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Study on Directed Trust Graph Based Recommendation for E-commerce System

H.D. Zhong, S. Zhang, Y. Wang, Y. Shu

Haidong Zhong
Institute of Modern Logistics, Zhejiang Wanli University
No. 8 South Qianhu Rd., Ningbo, Zhejiang, 315100, PR, China
zhong_hai_dong@163.com

Shaozhong Zhang
Institute of Electronics and Information, Zhejiang Wanli University
No. 8 South Qianhu Rd., Ningbo, Zhejiang, 315100, PR, China
dlut_z88@163.com

Yanling Wang
Institute of Modern Logistics, Zhejiang Wanli University
No. 8 South Qianhu Rd., Ningbo, Zhejiang, 315100, PR, China
yanling_wang1@yahoo.com.cn

Yonggang Shu*
School of Tourism and City Management, Zhejiang Gongshang University
Xuezheng Street, Hangzhou, 310018, PR, China
*Corresponding author: zhd_1981@163.com

Abstract: Automated recommender systems have played a more and more important role in marketing and ever increasingly booming e-commerce systems. They provide useful predictions personalized recommendations according to customers characteristics and a variety of large and complex product offerings. In many of these recommendation technologies Collaborative Filtering (CF) has proven to be one of the most successful recommendation method, which has been widely used in many e-commerce systems. The success of CF recommendation depends mainly on locating similar neighbors to get recommendation items. However, many scholars have found that the process of finding similar neighbors often fail, due to some inherent weaknesses of CF based recommendation. In view of this, we propose a trust feedback recommendation algorithm based on directed trust graph (DTG), which is able to propagate trust relationship. In our approach, there is no need to compute similarity between users, but utilize the trust relation between them to conduct prediction calculation. Based on the analysis of human trust perception, we incorporate the process into our recommendation algorithm. Experimental evaluation on real life Epinions datasets shows that the effectiveness and practicability of our approach.
Keywords: Trust, Recommendation, Graph, E-commerce, Feedback.

1 Introduction

With the fast development of networking systems, an ever-increasing number of merchants are attracted to swarm into e-Commerce all over the world [1]. Accordingly, the Internet is changing from generally simple information exchange and extraction tool into the biggest virtualized market space presenting a great number of commercial services, ranging from electronic web-stores, on-line booking and service center to other social services [2]. With the popularization of the Internet, the amount of available information are exponentially growing and e-commerce systems structure becomes more complicated when it provides more and more choices for users [3,4]. Under the circumstances, perform transaction tasks typically involved in e-Commerce, customers have often to spend a large amount of time navigating among thousands of web pages to explore desired products and make their purchases. On the other hand, electronic business suppliers suffer from the problems of promoting their commodities to their potential customers in an effective way, considering their preferences, habits and other personalized characteristics. To deal with this challenge, researchers have advanced a recommendation approach which automatically analyze and mining e-commerce system visitors trading and browsed items data to filter web page information, classified newsgroup messages, and recommend valuable merchandise items [5].

Recommender systems, one of the most important computer-based intelligent approaches to find out the most appropriate services or goods from a large amount of products, are proved to be important tools that overcome the information overload by sifting through the large set of data and recommending information relevant to the user [6–10]. Typically, in e-commerce environment a recommender system analyzes trading data between consumer and sellers and items to find associations among them, and the items bought by similar users are presented as recommendations. Using this technology, some e-commerce systems, such as Amazon.com, Ebay.com and Netflix.com, are reported to have enhanced e-commerce sales by transforming e-commerce system browsers to buyers, increasing cross-selling and building customer loyalty [11].

