國 立 交 通 大 學

資訊管理研究所

碩 士 論 文

基於序列信任模式之文件推薦

Sequence-Based Trust Model for Document Recommendation

研 究 生： 邱 璇

指導教授： 劉敦仁 博士

中華民國 九十八年六月

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研 究 生：邱 璇　　Student: Hsuan Chiu

指導教授：劉敦仁　　Advisor: Duen-Ren Liu

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摘要

協同式過濾推薦已廣泛應用在不同領域上，且有效解決資訊量過大的問題。該方法最主要精神是尋求相似興趣使用者以進行推薦。最近開始有學者提出以信任機制導入協同式過濾推薦以增加推薦結果的準度與可信度。而計算信任程度的方法，則是有學者提出以過去預測評分的準確度來當作衡量信任程度的機制，如果一個使用者在過去推薦的準確度越高，則被認為越值得信任。然而到目前為止，鮮少有相關研究有考慮到序列式信任計算方式。本研究提出的方法，考量了使用者對文章評分的先後順序而導出的信任程度。在知識密集的環境裡，使用者通常會存取不同的文章以滿足其在不同時間點的資訊需求，而此過程就形成了文章序列。本研究所提的序列式信任計算方法涵蓋了兩個因素，分別是時間因素與文件內容相似度因素。而在推薦的程序中則是將序列式信任帶入協同式過濾推薦模式進行對使用者評分的預測。最後透過實驗結果來印證所提的方法的確有效提高推薦的準確度。

關鍵字: 協同式過濾、推薦系統、序列式信任.

Sequence-Based Trust model for Document Recommendation Systems

Student: Hsuan Chiu **Advisor:Duen-Ren Liu**

Institute of Information Management

National Chiao Tung University

Abstract

Collaborative Filtering (CF) recommender systems have emerged in various applications to support item recommendation, solving the information-overload problem by suggesting items of interest to users. Recently, trust-based recommender systems have incorporated the trustworthiness of users into CF techniques to improve the quality of recommendation. They propose trust computation models to derive the trust value based on users' past ratings on items. A user is more trustworthy if s/he has contributed more accurate predictions than other users. Nevertheless, none of them derive the trust value based on a sequence of user's ratings on items. We propose a sequence-based trust model to derive the trust value based on users' sequences of ratings on documents. In knowledge-intensive environments, users normally have various information needs in accessing required documents over time, producing a sequence of documents ordered according to their access time. The model considers two factors - time factor and document similarity - in computing the trustworthiness of users. The proposed model is incorporated into a standard collaborative filtering method to discover trustworthy neighbors for making predictions. The experiment result shows that the proposed model can improve the prediction accuracy of CF method compared with other trust-based recommender systems.

Keywords: Collaborative Filtering, Recommender System, Sequence-Based Trust.

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本文承蒙恩師 劉敦仁教授悉心指導，並逐字斧正使臻於成。研究期間，舉凡觀念的釐清、相關文獻資料的提供與疑難問題的解決，無不竭盡心力，使學生獲益良多，萬分感謝。此外本文承蒙口試委員，魏志平、李永銘教授的細心審查與耐心指正，特此致謝。

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1. Introduction

Recommender systems have emerged in various applications to support item recommendation[35, 38], solving the information-overload problem by suggesting items of interest to users. Various recommendation methods have been proposed. The collaborative filtering (CF) method [34] has been successfully used in various applications. It predicts user preferences for items in a word-of-mouth manner. User preferences are predicted by considering the opinions (in the form of preference ratings) of other "like-minded" users.

Recently, trust-based recommender systems [39] have incorporated the trustworthiness of users into the CF techniques to improve the quality of recommendation. According to [2], trust can be defined as how much a trustor believes that a trustee is willing and able to perform under a given situation. Massa et al. [24-27] proposed a trust recommender system based on a user's web of trust, which explicitly specifies the friends s/he trusts. For instance, in Epinions.com, users are allowed to assign their personal trust value to the review writers. Through trust propagation from the web of trust, the trust value between two users can be predicted even though there is no direct trust value specified (connection) between them. Their work, however, relies on the user's explicit assignment of trust value that is not easy to collect and may create a heavy burden on users.

Some researches [13, 15, 28] have proposed trust computation models to derive the trust value based on users' past ratings of items. O'Donovan et al. [28] suggest that if a user has usually delivered accurate predictions in the past, s/he merits being called reliable and trustworthy. A prediction on an item contributed from a given user (producer) is accurate to a target user (consumer) if the difference between their ratings on the item is within a predefined error bound. Generally, a user is more trustworthy if s/he has contributed more accurate predictions than other users. Their proposed trust metrics is a global trust, which basically accumulates the given user's accurate predictions made to other users or a group of users. Their trust model includes the item level and profile level. The item-level / profile-level trust metric of a given user is derived by computing the ratio of accurate predictions that s/he has made to other users over a particular item / all items that s/he has rated in the past. In addition, Hwang and Chen [13] propose a relationship trust metric to derive the trust value between two users by calculating the ratio of accurate predictions over all co-rated items, i.e., those items that have been rated by both of them. The proposed relationship trust metric is more personalized than the reputation trust metric. Their proposed trust metrics are combined with the standard CF technique to improve prediction quality for a MovieLens dataset.

Nevertheless, no one has derived trust value based on a sequence of user's ratings of items. In the MovieLens dataset, a user only has one rating score on an item and there is no ordering relationship between the items (movies) in a user's rating history. That is, it does not matter whether a user saw a horror movie first and then a comedy movie, or a comedy movie first and then a horror movie. In knowledge-intensive environments, users normally have various information needs in accessing required documents over time, producing a sequence of documents ordered according to their access time. For such environments, the ordering of documents required by a user may be important. For example, a user may need to access documents with prerequisite and basic knowledge first and then documents with advanced knowledge.

In this work, we propose a sequence-based trust model to derive trust value based on users' sequences of document ratings. The proposed model considers time factor, document similarity and user's profile in computing the trustworthiness of users. Generally, an accurate prediction made in the recent past contributes more trustworthiness than one made earlier. Moreover, conventional trust computational models use the ratings on the same item to derive the accuracy of prediction and compute the trust value. In knowledge-intensive environments, users often have the information needs to access documents with similar contents. A user's rating of a document generally reflects the user's perception of the relevance of the document content to his/her information needs. Thus, the ratings on different documents with similar contents should also help to derive the trustworthiness of users. Accordingly, we consider the time factor and the ratings on similar documents to derive a sequence-based trust computation model. In addition, the recommended item is a text-based document, thus, content analysis is useful to select neighbors based on the similarity of user profiles which reveal users' interest on document content. The proposed model is incorporated into the standard CF method to effectively discover trustworthy neighbors for making predictions. The experiment result shows that the proposed model can improve the prediction accuracy of the CF method compared with other trust-based recommender systems.

The paper is organized as follows. We present the related works in Section 2. Section 3 describes our proposed trust computation models and the recommendation methods based on these models. The experiment results and evaluations are presented in Section 4. Finally, Section 5 describes the conclusions and future works.

2. Related Work

2.1 Recommender systems

As ecommerce prospers, an explosion of information has overwhelmed the Internet. The sheer volume of data emerging from the Web means that discovering useful knowledge is difficult and people cannot manipulate it. This is known as the information overloading problem. Internet users worry not that they cannot find the necessary knowledge but that they may waste too much time searching for information.

Given this problem, recommender systems (RS) have emerged in various applications for providing assistance. The main task that RS complete is not only filtering out useful information but also actively supplying valuable knowledge to interested users. In general, RS can be classified in two categories, collaborative filtering system (CF) and content-based recommender system (CB) [30]. The former filters or evaluates items by users' opinions, while the latter identifies items of special interest through analyzing item descriptions. Details are described below.

2.1.1 Collaborative filtering recommender systems

The collaborative filtering (CF) method has been successfully used in various applications. It predicts users' preferences for items in a word-of-mouth manner. Users' preferences are predicted by considering the opinions (in the form of preference ratings) of other "liked-minded" users. The GroupLens system [34], [16] applies the CF method to recommend Usenet News and movies. Video recommender [12] also uses CF to generate recommendations on music.

In general, collaborative filtering recommender systems can be roughly classified as user-based and item-based CF methods. User-based CF exploits historical data expressing preferences to form user neighbors and make recommendations based on those similar users' opinions. On the other hand, item-based CF determines recommendations by relying on items' associations, which are based on user's ratings among items. Sarwar et al. [37] built a user-item matrix to identify relationships between different items and then find other similar products that users might like.

