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A fuzzy recommender system based on the integration of subjective preferences and objective information

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ABSTRACT

This study proposes a novel collaborative filtering framework which integrates both subjective and objective information to generate recommendations for an active consumer. The proposed framework can solve the problem of sparsity and the cold-start problem which affect traditional CF algorithms. The fuzzy linguistic model, which is a more natural way for the consumer to present their preferences, is adopted within the proposed framework. Based on these concepts, two algorithms, a simple aggregated (SA) algorithm and aggregated subjective and objective users' viewpoint (ASOV) algorithm are developed. A series of experiments is performed, the results of which indicate that the proposed methodologies produce high-quality recommendations. Finally, the results confirm that the proposed algorithms perform better than the traditional method.

1. Introduction

E-commerce has been growing rapidly over the last decade, and consumers have become accustomed to purchasing products from online stores. Recommender systems have proven to be a successful way to assist customers by reducing redundant information and offering advice on finding suitable products to facilitate online decision-making [22–26]. The most successful technologies for recommender systems, known as collaborative filtering (CF) systems, have already been applied by several well-known commercial web sites such as Amazon.com, Netflix, and so on [1,2,16,17].

Prior studies about recommender systems have ignored the fact that expert opinion plays an important role in the consumer's decision-making process [25]. After the customer perceives the need to purchase something, they will refer not only to information given by producers and sellers, but also to opinion leaders and acquaintances that have had similar experiences [10–12]. This study proposes a novel CF system which integrates subjective and objective information to generate recommendations for an active consumer. The subjective information is comprised of opinions solicited from domain experts and opinion leaders [11,13,20,29]. The objective information clarifies the active user's preferences based on those of similar users and past experience. The proposed framework can overcome the weaknesses of traditional CF systems including the sparsity problem and the cold-start problem [15,18]. Another advantage of the proposed algorithm method is the adoption of a fuzzy linguistic model which makes it more natural and simpler for the consumer to present their thinking.

The CF systems use historical data related to user preferences or behavior to predict how new users will act [15,19]. The idea is that the user will receive recommendations based on their personal profile gleaned from previous transactions and those of other similar customers. However, the traditional CF systems have some common limitations, including cold-start and sparsity problems [15,18,27] which generally prevent the system from providing better quality recommendations. The cold-start problem means that the CF system cannot find similar users or user preferences from which to make predictions, for a new user or a new item that has just entered the system. This occurs when the CF system has no information about the new item and no knowledge about personal profile of the new user. The sparsity problem occurs when available data are insufficient to identify similar users. Collaborative filtering cannot generate useful recommendations for previous situations (cold-start and sparsity) because of the lack of a sufficient number of previous ratings or purchases. The current generation of recommender systems still requires further improvement to solve these serious problems [15].

Several studies have also suggested that information about expert opinions and other types of consumer evaluations should be included in the recommender systems [12,31]. To provide this kind of combined information can increase users' trust in and satisfaction with the recommender systems [12]. Whenever a new product has been launched, opinions are always solicited from

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domain experts and opinion leaders. Based on this subjective information, the proposed system can still provide the new user with a recommendation list, which may contain new items if the expert comments are good. In addition, if user preferences provided to the system are insufficient, the proposed method can still give recommendations based on subjective information alone. In this way the proposed system can solve the sparsity and cold-start problems.

Generally speaking, user preference representation for recommender systems can be classified into two types: crisp and fuzzy models [33]. The former allow users to express their preferences on a 5-point Likert-type scale while linguistic assessment is based on words rather than numbers. For example, a user perceives that he/she likes a product very much and scores this product somewhat higher than 4 points but lower than 5 but the user chooses 4 points to represent his preference. However, the result might be affected by personal differences in scoring behavior. It would be better if a user can choose a linguistic option such as "strongly like" that closely represents his/her opinion about the product. The linguistic term, "strongly like", can be adequately tackled by fuzzy modeling, since the member function can allow 80% as belonging to scale 5 and 20% belonging to scale 4. A fuzzy linguistic method, modeled on human perception, makes it easier to evaluate qualitative problems [21,35,36]. Accordingly, we adopt a fuzzy theoretical method for the proposed recommender system.

