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## ESTIMATING TRUST STRENGTH FOR SUPPORTING EFFECTIVE RECOMMENDATION SERVICES

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### Abstract

*In the age of information explosion, Internet facilitates product searching and collecting much more convenient for users. However, it is time-consuming and exhausting for users to deal with large amounts of product information. In response, various recommendation approaches have been developed to recommend products that match users' preferences and requirements. In addition to the well-known collaborative filtering recommendation approach, the trust-based recommendation approach is the emerging one. The reason is that most of online communities allow users to express their trust on other users. Based on the analysis of trust relationships, the trust-based recommendation approach finds out and consults the opinions of more reliable users and therefore makes better recommendations. Existing trust-based recommendation techniques consider all trust relationships in a given trust network equally important and give them the same trust strength. However, in a real-world setting, trust relationships may be of various strengths. In response, in this study, we propose a mechanism for trust strength estimation on the basis of the machine learning approach and estimate the trust strength for each existing trust relationship in a given trust network. To overcome the sparsity of the trust network, we also develop a modified trust propagation method to expand the original trust network. Finally, we perform a series of experiments to demonstrate the performance of our trust-based recommendation approach based on the trust strength estimation mechanism. Our empirical evaluation results show that our proposed approach outperforms our benchmark techniques, i.e., the traditional collaborative filtering approach and the original trust-based one.*

**Keywords:** Recommendation Systems, Collaborative Filtering Recommendation, Trust Network, Trust-based Recommendation, Trust Strength, Machine Learning.

# 1 INTRODUCTION

In the age of information explosion, Internet facilitates product searching and collecting much more convenient for users. However, it is time-consuming and exhausting for users to deal with large amounts of product information. It is the well-known information overload problem that human beings have limited information processing capability in terms of memory, attention, and motivation. In response, various recommendation approaches have been developed to recommend products that match users' preferences and requirements. Existing recommendation approaches can be generally classified into six types (Wei et al., 2002), including popularity-based (Schafer et al., 2001), association-based (Sarwar et al., 2001), demographics-based (Kim et al., 2001), reputation-based (or trust-based) (Massa and Avesani, 2004; Massa and Bhattacharjee, 2004; Massa and Avesani, 2006), content-based (Alsepector et al., 1998; Balabanovic and Shoham, 1997) and collaborative filtering approaches (Herlocker et al., 1999; Herlocker et al., 2000; Konstan et al., 1997; Resnick et al., 1994; Shardanand and Maes, 1995). Among these recommendation approaches, the collaborative filtering approach is the most successful and widely adopted one (Massa and Avesani, 2004; Massa and Avesani, 2006). The concept of the collaborative filtering approach is to determine the like-minded users whose tastes are similar to the active user and then recommend the products these like-minded users have liked. However, the traditional collaborative filtering approach still has several shortcomings, including cold start user problem, data sparsity problem, malicious or unreliable users, and coverage problem (Lathia et al., 2008; Massa and Avesani, 2004).

Recently, with the development of Web 2.0, the trust-based recommendation technique has emerged to provide collaborative recommendations (Jamali and Ester, 2009a). The reason is that most of online communities, e.g., Epinions.com and MovieLens, allow users to express their trust on other users. Based on the analysis of trust relationships, the trust-based recommendation approach finds out and consults the opinions of users trusted by the active user and then makes collaborative recommendations. Since the trust relationships are given by users themselves, the trust-based recommendation approach has greater potential to determine reliable users for reference and therefore achieves greater recommendation effectiveness. A series of experiments have been conducted to show that the trust-based recommendation approach can outperform the traditional collaborative filtering approach (Jamali and Ester, 2009a).

However, the existing trust-based recommendation approaches are restricted by the information sources such that these approaches only take the existence of trust relationship into account. That is, these online communities only provide the mechanism to construct the trust relationships with other users, without asking for corresponding trust strengths. For example, Epinions.com, which is a popular online community, simply offers a function for a user to express his/her own trustees in personal information webpage. As a result, in the existing trust-based recommendation approaches, all the existing trust relationships are deemed equally important and given the same trust strength. Conceivably, it is not a reasonable treatment in the real situation. For instance, top reviewers may be more trustworthy than other members. Moreover, according to the study by Ku et al. (2007), users who trust more trustworthy users tend to be more trustworthy than others. Therefore, it is necessary to estimate how much user  $u_a$  trusts user  $u_b$ , not only whether  $u_a$  trusts  $u_b$ . On the basis of trust relationships with estimated strengths, the trust-based recommendation approach is likely to select more reliable users trusted (directly or transitively) by an active user; thus, the resultant recommendation effectiveness would be improved.