As early as in the early 1990s intensive studies have been conducted in recommender systems, and many scholars deem them as knowledge discovery in database (KDD) systems or electronic agent systems [12–14]. Up to now, the existing recommendation means can be generally classified as content based, collaborative, knowledge-based, demographic, and utility based [15–17], among which collaborative filtering based personalized recommendation is proved to be one of the most successfully used technology [15]. In the newer, narrower sense, collaborative filtering builds correlations between pairs of items by making automatic predictions (filtering) about the interests of a user, and then figure out recommendations by finding items with high similarity to many users (collaborating). The acquiescent assumption of the collaborative filtering approach is that if a person A has the same opinion as a person B on an issue, A is more likely to have B's opinion on a different issue T than to have the opinion on T of a person chosen randomly. For example, a collaborative filtering recommendation system for laptop preferences could make forecasts about which laptop a user should like given a partial list of that user's preferences (likes or dislikes) [10]. However there are two main inherent weaknesses in the collaborative filtering based recommendation systems [8]: (1) It is a challenge to find similar user, because the probability of two random users have rated any items in common is very small, and hence they are hardly comparable. (2) If ad hoc user profiles with the goal of being considered as similar to the target user a created, CF based recommendation can be easily attacked and recommendation precision can be greatly influenced.

In order to overcome these shortages, Massa P. and Avesani P. proposed a trust-aware recommendation approach [8]: Make use of trust propagation to search for trustable users based on the trust network instead of finding similar users as collaborative filtering does. The products bought or preferred by these users are then recommended to the active user over the trust network. Three years later, Ray S. and Mahanti A. put forward a new idea to improve prediction accuracy for trust aware recommender systems by removing all the trust statements that fall below a threshold correlation value to reconstruct the trust network [18]. They assume that a trust statement passed between two users should imply that similarity between both users will be relatively high, and generally utilize all the trust statements present in the data of similar users, calculated based on ratings, to make predictions. Experiment on Epinions datasets shows their method has better performance and effectiveness than that of the original approach for different levels of trust propagation and threshold correlation values [18]. However, every trust statement passed between users does not imply the correlation between them will also be high, because one user may pass trust statements to another user on the basis of perceived notion that his (or her) predilections match with others, while similarity calculated based on ratings may show that they are different.

In our opinion, in trust based recommendation method users similarity calculating is not necessary. And we propose an approach where we construct a directed trust graph of users without considering the similarity between them. Based on the DTG we present a Trust Feed Back Recommendation Algorithm (TFBRA) to make recommendations for a user. It shows a substantial good performance for generating predictions through experimental evaluation on Epinions datasets [19].

The rest of the paper is organized as fellows. In section 2 we review some existing techniques, which are related to our work. In Section 3 the approach of trust based recommendation is explained in detail. Section 4 conducts verifying experiment, using real-life Epinions datasets, and the results of our evaluations is discussed. The last section draws conclusions and points out the related possible future work.

2 Related work

2.1 Trust

Since the birth of human beings and human social interactions trust came into being, and almost every aspect of a persons life is based on some form of trust. Undoubtedly, trust is positive and vital to humanity since it is part of love and friendship, and meaningful relationships depend upon it. Presently, trust is a research interest of many disciplines including management[18], marketing [21] and information systems [22]. However, scholars have difficult in reaching a consensus what exactly trust is, and they disagree even on the basic definitions. Presumptively, definitions of trust generally indicate a situation with characteristics of the following aspects [23–25]: One party (trustor) is willing to depend on the actions of another party (trustee); the situation is directed to the future. Moreover, the trustor (voluntarily or forcedly) abandons control over the actions performed by the trustee. As a consequence, the trustor is uncertain about the outcome of the other's actions; he can only develop and evaluate expectations. The uncertainty involves the risk of failure or harm to the trustor if the trustee will not behave as desired.

The rapid expansion of e-commerce conducts the research of trust in social science to new challenges. At the same time increasing the importance of trust and the urgency to know what customers shopping decision or preference [26], such as, interpersonal relationship between customers and sellers has been dis-intermediated by the method, and had to be improved upon. Additionally, e-commerce systems should be well designed or be made to imply the sellers are trustable, even if the regardless of seller's actual trustworthiness is not high. Many researchers have intensively studied the structure and formation mechanisms of trust from the aspects of both individual and organizational, and have identified five types antecedents to consumer trust, including institution-based, personality-based and calculation-based sources for trust building [27–30].

