. We present details of the trust analysis in the following.

3.3.1. Direct trust relationship and role analysis

Direct trust means that users in a social network can express their opinions in value to another person during their interaction. For example, *Epinions.com* allows a user to set 0 or 1 on another user to express the trust relationship. Based on this concept, the direct trust relationship in this work means a user explicitly indicates that he/she trusts other users. In addition, users in a social network may play different roles, and every social network may define different roles for users. In this work, the social network sets the roles of users based on user expertise and their reviews, e.g. leader, adviser, top reviewer, and so on. Meanwhile, the opinions or reviews given by users with specific roles may be more helpful and valuable than those of other users without specific roles. Each role has a specific weight to represent the importance of the role. Therefore, we combine both the values of users' direct trust and the weights of user roles in the computation of direct trust relationship, as defined in the following equation:

$$DT_{u_i \to u_j} = TV_{u_i \to u_j} \times w^{ro}_{u_j} \tag{9}$$

where $DT_{u_i \to u_j}$ is the degree of direct trust of user u_i on user u_j who plays a specific role; and $TV_{u_i \to u_j}$ is the value of direct trust of user u_i on user u_j. The direct trust relationship between two users (i.e. $TV_{u_i \to u_j}$) is defined in the following equation:

$$TV_{u_i \to u_j} = \begin{cases} 0, & if\ u_i\ does\ not\ trust\ u_j \\ 1, & if\ u_i\ trusts\ u_j \end{cases} \tag{10}$$

where $TV_{u_i \to u_j}$ is the value of direct trust of user u_i on user u_j. When the direct trust degree of user u_i on user u_j is 1, user u_i actively adds user u_j onto his/her trust list. Additionally, $w^{ro}_{u_j}$ is the weight of user u_j's role. Such weights of roles (i.e. $w^{ro}_{u_j}$) in this paper are set to: 1 for leader, 0.75 for advisor, 0.5 for top reviewer and 0.25 for normal member. Also, user roles may affect other users when giving trust values to others.

3.3.2. Indirect trust relationship

We infer the indirect trust between two users (i.e. the implicit trust relationship) based on the users' rating behavior concerning common products or common reviews of users. First, a user's predictions on items are measured by using Resnick's prediction formula (Resnick et al., 1994). Then, the Pearson correlation coefficient is used to measure the similarities between users. We summarize the difference between the predicted ratings and real ratings of items by weighting similarities as the degree of indirect trust. This calculation is defined in Eq. (11), to evaluate the degree of indirect trust between user u_i to user u_j.

$$IT_{u_i \to u_j} = \frac{1}{\left| I_{u_i} \cap I_{u_j} \right|} \sum_{s \in \left(I_{u_i} \cap I_{u_j} \right)} \left(1 - \frac{\left| \hat{P}_{u_i,s} - r_{u_i,s} \right|}{M} \right) \times PSim_{u_i,u_j} \tag{11}$$

where $IT_{u_i \to u_j}$ is the indirect trust degree between user u_i and user u_j; I_{u_i}/I_{u_j} is the rating set of user u_i / user u_j; $r_{u_i,s}$ is the rating of item s given by user u_i, and M is the maximum rating value. $\hat{P}_{u_i,s}$ is a predicted rating of a product or a product review s given by user u_i, as expressed in the following equation:

$$\hat{P}_{u_i,s} = \bar{r}_{u_i} + \left(r_{u_j,s} - \bar{r}_{u_j} \right) \tag{12}$$

where $\bar{r}_{u_i}/\ \bar{r}_{u_j}$ is the average rating of user u_i / user u_j, and $r_{u_j,s}$ is the rating of a product or a product review s given by user u_j. Then, $PSim_{u_i,u_j}$ in Eq. (11) represents the similarity between user u_i and user u_j, which is measured by using the Pearson correlation coefficient (Herlocker et al., 1999). The equation is defined as follows:

$$PSim_{u_i,u_j} = \frac{\sum_{s \in \left(I_{u_i} \cap I_{u_j} \right)} \left(r_{u_i,s} - \bar{r}_{u_i} \right) \left(r_{u_j,s} - \bar{r}_{u_j} \right)}{\sqrt{\sum_{s \in \left(I_{u_i} \cap I_{u_j} \right)} \left(r_{u_i,s} - \bar{r}_{u_i} \right)^2} \sqrt{\sum_{s \in \left(I_{u_i} \cap I_{u_j} \right)} \left(r_{u_j,s} - \bar{r}_{u_j} \right)^2}} \tag{13}$$

where I_{u_i}/I_{u_j} is a rating set of user u_i / user u_j; s is a common set of products or product reviews of users u_i and u_j; $r_{u_i,s}/r_{u_j,s}$ is the ratings of a product or product review s given by user u_i / user u_j; and $\bar{r}_{u_i}/\ \bar{r}_{u_j}$ is the average rating of user u_i / user u_j.

3.3.3. The combination of direct and indirect trust

The degree of the direct and indirect trust relationships are integrated by using Eq. (14) for inferring the overall trust relations among users:

$$HT_{u_i \to u_j} = (1 - \beta) \times DT_{u_i \to u_j} + \beta \times IT_{u_i \to u_j} \tag{14}$$

where $HT_{u_i \to u_j}$ is the trust degree between users u_i and u_j; $DT_{u_i \to u_j}$ is the degree of direct trust of user u_i on user u_j who plays a specific role (as described in Section 3.3.1); $IT_{u_i \to u_j}$ is the indirect trust degree between user u_i and user u_j (as described in Section 3.3.2); β is the weight of indirect trust, and its value is in the range of 0 to 1. A larger trust value between two users means that they more trustworthy to each other.

3.4. Popularity analysis

Popularity is associated with the number of votes an item receives (Kazai and Milic-Frayling, 2008). Generally, popularity may affect users' preferences (Pera and Ng, 2013). In some web ranking applications, popular web pages can be calculated by analyzing the time that users browse the web pages, the size of web pages, as well as the number of users accessing the web pages (Gunel and Senkul, 2013). However, user preference in social networks may be influenced by the relationships among users, as well as the product popularity. Therefore, product popularity in this work is based on the proportion of users who have reviewed the product, as defined in the following equation:

$$PD_k = \frac{FN_k}{TN} \tag{15}$$

where PD_k is the popularity degree of product k, FN_k is the number of people reviewing product k, and TN is the total number of users writing the product reviews. If a product has been reviewed by a large number of users, it means that more users are interested in the product, so it implies that the product popularity is also higher.