With the CF recommendation method, users first have to provide some opinions (i.e., ratings) on the items they have used or bought. Then, in order to recommend items to the target user, *c*, previous rating history is used to discover similar users, who are called neighbors and form the target user *c*'s neighborhood. Neighbors who expressed similar opinions on target user *c*'s past items recommend items to target user *c*. These items have been tested by neighbors but not yet by the target user. The assumption is that those who have had similar interests before will have similar tastes in the future.

To provide useful recommendations, the user-based CF approach involves two steps: neighborhood selection and target user's item rating prediction. The purpose of neighborhood selection, selecting those who have similar taste to the target user, is to supply accurate prediction; thus, a metric for measuring user similarity is vital. Several metrics have been proposed for similarity computing, e.g., Pearson Correlation Coefficient [34]. Eq. 1 is used to evaluate the Pearson Correlation between target user *c* and recommender *p*.

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

where S_c^D and S_p^D represent a document set rated by user *c* and *p* respectively; r_{c,d_k} is target user *c*'s rating of document d_k; and $\overline{r}_c$ is user *c*'s average rating of document set $(S_c^D \cap S_p^D)$.

In the prediction phase, the predicted rating score is derived from the target user's average rating and his/her neighbors' relative opinions on the common rated items, as shown below:

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

where $\hat{p}_{c,d_k}$ represents the predicted rating that target user *c* may provide for item d_k; $\overline{r}_p$ is his/her average rating; $w_{c,p}^{Pearson}$ is the user similarity between target user *c* and his/her neighbor *p*; and neighbors in *NS* set have been selected to provide their relative tastes.

2.1.2 Content-based recommender systems

Content-based recommender systems recommend interesting items to the user by analyzing their content description. The content is parsed and features are used to establish a characteristic profile. On the other hand, items that were previously rated by a user are used to generate a user profile. Therefore, to pre-process the item content, the content-based recommender systems depend heavily upon the techniques of information retrieval. A number of recommender systems apply a content-based technique to various domains, such as web pages [22, 31], news articles [40] and TV programs [1]. Most content-based recommender systems have two processes in common, which are profile establishing and user model building. The former adopts information retrieval to analyze item content and builds a profile for an item or a user, while the latter involves classification techniques such as decision trees [14, 33] or naïve Bayesian [4, 31] to learn users' traits.

2.2 Information retrieval and filtering

Information retrieval (IR) transforms textual documents into a meaningful model and is applied to knowledge management activities. There are three phases, stop-word removing, stemming and term weighting phases, in the process of document pre-processing to convert any textual documents into a list of features and filter out non-relevant ones. In the stop-word removing phase, the stop words (i.e.,, "a", "the", "to") are removed from documents. Then, in the stemming phase, the morphologic variations of a word are reduced to its morphologic root. For example, "comput-er", "comput-ational" and "comput-e" can be reduced to "comput". In our research, we follow Porter's stemming algorithm [32], which is used universally in the IR field, to process our documents. The derived terms are then employed to calculate term weights based on the well-known *tf-idf* approach.

According to Gerard and Chris [8], any codified knowledge item *d* (e.g., documents, reports, etc.) can be represented as a feature vector of weighted terms in a *n*-dimensional space. The feature vector of document *d* is represented as $\vec{d} =< w_{1,d}, w_{2,d}, \ldots, w_{n,d} >$. The weight of term *i* in document *d* is $w_{i,d}$

is derived by using Eq. 3.

$$w_{i,d} = (0.5 + \frac{0.5 \times tf_{i,d}}{\max tf_{i,d}}) \times (\log \frac{N}{df_{i,d}} + 1) \tag{3}$$

where $tf_{i,d}$ indicates the term frequency of term i in document d, $df_{i,d}$ means the number of documents which contain the specific term i and N is the total number of documents. Through the information-filtering techniques, the codified knowledge is transformed systematically for further analysis and exploitation in future knowledge activities.

2.3 The definition of trust

The feeling of trust is a common everyday experience but its concept is hard to define. Diverse definitions have been proposed in various areas such as computer science, economics, psychology, etc. and each of them offers a feasible explanation. Two common interpretations are *reliability trust* and *decision trust* [2]. Reliability trust is formulated as a belief (or subjectivity probability) between agent A and agent B in a P2P network which agent A expects agent B to perform well. According to the research of Golbeck and Hendler [9], " Trust in a person is a commitment to an action based on a belief that the future actions of that person will lead to a good outcome." When it comes to decision trust, the concept describes how much agent A is willing to depend on agent B no matter whether the results are positive or negative. In this scenario, the consequences may not be as correct as agent A assumed initially; agent A is, however, still willing to believe agent B. This is a commoner definition and suitable for more situations. A similar trust concept is one's expectation of a peer's competence in providing recommendations to reduce uncertainty in predicting new item ratings [41]. More examples of reliable trust and decision trust are discussed in [2, 9].

As trust is applied in social networks, it provides more functions and development areas especially for the expansion of internet intelligence. For example, when the number of users on a blogosphere increases, more and more people can publish their articles with simple web tools at any time. Moreover, users enjoy sharing documents with their friends or reading articles written by a credible writer. Those behaviors on the Internet form a so-called web of trust (WoT). The main concept of WoT is that even though two users were unknown to each other before, their friendship is still able to be inferred through other trust relationships which are known and related to the two users [10, 17]. People are linked through this relationship and then a social network is constructed. Lately, several social network applications on the Web have become mature such as MySpace and Facebook [19]. Therefore, the trust relationships among people have attracted more and more attention.

2.3.1 Trust statement

Since the trust notion is applied in diverse fields, it is necessary to manifest a measurement trust statement to represent the trust extent. For example, in a P2P system, the reliability information of a peer is taken as a standard measurement to determine the trust worthiness of a peer. Furthermore, in some open rating systems, the trust statement is seen as a certain user's feeling about whether the delivered information is correct and useful or not [21], such as the *Epinions* system. In such systems users are able to express their trust statements to product review writers depending on how valuable they consider the review to be [26]. After they have decided on a trust statement, the spectrum of trust between two users can be scaled.

2.3.2 Trust metrics indication: direct vs. indirect

The purpose of designing a trust metric is to help a user to quantify the degree of trust [41]. The trust value, however, is not always initialized already. Thus, according to the starting value generation method, it can be classified into direct trust and indirect trust depending on whether a user actively indicates or not [29]. The meaning of direct trust is that a user expresses their opinion in value or opinion format to another person during their interaction. The "friend" list in Epinions and Facebook or the feedback from eBay exemplifies direct trust. Massa and Avesani [26] take advantage of the Epinions direct trust relationship to balance collaborative recommender system's defects [24, 25, 27]. Conversely, indirect trust is derived through computation. Marsh claimed that trust can be viewed as a function of reputation, which can be computed over historical data [23]. Several trust relationships, which are exploited in the recommender system, are inferred from past rating data and details will be described later [5, 7, 13, 15, 20, 29, 41, 42].

2.3.3 Trust metric: relationship vs. reputation

With regard to trust metric procedure, it can be viewed from two dimensions: relationship and reputation [18]. Relationship trust relies on qualitative measurements depending upon social network connections. A user decides their trust decision on another based on some private knowledge which was gained through past direct experience or intimate relationship. Some researchers have named it personal trust or local trust, whose value is limited between two users and diversified with different user pairs. Several examples such as Facebook and Epinions by which the user includes a friend in his/her list are this type and, if the relationship trust is not explicitly indicated, it can be inferred from rating data or other indirect information [13, 20, 41]. On the other hand, reputation trust is a more quantitative assessment which allocates a score to a specific object or person for a particular context. An individual's reputation trust is collected from all members in the community and the reputation value of a user is equal to others. A famous example is eBay, on which each seller attains a trust value through several buyers' comments. Some researches call it global trust or expert degree with similar concept [5, 6, 15, 28].