2.2 Recommendation System

Since the first appearance of the first paper on collaborative filtering in the mid-1990s, recommender systems have attracted many scholars' attention, and become an important research areas [31]. Over the last decade new approaches have been proposed to improve the efficiency and practicability of recommender system both in the industry and academia. At present recommender system related researches are still popular issues because they constitute problem-rich research area and practical use requirement that help the potential buyers to solve information overload by providing personalized recommendation, and useful services according to their characteristics.

Over the past decades a lot of research work has been conducted on recommendation technologies (or algorithms), which used a wide range of statistical, artificial intelligence, information science and other techniques. These researches have observably improved the state-of-art in comparison to the previous recommender systems which used collaborative- and content-based heuristics. Up to now, Algorithmic means adopted in recommender systems can be divided into (1) content-based recommendation, collaborative, or hybrid, based recommendation and (2) heuristic-based or model-based recommendation based on the types of recommendation approaches used for the rating evaluation. Some of these methods are utilized in the industrial-strength recommender systems, e.g. the ones deployed at Amazon [32], MovieLens [33] and VERSIFI Technologies. However, despite there are many recommendation means, the present used recommender systems still need to be intensively improved, including better approaches for representing the recommended product items, more advanced and efficient recommendation algorithm or methods, utilization of multi-criteria ratings, to make recommendation methods more effective and applicable.

In recent years, scholars proposed a new recommendation method: trust based recommendation [8, 34, 35], and proved it more robust against shilling attacks and more capable and effective in generating recommendations for e-commerce system visitors, however they still need to calculate users similarity. Trust based recommendation systems are proved to make more accurate recommendation compared with traditional systems, because they utilize a new concept of trust propagation over a trust network. In [8], it has been experimentally shown how trust based recommender system outperform traditional recommendation methods on dataset from Epinions.com.

3 Trust based recommendation algorithm

In this section we start by introducing basic notations about trust cognitive process and concept of DTG. Based on the analysis of human trust perception, we incorporate the process into our recommendation algorithm. And then we present the logical architecture of trust based recommendation approach.

3.1 Trust cognitive analysis

From the viewpoint of recommendation in human society, it is easy to find that a person is usually more inclined to trust the recommendation information from his or her "acquaintance" than that of "strangers". In e-commerce recommendation systems all the people can be connected by trust relationship, which can be denoted as a DTG. As shown in Figure 1 (a), solid line represents the direct trust relationship between users (N_1 trustN_2, N_2 trustN_3). Through the trust relationship of N_2 andN_3, N_1 trust N_3 indirectly. If there is no trust relation between N_2 andN_3, it is impossible to create the trust relationship between N_1 and N_3 (As is shown in Figure (b)). Here we first define some basic trust related definitions in graph theory

Definition 1 *(Direct Trust)* Direct trust can be defined as an triple$< i, j, DT_{i,j} >$,stand for the directed edge from node i point to node$j$,and direct trust value of node i to node j is defined as$DT_{i,j}$, which is a discrete integer value in $[1, 5]$, and a greater value represents a deeper trust degree.

Definition 2 *(Indirect Trust)* Indirect trust can be defined as an triple$< i, j, IDT_{i,j} >$,Let $i$and$j$stand for nodes in the trust graph,$i$is attainable to$j$through limited hop$H(H > 1, H \in$

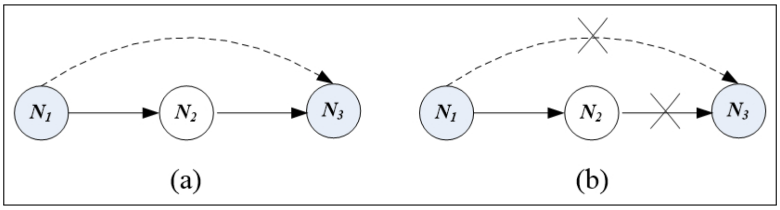

Figure 1: Trust process in human activity

N),and indirect trust value of node i to node j is defined as $IDT_{i,j}$, which is a discrete integer value in$[1, 5]$, and a greater value represents a deeper trust degree.

