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Nonadditive similarity-based single-layer perceptron for multi-criteria collaborative filtering

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ABSTRACT

The main aim of the popular collaborative filtering approaches for recommender systems is to recommend items that users with similar preferences have liked in the past. Although single-criterion recommender systems have been successfully used in several applications, multi-criteria rating systems that allow users to specify ratings for various content attributes for individual items are gaining in importance. To measure the overall similarity between any two users for multi-criteria collaborative filtering, the indifference relation in outranking relation theory, which can justify discrimination between any two patterns, is suitable for multi-criteria decision making (MCDM). However, nonadditive indifference indices that address interactions among criteria should be taken into account. This paper proposes a novel similarity-based perceptron using nonadditive indifference indices to estimate an overall rating that a user would give to a specific item. The applicability of the proposed model to recommendation of initiators on a group-buying website was examined. Experimental results demonstrate that the proposed model performs well in terms of generalization ability compared to other multi-criteria collaborative filtering approaches.

1. Introduction

Personalized recommender systems can avoid information overload by highlighting items that are more relevant to consumers [10]. They do this by requiring users to offer their opinions on items they have consumed [7,12]. Single-criterion recommender systems have been successful in a number of personalization applications. In particular, single-criterion collaborative filtering is a popular recommendation technique and is used on sites such as Amazon.com. The key property of such systems is that users are required to offer only a single-criterion or overall rating for each consumed item. In other words, users cannot express their preference for individual criteria for a given item. However, in a recommender system, user preferences may involve more variables [36]. For instance, a movie can be rated by story, acting, direction and visuals, as in Yahoo! Movies. Practical problems are often characterized by multiple criteria [43]. Furthermore, it is helpful to improve recommendation accuracy by incorporating multiple criteria that can affect user preferences in recommenders [13].

Multi-criteria recommender systems have already been reported in the literature, such as the meta-recommendation system with DynamicLens presented by Schafer [17], the intelligent agent-based systems of Lee et al. [48], and case-based querying to recommend travel planning proposed by Ricci and Werthner [9]. The recommendation service of Yahoo! Movies indicates that personalized multi-criteria recommender systems should be an important component of personalization applications. Multi-criteria rating systems that allow users to assign ratings to various content attributes of items they have consumed have become the focus in recommendation systems [12,13]. We focus on collaborative filtering since it can provide useful personalized recommendations. A key feature of collaborative filtering is that it recommends items that users with similar preferences have liked in the past. In addition, measures of similarity between two users play an important role in collaborative filtering. Several similarity-based approaches have been proposed by Adomavicius and Kwon [13].

Three issues are addressed in this paper. First, since the overall rating for a recommendation indicates the score a user gives to an item, every overall rating on a binary scale [20] can be defined as highly ranked or not highly ranked. The higher the overall rating, the preferable an item is to the user. Item recommendation can thus be treated as a two-class classification problem. This motivates us to use a single-layer perceptron (SLP), which is a traditional model for two-class pattern classification problems, to estimate an overall rating for a specific item. Next, since recommendation is a multi-criteria problem by nature, it is interesting to use the well-known indifference relation in multi-criteria decision making (MCDM) to measure similarity in collaborative filtering. The reason for using the indifference relation is that it justifies discrimination between any two alternatives and has been widely used to study pattern classification for nominal sorting problems [25,29] such as PROAFTN [22], PIP and K-PIP [27], and FBI [40]. Finally, an overall indifference index is usually computed as a weighted average, for which it is assumed that criteria do not

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interact. However, since criteria are not always independent, the assumption of additivity is not always reasonable [49,54]. Therefore, a nonlinear fuzzy aggregator, the Choquet integral [44–46] with respect to certain fuzzy measures, should be considered for the overall indifference index.

This paper aims to propose a novel similarity-based SLP with nonadditivity for recommendation. The connection weights are interpreted as the degree of importance of individual criteria. An overall nonadditive indifference index between two users can be generated from the output neuron using the Choquet integral to integrate the partial indifference index for each criterion. The goal of the proposed approach is to recommend correctly a set of a few relevant items to each user. To achieve high accuracy, a genetic algorithm (GA) is used to determine the parameter specifications. The main issue with a GA is that it is not easy for users to specify appropriate values to parameters.

The proposed method is applied to initiator recommendation for group buying. Group-buying websites are important transaction platforms for electronic commerce between businesses and consumers with the same needs for some items, who then negotiate with vendors to obtain the best price or a special discount. A market research institute in Virginia, BIA/Kelsey, has predicted that the group-buying market in the USA will reach US$ 39.3 billion in 2015 [5]. For a particular item, selection of appropriate initiators from a list of a large number of initiators provided by a group-buying website can be difficult and time-consuming for potential customers. This obstacle may be overcome by the development of initiator recommender systems that help users to easily select initiators according to their preferences.

The remainder of the paper is organized as follows. Section 2 briefly introduces various similarity measures for collaborative filtering. Section 3 describes a similarity-based SLP for recommendation that uses nonadditive indifference indices. A GA-based method for constructing the proposed recommendation model is demonstrated in Section 4. Section 5 applies the proposed method to initiator recommendation on a group-buying website in Taiwan. Section 6 contains a discussion and conclusions.