Based on the abovementioned consideration, we propose a mechanism for trust strength estimation by adopting the machine learning approach. The model built by a machine learning algorithm is then employed to estimate the corresponding trust strength for each existing trust relationship in the given trust network. After trust strength estimation, a trust propagation method is also required to redeem the sparsity of the trust network. In response, we also develop the modified trust propagation method to expand the trust network with various estimated trust strengths. For empirical evaluation, we collect the evaluation dataset from Epinions.com and implement the benchmarks, i.e., traditional collaborative filtering approach and the original trust-based recommendation approach. The

experimental results show that our proposed approach based on the trust strength estimation mechanism can outperform the two benchmarks.

The remainder of this paper is organized as follows. In Section 2, we review the literature related to this study. The proposed trust-based recommendation approach based on trust strength estimation mechanism is then depicted in Section 3. We describe our evaluation design and discuss some important evaluation results in Section 4. We conclude in Section 5 with a summary and some future research directions.

## 2 LITERATURE REVIEW

In this section, we briefly introduce the two related approaches, i.e., the collaborative filtering approach and the trust-based recommendation approach.

### 2.1 Collaborative Filtering Approach

The collaborative filtering approach is the most successful recommendation approach adopted by various recommendation systems, such as MovieLens (Herlocker et al., 2000), GroupLens (Resnick et al., 1994), and Amazon.com (Linden et al., 2003). The concept of the collaborative filtering approach is to share the opinions among users regarding items they have rated before so that other users can decide which items to consume easier (Herlocker et al., 2000). Specifically, the collaborative filtering approach first identifies a set of “nearest neighbors” whose known preferences are most similar to those of the active user based on the known user preference on items and a pre-defined user similarity measure. Subsequently, the preference for each unrated item is predicted for the active user based on the preferences of the previously identified nearest neighbors on this target item. Therefore, the collaborative filtering approach is also known as the social filtering or the user-to-user correlation recommendation approach.

There are a variety of techniques developed for collaborative filtering, including Bayesian networks (Breese et al., 1998), singular value decomposition with neural network classification (Billsus and Pazzani, 1998), induction rule learning (Basu et al., 1998), and neighborhood-based technique (Herlocker et al., 1999; Sarwar et al., 2001). Among these techniques, the neighborhood-based technique is the most prevalent one used for collaborative filtering recommendation. Generally, the process of a typical neighborhood-based collaborative filtering technique consists of two main phases, i.e., neighborhood formation and preference prediction (Sarwar et al., 2000).

The neighborhood formation phase is essentially a model-building process for collaborative filtering recommendation. Specifically, this phase computes the similarities between all other users and the active user, and then forms a proximity-based neighborhood with a number of like-minded users for the active user. Several methods have been proposed to measure user similarity (Herlocker et al., 1999; Sarwar et al., 2000; Shardanand and Maes, 1995), including Pearson correlation coefficient, constrained Pearson correlation coefficient, spearman rank correlation coefficient, cosine similarity, and mean squared difference. The most commonly used measures include Pearson correlation coefficient and cosine similarity. However, according to the experimental results in prior research (Herlocker et al., 1999), Pearson correlation coefficient is better than cosine similarity. The Pearson correlation coefficient is defined as:

$$\text{sim}(u_a, u_b) = \frac{\sum_i^{cr} (p_{a,i} - \bar{p}_a)(p_{b,i} - \bar{p}_b)}{\sqrt{\sum_i^{cr} (p_{a,i} - \bar{p}_a)^2} \sqrt{\sum_i^{cr} (p_{b,i} - \bar{p}_b)^2}}, \text{ where } p_{a,i} \text{ (or } p_{b,i})$$

represents the preference score of user  $u_a$  (or  $u_b$ ) on item  $i$ ,  $\bar{p}_a$  (or  $\bar{p}_b$ ) is the average preference score of user  $u_a$  (or  $u_b$ ), and  $cr$  is the number of items co-rated by both  $u_a$  and  $u_b$ .

The users with the highest user similarities are then identified as the neighbors of the active user. After the nearest neighbors of the active user are identified, the preference prediction is to estimate the unknown preference of the active user  $u_a$  on a target item  $i$  based on the known preferences of his/her neighbors. Typically, the unknown preference score on the target item of the active user is predicted by aggregating the known preference scores of the selected neighbors. The common methods used for predicting unknown preferences are weighted sum (Shardanand and Maes, 1995) and deviation-from-

mean (Konstan et al., 1997; Resnick et al., 1994). Nevertheless, the deviation-from-mean method has been proved better than other methods on prediction accuracy. Its preference prediction measure is defined as:  $p_{a,i} = \bar{p}_a + \frac{\sum_{x=1}^k \text{sim}(u_a, u_x) (p_{x,i} - \bar{p}_x)}{\sum_{x=1}^k \text{sim}(u_a, u_x)}$ , where  $p_{a,i}$  is the predicted preference for the active user  $u_a$  on item  $i$ ,  $\bar{p}_a$  is the average preference score of user  $u_a$ ,  $k$  is the number of neighbors, and  $\text{sim}(u_a, u_x)$  is the similarity between the active user  $u_a$  and his/her neighbor  $u_x$  based on a pre-defined user similarity measure.

