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A multi-level collaborative filtering method that improves recommendations

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ABSTRACT

Collaborative filtering is one of the most used approaches for providing recommendations in various online environments. Even though collaborative recommendation methods have been widely utilized due to their simplicity and ease of use, accuracy is still an issue. In this paper we propose a multi-level recommendation method with its main purpose being to assist users in decision making by providing recommendations of better quality. The proposed method can be applied in different online domains that use collaborative recommender systems, thus improving the overall user experience. The efficiency of the proposed method is shown by providing an extensive experimental evaluation using five real datasets and with comparisons to alternatives.

1. Introduction

Nowadays, more and more people find that the constant growth of the web in combination with the development of technologies such as smartphones and tablets results in spending more time accessing information online. However, these developments have brought a massive amount of information, resulting in an information overload problem (Bobadilla, Ortega, Hernando, & Gutiérrez, 2013; Moradi & Ahmadian, 2015). With too much information all over the web, users find it very challenging to find the data they need. For that reason most users find it frustrating when looking online for what movie to watch, whom to add as a friend in a social network and many other related search problems. The solution to this problem is recommender systems, which apply techniques developed to analyze user data and make recommendations that the user will probably like. It is a method that both the service provider and the user are benefited from. The main reasons for the mutual benefits include the fast processing of data for the service provider, the higher percentage of sales, the saving of time for the user and the discovery of products or services that otherwise would be difficult to find (Polatidis & Georgiadis, 2013).

Collaborative filtering is the most known and widely used technique for providing fast and accurate enough recommendations to users (Ekstrand, Riedl, & Konstan, 2011; Konstan & Riedl 2012; Shi, Larson, & Hanjalic, 2014; Su & Khoshgoftaar 2009). This method relies on a database of ratings submitted by each user for products or services, then the ratings are compared to each other with the use of suitable similarity method in order to provide recommendations to the user who makes the request. The main two functions of such systems are to identify a pre-specified number of neighbors according to similar ratings and then provide the recommendations. Collaborative filtering has been widely adopted by many real-world systems, such as Netflix and Amazon (Wang, Zhang, & Lu, 2015), and this is due to its simplicity and efficiency.

In addition to collaborative filtering, other recommendations methods include content-based, which is based on item metadata. In this method the user supplies a set of information and preferences and the algorithm makes recommendations according to the settings provided by Bobadilla et al. (2013) and Burke (2007). Moreover, knowledge-based recommender is another recommendation approach that uses inferences about user preferences and specific knowledge about the domain and also how the items or services to be recommended meet the preferences set by the users (Jannach, Zanker, Felfernig, & Friedrich, 2010). A widely used recommendation approach is the combination of one or more recommendation methods, and is called hybrid (Burke, 2002). It does not necessarily mean that the two methods must be different, but they could be two different collaborative filtering methods as well (Burke, 2007; Jannach et al., 2010).

This paper proposes the use of a new recommendation collaborative filtering method that aims to improve the accuracy of the recommendations. In most collaborative recommendation systems a similarity function, such as Pearson Correlation Coefficient (PCC) or Cosine (Shi et al., 2014), is utilized by the system to provide recommendations by taking in consideration the absolute ratings between users. Our motivation is to divide user similarity, as offered by PCC,

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Table 1
A database of ratings.

	Item/Service 1	Item/Service 2	Item/Service 3	Item/Service 4	Item/Service 5
User 1	–	2	3	5	–
User 2	1	2	4	5	5
User 3	2	5	1	1	2
User 4	3	–	–	–	3
User 5	–	3	4	–	–

into different levels and add constraints to each level. We show that by modifying the user similarity, which is a value from −1 to 1, according to the constraints that each user belongs, the accuracy of the recommendations is improved. Furthermore, we argue that the quality of the recommendations is improved as well when the constraints are at place. The proposed method attempts to provide recommendations of better accuracy and quality when compared to other alternatives. However for this to be done correctly, enough ratings should have already been submitted by users of the system.

The contributions of the paper are:

1. We propose a recommendation method that improves the accuracy of collaborative filtering and is based on multiple levels and constraints.
2. We perform extensive experiments using five real datasets in order to evaluate our proposed method and compare it against alternatives in order show that our proposed method is both practical and effective.

The rest of the paper is organized as follows: Section 2 is the related work part, Section 3 describes the proposed method, Section 4 explains the experimental evaluation and Section 5 contains the conclusions and future work part.

2. Related work

While collaborative filtering methods have been widely used by many real world systems, including Netflix and Amazon, there are not sufficient details available regarding the provided recommendations. Collaborative filtering techniques use a database of ratings among users and items, such as the one shown in Table 1, must be present (Shi et al., 2014).