2.4 Trust-based CF recommender systems

Recently, trust-based recommender systems have incorporated the trustworthiness of users into CF techniques to improve the quality of recommendation. According to the trust characteristic presented above, trust-based recommender systems can be classified in two categories: reputation trust and relationship trust. Reputation trust is calculated by accumulating a given user's accurate predictions that s/he has made to other users or a group of users. On the other hand, relationship trust, using partial trust graphs, is the belief between two agents and each user should have diverse opinions to the others. One should trust another on the basis of some experience or history [11, 13, 17, 20, 24, 25, 27, 41]

2.4.1 Reputation trust based recommender system

Many researchers propose reputation trust as an auxiliary factor in the recommending phase. Some papers [5-7, 15] refer to it as expert or professional degree as well. Cho et al. [6] and Kim et al. [15] adopt Riggs's model [36] for considering whether someone is qualified as an expert. Cho et al. [6] measure expertise of a user at category level, whose taste is closer to population has more opportunity to be an expert. Kim et al. [15] act similarly. With Epinion.com data, they try to decide who will be the expert among all category review writers. Additionally, before raters' judging, they need to measure raters' tastes and select the one who has more common taste. Others such as O'Donovan and Smyth [28] propose profile-level trust and item-level trust derived from user rating data. They claim that accurate recommendation in the past is important and reliable and a user is viewed as trustworthy if s/he always contributes a precise prediction, as shown in Eq. 4.

$$Correct(d_k, p, c) \Leftrightarrow |\hat{P}^{p}_{c,d_k} - r_{c,d_k}| < \varepsilon \quad , \tag{4}$$

where p is a recommender; c is a target user; d_k is an item; $\hat{P}^{p}_{c,d_k}$ (defined in Eq. 13) is a predicted rating of item d_k from the target user c's view; r_{c,d_k} is a real rating of the item d_k given by the target user c; and ε is an error bound measuring the closeness. According to this equation, recommender p is regarded as trustworthy if his/her prediction on item d_k in target user c's view is close to c's real rating r_{c,d_k}. All items, rated by p and the other recommenders c_n, form p's *RecSet*, as shown in Eq. 5. For each pair in *RecSet*, the trustworthiness on a specific item d_n is measured as in Eq. 6. *CorrSet* stores all pairs that p making approximate prediction on item d_k for recommender c_n.

$$RecSet(p) = \{(c_1, d_1), \ldots, (c_n, d_n)\} \tag{5}$$

$$CorrSet(p) = \{(c_k, d_k) \in RecSet : Correct(d_k, p, c_k)\} \tag{6}$$

The profile-level trust, $Trust^{P}(p)$, is calculated in the percentage of correct prediction that the recommender p has donated; while the concept of item-level trust, $Trust^{I}(p, d_k)$, is similar but focuses on a specific item d_k.

$$Trust^{p}(p) = \frac{|CorrSet(p)|}{RecSet(P)} \tag{7}$$

$$Trust^{I}(p, d_k) = \frac{|\{(c_k, d_k) \in CorrSet(p)\}|}{|\{(c_k, d_k) \in RecSet(p)\}|} \tag{8}$$

Both profile-level trust and item-level trust can be used in the recommendation phase. According to the profile-level trust, Eq. 9 is used to filter out users whose profile-level trust values are lower than a specified threshold. Thus, *NS* is a neighbor set for contributing their views in predicting. The weight between user *p* and the target user *c*, which combines the value of profile-level trust with user similarity in a harmonic mean, is derived by Eq. 10. Then, these user weights are applied in a modified version of Resnick's formula, i.e., Eq. 11, for prediction. Similarly, using item-level trust in the recommendation phase also has the same way.

$$NS = \{Trust^{p}(p) > threshold\} \tag{9}$$

$$w_{c,p}^{Trust^{p}} = \frac{2(sim(c,p))(Trust^{p}(p))}{sim(c,p) + Trust^{p}(p)} \tag{10}$$

$$p_{c,j} = \overline{r_c} + \frac{\sum_{p \in NS} w^{Trust^{p}}{}_{c,p}(r_{p,j} - \overline{r_p})}{\sum_{p \in NS} w^{Trust^{p}}{}_{c,p}} \tag{11}$$

2.4.2 Relationship trust based recommender system

Relationship trust metrics consider the trustor's subjective opinions when predicting the trust value which s/he placed on the trustee. Several researches apply relationship trust in recommender systems and attain quite precise results and more personalization effects, such as Massa and Avesani [26], who consider the relationship trust metric, depending on user's independent view to others, is different. They use Epionions.com data in their experiment. Epinions.com allows the user to express their trust opinion by adding a reviewer into their Web of Trust list or Block list. If s/he considers this reviewer's reviews are valuable, s/he puts him into the Web of Trust. If not, s/he puts him/her into the Block list. Even though they present an improvement on traditional CF recommender systems, the direct relationship trust data have some defects. This kind of data is not usual in most recommender systems and it is hard to collect. First, it is not easy to stimulate the user's incentive to present their trust value. Second, the quality of a reviewer's review cannot always maintain consistency. This relationship trust should vary according to the reviewer's quality and the user's taste. Last, this trust is a binary value type, either zero in Block list or one in Web of Trust list. The trust degree should, however, show some difference in all trusted reviewers in the Web of Trust list.

Similarly to [28], Hwang and Chen [13] calculate personal trust degree based on the user's past rating data, as shown in Eq. 12.

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

Recommender p predicting item d_k in target user c's view is denoted as $\hat{p}_{c,d_k}^p$ in Eq. 12. Instead of filtering with an error bound, however, they count all. All items that are co-rated by p and c involve n personal trust computing process and M is the range between maximum and minimum rating scores.

3. Sequence-based trust methods

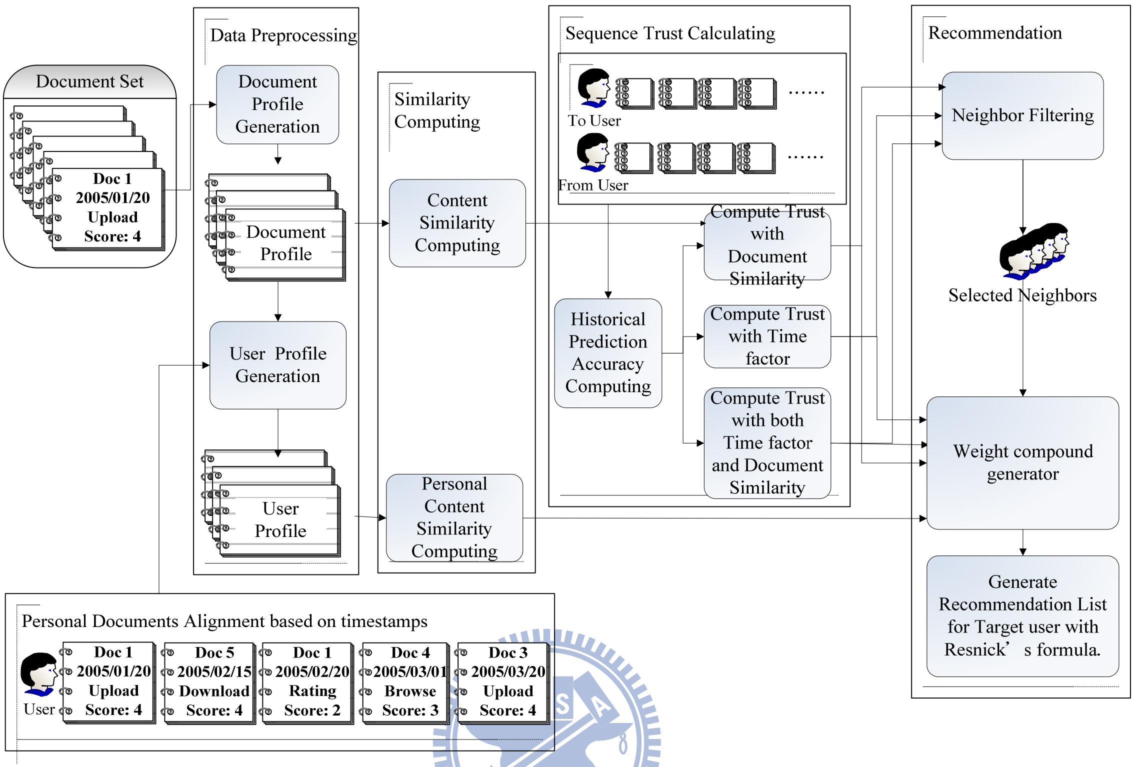

Fig. 1 Concept Overview

3.1 Overview

To provide required documents to users proactively and accurately, a sequence-based trust recommendation method is proposed. As illustrated in Fig. 1, our method consists of several steps. First, documents are pre-processed by the *tf-idf* approach to generate document profiles describing the key contents of documents. In addition, the system records the accessing time of documents, the accessing behavior or user's and ratings of documents. Because each user has various information needs at different times, his/ her documents are arranged as a document sequence by their access time. Then, the similarities among document profiles are derived in the similarity computation step. Next, these document similarities and document ratings in users' document sequences are incorporated into our trust model to obtain the sequenced-based trust values which denote the trustworthiness among users. We propose three sorts of trust models which consider time factor, document similarity and both time factor and document similarity, respectively. These trust values of users are used to discover highly trustworthy users as neighbors for a target user. Notably, the neighbors selected by use of different trust computation models for the same target user may vary. Based on the trust values and the document ratings of these neighbors, the proposed CF methods can predict required documents and generate a recommendation list for the target user.