Theorem 1 *(Direct trust preference principle)* For any node i in the trust graph, its direct trust nodes are more credible than indirect trust nodes, where there are trust edges from $i\prime s$direct trust nodes to its indirect trust nodes. For example, in Figure 1 (a) $DT_{N_1N_2}$ is more credible than IDT_{N_1N3} (or $DT_{N_1N_2} > IDT_{N_1N_3}$).

3.2 DTG based trust feedback

On the base of trust perception process presented above, we propose a DTG based trust feedback algrithm (The general principle is shown in Figure 2).

In figure 2 the edges represents the trust relationship between different nodes. While asking for recommendations of $\boldsymbol{U}_0$, the node just send a trust query information to its direct trust nodes ($\boldsymbol{U}_1$,$\boldsymbol{U}_3$,$\boldsymbol{U}_{15}$ and $\boldsymbol{U}_{16}$), and these nodes also send the trust query information to their trusted node similarly, until the end of trust inquiry control process and then all the queried node feedback their trust value of any products. Through the trust feedback process, comprehensive score of the items recommended by trusted node (include both direct trust nodes and indirect trust nodes) for $\boldsymbol{U}_0$.

3.3 DTG establishment

As narrated before, direct trust node and indirect nodes are used to represent the trust relationship based on graph theory. The step of establishing a DTG is instroduced here in detail below.

Definition 3 *(Direct Trust Node, DTN)* DTN of a certain node refers to any node that has direct trust relationship with it.

Definition 4 *(Indirect Trust Node, IDTN)* IDTN of a certain node refers to any node that has indirect trust relationship with it.

In this paper we adopt a five level value: 1,2,3,4,5 to repersent the trust(driect trust and indriect trust) value between one another. The higher trust value implies a further trust. In our framework the relationship between any node and its neighbor can be devided into three categories: direct trust relationship, indirect trust relationship and irrelevant nodes. For example, in table 1, U_0 has 4 DTNs. Figure 3 shows the process of establishing a DTG.

3.4 DTG based feedback trust recommendation fusion calculation

According to the transitivity attribute of trust, recommendated items for a specific node can be caculated on the base of feedback trust in DTG. If node N_i trust node N_j, N_i is more likely to accept the items that N_j gives a high rating value. And highly-rated-value items of DTNs of N_i account for a larger proportion in recommendated items than that of IDTNs of N_i.

