

Recommendation System Using Information Needs Radar Model

C. W. Shih, M. Y. Chen, H. C. Chu, and Y. M. Chen

Abstract—Recommendation systems attempt to recommend items that attract the attention of users, and information needs are the most important factors in recommendation systems, due to the means by which they influence information seeking behavior. To address the importance of information needs, this study proposes information needs radar model to quantify the degree of desirability expressed for items. Based on the information needs radar model, we developed a recommendation system to construct a net that filters items according to their degree of desirability and recommend items that meet the needs of users. Experimental results indicated that proposed recommendation system has good performance with regard to objective indicators and consistent performance regardless of data size, and could improve the applicability of the model.

Index Terms—Recommendation system, information needs, information needs radar model

I. INTRODUCTION

Recommendation systems employ information filtering techniques to recommend items that attract the attention of users [1]. Recommendation systems can be divided into two categories, according to the differences between filtering techniques: content filtering and collaborative filtering. Content filtering compares user profiles to the characteristics of items, and attempts to predict the ratings that users have not yet considered [2]. Collaborative filtering predicts user preferences or tastes based on the preferences of a group of users sharing similarities [3]. Content filtering depends on the description of items and tends to overspecialize its recommendations, while collaborative filtering is troubled by the cold-start problem [4],[5].

To address these problems, this study reconsidered the design of filtering techniques as they pertain to the interaction for users and recommendation systems. The interaction of users with recommendation systems is a form of information seeking, and the primary purpose of recommendation

systems is to satisfy user requirements. Information seeking begins by identifying the needs of users, followed by requirement analysis, collection and filtration, with the needed information transmitted to the users in the end. Information needs are the most important factors in information seeking, due to the means by which they influence information seeking behavior. Information needs comprise a complex, and dynamic combination of psychological factors, which are difficult to observe or decipher [6],[7]. Recommendation systems employ user behavior to describe information needs, and seeking behavior is related to the items that are sought. Therefore, the features of the items must be included within the broader concept of information needs.

To address the problems related to information filtering techniques and the importance of information needs, this study proposes an information needs radar model (INRM) to quantify the degree of desirability expressed for items. Based on the information needs radar model, we developed a recommendation system (InrRS) to construct a net that filters items according to their degree of desirability and recommend items that meet the needs of users.

The remainder of this paper is organized as follows. In Section 2, we investigate the concept of information needs and present our concept of INRM. In Section 3, we describe the InrRS and information techniques. In Section 4, we present experiments related to InrRS. We present our conclusions in Section 5.

II. MODELING INFORMATION NEEDS

Information needs are a dynamic, complicated grouping of psychological factors, that are difficult to observe or decipher [6],[7]. Shenton and Dixon [8] suggested that information needs are reflected in information seeking behavior and the target items obtained. Information needs can be observed through: (1) the user; (2) user behavior; or (3) target items. User behavior reflects the browsing activity of users and the request records of items, as well as the features of items reflect the needs of users. Consequently, this study employed these three elements to analyze the degree of desirability of items.

A. User commitment

Information needs vary among users, and the degree of commitment with which items are promoted may influence which items are desired. The degrees to which systems are committed to that selection they recommend indirectly enhance the degree of desirability users feel toward the item. On the contrary, when the degree of commitment is lower the impact on users is reduced, and the degree of desirability of items sought by users is also reduced.

Manuscript received February 13, 2011. This work was supported in part by the National Science Council of the Republic of China under Contract No. NSC99-2221-E-006-178-.

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B. Item utilization

Item utilization refers to the previous usage of items, such as the frequency with which items were reviewed. If items are often recommended or reviewed, the degree of desirability users feel towards it increases; if the items are not often recommended or not used at all, the degree of desirability of the items diminishes.

C. Item features

Item features refers to the important characteristics of items. Item features clearly illustrate information needs, enabling one to search for similar items [9]. In addition, the needs or preferences of users can be collected according to items features to construct personal profiles [10]. When items features match personal profiles, the items are more likely to meet user needs. However, a single personal profile only reflects the desire felt by a single user. This study constructed profiles of groups by clustering all of the personal profiles to reflect the needs of the whole.