3.5. The proposed hybrid recommendation method

In this section, a hybrid recommendation method integrating user interaction, trust relationship and product popularity is proposed. The proposed method can predict the product preference of users based on their interactions and connections in social networks, as defined in Eq. (16). In the recommendation process, the other users (i.e. user u_j) who have high connection degrees with a target user u_i are selected as neighbors. Then, according to the ratings of selected user u_j for product k and the popularity of product k, Eq. (16) predicts the rating given by the target user u_i to product k (i.e. $\hat{P}_{u_i,k}$).

$$\hat{P}_{u_i,k} = \bar{r}_{u_i} + \frac{\sum_{u_j \in NB(u_i)} ST_{u_i,u_j} \times (r_{u_j,k} - \bar{r}_{u_j})}{\sum_{u_j \in NB(u_i)} ST_{u_i,u_j}} \times \frac{(1 - PD_k)}{2} \tag{16}$$

where $\bar{r}_{u_i}/\bar{r}_{u_j}$ is the average ratings of user u_i / u_j, $NB(u_i)$ is a neighbor set of the target user u_i, in which the connection degrees of neighbors are larger than a specified threshold, $r_{u_j,k}$ is the ratings given by user u_j to product k, PD_k is the popularity of product k, and ST_{u_i,u_j} is the degree of connection between users u_i and u_j, which combines users' social interaction and trust relationship, as defined in the following equation:

$$ST_{u_i,u_j} = HT_{u_i \to u_j} \times \left(SL_{u_i \to u_j} + 1 \right) \tag{17}$$

where $SL_{u_i \to u_j}$ signifies the degree of social interaction between users u_i and u_j, $HT_{u_i \to u_j}$ is the trust degree between users u_i and u_j, which combines the trust degrees of both direct and indirect trust (as described in Section 3.3.3). The interaction and trust degrees between users are greater, and the connection degree between users is also greater.

Based on the predictions derived from Eq. (16), the proposed method selects top-N products with high prediction scores to make recommendations for target user u_i. Additionally, among the highly connected neighbors, products with higher popularity have higher priority to be recommended to target users.

4. Experiments and evaluations

In this section, several experiments are conducted to validate the recommendation performance of the proposed methods. The experimental results are then compared with the traditional CF method and other trust-based recommendation methods. Furthermore, the design of the experiments, the experimental results, performance evaluation and method comparison are described as follows.

4.1. Data collection

The data adopted in this work were collected from *Epinions*,[1] a popular website for product review. This website enables users to share product information in various product categories, product reviews and ratings of products. It is very helpful in assisting other users in their purchasing decision making. Because the amount of data in the categories of electronic products and computer hardware is larger than that of other categories, our dataset is mainly collected from these two categories for conducting the experiments.

The collected dataset consists of three parts: user information, users' trust lists, and product information. Generally, user information contains the users' names, roles, their ratings of products and other records. Meanwhile, the role of a user is usually determined on the basis of the user's actions on the website, such as the number of comments and the quality of comments written by the user. Also, the roles can be classified into 4 roles: lead, advisor, top reviewer and normal member. The user can actively specify his/her trustworthy users. Moreover, the product information contains the product name, product ID, user comments,

[1] www.epinions.com

the corresponding ratings and the time of ratings. A product review is text information which contains a user's opinions of the product (i.e. a user comment). Users can give ratings to the product reviews written by other users for expressing the usefulness of the reviews. Basically, the range of product rating and review rating is between 1 and 5. A greater rating given by a user indicates that the user prefers the product or its corresponding comments, and vice versa.

The period of data collection for this experiment was from November 1, 2007 to November 1, 2010; it included 548 users, 4773 products, 6052 product reviews, as well as 84,581 ratings of product reviews. Each user has at least 5 product reviews. To validate the recommendation performance of the proposed methods, the dataset is randomly divided into 70% for the training samples and 30% for the testing samples for conducting the experiments. We basically applied the stratified sampling approach to pick out the target users with specific roles from each group. However, some users with very few ratings or reviews are not suitable for testing evaluation. Therefore, we may need to reselect the target users for avoiding the negative impact brought by the uncertainty of outliers as far as possible. Accordingly, around 30% users in the data set are randomly selected as the target workers for the purpose of modelling, and the non-target users are also included in the training set. In the experiments, we not only implement and evaluate the proposed methods, but also compare the experimental results with other methods, including the traditional collaborative filtering method as well as the trust-based recommendation methods.

4.1.1. Evaluation metrics

The Mean Absolute Error (MAE) (Bobadilla et al., 2013; Herlocker et al., 1999) is a predictive accuracy metric widely used in the research field of recommender systems. The advantages of MAE are that it is simple and easy to understand (Herlocker et al., 2004). To examine the performance of the recommendation methods, MAE measures the average of the absolute difference between the predicted ratings provided by the recommendation methods and the true ratings given by users. The smaller the value of MAE, the closer the predicted rating is to the actual rating. Furthermore, the MAE is defined in Eq. (18) as follows:

$$MAE = \frac{\sum_{x=1}^{N} \left| \hat{P}_x - r_x \right|}{N} \tag{18}$$

where $\hat{P}_x$ signifies the predicted rating of product *x*, r_x is the actual rating of product *x* given by the user, *x* is the product recommended to the target user, and *N* means the total number of recommended products.