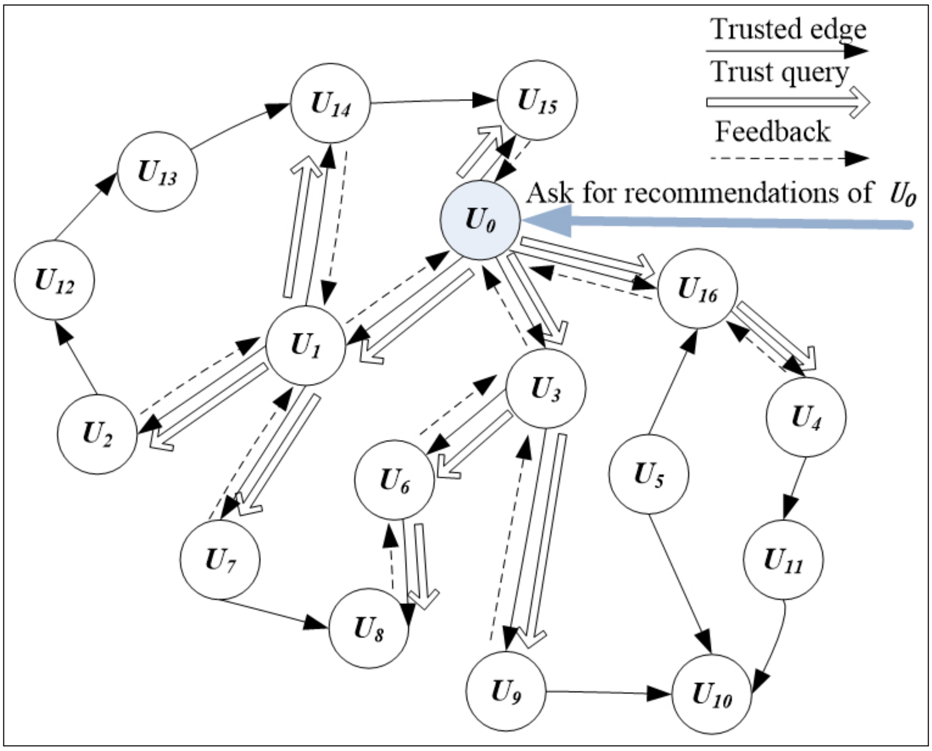

Figure 2: DTG based trust feedback principle

Table 1: Relationship between U_0 and its neighors

Peer	Neighbors	DTN
U_0	U_1	yes
U_0	U_3	yes
U_0	U_{15}	yes
U_0	U_{16}	yes

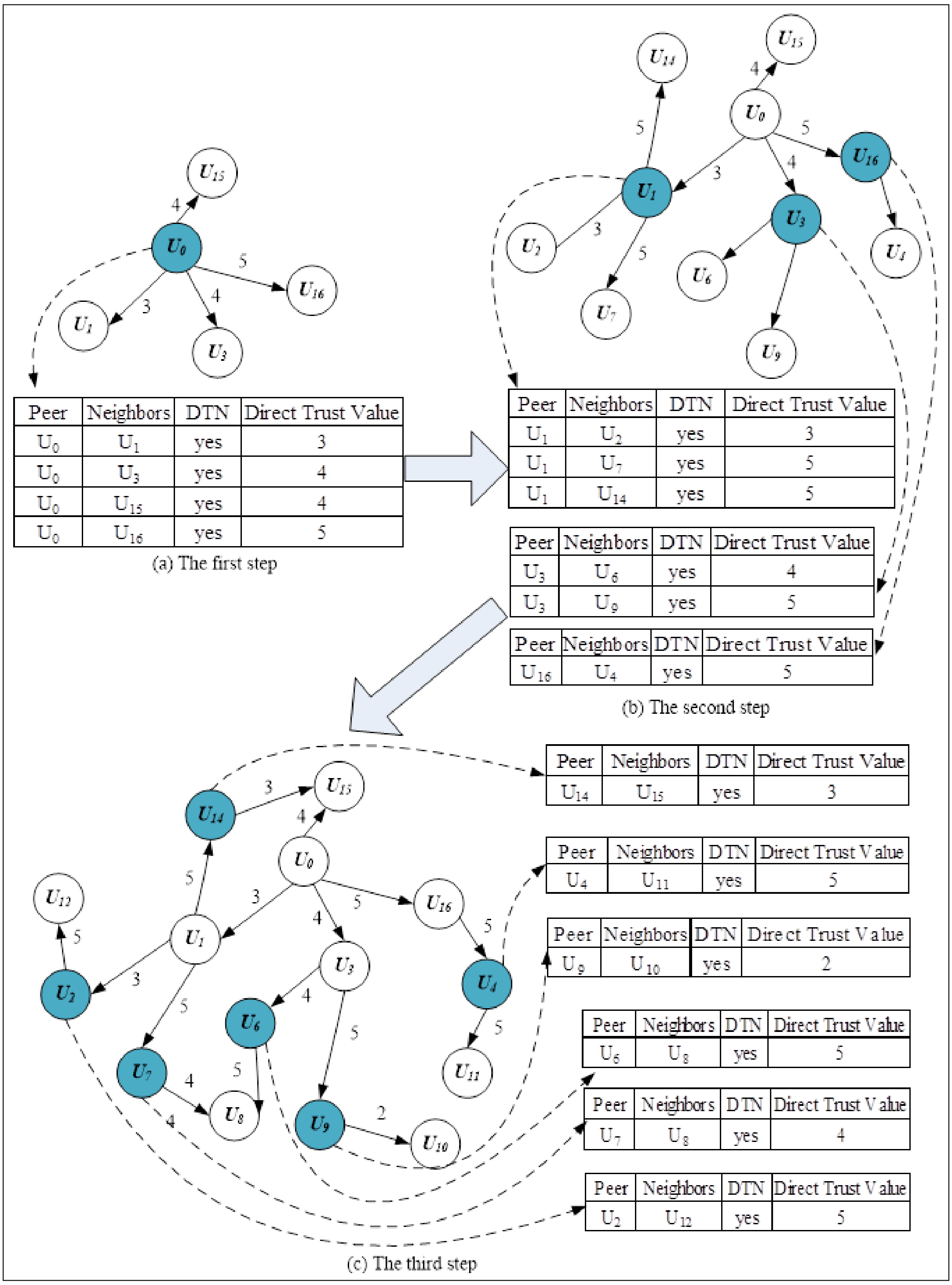

Figure 3: The process of establishing a DTG

Definition 5 The recommendated items $PRV(i)$of a certain node N_i can be abtained by comprehensive evaluation on the feedback trust value and high-rated-value items of its IDTNs and DTNs. Recommedated items from the trusted nodes(include DTNs and IDTNs) of N_i can be defined as the fellowing formula:

$$PRV(i) = \frac{\sum\limits_{l=1}^{Level} W(l,\alpha) \sum_{v \in TNL_l} T_{sv} * R_{vi}}{\sum\limits_{l=1}^{Level} W(l,\alpha) \sum_{v \in NTL_l} T_{sv}} \tag{1}$$

In the formula *Level* denotes the distance from node N_i,$W(l,\alpha)$ denotes weighted control factor function of the trust feedback value, which is related to the *Level* and attenuation factor α. In our opinion $W(l,\alpha)$ be defined as the fellowing formula:

$$W(l,\alpha) = \begin{cases} \alpha & , Level = 1 \\ \alpha \prod\limits_{l=1}^{Level} \frac{1}{l} & , \ Level > 1 \end{cases} \tag{2}$$

In the formula α denotes the trust attenuation factor or initial trust factor.

3.5 Trust Feedback Recommendation Algorithm

As it has already been stated above, in e-commerce trading process people are more likely to accept the recommendations from direct trust persons. In order to simulate the trust based recommendation idea, we designed the trust feedback recommedation algrithm, the pseudo-code is as follows.

//TFBRA Pseudo-code

TrustFeedBackRecommedationAlgrithm

Input: *s, MaxLevel,* α /* s denotes the active user needs for recommendations, MaxLevel denotes maxium search level, α denotes attenuation factor*/

Output: PR /*Recommended items list with high predict rating value */

Begin

