Applying Improved Recommendation Techniques for Recommending Learning Resources in Web

Khin Nila Win, and Thiri Hay Mar Kyaw

***Abstract*—**World Wide Web is a large source of information. The various items of information can be found in World Wide Web. However, the users find it difficult to get the accurate information they actually require. To overcome this problem of information overloading, recommender systems have been developed. Recommender systems help users to get the items of their interests from large collections of data with little effort. There are various popular recommendation techniques in recommender systems. Among them, the most widely used approach is Collaborative Filtering techniques, sometimes known as Social Filtering. Various Recommendation Techniques have been trying to overcome the various challenges of recommendation systems. The proposed system improves the item-based collaborative filtering recommendation techniques to overcome the cold-start problem, to get the satisfied recommendation results for the learners. The system collects the various learning resources from the web and recommends the learners based on not only the learners' proficiency but also explicit rating of the users. The links useful for the learners are collected and the similarity of these links are pre-computed based on content similarity before recommendation. This similarity is collaborated with the explicit rating of the users. This system expects to provide the superior support for the learners who require the recommendation of the learning resources of their interests.

***Keywords*—** recommender systems, collaborative filtering techniques, item-based collaborative filtering, cold-start problem, explicit rating

I. Introduction

AMONG all personalization tools, recommendation systems are the most employed tools in e-commerce businesses [1]. Recommender systems try to automate aspects of a completely different information discovery model where people try to find other people with similar tastes and then ask them to suggest new things [2]. In a world where the number of choices can be overwhelming, recommender systems help users find and evaluate items of interest. They connect users with items to "consume" (purchase, view, listen to, etc.) by associating the content of recommended items or the opinions of other individuals with the consuming user's actions or opinions. Such systems have become powerful tools in domains from electronic commerce to digital libraries and knowledge management [3].

In these days, recommender systems are also widely used in learning systems to support the learners. Some systems analyze the learning activities of experienced learners and recommend the inexperienced learners the suitable learning activities according to the usual styles of the learning activities of the successful learners.

In recommender systems correlations are used to measure the extent of agreement between two users (Breese et al, 1998) and used to identify users whose ratings will contain high predictive value for a given user. Care must be taken, however, to identify correlations that are actually helpful. Users who have only one or two rated items in common should not be treated as strongly correlated. Herlocker et al. (1999) improved system accuracy by applying a significance weight to the correlation based on the number of co-rated items [3].

One of the best-known examples of data mining in recommender systems is the discovery of association rules, or item-to-item correlations (Sarwar et. al, 2001). These techniques identify items frequently found in "association" with items in which a user has expressed interest. Association may be based on co-purchase data, preference by common users, or other measures. In its simplest implementation, item-to-item correlation can be used to identify "matching items" for a single item, such as other clothing items that are commonly purchased with a pair of pants. More powerful systems match an entire set of items, such as those in a customer's shopping cart, to identify appropriate items to recommend. These rules can also help a merchandiser arrange products so that, for example, a consumer purchasing a child's handheld video game sees batteries nearby. More sophisticated temporal data mining may suggest that a consumer who buys the video game today is likely to buy a pair of earplugs in the next month [3].

Item-to-item correlation recommender applications usually use current interest rather than long-term customer history, which makes them particularly well suited for ephemeral needs such as recommending gifts or locating documents on a topic of short lived interest. A user merely needs to identify one or more "starter" items to elicit recommendations tailored to the present rather than the past [3].

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The rest of the paper is organized as following. In section 2, challenges and solutions of recommendation techniques is described. Section 3 explains motivations of the system. And section 4 explains how to improve recommendation by the proposed system. The system is concluded in the last section.

II. CHALLENGES AND SOLUTIONS IN RECOMMENDER SYSTEMS

A. *Challenges and Solutions in Recommender Systems*

Recommender systems are facing many challenges in these days. Despite being many recommendation techniques for those systems, no one of these techniques can solve the full range of information overloading problems. In Collaborative Filtering Techniques, they find the following challenges.

- New User Problem (Cold-start User Problem)
- New Item Problem (Cold-start Item Problem)
- Sparsity Problem

B. *Solutions in Recommender Systems*

In spite of various challenges in recommender systems, there are corresponding solutions to overcome these challenges. Hybrid recommendation approaches, which combine content-based and collaborative filtering approach, are mostly used to overcome the cold-start problem for both items and users.

To overcome the rating sparsity problem, user profile must be collaborated with the rating value when grouping the similar users. Similarly, for the sparsity problem for the item, item demographic data must be considered besides the similarity value resulted from only explicit rating of the users in computing the item similarity.

III. RELATED WORK

In these days, many researchers have been interested in developing recommender systems in supporting learning resources. In [6], a model of the simulation for the exploration of CF for the navigation support in LNs are presented. This system analyses the relationship between the micro (learner) and macro level (LN) of recommender systems in LNs. Learning activities that have been rated by comparable learners are recommended to the learners as navigational support. The simulation tool models a Learning Network in which learners search for, enrol in, study and rate learning activities.

In e-learning systems, web mining techniques are used to learn all available information about learners and build models to apply in personalization. A detailed description about using and applying educational data mining was given in (Romero et al., 2006) and (Romero et al., 2007) [7].

Sarwar et al. [8] proposed an alternative kNN CF algorithm based on similarity among items. This variant is often called item-item CF.