4.1.2. Methods compared in the experiment

The proposed methods select neighbors who strongly connect with the target user, and then make product recommendations for the target user. In the experiments, the proposed methods are evaluated and compared with several relevant methods which make recommendations based on the users' relationships in a social network. The compared methods are described as follows:

(1) *Collaborative Filtering (CF)*: It firstly calculates the Pearson similarity in accordance with the data on users (by Eq. (1)) for finding high-similarity users. The CF method then predicts the ratings of products for a target user by using Resnick's formula (Massa and Avesani, 2007; Resnick et al., 1994), as described in Section 2.2.
(2) *Personal Trust CF (PT-CF)*: The personal trust between two users is calculated by averaging the prediction error of their co-rated items (Hwang and Chen, 2007). The CF method makes recommendations for a target user based on his/ her trusted neighbors, as described in Section 2.3.
(3) *Item-Level Trust CF (ILT-CF)*: Item-level trust is used in filtering; 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), as described in Section 2.3.
(4) *Profile-Level Trust CF (PLT-CF)*: Profile-level trust is used in filtering; 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), as described in Section 2.3.
(5) *Direct Social Interaction CF (DSI-CF)*: It selects users based on their degrees of direct social interaction (i.e. Eq. (3)) for a target user, and then makes recommendations by the CF method, as described in Section 3.2.1.
(6) *Indirect Social Interaction CF (ISI-CF)*: It selects users based on their degrees of the indirect interactions (i.e. Eq. (5)) for a target user, and then makes recommendations by the CF method, as described in Section 3.2.2.
(7) *Social Interaction CF (SI-CF)*: It makes recommendations based on the degrees of users' social interaction (i.e. Eq. (7)), derived from the combination of direct and indirect social interaction, as described in Section 3.2.3.
(8) *Direct trust CF (DT-CF)*: It selects users based on the direct trust relationship among users (i.e. Eq. (9)), and then makes recommendations by the CF method, as described in Section 3.3.1.
(9) *Indirect Trust CF (IT-CF)*: It selects users based on the indirect trust relationship among users (i.e. Eq. (11)), and then makes recommendations by the CF method, as described in Section 3.3.2.
(10) *Hybrid Trust in CF (HT-CF)*: It makes recommendations based on users' hybrid trust relationship (i.e. Eq. (14)), derived from the combination of the direct and indirect trust relationships among users, as described in Section 3.3.3.
(11) *Hybrid Social Interaction and Popularity in CF (HSP-CF)*: It makes recommendations based on the combination of social interaction (i.e. Eq. (7)) and product popularity (i.e. Eq. (15)). A recommendation list is generated by using Eq. (16), where ST_{u_i,u_j} is replaced by the Eq. (7), as described in Section 3.5.
(12) *Hybrid Trust and Popularity in CF (HTP-CF)*: It makes recommendations based on the combination of hybrid trust relationship (i.e. Eq. (14)) and product popularity (i.e. Eq. (15)). A recommendation list is generated by using Eq. (16), where ST_{u_i,u_j} is replaced by Eq. (14), as described in Section 3.5.
(13) *Hybrid Social Interaction and Trust in CF (HST-CF)*: It makes recommendations based on the combination of social interaction and hybrid trust relationship (i.e. Eq. (17)). A recommendation list is generated by the CF method.
(14) *Hybrid of Social Interaction, Trust and Popularity in CF (HSTP-CF)*: It makes recommendations based on the combination of social interaction, hybrid trust relationship and product popularity; a recommendation list is then generated by using Eq. (16), as described in Section 3.5.

4.2. The impact of social interaction on the recommendation methods

Since users usually have direct and indirect interactions in social networks, this experiment focuses on discussing the impact of social interactions on the recommendation accuracy. In the experiments, we will evaluate and compare the methods based on the direct interaction only, indirect interaction only, as well as the integration of direct and indirect interaction.

4.2.1. Determining the number of neighbors for the DSI-CF method

The DSI-CF method makes recommendations based on the users' direct interaction behavior, such as giving ratings to other users' reviews. It selects the top-*N* users with high direct interactions in the social networks to predict the preferred products for the target users. In order to determine the appropriate number of neighbors, this experiment compares the results from the top-15 to top-90, and determines the number of neighboring users as recommenders by the smallest MAE value. The results are shown in Fig. 3.

According to the above results, selecting a small number of neighbors in making recommendations may cause a high MAE value. As the

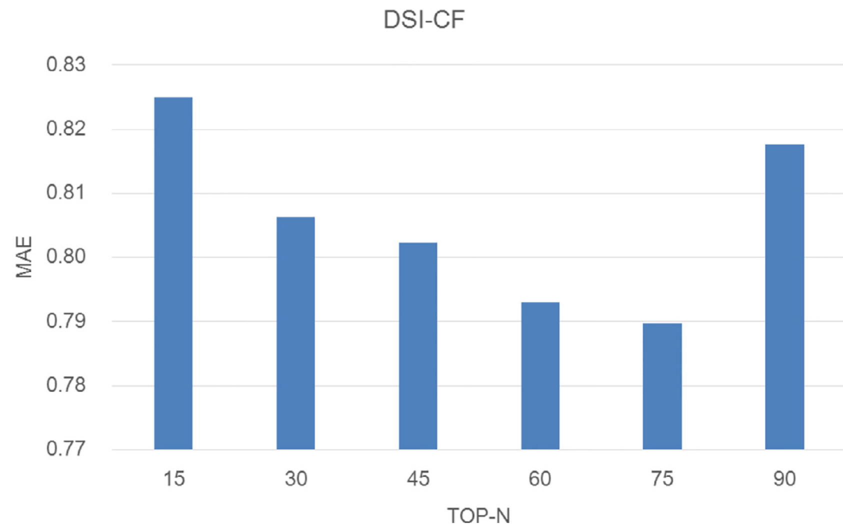

Fig. 3. The recommendation performance of DSI-CF Method under different Top-N neighbors.

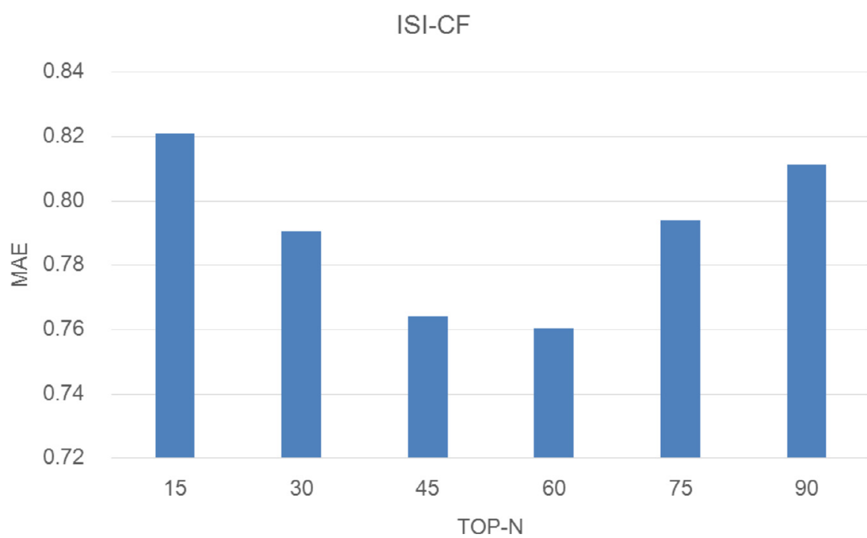

Fig. 4. The recommendation performance of ISI-CF Method under different Top-N neighbors.