While $l <= MaxLevel$ ***do***

Search DTNs in the lth level in DTG

if(nodes in searched DTNs of s is not in the trust nodes list TNL_l)

put the nodes into a trust nodes list TNL_l

endif

search the DTNs in TNL_l

if($l > MaxLevel$)

endwhile

else

l add-self

endwhile

$PRV(i) = \frac{\sum\limits_{l=1}^{Level} W(l,\alpha) \sum_{v \in TNL_l} T_{sv} * R_{vi}}{\sum\limits_{l=1}^{Level} W(l,\alpha) \sum_{v \in NTL_l} T_{sv}}$ /* calcuate the predict rating value of each item of users in TNL, let $PRV(i)$ represent the predict rating value of item i*/

put the items with highest predicted rating value (PRV) into PR

End

4 Experimental evaluation and result discussion

4.1 Experiment Dataset

In order to examine the effectiveness of our algorithm, we perform our experiment on dataset from Epinions. The Epinions dataset was collected by Paolo Massa in a 5-week crawl (November/December 2003) from the Epinions.com web site. The dataset contains 49,290 users who rated a total of 139,738 different items at least once, writing, 664,824 reviews and 487,181 issued trust statements. Users and Items are represented by anonymized numeric identifiers [19].

The Epinions datasets contain two files: (1) ratings_data.txt.bz2 (2.5 Megabytes), which contains the ratings given by users to items. In this file every line has the format "user_id item_id rating_value". User_id is an integer in [1,49290], item_id is an integer in [1,139738] and rating_value is an integer in the range [1,5]; (2) trust_data.txt.bz2 (1.7 Megabytes), which contains the trust statements issued by users. In the file every line has the format "source_user_id target_user_id trust_statement_value". Source_user_id and target_user_id are integer in [1, 49290], and trust_statement_value is always 1 (since in the dataset there are only positive trust statements and not negative ones (distrust)).