To sum up, this study proposed an information needs radar model (INRM), with the intention of quantifying the degree

of desirability users feel for items in terms of user commitment, item utilization, and item features, and analyzed whether recommended items are representative of information needs. The information needs radar model is shown in Fig. 1. The degree of desirability of items is influenced by user commitment, item utilization, item feature and intersecting regions, i.e. behavior, importance, and interest. Behavior reflects the popularity of items, representing the intersection between user commitment and item utilization. Importance reflects the importance of the features provided by items, representing the intersection between item utilization and item features. Interest reflects the interest level of interest users feel toward items, representing the intersection between item features and user commitment. The intersection of the three dimensions is referred to as the needs area, representing the degree of desirability of an item. When an item with high user commitment, high item utilization, and desirable item feature matches the preferences of a group profile, the item has a higher degree of desirability.

III. SYSTEM ARCHITECTURE

This study proposed a recommendation system based on the information needs radar model (InrRS) (Fig. 2). The system architecture comprises three modules: user index, item index, and filtering net. The inputs were the usage logs related to users and items, and the output was a filtering net. The details are as follow.

A. User index

The purpose of the user index module was to quantify the dimensions of user commitment. The needs of users determine information seeking behavior; however, defining information needs using the needs of single user is one-sided. This study applied the behavior of like-minded users to determine the comprehensive needs of users [11]. First, the user index module was used to construct personal profiles and divide the profiles into different groups (G_k), using clustering technique, such as self-organizing maps [12].