3.2 Concept of sequence-based trust

Most trust computation models consider accurate predictions derived from past rating records to infer the trust value. A prediction on an item contributed from a recommender (producer) is accurate for a target user (consumer) if the difference between their ratings on the item is within a predefined error bound. Generally, a user is more trustworthy if s/he has contributed more precise predictions than other users. From our point of view, the inference of trust value should not only depend on accurate predictions but also on the time when the rating was made. In knowledge-intensive environments, users normally have various information needs in accessing required documents over time, producing a sequence of documents ordered according to their access time. The sequence of required documents for a given user may also reveal the change in their information needs over time. Generally, the latest documents accessed by a given user more precisely reflect their current information needs. Similarly, an accurate prediction made in the recent past contributes more trustworthiness than one made some time ago

Moreover, users often have the information needs to access documents with similar contents. A user's rating of a document generally reflects the user's perception of the relevance of the document content to his/ her information needs. Even though two users do not access the same documents, we can still infer that they may have similar information needs. It is possible that they may also have the same perspective on the usefulness of the document contents to their information needs, if the contents of their required documents are similar. Thus, the ratings of different documents with similar contents should also help to derive the trustworthiness of users. Accordingly, we consider the time factor and the ratings of similar documents to derive a sequence-based trust computation model.

3.3 Data Pre-Processing

Because our system is based on a knowledge-intensive environment, most items are codified documents and are valuable for analyzing further. Thus, it is beneficial to build each user's and each document's profile. All documents in the system form a document set and will be input into an information retrieval procedure to generate a document profile. The details are described in Section 2.2. On the other hand, each user's documents should be aligned according to their accessing time. We believe that the document access sequence expresses how a user's trait changes implicitly. Therefore, the aligned documents in user accessing history can form a personal aggregate profile representing user characteristics more generally.

3.4 Sequence-based trust computation

The degree of personal trust interaction will be calculated considering time factor or document similarity. Complete details will be illustrated in this section. In short, we expect that accurate rating history will be the foundation for trust degree derivation. In our research, we use the term "target user" to describe the one who is recommended and the term "recommender" to describe the one selected for recommending items to the target user.

3.4.1 Sequence-based trust with time factor

In this section, we illustrate the trust computation model considering the time factor. Each user has a document sequence and corresponding rating sequence, where the ratings of documents are ordered by a time index. The documents / ratings of users are aligned according to their relative time index in corresponding sequences.

The conventional trust model calculates the ratio of accurate predictions made according to past ratings without considering the time factor. Our proposed trust model derives the trust value of a given user not only based on the ratio of accurate predictions but also on the time that the accurate predictions were made.

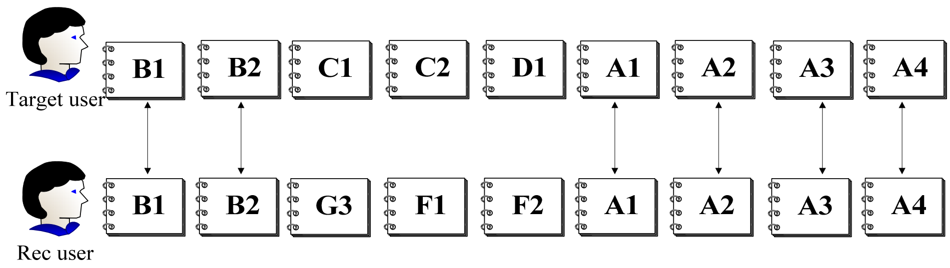

Fig. 2 Concept of trust involved with time

For example, in Fig. 2, both Target user and Recommend user have a set of documents aligned according to accessing time and each document is specified by a distinct ID. Rec user is a recommender preparing a suggested document for the target user. Suppose Rec user gives an accurate prediction to Target user on documents which were accessed by both Rec user and Target user. With Hwang and Chen's trust model [13], each document prediction provides equal weight when counting how much the Target user may trust Rec user. Those predictions which are closer to now should, however, instill more confidence in the target user, because people normally pay more attention to recent events. Thus, in order to show time effect on trust relationship, we present a sequence-based trust model.

Similarly to the conventional trust computation models [13, 28], we also use a simple version of Resnick's prediction formula [34] to calculate a target user c's predicted rating of a document d_k, $\hat{p}^{p}_{c,d}$, which is derived from a recommender p's rating of d_k, as defined in Eq. 13.

$$\hat{P}^{p}_{c,d_k} = \bar{r}_c + (r_{p,d_k} - \bar{r}_p) \tag{13}$$

where $\bar{r}_c$ and $\bar{r}_p$ refer to the mean ratings of target user c and recommender p; and r_{p,d_k} is p's rating of document d_k. If $\hat{P}^{p}_{c,d_k}$ is close to the real rating score of user c on d_k, i.e., r_{c,d_k}, we conclude that both the target user c and the recommender p have a similar perspective on document d_k. The more similar the perspective, the more trust they have, as illustrated in Eq. 14.

$$T^{pure}_{c,p,d_k} = 1 - \frac{\left|\hat{P}^{p}_{c,d_k} - r_{c,d_k}\right|}{M} \tag{14}$$

where T^{pure}_{c,p,d_k} is the pure trust value between target user c and recommender p pertaining to document d_k that is derived from the rating data without considering the time factor; and M is the range of the rating score, which equals the difference of the maximum and minimum rating scores.

Generally, the latest documents accessed by a given user more precisely reflect his/her current information needs. Similarly, an accurate prediction made in the recent past contributes more trustworthiness than the one made some time ago.

A document sequence of a user c is a time-ordered sequence arranged by the access times of the documents. Let S^D_p and S^R_p be the document sequence and rating sequence of a recommender p respectively. The document sequence is defined as $S^D_c = \langle d^{t_{c1}}_{k1,c}, \ldots, d^{t_{cj}}_{kj,c}, \cdots, d^{t_{cf}}_{kf,c} \rangle$ and $t_{c1} < t_{c2} < \cdots < t_{cf}$, where $d^{t_{cj}}_{k,c}$ denotes the document d_k that the user c accessed at time t_{cj}; t_{c1} is the starting time index of the first document accessed in his/her sequence; and t_{cf} is the index of the time the user accessed the most recent document in his/her sequence. The rating sequence of user c, S^R_c, can be similarly defined. Assume that a document d_k is accessed by user c at time t_{cj} and accessed by recommender p at time t_{pi}. The time factor $TF^{p,t_{pi}}_{c,t_{cj}}$ is defined in Eq. 15, which considers the time weights of user c's rating $r^{t_{cj}}_{c,d_k}$, where $r^{t_{cj}}_{c,d_k}$ denote user c's rating on document d_k accessed at time t_{cj} and user p's rating $r^{t_{pi}}_{p,d_k}$.

$$TF^{p,t_{pi}}_{c,tcj} = \frac{2 \times tw^{cj}_c \times tw^{pi}_p}{tw^{cj}_c + tw^{pi}_p} \tag{15}$$

The two time weights are calculated from the time index t_{cj} of user c's sequence and the time index t_{pi} of user p's sequence respectively. Higher time weights are given to ratings with more recent time indices. The time weight of a rating made at time t_{pi} by user p is defined as $tw^{pi}_p = \frac{t_{pi} - t_{p1}}{t_{pf} - t_{p1}}$, where t_{p1} / t_{pf} is the starting / latest time index in user p's sequence. The time weight of a rating made at time t_{cj} by user c is defined similarly. The time factor uses the harmonic mean of the two time weights; thus the time factor of a prediction will be high if both the time weights of the ratings are high, i.e., both the ratings are made in more recent time. Here is a scenario.

Fig. 3 Illustration of time factor calculation

For example, if user U_c has ten documents ordered by accessed sequence, so does U_p. As the result of Doc5 in U_c's flow is in the ninth position while in U_p's flow it is in eighth position, the time factor $TF_{c,tcj}^{p,t_{pi}}$, is calculate by $\frac{2\times\frac{9}{10}\times\frac{8}{10}}{\frac{9}{10}+\frac{8}{10}}=0.847$.