number of neighbors gradually increases, the MAE value gradually decreases. However, a large number of neighbors may lead to a high MAE value. Therefore, in accordance with the experimental results, the DSI-CF method has good recommendation performance in selecting the top-75 neighbors but is poor in selecting top-15 or top-90 neighbors. It therefore implies that, as too few or too many neighbors are selected, information derived by direct interactions cannot accurately predict the preferences of target users.

4.2.2. *Determining the number of neighbors for the ISI-CF method*

The indirect interaction between two users means that these two users give ratings to the same products or product reviews; this may indirectly affect users' preference. Basically, the ISI-CF method selects the top-*N* users with high indirect interactions as recommenders to make product predictions for target users. To determine the appropriate number of neighbors, this experiment compares the recommendation performance of the ISI-CF method from the top-15 to top-90, and then determines the appropriate number of neighbors according to the minimum MAE value, as shown in the Fig. 4.

According to the above results, choosing small or large neighbors for ISI-CF method in making recommendations may cause a high MAE value (i.e. top-15 or top-90). As too few or too many neighbors are selected, information derived by indirect interactions cannot accurately predict the preferences of target users. Hence, the best MAE value appears in selecting the top-60 neighbors in this experiment. The indirect interactions among users are helpful in improving the performance of product recommendation when the number of neighbors is 60.

4.2.3. *Determining the number of neighbors for the SI-CF method*

The SI-CF method integrates both the direct and indirect interactions between users as social interaction, and selects the top-*N* users with high interaction to predict the preference of target users. In this experiment, the results of the SI-CF method from the top-15 to top-90 are compared; the appropriate number of neighboring users is then determined according to the minimum MAE value, as shown in Fig. 5.

According to the above results, the SI-CF method can obtain the minimum MAE value at the top-30, while the worse recommendation performance appears at the top-15 and top-90, respectively. Therefore, the SI-CF method has good performance and enhances the recommendation accuracy when selecting top-30 neighbors with high social interactions in recommendations. Otherwise, selecting a few neighbors or too many neighbors for SI-CF method may lead to low recommendation performance because insufficient or excessive neighbor information makes it difficult to predict the preferences of target users.

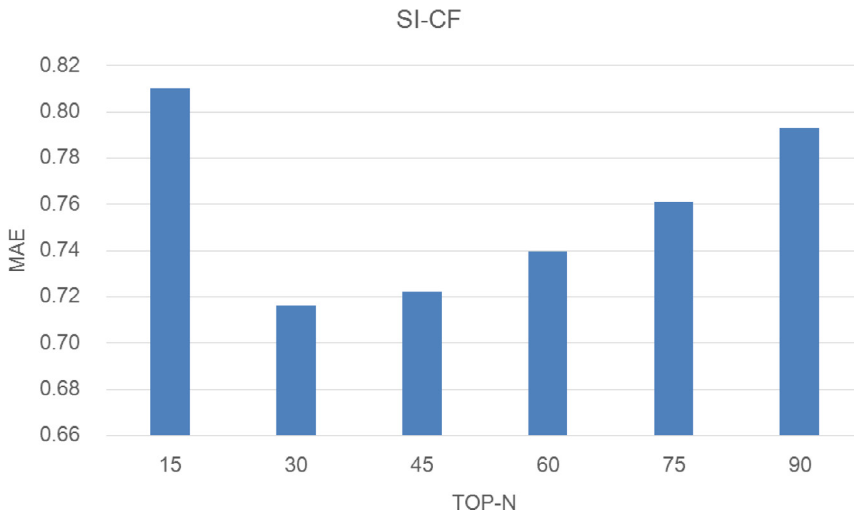

Fig. 5. The performance of SI-CF method under different Top-N neighbors.

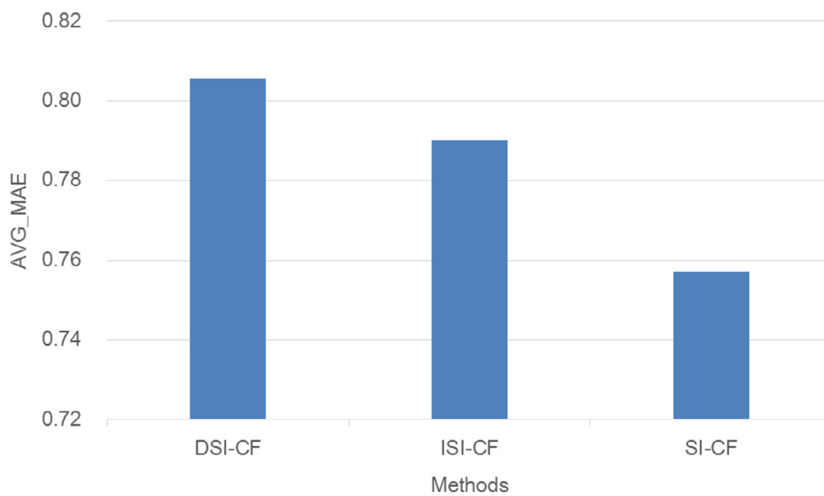

Fig. 6. The performance of CF methods based on different interactions.

4.2.4. Comparisons of the methods based on different interaction

In the experiments, we compare three methods which use different interactions in making recommendations: the DSI-CF method based on direct interaction, the ISI-CF method based on indirect interaction, and the SI-CF method based on the combination of direct and indirect interactions. The results are illustrated in Fig. 6. From the experimental results, the recommendation performance of SI-CF method is obviously better than those of the DSI-CF and ISI-CF methods. The SI-CF method utilizes the degrees of social interaction among users to choose high interactive users as recommenders, and then predicts the preference of the target users according to the preference of the neighbors. Therefore, the social interaction which considers both direct and indirect interactions can fit the actual situation in the social networks and indeed improve the quality of recommendation.