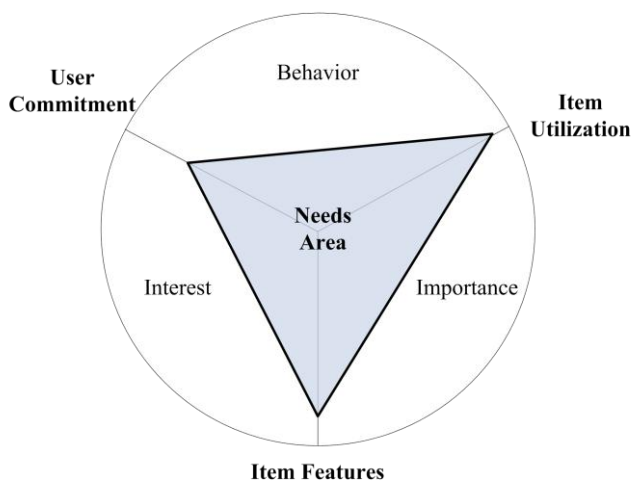


Fig. 1. Information needs radar model

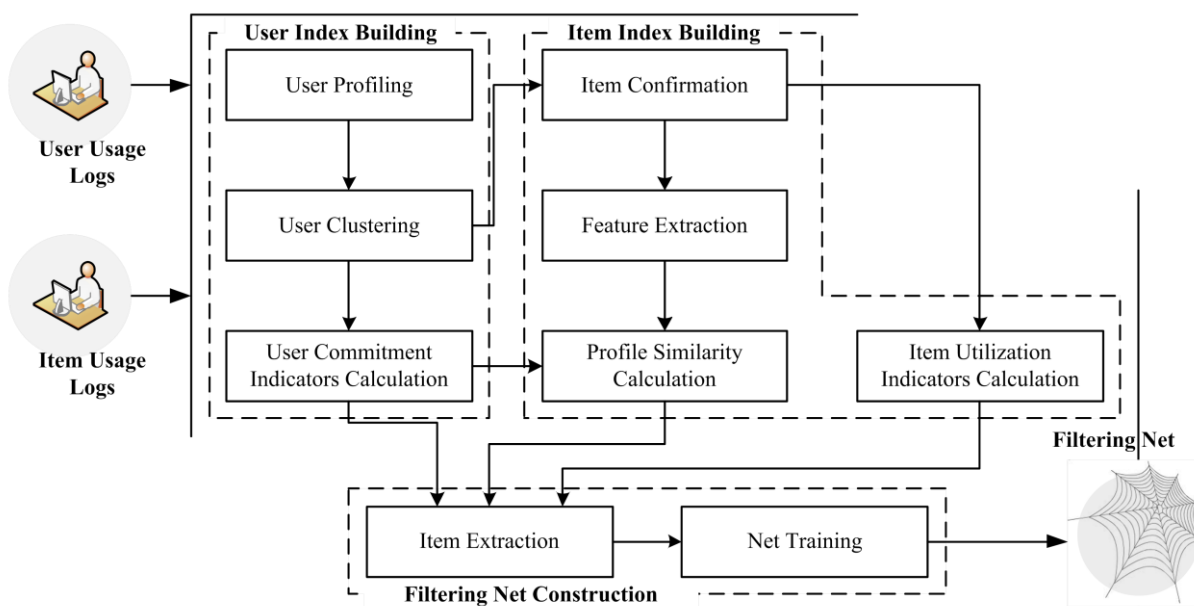


Fig. 2. Recommendation system architecture based on information needs radar model

According to the RFM model, the usage of users was extended to recent participation time (RPT_i), participation frequency (PF_i), and participation quantity (PQ_i) (refers to the quantity of items that users have reviewed in a given time) [13], and acquired the user commitment ($UC_{k,i}$) of user i in group k (Eq. 1).

$$UC_{k,i} = 3 \times (RPT_i^{-1} + PF_i^{-1} + PQ_i^{-1})^{-1} \quad (1)$$

B. Item index

The purpose of the item index module was to quantify the dimensions of item users and item features. Above, the usage of item j was extended to recent reviewed time (RRT_j), reviewed frequency (RF_j), and reviewed quantity (RQ_j) (refers to the total number of users who have reviewed the item in a given time), and acquired the item utilization ($IU_{k,j}$) of item j in group k (Eq. 2). In addition, this study employed the similarity of item j and group profile k to replace the item features ($IF_{k,j}$) (Eq. 3).

$$IU_{k,j} = 3 \times (RRT_j^{-1} + RF_j^{-1} + RQ_j^{-1})^{-1} \quad (2)$$

$$IF_{k,j} = \frac{F_j \cdot G_k}{|F_j| |G_k|} \quad (3)$$

C. Filtering net

The purpose of the filtering net module was to integrate user commitment ($UC_{k,i}$), item utilization ($IU_{k,j}$), and item features ($IF_{k,j}$), to construct a filtering net according to the degree of desirability of items. User commitment $UC_{k,i}$ was utilized to evaluate the participation of users, and this study employed the harmonic mean of the three dimensions of user commitment of all users who reviewed item i to evaluate the degree of desirability of item i , where n_k is the number of users (Eq. 4).

$$UC_{k,j} = n_k \times \left(\sum_i \frac{1}{UC_{k,i}} \right)^{-1} \quad (4)$$

After the construction of INRM by $UC_{k,j}$, $IU_{k,j}$, and $IF_{k,j}$, this study projected the INRM to a Euclidean space to calculate the needs area $A_{k,j}$ of item i (Eq. 5), and train the filtering net (the sphere) of support vector data description by items exceeding the threshold in group k [14]: the input vector represents the features of items (F_j). If a new item i satisfies Eq. 6 (where \mathbf{a} is the center of the sphere, and R is the radius of the sphere), item i meets the information needs of

users, and it is subsequently recommended.

$$A_{k,j} = IF_{k,j} IU_{k,j} \begin{vmatrix} \cos 0 & \sin 0 \\ \cos \frac{2\pi}{3} & \sin \frac{2\pi}{3} \end{vmatrix} + IU_{k,j} UC_{k,j} \begin{vmatrix} \cos \frac{2\pi}{3} & \sin \frac{2\pi}{3} \\ \cos \frac{-2\pi}{3} & \sin \frac{-2\pi}{3} \end{vmatrix} + UC_{k,j} IF_{k,j} \begin{vmatrix} \cos \frac{-2\pi}{3} & \sin \frac{-2\pi}{3} \\ \cos 0 & \sin 0 \end{vmatrix} \quad (5)$$