Equation 14 derives the pure trust value of a prediction without considering the time factor. We further use the time factor of a prediction to denote the importance (weight) of the prediction contributing to the trustworthiness. The trust value of user c with respect to recommender p is then derived by taking the weighted average of the pure trust values of predictions made on co-rated documents between them. Consequently, $T_{c,p}^{TF}$, the sequence-based trust metric considering time factor is defined as in Eq. 16.

$$T_{c,p}^{TF}=\frac{\sum_{d_{k,c}^{tcj}\text{in }S_c^D}\sum_{d_{k,p}^{tpi}\text{in }S_p^D}\left(1-\frac{\left|\hat{P}_{c,d_k}^{p,t_{pi}}-r_{c,d_k}^{t_{cj}}\right|}{M}\right)\times TF_{c,t_{cj}}^{p,t_{pi}}}{\sum_{d_{k,c}^{tcj}\text{in }S_c^D}\sum_{d_{k,p}^{t_{pi}}\text{in }S_p^D}TF_{c,t_{cj}}^{p,t_{pi}}} \tag{16}$$

where $\hat{P}_{c,d_k}^{p,t_{pi}}$ is the target user c's predicted rating on a document d_k, which is derived from a recommender p's rating on d_k at time t_{pi}, as defined in Eq. 13; S_c^D and S_p^D are document sequences of the target user c and recommender p respectively; and M is the range of the rating score, which equals the difference of the maximum and minimum rating scores.

In addition, any one document may appear in the user's document sequence several times. Because each user has different information demand over time, it is possible that he gives different ratings to the same document accessed at different time. Therefore, each document in the user's document sequence should be counted respectively.

Here is a simple example.

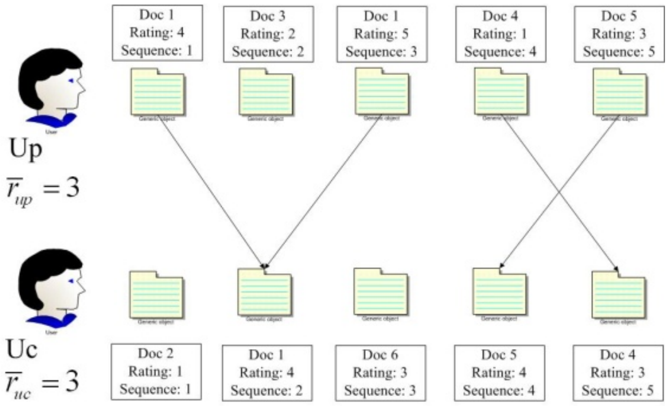

Fig. 4 Illustration of sequence-based trust with time factor

U_p is a recommender and U_c is a target user. Both of them have average rating with a score of three. Note that U_p is trustworthy if s/he has a similar view to U_c on identical documents at recent time index of their document sequences. Referring to the Fig. 4, Doc1, Doc4 and Doc5 exist in both knowledge flows. We use U_p's opinion to predict U_c's score.

According to Eq. 13, U_c may give Doc1 a rating score of four in U_p's opinion. Considering the time factor in Doc1 in U_c's and U_p's document sequence, U_c may trust U_p as below.

$$\frac{[1-\frac{|(4-4)|}{5}][\frac{2\times\frac{1}{5}\times\frac{2}{5}}{\frac{1}{5}+\frac{2}{5}}]+[1-\frac{|(3-4)|}{5}][\frac{2\times\frac{3}{5}\times\frac{2}{5}}{\frac{3}{5}+\frac{2}{5}}]}{[\frac{2\times\frac{1}{5}\times\frac{2}{5}}{\frac{1}{5}+\frac{2}{5}}]+[\frac{2\times\frac{3}{5}\times\frac{2}{5}}{\frac{3}{5}+\frac{2}{5}}]}=0.872$$

The trust value, by which U_c may trust U_p based on Doc1, is 0.872. According to Eq. 16, we compute the weighted average on all co-rated items, and then we obtain the trust degree with time factor 0.8217.

$$\frac{[1-\frac{(4-4)}{5}][\frac{2\times\frac{1}{5}\times\frac{2}{5}}{\frac{1}{5}+\frac{2}{5}}]+[1-\frac{(3-4)}{5}][\frac{2\times\frac{3}{5}\times\frac{2}{5}}{\frac{3}{5}+\frac{2}{5}}]+[1-\frac{(4-3)}{5}][\frac{2\times\frac{4}{5}\times\frac{5}{5}}{\frac{4}{5}+\frac{5}{5}}]+[1-\frac{(5-4)}{5}][\frac{2\times\frac{4}{5}\times\frac{5}{5}}{\frac{4}{5}+\frac{5}{5}}]}{[\frac{2\times\frac{1}{5}\times\frac{2}{5}}{\frac{1}{5}+\frac{2}{5}}]+[\frac{2\times\frac{3}{5}\times\frac{2}{5}}{\frac{3}{5}+\frac{2}{5}}]+[\frac{2\times\frac{4}{5}\times\frac{5}{5}}{\frac{4}{5}+\frac{5}{5}}]+[\frac{2\times\frac{4}{5}\times\frac{5}{5}}{\frac{4}{5}+\frac{5}{5}}]}=0.8217$$

3.4.2 Sequence-based trust with document similarity

In this section, we consider the ratings of similar documents to derive a sequence-based trust computation model. Even though two users do not access the same documents, their ratings of different documents with similar contents should also help to derive the trustworthiness of users. The cosine similarity is used to derive the similarity of documents based on their document profiles which are represented as term vectors by the *tf-idf* approach [3]. The reason for using content similarity is that the trust still exists if users have similar views on documents with similar contents.

Eq. 14 derives the pure trust value of a prediction for an identical document without considering the document similarity. Eq. 17 is used to predict a trust value based on documents with similar contents.

$$T_{c,p}^{DS} = \frac{\sum_{d_{k,c}^{t_{cj}} \text{ in } S_c^D} \sum_{d_{l,p}^{t_{pi}} \text{ in } S_p^D \text{ and } DS_{c,d_k}^{p,d_l} \geq \theta} \left(1 - \frac{\left|\hat{P}_{c,d_k}^{p,t_{pi},d_l} - r_{c,d_k}^{t_{cj}}\right|}{M}\right) \times DS_{c,d_k}^{p,d_l}}{\sum_{d_{k,c}^{t_{cj}} \text{ in } S_c^D} \sum_{d_{l,p}^{t_{pi}} \text{ in } S_p^D \text{ and } DS_{c,d_k}^{p,d_l} \geq \theta} DS_{c,d_k}^{p,d_l}} \tag{17}$$

$T_{c,p}^{DS}$ is the sequence-based trust metric considering document similarity. $\hat{P}_{c,d_k}^{p,t_{pi},d_l}$ is the target user *c*'s predicted rating of a document d_k, which is derived from a recommender *p*'s rating of document d_l at time t_{pi}, as defined similarly in Eq. 13; DS_{c,d_k}^{p,d_l} is the document similarity between documents d_k and d_l that is derived by use of the cosine similarity.

Note that predictions are conducted for those documents with similarity higher than a predefined threshold, θ. The document similarity is regarded as a weight of the prediction contributing to the trustworthiness. The trust value of target user *c* with respect to recommender *p* is then derived by taking the weighted average of the predicted trust values based on similar documents.

The trust degree with document similarity solves the problem whereby both users have no item in common. The following example describes it.

U_p is a recommender with mean rating 4 and U_c is a target user with mean rating 2. Note that U_p is trustworthy if s/he has a similar opinion to U_c on similar documents. Referring to Fig 5, Doc7 is similar to Doc1 and Doc3 is similar to Doc6. Therefore, U_p's opinion on these documents is exploited to predict U_c's score.

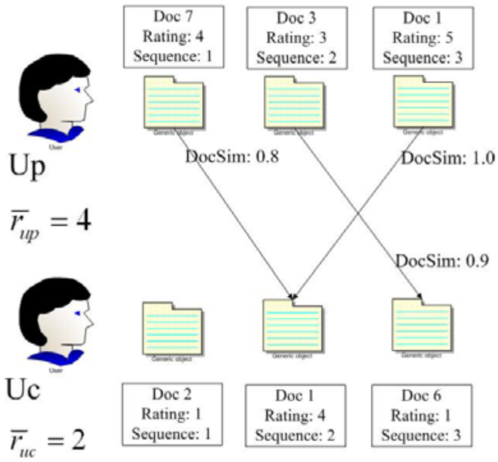

Fig. 5 Illustration of sequence-based trust with document similarity

Based on Eq. 17, the predicted trust value between user U_p and user U_c is 0.8074.

$$\frac{[1-\frac{|(2-4)|}{5}]\times 0.8+[1-\frac{|(3-4)|}{5}]\times 1+[1-\frac{|(1-1)|}{5}]\times 0.9}{0.8+1+0.9}=0.8074$$

3.4.3 Sequence-based trust with both time factor and document similarity

In order to gain the advantage of both time factor and document similarity, we combine them to derive a sequence-based trust metric, $T^{H}_{c,p}$, as defined in Eq. 18. The trust metric in this method is a hybrid of time factor and document similarity. The trust value of target user c on recommender p will be higher if p has contributed more recent and accurate predictions on documents more similar to user c's documents.