4.3. The impact of trust relationships on recommended methods

Both direct and potentially indirect trust relationships among users may exist in social networks. This experiment mainly focuses on the performance of the recommendation methods based on users' trust relationships. Therefore, we evaluate and compare the trust-based CF methods, including the DT-CF method based on direct trust, the IT-CF method based on indirect trust and the HT-CF method based on hybrid of direct and indirect trust. The experimental results are described as follows.

4.3.1. Determining the number of neighbors for the DT-CF method

The DT-CF method mainly considers the direct trust relationship among users in the social network in order to make recommendations. Creating direct trust depends on whether or not a user trusts others. Direct trust can be directly specified by users. In addition, users also play different roles in a social network. The DT-CF method considers the role of the weights of users to calculate the degrees of direct trust between users (see Section 3.2.1). Afterwards, top-*N* users with high degrees of direct trust are selected to predict the preferences of the target users. In this experiment, the recommendation performance of DT-CF under top-15 to top-90 neighbors is compared in Fig. 7.

According to the above results, the DT-CF method can perform well at the top-45, but poorly at the top-15. Choosing too few or too many users (i.e. top-15 or top-90) to make recommendations generates high MAE values. When the number of neighbors is greater than 60 (i.e. top-60), the MAE value gradually becomes high. Therefore, when the DT-CF method selects high trustworthy top-45 users to predict the preferences of target users, the direct trust relationship can improve the performance of product recommendations.

4.3.2. Determining the number of neighbors for the IT-CF method

The IT-CF method takes the indirect trust relationship between users in the social networks into account (see Section 3.3.2) and selects the top-*N* users with high indirect trust to predict the potential preferences

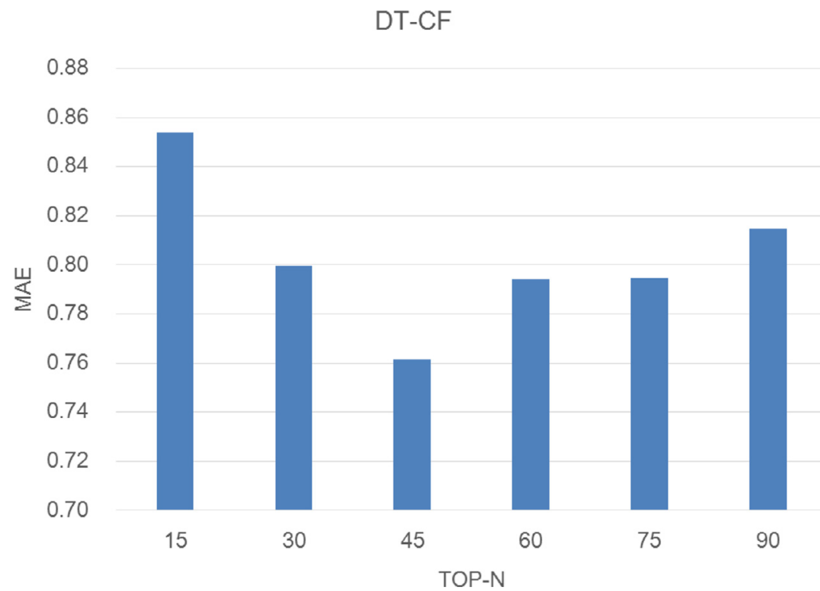

Fig. 7. The performance of DT-CF method under different Top-N neighbors.

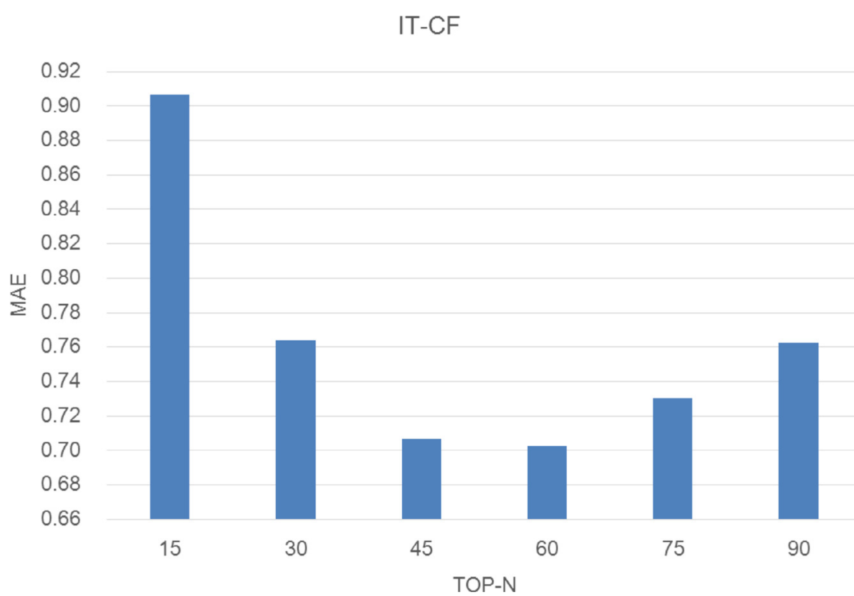

Fig. 8. The performance of IT-CF method under different top-N neighbors.

of the target users. This experiment focuses on determining an appropriate number of neighbors as recommenders for the IT-CF method. The recommendation quality of IT-CF method under top-15 to top-90 neighbors is evaluated and compared in Fig. 8.

According to the above results, the IT-CF method under the top-60 neighbors has the lowest MAE value, that is, a better recommendation performance can be acquired at the Top-60. However, it has the worst performance when selecting the top-15 neighbors in recommendations. Due to insufficient neighbors, the IT-CF method does not have enough information, so it cannot accurately predict the preference of users. Contrarily, when the number of selected neighbors exceeds 75, the MAE value rises high as well.

4.3.3. *Determining the number of neighbors of the HT-CF method*

The HT-CF method applies a parameter to integrate both direct and indirect trust as a hybrid trust, and selects the top-N users with high trust values for predicting the preferences of target users (see Section 3.3.3). In this experiment, the optimal parametric value is determined first for integrating both the direct and indirect trusts. Then, an appropriate number of neighbors for making recommendations is determined. The HT-CF methods with different parameters are compared and described as following.