2. Similarity-based collaborative filtering

2.1. Multi-criteria collaborative filtering

Assume that a system asks each user to offer feedback on n criteria with respect to a consumed item or a person with whom he or she has a connection. Let R_0 denote the set of possible overall ratings and let R_i denote the set of possible ratings for each individual criterion i ($1 \le i \le n$). For the (user, item) pairs, the rating function R in a multi-criteria recommender system is defined as follows:

$$R : Users \times Items \rightarrow R_0 \times R_1 \times \ldots \times R_n \tag{1}$$

Let $R(u, u')$ be equal to $(r^u_{0u'}, r^u_{1u'}, \ldots, r^u_{nu'})$ consisting of an overall rating $r^u_{0u'}$, and n multi-criteria ratings. For instance, suppose that reputation (criterion 1) and response (criterion 2) are used to evaluate an initiator on a group-buying website (i.e., $n=2$) to make an initiator recommendation. User C might assign ratings of 5, 7 and 6 to reputation, response and overall rating, respectively for initiator B. C must have already joined the group confirmed by B. Therefore, $R(C, B)=(6, 5, 7)$, where r^C_{0B}, r^C_{1B} and r^C_{2B} are 6, 5 and 7, respectively. If user A has not yet joined the group confirmed by B, the recommender system directly estimates the overall rating that A would give to B (i.e., r^A_{0B}) by estimating R. To sum up, an estimate of the overall rating that A would give to B can be based on the similarity, denoted by sim(A, u), between A and user u who rated B. The similarity is calculated according to the initiators that A and user u have both rated previously. The more similar A and u are, the more strongly will r^u_{0B} contribute to r^A_{0B}.

Several similarity measures are introduced below. The cosine-based similarity measure, denoted by $\mathrm{sim}^c_i(A, u)$, is most commonly used to derive similarity for criterion i. $\mathrm{sim}^c_i(A, u)$ $(i=1,\ldots, n)$ is defined as follows:

$$\mathrm{sim}^c_i(A,u) = \frac{\sum_{u' \in C(A,u)} r^A_{iu'} r^u_{iu'}}{\sqrt{\sum_{u' \in C(A,u)} (r^A_{iu'})^2 \sum_{u' \in C(A,u)} (r^u_{iu'})^2}} \tag{2}$$

where $C(A, u)$ represents the sets of initiators rated by both A and u. Then an overall similarity can be obtained by aggregating the individual similarities in one of the following ways [13]:

1. Average similarity:

$$\mathrm{sim}_{\mathrm{avg}}(A,u) = \frac{1}{n+1} \sum_{i=0}^{n} \mathrm{sim}_i(A,u) \tag{3}$$

2. Worst-case similarity:

$$\mathrm{sim}_{\min}(A,u) = \min_{i=0,\ldots,n} \mathrm{sim}_i(A,u) \tag{4}$$

Besides the cosine-based similarity measure, Pearson correlation and the Spearman rank correlation coefficients are commonly used to measure $\mathrm{sim}_i(A, u)$. The Pearson correlation coefficient $\mathrm{sim}^P_i(A, u)$ $(i=1,\ldots, n)$ is defined as follows:

$$\mathrm{sim}^P_i(A,u) = \frac{\sum_{u' \in C(A,u)} (r^A_{iu'} - \overline{r^A_i})(r^u_{iu'} - \overline{r^u_i})}{\sqrt{\sum_{u' \in C(A,u)} (r^A_{iu'} - \overline{r^A_i})^2 \sum_{u' \in C(A,u)} (r^u_{iu'} - \overline{r^u_i})^2}} \tag{5}$$

where $\overline{R_i(A,u')}$ denotes the average rating of user A for criterion i. For A, the Spearman rank correlation ranks $|C(A, u)|$ ratings for criterion i in ascending order, with the smallest value receiving rank 1, the second smallest rank 2, and so on. The same process is also performed for u. The Spearman rank correlation coefficient $\mathrm{sim}^s_i(A, u)$ is then defined as follows:

$$\mathrm{sim}^s_i(A,u) = 1 - \frac{6\sum_{u' \in C(A,u)} (rank(r^A_{iu'}) - rank(r^u_{iu'}))^2}{|C(A,u)|(|C(A,u)|^2 - 1)} \tag{6}$$

where $rank(r^A_{iu'})$ and $rank(r^u_{iu'})$ denotes the ranks of $r^A_{iu'}$ and $r^u_{iu'}$, respectively. $\mathrm{sim}_{avg}(A, u)$ and $\mathrm{sim}_{min}(A, u)$ can be obtained using $\mathrm{sim}^c_i(A, u)$, $\mathrm{sim}^P_i(A, u)$, or $\mathrm{sim}^s_i(A, u)$ as $\mathrm{sim}_i(A, u)$.

Adomavicius and Kwon [13] introduced a natural approach, the use of multidimensional distance metrics, to compute the similarity between two users. A distance-based similarity measure can be formulated as follows:

$$\mathrm{sim}_{dis}(A,u) \frac{1}{1 + (1/|C(A,u)|) \sum_{u' \in C(A,u)} d(R(A,u'), R(u,u'))} \tag{7}$$

where $d(R(A, u'), R(u, u'))$ can be derived using various distance metrics such as the following:

- Manhattan distance:

$$d(R(A,u'), R(u,u')) = \sum_{i=0}^{n+1} |r^A_{iu'} - r^u_{iu'}| \tag{8}$$

- Euclidean distance:

$$d(R(A,u'), R(u,u')) = \sqrt{\sum_{i=0}^{n+1} (r^A_{iu'} - r^u_{iu'})^2} \tag{9}$$

- Chebyshev distance:

$$d(R(A,u'), R(u,u')) = \max_{i=0,\ldots,n} |r^A_{iu'} - r^u_{iu'}| \tag{10}$$