$$T^{H}_{c,p}=\frac{\sum_{d^{t_{cj}}_{k,c}\text{ in }S^{D}_{c}}\ \sum_{d^{t_{pi}}_{l,p}\text{ in }S^{D}_{p}\text{ and }DS^{p,d_l}_{c,d_k}\geq\theta}(1-\frac{\left|\hat{P}^{p,t_{pi},d_l}_{c,d_k}-r^{t_{cj}}_{c,d_k}\right|}{M})\times TF^{p,t_{pi}}_{c,t_{cj}}\times DS^{p,d_l}_{c,d_k}}{\sum_{d^{t_{cj}}_{k,c}\text{ in }S^{D}_{c}}\ \sum_{d^{t_{pi}}_{l,p}\text{ in }S^{D}_{p}\text{ and }DS^{p,d_l}_{c,d_k}\geq\theta}TF^{p,t_{pi}}_{c,tcj}\times DS^{p,d_l}_{c,d_k}} \tag{18}$$

3.5 Sequence-based trust recommendation

In the recommendation phase, the trust value is used as a filtering mechanism to select neighbors with high trust degrees for a target user. Such trust values and the item ratings of neighbors are incorporated into our recommendation methods to make document predictions for the target user. In addition, the recommended item is a text-based document, thus, content analysis is useful to select neighbors based on the similarity of user profiles which reveal users' interest on document content. The following section describes the details.

3.5.1 Recommendation with Sequence-based Trust Filtering

According to the trust relationship between users as illustrated in Section3.4, users whose trust values are higher than a pre-specified threshold are selected as neighbors for a target user. Let *NS* be a neighbor set; $T_{c,p}^{Factor}$ be the sequence-based trust degree between a target user *c* and other user *p*; and *Factor* may be *TF*, *DS* or *H* which represents one of our proposed trust models, as described in Section3.4. *TF* which denotes the sequence-based trust model with time factor utilizes users' time-ordered sequences arranged according to the access times of the documents to derive trust values. *DS* which denotes the sequence-based trust model with document similarity obtains the trust value of a prediction on users' different documents with similar content. *H* which denotes the sequence-based trust model with both time factor and document similarity derives the trust value by combing the effects of time factor and document similarity. To choose the trustworthy users as neighbors for a target user, we define Eq. 19 as the principle of the neighbor selection. That is, the neighbors of a target user have to fulfill this requirement.

$$NS = \{T_{c,p}^{Factor} > threshold\} \tag{19}$$

3.5.2 Recommendation with Sequence-based Trust Weighting

To predict documents that may interest a target user, we propose a recommendation method based on our sequence-based trust models. Such method utilizes the sequence-based trusts as weightings and the document ratings of the selected neighbors to make recommendations. The predicted rating of a document *d* for a target user *c*, $\hat{P}_{c,d}$, is calculated by Eq. 20.

$$\hat{P}_{c,d} = \bar{r}_c + \frac{\sum_{p \in NS} T_{c,p}^{Factor} (r_{p,d} - \bar{r}_p)}{\sum_{p \in NS} T_{c,p}^{Factor}}, \tag{20}$$

where *NS* is a neighbor set of the target use *c*; *p* is a neighbor of user *c*; $\bar{r}_c$ / $\bar{r}_p$ is the average rating of documents given by the target user *c*/ user *p*; $r_{p,d}$ is the rating of a document *d* given by user *p*; $T_{c,p}^{Factor}$ is the sequence-based trust degree between a target user *c* and user *p*; and *Factor* may be *TF*, *DS* or *H* which represents one of our proposed trust models, as described in Section 3.4. According to the Eq. 20, documents with high predicted ratings are used to compile a recommendation list, from which the top-*N* documents are chosen and recommended to the target user.

3.5.3 Recommendation with sequence-based trust considering time factor, document similarity and profile similarity

In this section, we introduce profile similarity and employ it to improve the predicting process. Since the recommended item is a text-based document, content analysis is useful to provide other preference information which cannot be discovered through rating data only. A user profile contains useful information which reveals a user's interest on document content in his/her history of document access. Therefore, when we judge whether a recommender is qualified to be a target user's neighbor, rating behavior similarity is not the only measure. On the other hand, the user profile similarity offers another dimension to be explored.

A user profile expressed as a vector of keywords represents a user's interested document content. The profile of a user is derived by aggregating the profiles of documents in his document sequence considering time factor and document ratings. Each user's documents are arranged in sequence according to their usage log file. In aggregating the document profiles, a document's term weight is multiplied by the time weight, which is determined according to the time index of the document, and the normalized rating of the document, as defined in Eq. 21.

$$\overrightarrow{AP_c} = \sum_{t=1}^{T} tw_{t,T} \times \overrightarrow{DP_{c,t}} \times \frac{r_{DP_{c,t}}}{M} \tag{21}$$

In Eq. 21, $\overrightarrow{AP_c}$ is a term vector of user *c*'s aggregated profile. Note that only top-N keywords will be selected. $DP_{c,t}$ is a vector of keyword weights for a document *DP* accessed by user *c* at time *t*. At this time point, user c gives rating r_{DP_t} on document DP and the whole score range is M. On the other hand, $tw_{t,T}$ is the time weight of this document defined in Eq. 22.

$$tw_{t,T} = \frac{t - St}{T - St} \tag{22}$$

where t is document-referenced time; St is the start time of this user's document sequence; and T is the time point of the last document accessed.

After derivation of the user profile, the next step is to calculate personal content similarity $PCS(c\ ,\ p)$ with the cosine formula.

$$PCS(c\ ,\ p) = cosine(\overrightarrow{AP_c}, \overrightarrow{AP_p}) = \frac{\overrightarrow{AP_c} \bullet \overrightarrow{AP_p}}{|\overrightarrow{AP_c}||\overrightarrow{AP_p}|} \tag{23}$$

where c is the target user and p is the recommender. $\overrightarrow{AP_c}$ is c's aggregate profile vector and $\overrightarrow{AP_p}$ is p's aggregate profile vector.

In the recommendation step, the trust degree with time factor and document similarity is used as a filtering strategy, as shown in Eq. 19. Nevertheless, some minor modification is made in the prediction of the target user's interest document (see Eq. 24).

$$\hat{P}_{c,d} = \bar{r}_c + \frac{\sum_{p \in NS} H(PCS(c,p), T^H_{c,p})(r_{p,j} - \bar{r}_p)}{\sum_{p \in NS} H(PCS(c,p), T^H_{c,p})} \tag{24}$$

$H(PCS(c,p), Trust^H_{c,p})$ is the harmonic mean of trust degree considering time factor and document similarity $Trust^H_{c,p}$ and user profile similarity $PCS(c,p)$.

$$H(PCS(c,p), Trust^H_{c,p}) = \frac{2(PCS(c\ ,p))(Trust^H_{c,p})}{PCS(c\ ,p) + Trust^H_{c,p}} \tag{25}$$

The new weight used in prediction computation is to improve forecasting accuracy. Also, the advantage of using a harmonic mean is that the value is high when both $Trust^H_{c,p}$ and $PCS(c\ ,\ p)$ are high.

4. Experiments and Evaluations

In this section, we conduct experiments to evaluate the recommendation quality for our proposed methods and compare them with other trust-based recommendation methods. We describe the experiment set-up in Section 4.1 and demonstrate the experimental results in Section 4.2.

4.1 Experiment Set-Up

In our experiment, we collect a data set from the laboratory of a research institute. There are over 500 research-related documents and about 50 users in the data set. We extract knowledge from these documents to derive the document profiles. Generally, each document profile consists of 800 distinct terms after information extraction and document pre-processing, i.e., case folding, stemming and stop words removal. Besides the documents, other information such as user information and user behaviors is necessary to implement our methods. Since the information needs may change over time, users will access, i.e., upload, download, browse and rate, documents to fulfill their research work. Such user behavior, e.g., upload, download, browse and rate, is recorded in a log. Thus, each user may access 45 documents on average according to the log data. In addition, each behavior except rate is given a default score (three for browsing behavior and four for uploading or downloading behavior) to represent how much a user may be interested in a document. For the rating behavior, the user may give a document a rating score on a scale of 1 to 5 to indicate whether the document is perceived as useful and relevant. A high rating, i.e., 4 or 5, indicates that the document is perceived as useful and relevant; while a low rating, i.e., 1 or 2, suggests that the document is deemed not useful. Since it is difficult to obtain such a data set, using the real application domain restricts the sample size of the data in our experiments.