## 2.2 Trust-Based Recommendation

Following the idea of the collaborative filtering approach, the trust-based recommendation approach utilizes explicit trust relationships to make collaborative recommendations. Note that the trust relationships are unidirectional. Given the trust network and trust relationships as shown in Figure 1, the trust-based recommendation approach first identifies the neighbors for the active user based on the related trust relationships. After neighbor identification, the trust-based recommendation approach consults the opinions of the neighbors trusted by the active user and then makes preference predictions as the collaborative filtering approach does. However, the trust-based recommendation approach still suffers the sparsity problem. To reduce the sparsity problem, several trust propagation mechanisms (Jamali and Ester, 2009a; Jamali and Ester, 2009b; Massa and Avesani, 2004; Massa and Avesani, 2007) have been developed to expand the trust networks.

Massa and Avesani (2004) first proposed a linear decaying method of distance between two users to propagate trust. Take the trust network in Figure 1 as an example. The trust strength of each direct (existing) trust relationship is regarded as 1 and then the possible trust strengths of indirect (transitive) trust relationship, such as  $\langle u_a \rightarrow u_3 \rangle$  or  $\langle u_a \rightarrow u_b \rangle$  are estimated. Massa and Avesani (2004) considered the distance could decrease the trust strength. Specifically, the trust strength of an indirect trust relationship  $\langle u_a \rightarrow u_b \rangle$  decreases as the number of steps from source user  $u_a$  to sink user  $u_b$  increases. For example, in Figure 1, the trust strength of trust relationship  $\langle u_a \rightarrow u_3 \rangle$  with two steps is estimated to be 0.8. As a result, the trust strength of each indirect trust relationship is estimated to expand the original trust network. Since the existing trust propagation mechanisms are derived from the linear decaying method, we implement the trust-based recommendation approach with linear decrease trust propagation proposed by Massa and Avesani (2004) as one of our benchmarks.

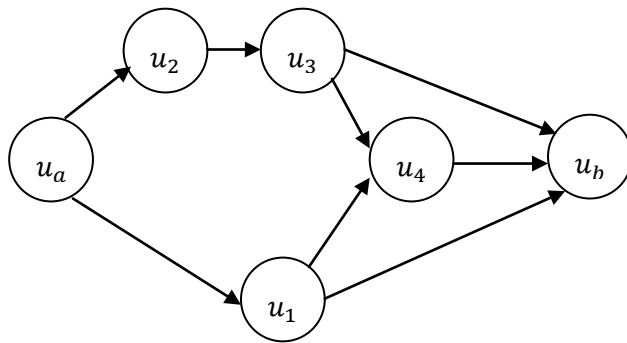


Figure 1. Example of a trust network.

As with the collaborative filtering approach, the trust-based recommendation approach also needs to identify the neighbors of the active user for consulting their opinions. In the trust-based recommendation approach, users with the higher trust strengths are considered to be more reliable. Based on this assumption, Massa and Avesani (2004) modified the deviation-from-mean method by considering the trust strengths, not user similarities, to predict preferences. The corresponding formation is defined as:  $p_{a,i} = \bar{p}_a + \frac{\sum_{x=1}^k T(u_a, u_x) (p_{x,i} - \bar{p}_x)}{\sum_{x=1}^k T(u_a, u_x)}$ , where  $p_{a,i}$  is the predicted preference for the active user  $u_a$  on item  $i$ ,  $\bar{p}_a$  is the average preference score of the user  $u_a$ ,  $k$  is the number of neighbors, and  $T(u_a, u_x)$  is the trust strength of the trust relationship  $\langle u_a \rightarrow u_x \rangle$ .

### 3 TRUST-BASED RECOMMENDATION APPROACH BASED ON TRUST STRENGTH ESTIMATION

In the existing trust-based recommendation approaches, all the existing trust relationships are deemed equally important and given the same trust strength. However, as we mentioned in Section 1, it is not a reasonable treatment in the real situation. In response, we propose the trust-based recommendation approach based on trust strength estimation to solve this problem. As shown in Figure 2, there are three phases in our proposed approach, i.e., trust strength estimation model learning, trust strength estimation and propagation, and trust-based preference prediction. The phase of trust strength estimation model learning is to build a model for estimating the existence possibility (used as the corresponding trust strength) of a trust relationship, training by a machine learning algorithm. Subsequently, based on the trained model, the second phase is to estimate the trust strength for each existing trust relationship and then calculate the propagated trust strength for each transitive trust relationship to get the expanded trust network. After trust network expansion, the phase of trust-based preference prediction is to identify the neighbors for the active user based on the trust strengths and then estimate the preference score for the active user on the target item based on the opinions of his/her neighbors.