$$\|F_j - \mathbf{a}\|^2 \leq R^2 \quad (6)$$

IV. EXPERIMENT RESULTS

To verify whether the new items recommended by INRIS meet the needs of users, the experimental data (<http://www.grouplens.org/node/73>) was used to provide user feedback (the range was 1 (dislike very much) to 5 (like very much)). When the user feedback exceeded 3, the data appeared to meet the needs of users. To evaluate the advantages and disadvantages of InrRS, *Precision*, *Recall* and *F1* measures were adopted for evaluation. *Precision* represents the percentage of correct items among those that INRIS estimated that meet user needs. *Recall* represents the percentage of correct items among all items that actually meet user needs, and *F1* is a measure that is the harmonic mean of *Precision* with *Recall* (Eq. 7).

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (7)$$

The data set of the experiment was divided into DS1, DS2, and DS3 (Table 1). The results of experiments comparing InrRS and traditional collaborative filtering approaches (TCF) are shown in Fig. 3. In DS1, *Precision* and *F1* of InrRS and TCF showed no significant difference, but the TCF was higher than InrRS, and the *Recall* of TCF was better than InrRS. In DS2 & 3, InrRS and TCF showed no significant difference in *Precision*, but InrRS was higher than TCF. The *Recall* and *F1* of InrRS were better than TCF.

TABLE 1 THE DESCRIPTION OF DATA SETS

	# of user feedback	# of users	# of items
DS1	100,000	943	1,682
DS2	1,000,209	6,040	3,900
DS3	10,000,054	71,567	10,681

In terms of simplicity, the performance of InrRS was superior to TCF in large samples. Compared to TCF, InrRS had consistent performance in the *Precision*, *Recall* and *F1*

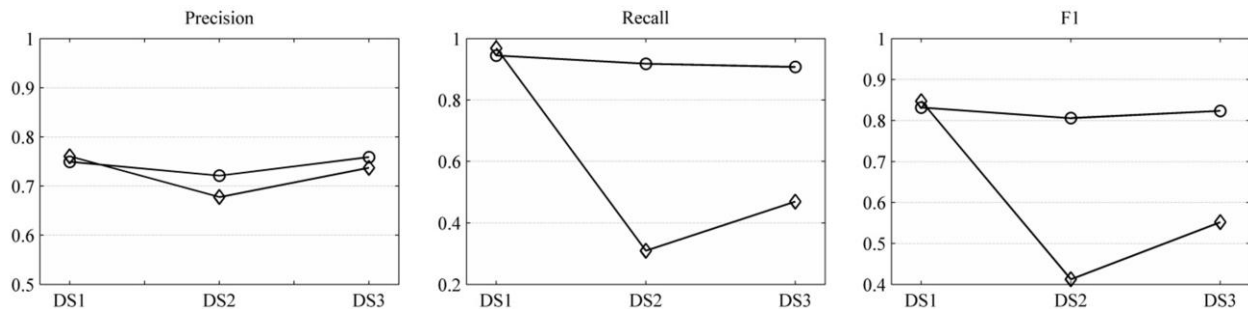


Fig. 3. Comparisons of our proposed system (circle) and traditional collaborative filtering (diamond)

(greater than 0.7), particularly with the *Recall* measure, which exceeded 0.9. This demonstrates that InrRS correctly identified all items that meet the needs of the users. Overall, the efficiency of InrRS was superior to TCF, with superior performance and stability, irrespective of data size, demonstrating the applicability and effectiveness of InrRS.

V. CONCLUSIONS

This study proposed information needs radar model based on user commitment, item utilization, and item features, to recommend items that satisfy user needs. Based on INRM, this study proposed a recommendation system (InrRS) that applied various information technologies, including self-organizing maps and support vector data description. The experimental results indicated that InrRS has good performance with regard to objective indicators and consistent performance regardless of data size, and could improve the applicability of the model. Through the information needs radar model (INRM), InrRS was able to automatically and accurately recommend items needed by users, increase the efficiency of the recommendation system, and enhance the loyalty of users for the recommendation system.

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