In our experiment, the data set is divided as follows: 70% for training and 30% for testing. The training set is used to generate recommendation lists, while the test set is used to verify the quality of the recommendations. Accordingly, we evaluate the performances of our proposed methods and compare them with the traditional CF method and other trust-based recommendation methods.

4.1.1 Evaluation metrics

To measure the quality of recommendations, the Mean Absolute Error (MAE) which evaluates the average absolute deviation between a predicted rating and the user's true rating is used to measure the sequence-based trust methods, as shown in Eq. 26. The lower the MAE, the more accurate the method will be.

$$MAE = \frac{\sum_{i}^{N} \left| \hat{P}_i - r_i \right|}{N} \tag{26}$$

Here N is the amount of testing data, $\hat{P}_i$ is the predicted rating of document i and r_i is the real rating of document i.

4.1.2 Methods compared in the experiment

In the trust-based recommendation methods, the trust degree is obtained by the use of different trust computation models for selecting neighbors for a target user. Thus, we use different strategies based on these models to make recommendations and then analyze their recommendation performances. These recommendation strategies are defined as follows.

CF: The standard Resnick model in GroupLens [34]. The Pearson correlation coefficient is used in filtering and making predictions.

Profile-TrustCF (Profile-TCF): The profile-level trust is used in filtering and the weight which combines both profile-level trust and user similarity derived by Pearson correlation coefficient is used to make predictions [28].

Item-TrustCF (Item-TCF): The item-level trust is used in filtering and the weight which combines both item-level trust with user similarity derived by Pearson correlation coefficient is used to make predictions [28].

Personal-TrustCF (Personal-TCF): Personal trust between two users is calculated by averaging the prediction error of their co-rated items [13].

Time-SeqTrustCF (T-STCF): Recommendation with sequence-based trust with time factor, derived by using Eq. 16.

DocSim-SeqTrustCF (DS-STCF): Recommendation with sequence-based trust with document similarity, derived by using Eq. 17.

Time-DocSim-SeqTrustCF (T-DS-STCF): Recommendation with sequence-based trust with both time factor and document similarity, derived by using Eq. 18.

Time-DocSim-UserProfile-SeqTrustCF (T-DS-UP-STCF): Recommendation with sequence-based trust with both time factor and document similarity, derived by using Eq. 18. The weight in prediction formula involve in trust value and personal content similarity.

4.2 Experimental results

In the experiment, we compare various recommendation methods from four aspects. Their MAE values are listed in Table 1 and their trends are presented in a line graph. In our recommendation method, we select 2 to 10 qualified users as target user's neighbors and we compare the MAE under different number of neighbors.

Table 1 Comparing the MAE values of all methods with different numbers of neighbors

Methods \ Neighbors	2	4	6	8	10
CF	0.7450	0.7843	0.8378	0.8652	0.8636
Profile-TCF	0.7430	0.7909	0.8033	0.8236	0.8228
Item-TCF	0.7318	0.7221	0.7273	0.7168	0.7168
Personal-TCF	0.7181	0.6902	0.7024	0.7154	0.7432
T-STCF	0.7004	0.6645	0.6622	0.6937	0.6897
DS-STCF	0.7043	0.6809	0.6990	0.6960	0.6964
T-DS-STCF	0.7043	0.6558	0.6665	0.6854	0.6833
T-DS-UP-STCF	0.7002	0.6677	0.6582	0.6622	0.6469

4.2.1 The effect of the time factor and document similarity

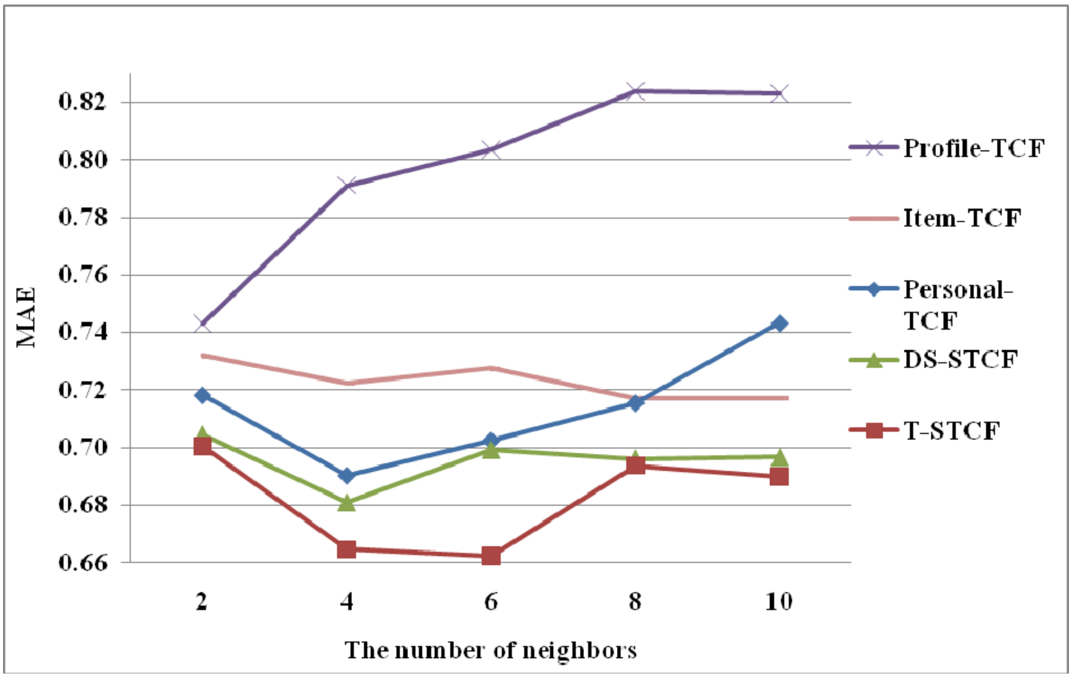

Fig. 6 Comparison of Profile-TCF, Item-TCF, Personal-TCF, T-STCF and DS-STCF

In previous discussion, our proposed sequence-based trust model considering time factor and document similarity are expected to increase the recommended accuracy and reliability. In Fig. 6, our proposed sequence-based trust methods T-STCF and DS-STCF indeed perform better than conventional trust-based CF methods that do not consider sequence-based trust, including Personal-TCF, Profile-TCF and Item-TCF. Moreover, the time factor contributes more than document similarity in sequence-based trust model. The largest performance gap between T-STCF and DS-STCF occur when six neighbors are selected for recommendation.

4.2.2 Comparison of sequence-based trust with vs. without time factor

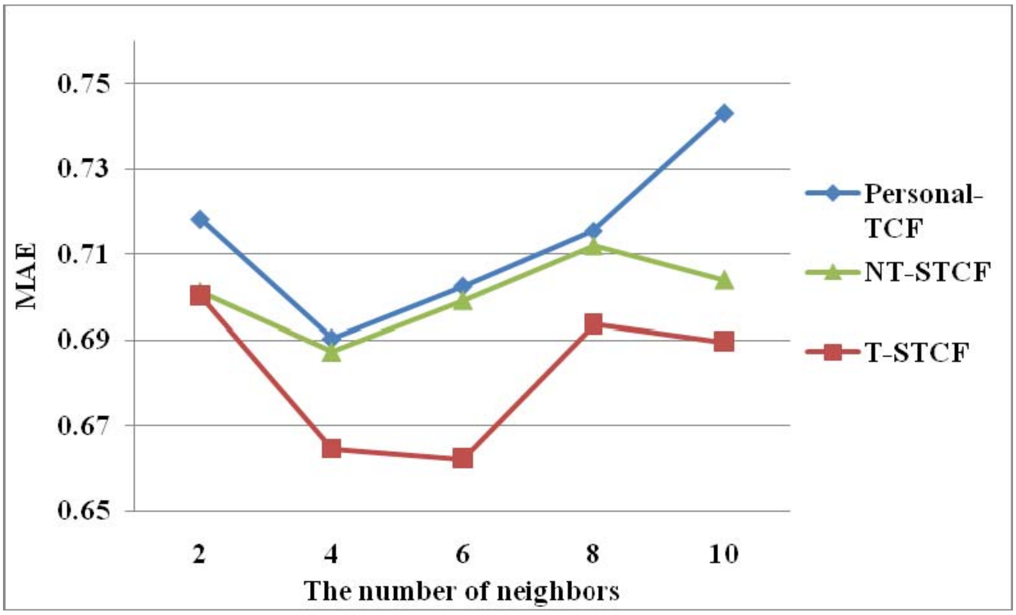

Fig. 7 The effect of the time factor

In this section, we evaluate the effect of time factor in sequence-based trust model. NT-STCF is a recommendation method with sequence based trust and without considering time factor, which is derived from Eq. 16 by setting the time factor as 1. Fig. 7 shows that T-STCF performs better than NT-STCF, while NT-STCF performs better than Personal-TCF. The time factor indeed contributes to improve the sequence-based trust metric. The MAE values of them are presented in Table 2.