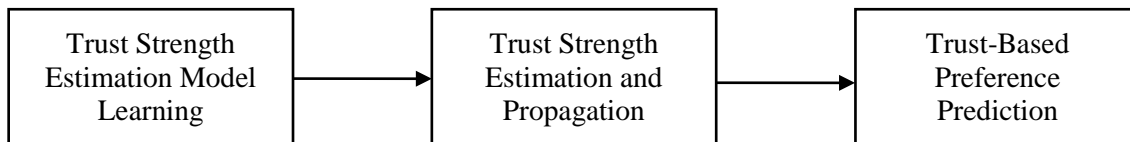


Figure 2. Overall process of our proposed approach.

#### 3.1 Trust Strength Estimation Model Learning

For trust strength estimation model learning, we adopt the decision-tree induction technique, i.e., C4.5, to build the model. Other learning algorithms, such as backpropagation neural network, nearest-neighbor classification, and Bayesian network, are also applicable in this phase. Before learning the model, we have to collect training instances and then extract representative features from the training instances as the inputs to the learning algorithm.

In this study, we prepare our training dataset in an online community, i.e., Epinions.com. Specifically, we collected a trust network at time  $T_0$  from the target online community and recollected another trust network at time  $T_1$  (i.e., five months later in this study). Then, we derive positive instances and negative instances from these two trust networks. The trust relationships that exist in the entire time period, i.e., both trust networks collected, are regarded as positive instances (or survival instances). On the contrary, the trust relationships that exist in the first trust network but disappear in the second trust network are regarded as negative instances (or disappeared instances). The details of deriving the training instances will be described in Section 4.1.

However, the survival instances may be more than the disappeared instances in our training dataset. Once the distribution of the decision classes is extremely asymmetric in the training dataset, the decision made by the trained model may favor the majority class in the training dataset (Forman, 2003). To overcome the possible skewness problem, we adopt the technique of random bagging. Specifically, we build a classifier for each bag, in which the number of survival instances is the same as the number of disappeared instances. In practice, we maintain all disappeared instances and randomly select survival instances for each bag to keep them balanced. As a result, there are  $BN$  models of  $BN$  bags and each classifier can estimate the corresponding existence probability for each trust relationship whose strength is to be predicted. Subsequently, we average the existence probabilities (or survival probabilities) estimated by all the  $BN$  classifiers to get the final estimated trust strength. Note that  $BN$  is set to 10 in this study.

For the survival and disappeared instances in each bag, we have to extract the representative features as the input variables for the adopted learning algorithm. In this study, we consider the 11 structural predictors proposed by Wei et al. (2007) and the PageRank score of sink node (Page et al., 1998) as

the input variables. For briefness, we define the following important notations: A trust network is defined as  $G = \langle V, E \rangle$ , where  $V$  is a set of users represented as nodes, and  $e = \langle u_i \rightarrow u_j \rangle \in E$  represents a trust relationship from  $u_i$  to  $u_j$ , where  $u_i \in V$  and  $u_j \in V$  (Guha et al., 2004);  $Trustor(u_i)$  is the set of users who trust  $u_i$  and  $Trustor(u_i) = \{u_k \mid u_k \in V \text{ and } \langle u_k \rightarrow u_i \rangle \in E\}$ ;  $Trustee(u_i)$  is the set of users trusted by  $u_i$  and  $Trustee(u_i) = \{u_k \mid u_k \in V \text{ and } \langle u_i \rightarrow u_k \rangle \in E\}$ . The involved structural predictors are defined in the following:

**Similarity of Trustors:** This structural predictor is defined as:  $Trustor-Similarity(u_a \rightarrow u_b) = \begin{cases} \frac{|Trustor(u_a) \cap Trustor(u_b)|}{|Trustor(u_a) - \{u_b\}|} & \text{if } |Trustor(u_a) - \{u_b\}| \neq 0 \\ 0, & \text{otherwise} \end{cases}$

**Adamic/Adar Similarity of Trustors:** This structural predictor is from the perspective of  $u_a$  (Adamic and Adar, 2003), defined as:  $Adamic/Adar-Trustor-Similarity(u_a \rightarrow u_b) =$

$$\begin{cases} \frac{\sum_{u_i \in Trustor(u_a) \cap Trustor(u_b)} \frac{1}{\log(|Trustee(u_i)|)}}{\sum_{u_j \in Trustor(u_a) - \{u_b\}} \frac{1}{\log(|Trustee(u_j)|)}} & \text{if } |Trustor(u_a) - \{u_b\}| \neq 0 \\ 0, & \text{otherwise} \end{cases}$$

**Similarity of Trustees:** This structural predictor is defined as:  $Trustee-Similarity(u_a \rightarrow u_b) = \begin{cases} \frac{|Trustee(u_a) \cap Trustee(u_b)|}{|Trustee(u_a) - \{u_b\}|} & \text{if } |Trustee(u_a) - \{u_b\}| \neq 0 \\ 0, & \text{otherwise} \end{cases}$