4.2 Evaluation measures

To use the Epinions datasets in a more flexible way, we imported the two files (ratings_data.txt and trust_data.txt) into Microsoft SQL Server 2005 to create two tables (rating_data and trust_data). And we add a trust_value column into the trust_data table and set a random integer value in [1, 5] to represent the trust value between two users. Evaluation of the approach put forward in chapter 3 is conducted in our self-development recommendation prototype system, which is implemented on Microsoft Visual 2008 platform in Windows 7 Ultimate environment with a Intel Core i3-2310 2.1GHz (4 CPUs) Processor and 6 gigabyte memory. Main interface of the prototype system is shown in Figure 4.

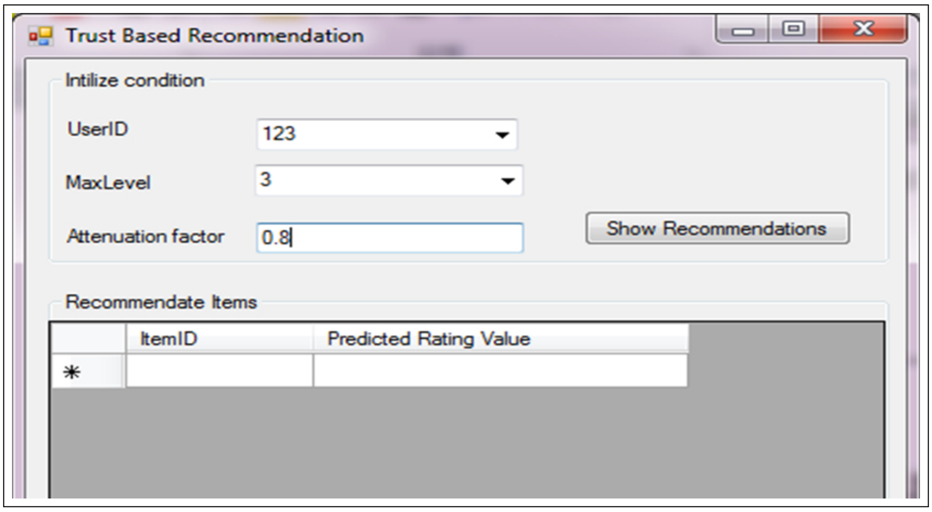

Figure 4: Main interface of the self-developed recommendation prototype system

4.3 Result and discussion

All the results are based on the self-developed trust based recommendation system. There are thousands of combination modes of the trust attenuation factor (α) with the maximum search

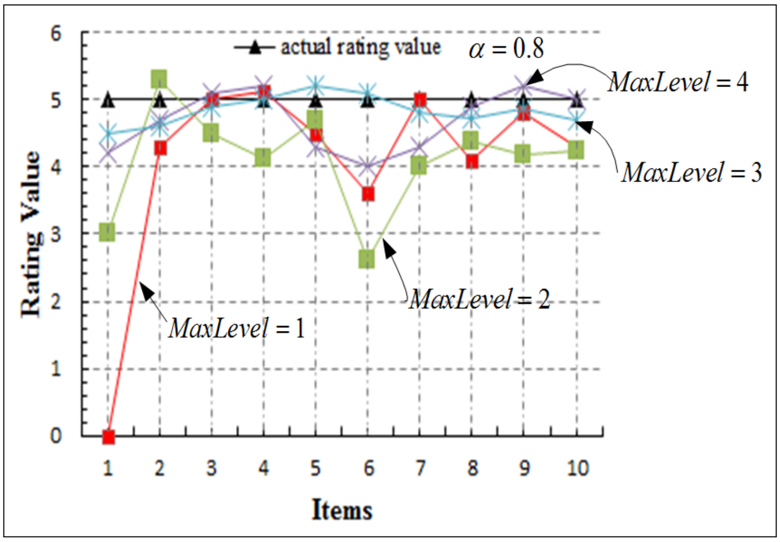

Figure 5: Ten recommended items for a randomly selected user are calculated according to TFBRA with αset to be 0.8