Determining the parameter β for integrating direct and indirect trust

As shown in the Eq. (14), parameter β is the weight of the indirect trust to represent its relative importance. Similarly, 1-β presents the weight of direct trust. In order to determine the most suitable value of parameter β, the β value ranges from 0 and 1 with 0.1 increments for each experiment until the β value is equivalent to 1. Fig. 9 shows the average MAE values of HT-CF method under different values of β. The most suitable value of β is determined by the lowest value of MAE.

In the HT-CF method, the DT-CF method applies the β value equal to 0, while the IT-CF method applies the β value equal to 1. As the β value is 0.9 in HT-CF method, it means that weight of the DT-CF method takes 90% into account and the IT-CF method takes 10% into account. In this situation, the HT-CF method obtains the lowest average MAE value and has the best recommendation performance compared to the

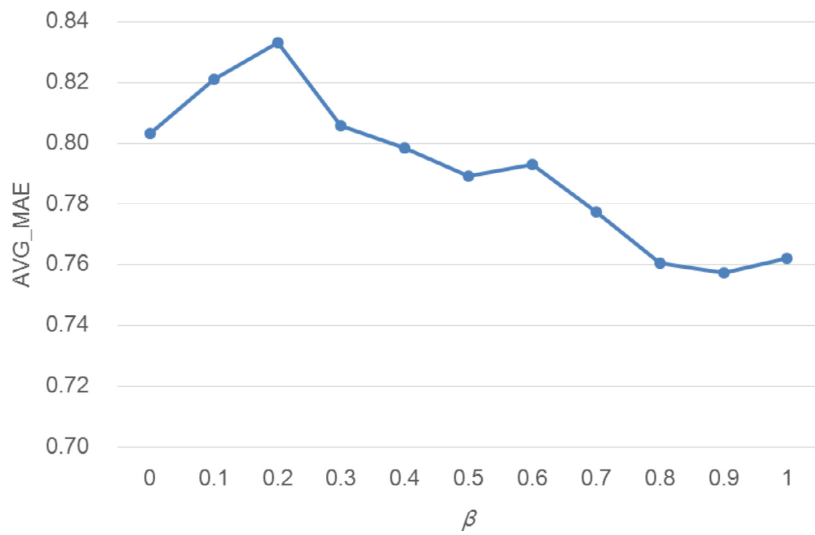

Fig. 9. The performance of HT-CF under different values of β.

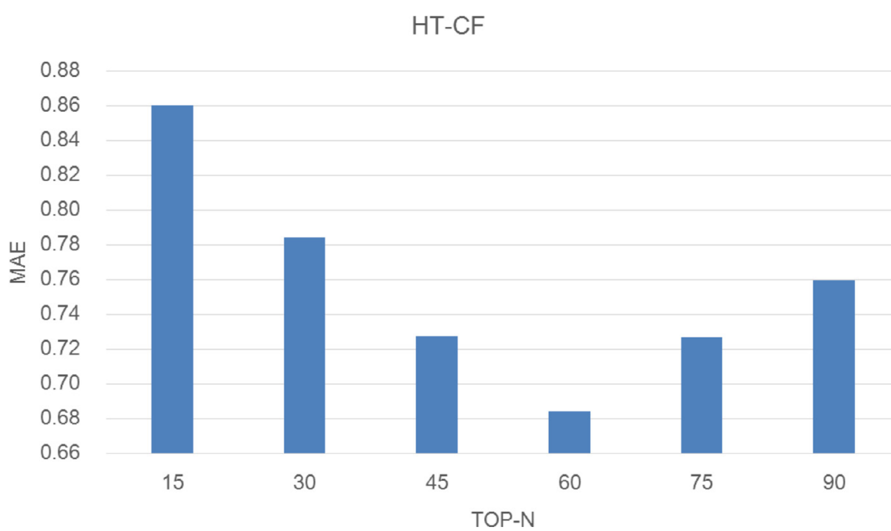

Fig. 10. The performance of HT-CF method under different top-N neighbors.

others. However, once the β value is smaller than 1-β, the HT-CF method obtains worse recommendation quality. The worst performance of HT-CF especially occurs when the values of β and 1-β are 0.2 and 0.8, respectively. This means that the DT-CF method is worse than the IT-CF method. Thus, the HT-CF method would have poor performance if the direct trust takes a large proportion of the hybrid trust.

Determining the number of neighbors for the HT-CF method

According to the previous experimental result, the HT-CF method performs well when the value of β equals 0.9. Based on the values of the hybrid trust, the HT-CF method selects the top-*N* neighbors with high trust values for recommending preferred products to target users. To determine the optimal top-*N* neighbors, the recommendation performances under the top-15 to top-90 neighbors are compared in this experiment. As shown in Fig. 10, the HT-CF method can obtain the lowest MAE value at the top-60, while the worst performance appears at the top-15. Consequently, the appropriate number of neighbors for the HT-CF method is the Top-60.

4.3.4. Comparisons of the trust-based recommendation methods

In the experiments, the average performance of the trust-based CF methods, i.e. DT-CF, IT-CF and HT-CF methods under the Top-15 to Top-90 neighbors are compared, as shown in the Fig. 11. Among these methods, the DT-CF method has the worst performance among the compared methods. The recommendation performance of the HT-CF method (with $\beta = 0.9$) is better than the DT-CF and IT-CF methods. Because indirect trust takes a large proportion in computing the hybrid trust, the performance of IT-CF and HT-CF methods differ slightly. For the HT-CF method, taking both the direct and indirect trusts into consideration can improve the recommendation quality in a social network.

4.4. The impact of product popularity on recommendation methods

Besides the interaction and trust relationships, product popularity also affects users' preference. To realize the impact of product popularity on recommendation methods, product popularity is integrated into the proposed methods, i.e. SI-CF, HT-CF and HST-CF methods, respectively. Then, the average MAE values of the methods with product popularity (i.e. HSP-CF, HTP-CF and HSTP-CF methods) and the methods without product popularity (i.e. SI-CF, HT-CF and HST-CF methods) are compared in this experiment. The recommendation results are shown in Fig. 12.