**Adamic/Adar Similarity of Trustees:** This structural predictor is from the perspective of  $u_b$  (Adamic and Adar, 2003), defined as:  $Adamic/Adar-Trustee-Similarity(u_a \rightarrow u_b) =$

$$\begin{cases} \frac{\sum_{u_i \in Trustee(u_a) \cap Trustee(u_b)} \frac{1}{\log(|Trustor(u_i)|)}}{\sum_{u_j \in Trustee(u_a) - \{u_b\}} \frac{1}{\log(|Trustor(u_j)|)}} & \text{if } |Trustee(u_a) - \{u_b\}| \neq 0 \\ 0, & \text{otherwise} \end{cases}$$

**Existence of Transpose Trust:** This structural predictor is defined as:  $Transpose-Trust(u_a \rightarrow u_b) = \begin{cases} 1, & \text{if } \langle u_b \rightarrow u_a \rangle \text{ exists} \\ 0, & \text{otherwise} \end{cases}$

**Indirect Path Existence (from  $u_a$  to  $u_b$ ):** This structural predictor is defined as:

$$Indirect-Path-Existence(u_a \rightarrow u_b) = \begin{cases} 1, & \text{if there exists a indirect path from } u_a \text{ to } u_b \\ 0, & \text{otherwise} \end{cases}$$

**Length of Shortest Indirect Path (from  $u_a$  to  $u_b$ ):** We consider the length of shortest indirect path from  $u_a$  to  $u_b$  as a structural predictor to determine whether the trust relationship  $\langle u_a \rightarrow u_b \rangle$  would be likely to exist in the future.

**Katz <sub>$\beta$</sub>  Sum of Indirect Paths (from  $u_a$  to  $u_b$ ):** The width of indirect paths is defined as follows:  $Katz_{\beta}\text{-Sum-of-Path}(u_a \rightarrow u_b) = \sum_{\gamma=2}^6 \beta^{\gamma} \times |paths_{ab}^{(\gamma)}|$ , where  $paths_{ab}^{(\gamma)}$  is the set of all paths from  $u_a$  to  $u_b$  with length  $\gamma$ , and  $\beta$  is 0.5, 0.05 and 0.005 in this study.

**Width of Indirect Paths (from  $u_a$  to  $u_b$ ):** We consider the number of all indirect paths from  $u_a$  to  $u_b$  as a structural predictor.

**Number of Trustees of the Source (i.e.,  $u_a$ ):** We consider the number of trustees of the source as a structural predictor.

**Trust Intensity of the Sink (i.e.,  $u_b$ ):** We consider the number of trustors of the sink as a structural predictor.

**PageRank of the Sink (i.e.,  $u_b$ ):** We consider the PageRank score of the sink (Page et al., 1998) as a structural predictor.

### 3.2 Trust Strength Estimation and Propagation

After the model of trust strength estimation is built, we can estimate the corresponding trust strength for each existing trust relationship in the testing trust network. To expand the trust network, we then adopt the modified trust propagation method for each transitive relationship to estimate the possible trust strength. The measure of the modified trust propagation method to estimate the trust strength  $T(u_a, u_b)$  of the transitive relationship  $\langle u_a \rightarrow u_b \rangle$  is defined as:

$$T(u_a, u_b) = \max \left[ \frac{d - \text{Length}(\text{Path}_i) + 1}{d} \prod_{j=1}^{\text{Length}(\text{Path}_i)} T(PM_{i,j}, PM_{i,j+1}) \right], i=1 \text{ to } m$$

where  $d$  is the maximum steps from  $u_a$  to  $u_b$ ,  $\text{Length}(\text{Path}_i)$  is the number of steps in  $\text{Path}_i$ ,  $PM_{i,j}$  is the member in  $\text{Path}_i$  at the  $j$ -th step,  $m$  is the number of indirect paths from  $u_a$  to  $u_b$  in the trust network.

Since there may be more than one path from  $u_a$  to  $u_b$ , we use the maximum one as the final trust strength for the transitive trust relationship in our approach. Also,  $d$  is set to 6 as Ziegler and Lausen (2004) suggested. We take the transitive trust relationship  $\langle u_a \rightarrow u_b \rangle$  in Figure 3 for example. There are three paths from  $u_a$  to  $u_b$ : 1)  $P_1: u_a \rightarrow u_1 \rightarrow u_2 \rightarrow u_3 \rightarrow u_b$ , 2)  $P_2: u_a \rightarrow u_4 \rightarrow u_b$ , and 3)  $P_3: u_a \rightarrow u_5 \rightarrow u_6 \rightarrow u_b$ . The corresponding trust strengths of  $P_1$ ,  $P_2$ , and  $P_3$  are 0.1134, 0.35, and 0.2987, respectively. Therefore, the trust strength of  $\langle u_a \rightarrow u_b \rangle$  is set to 0.35 according to the proposed measure.