Table 2 Comparing the MAE values of Personal-TCF, NT-STCF and T-STCF

Neighbors	Personal-TCF	NT-STCF	T-STCF
2	0.7181	0.7012	0.7004
4	0.6902	0.6873	0.6645
6	0.7024	0.6992	0.6622
8	0.7154	0.7122	0.6937
10	0.7432	0.7040	0.6897

4.2.3 Comparison of the weighting methods in prediction

In this experiment, we apply different weighting methods in the recommendation methods to derive the predicted ratings for documents (Eq. 20), and then compare their performance. T-STCF uses the trust degree derived from the time-factor (T-trust) as the weighting; H-T-STCF-PS uses the harmonic mean of T-trust and Pearson similarity (PS) of users as the weighting; and H-T-STCF-UPS uses the harmonic mean of T-trust and user profile similarity (UPS) as the weighting. Table 3 demonstrates their MAE values under different number of neighbors. Note that, these methods combine the trust value and the similarity value (i.e. Pearson similarity or user profile similarity) in a harmonic mean to predict the ratings of a document. For these three methods, the sequence-based trust derived from T-STCF method is used as a filtering mechanism to select the qualified neighbors for a target user. Then, in the prediction phase, the weight can be derived by using T-STCF, H-T-STCF-PS and H-T-STCF-UPS, respectively to predict a rating for a document.

Table 3 The MAE values of T-STCF vs. T-STCF with Pearson vs. T-STCF with user profile similarity.

Neighbors	T-STCF	H-T-STCF,-PS	H-T-STCF-UPS
2	0.7004	0.7107	0.7017
4	0.6645	0.6784	0.6706
6	0.6622	0.6756	0.6586
8	0.6937	0.7898	0.6891
10	0.6897	0.8602	0.6829

Table 4 MAE values of DS-STCF vs. DS-STCF with Pearson vs. DS-STCF with user profile similarity.

Neighbors	DS-STCF	H-DS-STCF-PS	H-DS-STCF-UPS
2	0.7043	0.6974	0.6984
4	0.6809	0.6938	0.6727
6	0.6990	0.7251	0.6749
8	0.6960	0.7301	0.6692
10	0.6964	0.9683	0.6669

Table 5 The MAE values of T-DS-STCF, T-DS-STCF with Pearson and T-DS-STCF with user profile similarity.

Neighbors	T-DS-STCF	H-T-DS-STCF-PS	H-T-DS-STCF-UPS
2	0.7043	0.7119	0.7002
4	0.6558	0.6742	0.6677
6	0.6665	0.6820	0.6582
8	0.6854	0.6840	0.6622
10	0.6833	0.7839	0.6469

Similarly, three weighting methods, DS-STCF (DS-trust), H-DS-STCF-PS (harmonic mean of DS-trust and PS); and H-DS-STCF-UPS (harmonic mean of DS-trust and UPS) are compared, and their values of MAE under different number of neighbors are presented in Table 4. Furthermore, Table 5 compare the performances of three weighting methods, T-DS-STCF, (T-DS-trust), H-T-DS-STCF-PS (harmonic mean of T-DS-trust and PS); and H-T-DS-STCF-UPS (harmonic mean of T-DS-trust and UPS).

From these comparison results, the observed pattern is that the sequence-based trust combined with user profile similarity performs better than that combined with Pearson similarity. That is, discovering user's preference based on document content is very helpful in improving recommendation quality. On the other hand, in the most situations, the document prediction is more accurate when the weight is derived by combining the sequence-based trust with the user profile similarity than when the weight is obtained by only using the sequence-based trust. This also implies that the user profile similarity can improve the recommendation quality in most circumstances.

4.2.4 Comparison of all methods

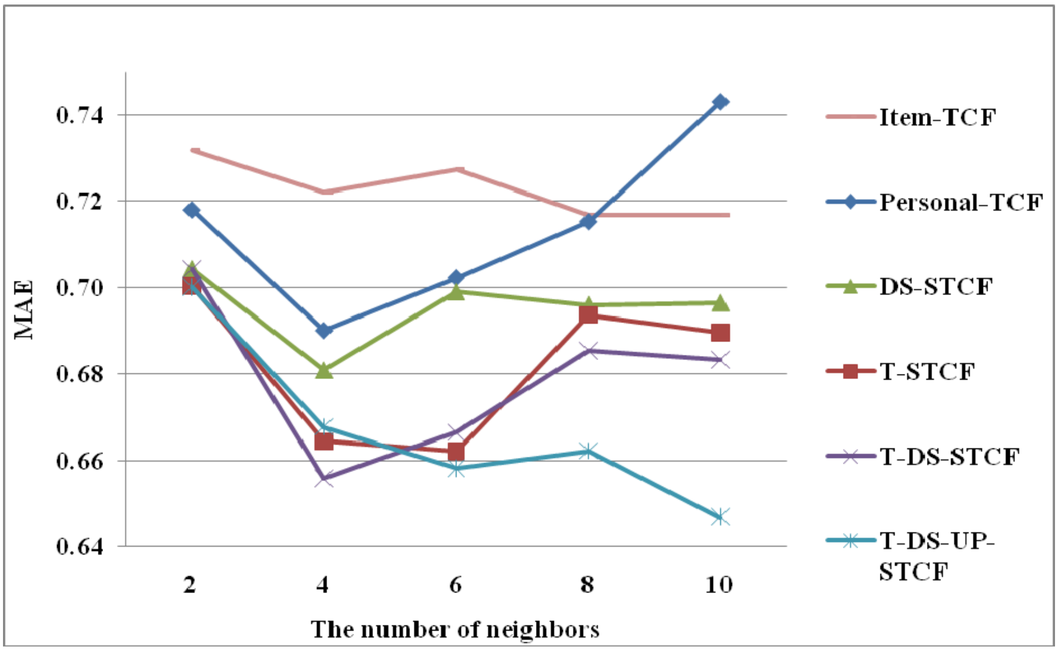

Fig. 8 Comparison of all methods

In the last experiment, all methods are compared and their pros and cons are discussed, as shown in Fig. 8. From Table 1, the traditional CF method performs worse than others no matter what the number of neighbors is. Profile-TCF, whose neighbors-selecting standard is similar to CF, also performs unsatisfactorily. Both of them show a wide gap from the other metrics and the difference grows as the number of neighbor increases. For clarity, the CF and Profile-TCF methods are not shown in Fig 8. It is clear that the MAE values of our proposed sequence-based trust methods are smaller than others. This indicates that the time factor and document similarity contribute to derive more reliable personal trust degree and make more accurate recommendations for target users. T-STCF and DS-STCF perform better than conventional trust-based CF methods, Personal-TCF, Profile-TCF and Item-TCF. The hybrid of time-factor and document similarity, T-DS-STCF, performs better than T-STCF and DS-STCF in most circumstances. In addition, T-DS-UP-STCF, which uses a harmonic mean of user profile similarity and trust degree considering both time factor and document similarity in the computation model, generally performs better than other methods. The result shows that adopting our proposed sequence-based trust model in CF methods can have better improvement on recommendation quality than conventional trust-based CF methods.

5. Conclusions and Future Works

In this research, we propose sequence-based trust recommendation methods to derive the degree of trust based on user's sequences of ratings of documents. Such methods involve two main factors, time factor and document similarity, in computing the trustworthiness of users and combine them with user profile similarity in the recommendation phase. The rationale behind using the time factor is that the predictions generated close to the current time provide more trustworthiness than those far away from the current time. In addition, the ratings of different documents with similar contents should also help to derive the trustworthiness of users. Accordingly, we employ the time factor and the ratings of similar documents to derive a sequence-based trust computation model. On the other hand, the purpose of exploiting user profile similarity is to discover more user preference information which is not easy to observe though rating data. Eventually, the proposed model is incorporated into the standard CF method effectively to discover trustworthy neighbors for making recommendations. From the experimental results, we discover that the prediction accuracy of recommendation is indeed improved by using these two factors and our trust metric performs satisfactorily when both factors are combined and incorporated with user's interest over time. In future work, we will investigate how to infer user's reputation with respect to profile level and item level from our basic concept. We also expect that our methods will be applied in various domains and further applications will be developed.

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