In this experiment, the recommendation performance of the HSP-CF method is better than that of SI-CF, the recommendation quality of HTP-CF is better than that of HT-CF, and the recommendation quality of

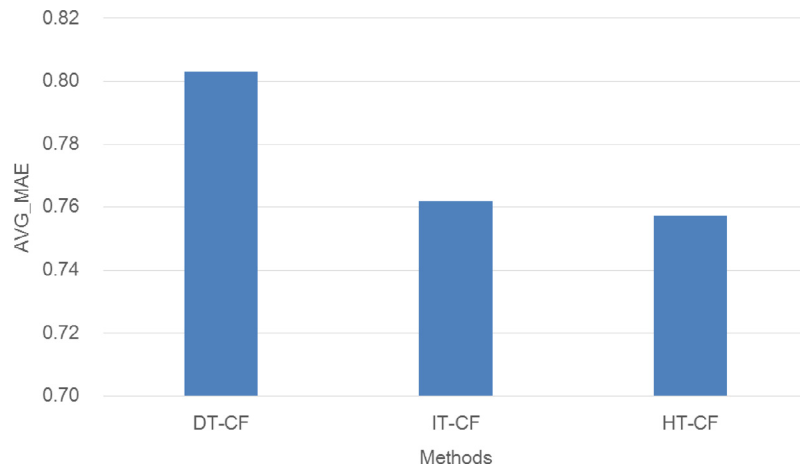

Fig. 11. The average MAE values of the proposed trust-based CF methods.

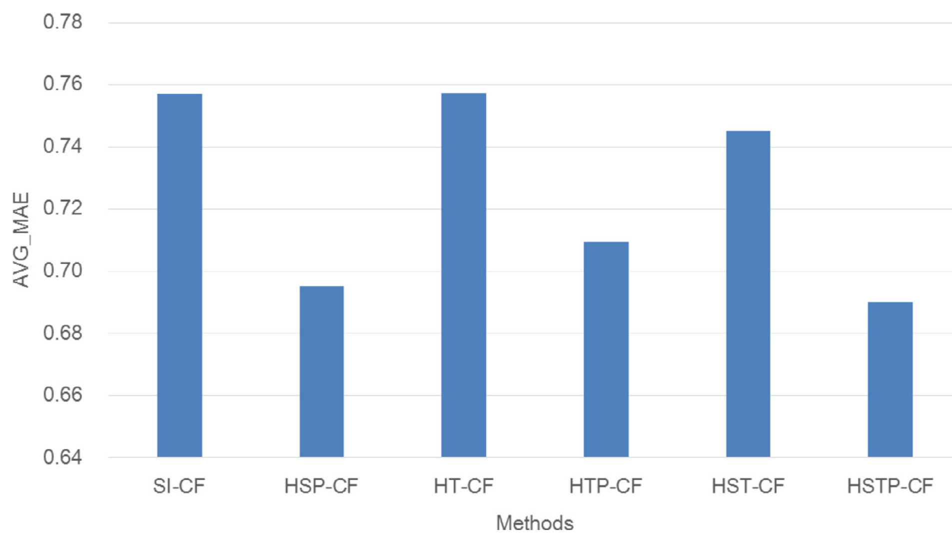

Fig. 12. Comparisons of the proposed methods with product popularity.

HSTP-CF is better than that of HST-CF. Therefore, the recommendation methods (i.e. SI-CF, HT-CF and HST-CF methods) taking product popularity into account can effectively enhance the recommendation quality. As for the CF methods based on product popularity integration, the HSTP-CF method has a much better performance than the HSP-CF and HTP-CF methods. In addition to the interaction and trust relationships among users, the product's popularity is also an essential factor affecting the users' preferences in social networks. In general, as product popularity increases, users will become more interested in this product. When popular products are recommended to users, users generally have high possibilities of accepting these recommended products. Thus, the proposed HSTP-CF method which particularly considers the factor of product popularity can recommend highly popular products and effectively improve the recommendation quality as well.

4.5. Comparison of all methods

To validate the effectiveness of the proposed methods, the HST-CF and HSTP-CF methods are compared with traditional recommendation methods, including CF and the trust-based methods (i.e. PT-CF, PLT-CF and ILT-CF). When making recommendations, each method selects neighbors from the Top-15 to Top-90. Then, the MAE values under the different top-N neighbors are averaged to represent the performance of the methods. Furthermore, the recommendation results of all the compared methods are shown in Fig. 13.

In addition, the traditional CF method (i.e. CF) only utilizes user similarities measured from the corresponding ratings of products to predict user preference. When it is applied to the social networking environments for making recommendations, it has the worst performance among the compared methods because it does not consider users' relationships in a social network and product popularity. Moreover, the traditional trust-based CF methods, including profile-level trust CF (PLT-CF) (O'Donovan and Smyth, 2005), item-level trust CF (PT-CF) (O'Donovan and Smyth, 2005) and personal trust CF (PT-CF) (Hwang and Chen, 2007) methods are also compared. Generally, these methods calculate the trust value between two users by summarizing the difference between the actual ratings given by these two users and the predicted ratings. Although these methods do not measure the trust values by analyzing users' behavior in a social network, the performance of these three methods are slightly better than that of the CF method. Furthermore, the proposed method (HST-CF) performs better than the traditional trust-based methods. Therefore, analyzing user interactions and trust relationships in a recommendation method can enhance the recommendation quality.

According to the results in Fig. 13, the HSTP-CF method which integrates user interaction, trust relationships and product popularity has the best recommendation quality compared to the other methods. It even performs better than the traditional CF and trust-based CF methods. Besides analyzing user preferences, the recommendation method applied