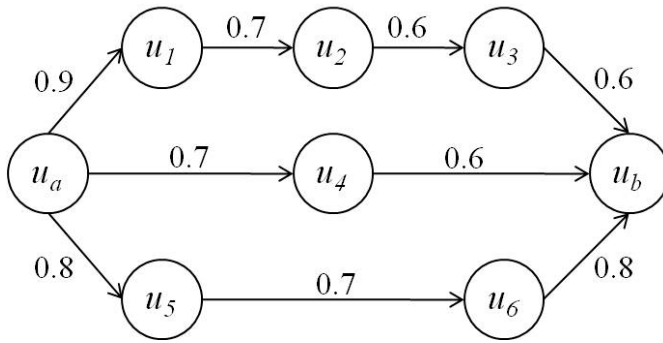


Figure 3. Example for trust strength propagation.

### 3.3 Trust-Based Preference Prediction

After trust strength estimation and trust propagation, we get the expanded trust network for preference prediction. Similar to the traditional collaborative filtering approach, we also need to identify the neighbors for the active user in this phase. In our proposed approach, we select the top- $k$  users with the highest trust strengths who are trusted (directly or transitively) by the active user from the user group that have expressed their preferences on the target item before. Based on the opinions of the neighbors, the predicted preference on the target item  $i$  for the active user  $u_a$  is calculated as:  $p_{a,i} = \bar{p}_a + \frac{\sum_{x=1}^k T(u_a, u_x) (p_{x,i} - \bar{p}_x)}{\sum_{x=1}^k T(u_a, u_x)}$ , where  $p_{a,i}$  is the predicted preference for the active user  $u_a$  on item  $i$ ,  $\bar{p}_a$  is the average preference score of user  $u_a$ ,  $k$  is the number of neighbors, and  $T(u_a, u_x)$  is the trust strength of the trust relationship  $\langle u_a \rightarrow u_x \rangle$ .

## 4 EMPIRICAL EVALUATION

In this section, we present the data collections for empirical evaluation and the important experimental results. In Section 4.1, data collection for trust strength estimation model learning is first illustrated. Then, data collection for recommendation evaluation is introduced in Section 4.2. Subsequently, we illustrate the performance benchmarks and evaluation criteria, in Section 4.3. Finally, the experimental results are displayed in Section 4.4 to show the performance of our proposed approach by comparing with that of the two benchmarks.



#### 4.1 Data Collection for Trust Strength Estimation Model Learning

In this study, we collected the data of the category “Home and Garden” for trust strength estimation model learning from the most popular online opinion-sharing community, i.e., Epinion.com. Specifically, we first collected a trust network at time  $T_0$  from the target online community. Then, we recollected another trust network five months afterward, which is at time  $T_1$ . For representativeness and bias reduction, both of the trust networks at  $T_0$  and  $T_1$  only consist of the members, i.e., the top reviewers (i.e., a total of 26) of the category “Home and Garden” and their trustors and trustees of the category “Home and Garden”, as well as the corresponding trust relationships among the concerned members. The trust relationships that exist in both trust networks at  $T_0$  and  $T_1$  are regarded as positive instances (or survival instances). On the contrary, the trust relationships that exist in the first trust network but disappear in the second trust network are regarded as negative instances (or disappeared instances). Specifically, if a trust relationship  $\langle u_a \rightarrow u_b \rangle$  exists in the first trust network but disappears in the second trust network, this relationship is regarded as the disappeared instance. For example, in Figure 4, the trust relationships  $\langle u_c \rightarrow u_d \rangle$  and  $\langle u_d \rightarrow u_e \rangle$  are regarded as survival instances. On the contrary, the trust relationships  $\langle u_a \rightarrow u_b \rangle$ ,  $\langle u_a \rightarrow u_e \rangle$ ,  $\langle u_c \rightarrow u_a \rangle$ , and  $\langle u_c \rightarrow u_e \rangle$  are regarded as disappeared instances. Note that the structural predictors of each survival instances (or disappeared instance) are extracted based on the trust network on  $T_0$  as the input variables to the machine learning algorithm. Finally, there are 285 survival instances and 132 disappeared instances in this data collection. As introduced in Section 3.1, the trust strength estimation model of our proposed approach (employing C4.5 classification with the random bagging technique) is then built based on this data collection.

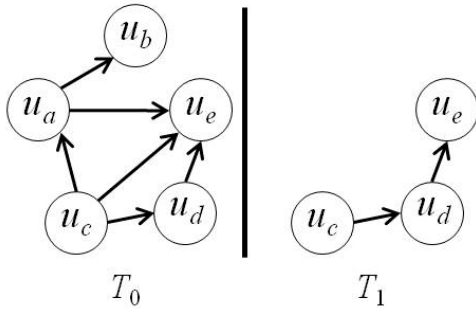


Figure 4. Example of deriving survival instances and disappeared instances.