Since this is an initial study of the proposed framework concept, we develop only two algorithms, a simple aggregated (SA) algorithm and an aggregated subjective and objective users' viewpoint (ASOV) algorithm for comparison. To evaluate the proposed algorithms, we compare it with the traditional CF system. The effectiveness of fuzzy modeling can be proven by comparison with the other two approaches, CSA and CASOV, based on the crisp value. This illustrates that employing linguistic terms is a better way to understand the users' preferences. We carried out a series of detailed experimental evaluations with a real dataset to demonstrate how the proposed methods improve recommendation quality for very sparse datasets and cold-start users.

The rest of the paper is organized as follows. In Section 2, we briefly review previous research studies. We formally define the problem in Section 3 and discuss the proposed algorithms in Section 4. Then, we evaluate the effectiveness of the proposed methods in Section 5. Finally, some conclusions are stated in Section 6.

2. Related work

2.1. Fuzzy linguistic approach

Fuzzy set theory was developed by Zadeh in 1965 and later extended and applied to many fields [6–8,34–36]. It is well suited to handle various evaluation problems based on the aggregation of imprecise information from individual opinions. A fuzzy set A in X is characterized by its membership function, which is defined as $\mu_A(x)$: $x \in X \rightarrow [0,1]$, where X is the domain space. According to the context in which X is used and the concept presented, the fuzzy membership function, μ_A (x), can have different interpretations. Sometimes it is hard for users to assign exact numerical values to an expressed opinion. A more realistic alternative is to use linguistic terms instead of numerical assessments [31,32,37,38]. The linguistic terms used to represent imprecise assessments for decision problems are expressed as fuzzy sets [14]. They are qualitative descriptions but are treated as fuzzy sets for computational purposes. The linguistic terms can be expressed as a 5-tuple, the parameters of which can be subjectively defined by the domain expert.

2.2. Recommender systems

A recent survey of state-of-the-art recommender systems classifies them into collaborative, content-based and hybrid approaches depending on how the recommendations are made [15].

Collaborative filtering is widely used and is the preferred method for personal recommendation [1,16–18,30]. CF algorithms can also be divided into two main categories: user-based and item-based [15]. Both recommendation approaches are designed for items that people with similar tastes and preferences have liked in the past [4,5,22]. This technique has been adopted by many well-known systems, such as that of Amazon.com [16], Sarwar [25], Hofmann [19], and GroupLens [24].

The CF algorithm procedure can typically be divided into three steps [13,14]. First, the system forms a neighborhood for the active user or item based on the similarity value, which is usually defined by different similarity measures such as cosine, Pearson correlations and so on. Next, the prediction for the active user is derived using a weighted combination calculation of selected neighbors' ratings. Finally, the system filters the top N recommendations from a list in descending order of predications.

According to Breese et al., algorithms for making collaborative recommendations can be grouped into two general classes: memory-based and model-based [2]. Memory-based algorithms are heuristics that make ratings predictions based on the entire collection of items previously rated by users. Model-based algorithms construct a model from collected ratings. The model is then used to make ratings predictions.

2.3. Fuzzy recommender system

The core idea of Yager's proposed content-based recommender framework is to adopt content gleaned using fuzzy set methods [10,32]. The framework was just a prototype showing how to adopt a fuzzy model within the recommender system. It was assumed that each object can be appropriately represented as a fuzzy scheme after which an appropriate tool to calculate the similarity relationship for the set of objects can be developed. A different approach is to use fuzzy values to represent the attributes of an item. Zenebe proposed a new approach based on the concepts of Yager which used item features such as background knowledge and user feedback as input [37]. Recently, several research studies have utilized fuzzy modeling to develop recommender systems to retrieve recommendations. In order to facilitate consumer decision making, the recommendation methodologies are based on the users' current needs obtained from system–user interactions [3–5,10,22,28,30,35].

3. Problem statement and definitions

In this section, we describe the problem encountered with fuzzy recommender system, present some definitions and discuss an example. Section 3.1 introduces the fuzzy recommender system. In Section 3.2, we formally define the important components of the recommender system. Finally, an example is given to illustrate the proposed definitions and the fuzzy linguistic approach.

3.1. Problem description

Let $U = \{u_1, u_2, \ldots, u_m\}$ and $I = \{i_1, i_2, \ldots, i_n\}$ denote all users and the set of all distinct items, respectively. The domain expert is a subject user denoted by u_s. The active user is u_a. Neighborhood, *Neighbor* (u_a), is a set of users similar to the active user u_a. The objective users belong to the set of *Neighbor* (u_a). The purpose of the proposed framework is to aggregate both the subject user's and the objective users' preferences in order to make prediction