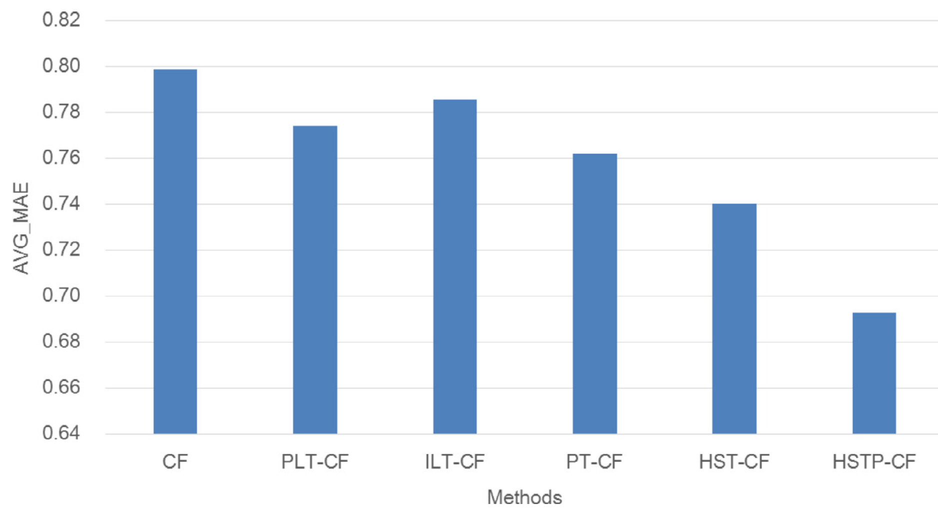

Fig. 13. Comparison of all recommendation methods.

to social networks not only takes both user interactions and trust relationships into account, but also considers the effects of product popularity. In addition, the HSTP-CF method can positively enhance the prediction accuracy by using users' linking relationships and further improve the recommendation performance in social networks.

4.6. Discussion and limitations

In a social networking environment, users' social relationships and social interactions may influence users' preferences. Using these relationships in recommendation methods may affect the prediction accuracy. Additionally, the traditional recommendation methods only focus on finding the connections between users and products based on similarity measurements. As the number of users and products increase, the computation overhead will also increase and the scalability will be very poor. To resolve these problems, this work proposes a recommendation method which combines user interaction, trust relationship and popularity of products to make product predictions for users on a social network. We analyze the relationships of users and products, and use the interrelatedness of the social networking structure in making recommendations. The user interaction among users is a combination of direct and indirect interactions according to users' rating behavior. Meanwhile, the trust relationship among users is a combination of direct and indirect trust relationships, inferred by explicit trust relations specified by users and implicit trust relation based on users' common items, respectively.

In the experiment results, the DSI-CF, ISI-CF and SI-CF methods, which make recommendations based on different social interaction, have different recommendation performance when selecting different numbers of neighbors with high interaction. Generally, recommendation based on both direct and indirect social interaction (i.e. SI-CF) performs better than the methods which only consider direct or indirect interaction (i.e. DSI-CF and ISI-CF). Similar to the results of the methods based on social interaction, the method based on hybrid trust relationships which combines both direct and indirect trust (i.e. HT-CF) has better performance than the methods which only consider direct or indirect trust (i.e. DT-CF and IT-CF). Because indirect trust contributes more than the direct trust in HT-CF method (i.e. $\beta = 0.9$), the performance of HT-CF is very close to that of IT-CF. Additionally, we give specific values to different roles as role weights in computing the direct trust according to users' expertise.

Moreover, the proposed methods with product popularity are better than the methods without product popularity. The HSTP-CF method, which combines social interaction, trust relationship and product popularity, has the best performance, and the best prediction accuracy compared to the traditional CF method and the trust-based recommendation methods (i.e. item-level trust, profile-level trust and personal trust CF). Based on users' rating behavior in a social network, this work develops new methods to define and analyze users' relations based on social interactions and trust relationships. The proposed methods differ from other social-based or trust-based recommendation methods. They can also improve the recommendation performance and increase the applicability in social networks.

In accordance with the theoretical evidence and practical evidence supported by the experimental results, the limitations of this work can be summarized as follows.

- The dataset of this work is only adopted from *Epinions*. We also realize that the experimental results based on different datasets may differ on the basis of same CF methods. The reason is that the modeling of recommender systems is recognized as a kind of data-driven problem, and this problem is still one of conventional limitations on developing reliable generalized recommender systems at present.
- The stratified sampling approach is applied to select the target users from each group of users with specific roles in this paper, instead of systematic cross-validation and Monte-Carlo analysis, so it may potentially decrease the reliability of the proposed recommender systems.
- In addition to the conventional data-driven problem, another conventional limitation to the proposed method is that the recommendation accuracy may decrease when the samples are quite insufficient or carry much useless information.
- An intelligent-based method for role analysis is needed to investigate the role and measure the role weights automatically. In addition to the direct trust analysis, the roles and role weights of users also can be used in the computation of the social interaction. Besides analyzing users' rating behavior, we can analyze other behaviors and relationships of users to further identify the potentially valuable users in a complicated structure of social network.

5. Conclusions and future works

Because the social networks contain huge amounts of diverse information, users usually have difficulty in finding the required information to make their purchasing decisions. Users may spend a lot of time seeking useful information; this is the so-called problem of information overload. In addition, social networks allow users to share opinions and other information, so that users' interactions and the corresponding connections become increasingly more complicated. Therefore, this work proposes a novel product recommendation method in a social network.

It precisely analyzes users' behavior and effectively integrates social interaction, trust relationship and product popularity to make product prediction for target users. Based on users' rating behavior, the social interaction is classified into direct and indirect interactions. Similarly, the trust relationship is also explored and classified into direct and indirect trust relationships. User interaction and trust relationships are integrated in the proposed method to identify the connections of a target user and other users. On the basis of the preference of highly connected users, popular products have high priority to be recommended to target users. Thus, the proposed method can analyze the connections among users based on their explicit and implicit relationships. It also considers the impact of popular products on user preference when making product recommendations to target users.

In accordance with the experimental results, the proposed method has the best recommendation performance compared to the traditional CF and trust-based recommendation methods. It can effectively improve the recommendation performance in social networks. Therefore, user interactions, trust relationships and product popularity are the essential factors for recommendation methods to identify highly connected users. They are very useful for increasing the accuracy of predicting users' preferred products, and further enhance the recommendation performance in social networks.

In future work, user interactions or other information will be analyzed to measure the role weights of users in social networks, and the impact of role weights on recommendation methods will then be evaluated. Additionally, the content of user reviews will be investigated by text mining and semantic analysis methods to precisely recognize user preferences and effectively enhance the performance of recommendations. To resolve the sparsity problem in a dataset and improve the predictive accuracy, the matrix factorization technique will be used to analyze the latent factors from users and items in a social network. Moreover, according to the analysis of users' behavior and linking relationships, the potential and valuable users in social networks can possibly be identified. The churn prediction of users can then be further explored through appropriate machine learning algorithms.

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