#### 4.2 Data Collection for Recommendation Evaluation

In Epinions.com, a user can post reviews of all products he/she experienced and give them preference scores in the range from 1 (min) to 5 (max). Moreover, each user can express his/her trust statements to other users. If user  $u_a$  expresses the trust statement to user  $u_b$ ,  $\langle u_a \rightarrow u_b \rangle$  is constructed in the trust network with trust strength 1. In this study, we collected the trust networks and product preferences of the category “Home and Garden” from Epinions.com to construct the dataset for recommendation evaluation. Then, each investigated approach is employed to predict the preferences that are given in the next 15 days based on a given trust network. As shown in Figure 5, we collected the first trust network  $TN_1$  on December 31st, 2008 (i.e.,  $t_1$ ). Given  $TN_1$ , each investigated approach is employed to predict the preferences that are given from January 1st, 2009 to January 15th, 2009 (i.e., recommendation period  $R_1$ ). Then, we collected the following trust networks every 15 days afterward. Finally, we collected the last trust network  $TN_{28}$  on February 9th, 2010 (i.e.,  $t_{28}$ ). As a result, we have 28 trust networks at  $t_1, t_2, \dots, t_{28}$  in the data collection for recommendation evaluation, including 610 users and 1,300 relationships with 22,704 ratings for 13,788 items.

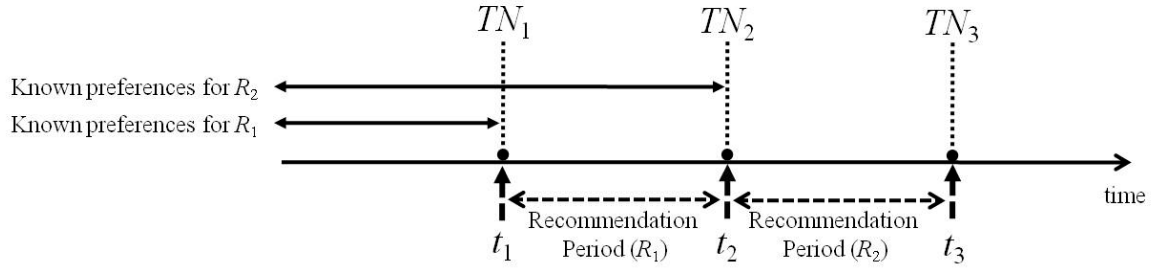


Figure 5. Example of data collection for recommendation evaluation.

### 4.3 Performance Benchmarks and Evaluation Criteria

For comparison, we implement the traditional collaborative filtering approach (namely CF) (Herlocker et al., 1999) and the trust-based recommendation approach with the linear decaying propagation method (namely TP) (Massa and Avesani, 2004) as our benchmarks. Moreover, we adopt two evaluation criteria, i.e., mean absolute error (MAE) and coverage to evaluate our performance (Herlocker et al., 1999; Massa and Avesani, 2004). MAE is a widely adopted measure to evaluate the prediction accuracy and is defined as the average absolute difference between the predicted preference scores and the actual preference scores:  $MAE = \frac{\sum_{i=1}^T |p_i - q_i|}{T}$ , where  $p_i$  is a predicted preference score,  $q_i$  is the actual preference score for the same preference prediction task, and  $T$  is the total number of preference prediction tasks. Moreover, coverage is defined as the percentage of the preference prediction tasks that can be predicted by a recommendation technique investigated.

### 4.4 Evaluation Results of Our Trust-Based Recommendation Approach

For each trust network at  $t_i$  and the corresponding known user preferences, we employ the three approaches, i.e., TSE, CF, and TP, to predict the preferences that will be given in next 15 days. Here, we range the number of neighbors, i.e.  $k$ , from 1 to 10. According to Figure 6, across the range of  $k$  investigated, the average MAE of our proposed approach is lower than that of CF and TP. The results indicate that both trust-based approaches (i.e., TSE and TP) outperform CF. Moreover, the results suggest that our trust strength estimation mechanism is practical to return the likely trust strength of a trust relationship. Therefore, our proposed approach can identify more reliable neighbors for the active user and then achieve the best prediction accuracy. However, the coverage of our proposed approach (4.7%) is worse than that of CF (7.5%). The results imply that there may be some users who can share their opinions with the active user but the active user has no chance to reach them, even through our trust propagation method.