When recommendations need to be generated for a user, then the ratings are loaded into memory and a similarity function is used. The main part is how to estimate the similarity value between two users. This is called neighborhood identification and the job of the similarity function is to firstly identify a pre-specified of k nearest neighbors according to their similarity value. In present recommendations systems the value of k can vary from a few, possibly 2 to 5, to as many as possible with the number ranging from 10 to 20 to 30 and so on up to hundreds of neighbors. A high number of neighbors does not necessarily mean that the accuracy of the recommendations will be high though.

Now, as mentioned for the identification of the nearest neighbors a similarity function such as PCC is necessary to be used. PCC is defined in Eq. (1). In PCC the sum of ratings between two users is compared. $Sim(a, b)$ is the similarity between users a and b, also $r_{a,p}$ is the rating of user a for product p, $r_{b,p}$ is the rating of user b for product p and $\bar{r}a$ and $\bar{r}b$ represent the user's average ratings. P is the set of all products. Moreover, the similarity value ranges from −1 to 1 and higher is better.

$$Sim\begin{matrix} PCC \\ a,\ b \end{matrix} = \frac{\sum p \in P(r_{a,p} - \bar{r}a)\left(r_{b,p} - \bar{r}b\right)}{\sqrt{\sum p \in P(r_{a,p} - \bar{r}a)^2}\sqrt{\sum p \in P\left(r_{b,p} - \bar{r}b\right)^2}} \tag{1}$$

After the similarity values are computed according to the equation used and the formation of the k nearest neighborhood, then the rating procedure takes place, where ratings are being predicted for items. The items with the highest rating predicted value are being recommended to the user who made the request. On the other hand, PCC has inspired other similarity methods such as the weighted PCC (WPCC) (Herlocker, Konstan, Borchers, & Riedl, 1999) defined in Eq. (2). WPCC is based on PCC and provides recommendations based additionally on the number T of co-rated items between users. In their work the value was set to 50, which means that if the number of the co-rated items was 50 or more the recommendations from these users are preferred. Also in the case that less ratings are available then the algorithm switches to ordinary PCC.

$$Sim\begin{matrix} WPCC \\ a,\ b \end{matrix} = \left\{ \begin{matrix} \frac{|Ia \cap Ib|}{T} \cdot Sim\begin{matrix} PCC \\ a,\ b \end{matrix}, & \text{if } |Ia \cap Ib| < T \\ Sim\begin{matrix} PCC \\ a,\ b \end{matrix}, & \text{otherwise} \end{matrix} \right\} \tag{2}$$

A somewhat similar approach for identifying neighbors is proposed by Jamali and Ester (2009) and is defined in Eq. (3). In this method the similarity of small number of co-rated items is weaken.

$$Sim\begin{matrix} SPCC \\ a,\ b \end{matrix} = \frac{1}{1 + \exp(-|Ia \cap Ib|/2)} \cdot Sim\begin{matrix} PCC \\ a,\ b \end{matrix} \tag{3}$$

Another approach to recommendations based on collaborative filtering is Jaccard's similarity (Koutrika, Bercovitz, & Garcia-Molina, 2009). In this approach the similarity computation of PCC is not used, but only the number of co-rated items is taken into consideration. Jaccard's similarity is defined in Eq. (4).

$$Sim\begin{matrix} Jaccard \\ a,\ b \end{matrix} = \frac{|Ia \cap Ib|}{|Ia \cap Ib|} \tag{4}$$

Other proposed similarities for collaborative filtering include the mean squared difference (MSD) (Cacheda, Carneiro, Fernández, & Formoso, 2011). This method captures the difference that the users have in their ratings. Furthermore, another proposed similarity measure has been proposed by Lu, Shambour, Xu, Lin, and Zhang (2013) where the use of fuzzy set theory is used with the aim to assign different weight values to different rating differences. Another method, proposed by Wang et al. (2015), uses entropy to provide user similarity in collaborative filtering. In this work the majority of ratings used by PCC must be similar. Liu, Hu, Mian, Tian, and Zhu (2014) proposed a collaborative filtering improvement that does not only consider the local user rating information, but also the global behavior of the user. Son (2014) proposed a fuzzy recommendation method that uses demographic data instead of user ratings. One more similarity measure found in the literature is proposed by Bobadilla, Ortega, Hernando, and Bernal (2012a). This recommendation method tries to solve the cold start problems found in recommender systems. In particular it aims to solve the problem of new users stop using the system because of low accuracy found at the initial stages (when just a few ratings are available). For this reason, the authors propose a new similarity measure based on neural learning and uses optimization that provides better accuracy to users with few submitted ratings. An alternative similarity measure based on singularities is described in Bobadilla, Ortega, and Hernando (2012b). In this approach contextual information derived from users is used to calculate the singularity for each item. According to their results the similarity is improved