level ($MaxLevel$). We find it really hard to determine how α and $MaxLevel$ can be chosen. In order to prove the effectiveness of our recommend algorithm, two values (0.8 and 0.6) are chosen for parameterα, and ten recommended items for a randomly selected user are calculated according to TFBRA. Figure 5 shows the graphs for trust attenuation factor values with 0.8 and 0.6 respectively. Error between recommended value and actual rating value is shown in table 2. In the paper Mean Absolute Erro [36] (MAE) is used to evaluate the practical applicability of the trust feedback recommendation algorithm, a smaller MAE value means the higher accuracy. The calculation method of MAE is listed below:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|e_i| \qquad (3)$$

Where e_i is the difference between recommended rating value and actual rating value on the same item (product).

If a recommendation needed node have very few (or no) $DTNs$, MAE may be relatively great (As can be seen from Figure 5 and Figure 6 when$MaxLevel = 1$). With the increasing of$MaxLevel$,available feedback trust calculation nodes (include $DTNs$ and $IDTNs$) grows rapidly, which leads to more accurate recommendations. Although there are a great variety of combination modes of α with $MaxLevel$, it can be easily find from table 2 that MAE decrease obviously while $MaxLevel$ increase.

Table 2: Error between recommended rating value and actual rating value

MAE	MaxLevel=1	MaxLevel=2	MaxLevel=4	MaxLevel=5
$\alpha = 0.8$	0.954	0.957	0.41	0.221
$\alpha = 0.6$	0.757	0.49	0.4	0.331

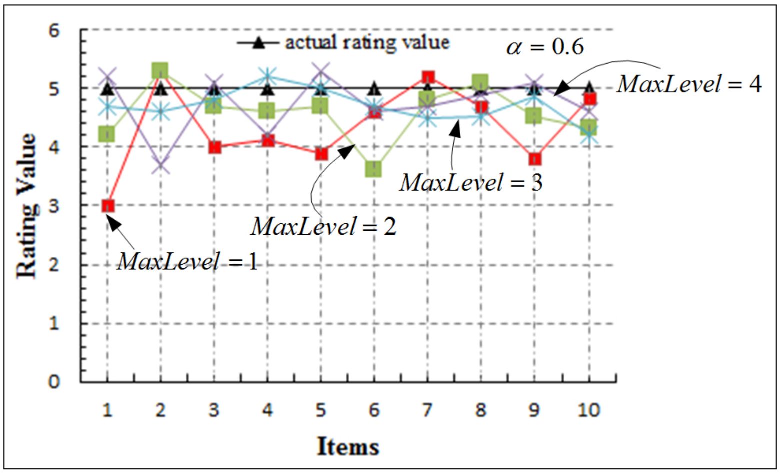

Figure 6: Ten recommended items for a randomly selected user are calculated according to TFBRA with αset to be 0.6

5 Conclusions

Recommendation is an important issue in information science; also it is a hot topic in e-commerce systems. When computing recommendations for users in e-commerce systems, most of the existing researches usually focus on find recommendations from similar users. However, many scholars have proved that there are many challenges in finding similar neighbors. The research tries to overcome the difficulties in traditional recommendation methods and put forward a new idea to get more to reasonable recommendations from trusted users. Based on the basic notations about trust cognitive process and DTG, which is constructed according to trust links between users, the paper proposes a trust feedback recommendation algorithm. We show through experiments on secondary processed Epinions datasets to better highlight the relative advantages of the different algorithms, and the experimental results indicate good effectiveness of our trust based recommendation approach.

One limitation of our method is that it has been test and verified on only one dataset i.e. Epinions datasets. In future we would like to prove the effectiveness of our trust feedback recommendation algorithm on trust datasets that exhibit characteristics different from Epinions datasets. Three important research questions that we would like to examine are: (1) Study the effect on recommendation accuracy when the way of setting trust value between two users varies; (2) Study the relation between weighted control factor function and the accuracy of our trust feedback recommendation algorithm; (3) Study the effectiveness of our approach using other datasets and compare the practicability of our method with other analogous means. We believe our approach can improve the coverage of recommender systems; however there is still much work need to be done.

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