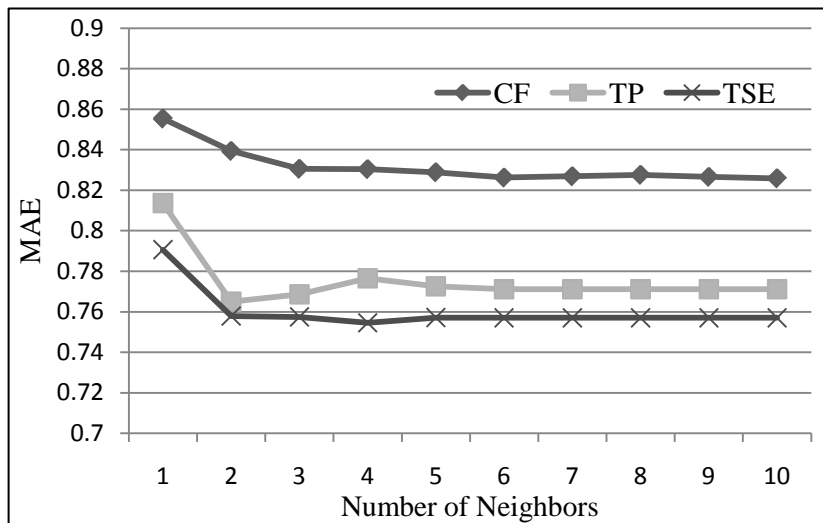


Figure 6. Comparative evaluation results of CF, TP, and TSE on MAE.

In Section 3.2, we propose a modified trust propagation method to estimate the trust strength of a transitive trust relationship. In the corresponding measure, we include the decaying factor  $\frac{d-\text{Length}(\text{Path}_i)+1}{d}$  based on the idea that the distance could decrease the trust strength (Massa and Avesani, 2004). Finally, we examine the effects of this decaying factor for our proposed approach. The experimental results of the effects on the decaying factor for TSE on MAE in next 15 days are shown in Figure 7. These results indicate that the decaying factor is important for trust propagation. That is, the concept that the distance could decrease the trust strength is still applicable to the trust network with various trust strengths.

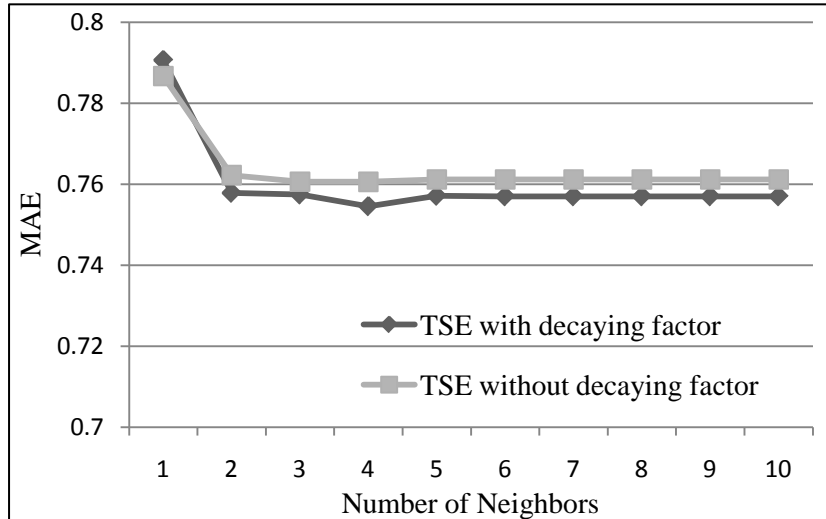


Figure 7. Effects on the decaying factor for TSE on MAE.

## 5 CONCLUSION

With the development of Web 2.0, the trust-based recommendation techniques have emerged to provide collaborative recommendations. Based on the analysis of trust relationships, the trust-based recommendation approach finds out and consults the opinions of more reliable users and then makes collaborative recommendations. However, in the existing trust-based approaches, the trust relationships are deemed equally important and given the same trust strength. This is not reasonable in the real situation. One of the examples is that users may have much confidence on top reviewers than on other individuals. Therefore, we propose a trust-based recommendation approach based on the trust strength estimation mechanism and the trust strength propagation method. For trust strength estimation, we extract the structural predictors as the input variables for the machine learning algorithm to build the model. To expand the trust network, we also develop a measure for the modified trust propagation method. For performance comparison, we collect the evaluation dataset from Epinions.com and implement the benchmarks, i.e., traditional collaborative filtering approach and the original trust-based recommendation approach. The experimental results demonstrate that our proposed approach based on the trust strength estimation mechanism can outperform the benchmarks on prediction accuracy.

Some ongoing and future research directions are briefly discussed as follows. First, in this study, we only use the trust networks related to the Home & Garden category from Epinions.com as the evaluation dataset to compare the performance of our approach with that of the benchmarks. Evaluating our proposed approach with additional datasets that involve other product categories will extend the generalizability of the results found in this study. Second, in this study, we do not consider that the trust strength of a trust relationship may decrease as time passes. Such extension of our proposed approach may further improve recommendation effectiveness. Finally, according to the experimental results, the coverage of our proposed approach is worse than that of CF. The extension and improvement of our trust propagation method is an essential direction for our proposed approach to achieve higher coverage but still maintain similar accuracy level.

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