IV. MOTIVATIONS

Nowadays, people tried to find the better response of the systems which are able to provide the accurate information fitted with their desires. They find it very difficult to get the desired information from a vast amount of data in World Wide Web. Therefore, they rely on the personalization and recommendation systems to acquire the required information from the web.

In this age of lifelong learning, the learners are willing to get the learning resources in a short time. They are relying on the web to get the desired resources required for supporting their learning. Unfortunately, information extraction from the web has various challenges. There are many sites and links in the web which discussed various topics about Information Technology and Engineering knowledge, and which described solutions and suggestions for the usual problems in these fields. The fields of learning and interests are different from each other for the learners. Analyzing the respective fields and interests of the learners are very important in searching the suitable learning resources. The recommender systems are taking into account knowing the fields and interests of each learner in advance.

The proposed system emphasizes providing the learning resources and information for the learners interesting in various fields. The system considers the demographic similarity of the educational links in the web and requests the rating from the learners to analyze how these links are useful for their respective fields and interests. Finally, the new learners are recommended the useful links according to the results from the explicit rate values of other learners in collaborating with the demographic similarity of these links.

V. IMPROVING THE RECOMMENDATION SYSTEMS

A. *Computing the similarity of the items*

Figure 1. (a) Sample Rate Value of User u on Item I (b) An Example of User-Item Matrix

(a)

Theint: Java Web Development (2), Java & XML (3), Mobile Java (3)

Thiri: Mobile Java (2), Core Java (2), Java & XML (2)

Khin: Java Security (4), Mobile Java (3), Mobile Wireless (3)

(b)

	J W D	J & X	Mobile J	Core Java	J Security	M Wireless
Theint	2	3	3	?		
Thiri		2	2	2		
Khin	?		3		4	3

B. *Normalizing the casual rating value*

In the rating-based recommender systems, some strict users don’t usually give the highest rate value to the most-like item while some users give the highest rate value. For this reason, the proposed system normalized the rate value of the users and

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the normalized rate values are used in computing the similarity.

TABLE I
SAMPLE RATE VALUE DIFFERENCE BETWEEN EXISTING SYSTEMS AND PROPOSED SYSTEM

User	Rate Value ($R_{u,i}$)	Item No.	Highest Rate Value for System (HS)	Highest Rate Value for Current User (HR_u)	Existing Systems (Rate Value, $R_{u,i}$)	Proposed System (Normalized Rate Value, $NR_{u,i}$)
Su Su	3	6	5	4	3	3.75
Mu Mu	4	7	5	5	4	4
Mya Mya	3	7	5	5	3	3
Hla Hla	2	5	5	4	2	2.5
Soe Soe	2	6	5	3	2	3.33
Moe Moe	1	4	5	4	1	1.25

C. Enhancing the similarity with item demographic data

The similarity values computed in the previous step are enhanced by the demographic correlation of the items. This can produce more accurate similarity value since the demographic similarity value can strengthen the rating-based similarity value. The demographic similarity of the web page is computed based on the content similarity. The users who have the same interests may have the same rate value on the same item and also they have the same interests on the items which have the similar content. The proposed applies this assumption and uses content similarity of the item in similarity computation to analyze which item is the actual user interests.

TABLE II
ENHANCED CORRELATION SIMILARITY VALUES VS. SIMPLE MODIFIED ADJUSTED COSINE SIMILARITY VALUES

Modified Adjusted Cosine Similarity ($sim_{i,j}$)	Demographic Similarity or Content Similarity of Items (dem_cor)	Enhanced Correlation Similarity (enh_cor)
0.5	0.2	0.6
0.3	0.4	0.42
0.6	0.2	0.72
0.4	0.8	0.72
0.5	0.5	0.75
0.8	0.1	0.88
0.7	0.3	0.91

D. Predicting the recommendation

In prediction computation, the proposed system computes the prediction on an item i for a user u by computing the sum of the normalized ratings given by the user on the items similar to i. Each rating is weighted by the enhanced similarity $s_{i,j}$ between items i and j. These two operands, enhanced similarity and normalized rate value, can support in producing more accurate prediction value for the proposed system.

TABLE III
PREDICTION VALUES WITH DEMOGRAPHIC SIMILARITY VS. PREDICTION VALUES WITH NO DEMOGRAPHIC SIMILARITY

Prediction Value With Modified Adjusted Cosine Similarity ($P_{u,j}$) $P_{u,j} = \frac{\sum_{allsimilaritems,N}(s_{j,N} * NR_{u,N})}{\sum_{allsimilaritems,N}(\lvert s_{j,N} \rvert)}$	Prediction Value of Proposed System ($P_{u,j}$) $P_{u,j} = \frac{\sum_{allsimilaritems,N}(enh\_cor_{jN} * NR_{u,N})}{\sum_{allsimilaritems,N}(enh\_cor_{jN})}$
2.84	3.7
4.48	4.53
4.53	5.69
4.13	4.61
2.82	3.53

VI. CONCLUSIONS

In spite of recommending different items, all of the recommender systems tried to provide recommendation to the users as accurately as possible. To point the user which item is the most suitable for his/her interest, various recommender systems applied various methods according to the system requirements. Some system emphasizes on user similarity and some system targets to the item similarity.

The proposed system computes the demographic correlation of the educational links according to the content similarity. These similarity values are used to strengthen the similarity computed based on the rate values of the users. The system also takes the advantages of normalizing rate values. The system applies these methods in supporting to recommend the suitable educational links to the learners on the World Wide Web.

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