

A Novel Fuzzy Recommendation System Integrated the Experts' Opinion

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Abstract—Collaborative Filtering (CF) has been applied to many commercial systems successfully, such as IMDB, Netflix and son on. The basic idea of a CF system is to generate recommendations based on the experiences of past similar users. The users' option can be categorized into objective and subject information. The former was furnished by the common users and the later represents solicit opinions provided by experts (such as film critics). Both information types are valuable and important for the CF system. This study attempts to propose a novel collaborative filtering framework based on fuzzy set theory which integrates the subjective and objective information. The new methodology not only provides a comprehensive result but also solve the problems of traditional CF system, new user and new item. Finally, an experiment is performed, and the result indicates that the proposed methodology produces high-quality recommendations.

Keywords- Data mining, recommender system, collaborative filtering, fuzzy set theory, objective evaluation, subjective evaluation

I. INTRODUCTION

E-commerce (EC) has been growing rapidly in the last decade. More and more items, however, result in an information overloading problem. In other words, consumers have to browse a huge of product lists to determine their final needs. In response to the above issue, an idea of the online product recommendation systems is proposed to assist customers for reducing these redundant information and offer advice to find suitable products for facilitating online decision-making [9, 15].

Generally, the study of recommender systems can be divided into three categories: (1) content based recommendation, (2) collaborative recommendation and (3) hybrid approaches [1]. Collaborative filtering (CF) is the most successful technologies among the above-mentioned systems and has been applied in many applications such as Amazon.com, Netflix, and MovieLens [8, 14, 15]. Basically, the idea of CF is to provide the users the recommendation based on their personal profile of previous rentals and the rentals of other similar customers. That is, the CF systems use historical data on user preferences or behavior to predict how new/old users will act.

The recommender system is the most useful way to help consumers to purchase products in an EC system. The

information generated from the experiences of past similar users in a traditional recommender system is called the objective information. This kind of information does not include the influence of domain experts or opinion leaders on the customers' purchasing decision. Consider the following scenario: someone goes to see a movie on Saturday; he will check the film review from many difference ways, such as: Yahoo movie and IMDB. Because the influence of domain expert on consumers is self-evident, it will be better if the opinion from domain expert can be involved in the recommender system. Therefore, this research proposes a new integrated approach, which combines the subjective and objective information to generate recommendations for an active consumer. The subjective information solicits opinion from domain experts or option leaders [5, 12, 22]. The objective information clarifies the active user's preference based on the similar users' preference or the perdition from his past experience.

There are some common limitations in the traditional CF systems: (1) the new user, (2) new item and (3) sparsity problems [1]. They may cause the system to provide the lower quality recommendations. Therefore, this study attempts to propose a novel recommendation methodology which aggregates both the subjective and objective information to recommend items to address these limitations. In addition, if a user's preference to be provided in systems is not sufficient, the proposed method still can give recommendations from the subjective information.

Also noted herein, most previous methods are based on users' ratings which suffer from the effects of personal differences in scoring behavior. Generally, assessing users' preference by assigning precise values (rating) is difficult for users. Therefore, a fuzzy linguistic assessment (called fuzzy set theoretic method, FTM) is adopted in the proposed methodology. Linguistic assessment is based on words rather than numbers. This assessment can approach human perception, making it easier to evaluate qualitative problems [8, 20].

The proposed approach has the following two major advantages for recommender systems. First, the proposed algorithm aggregates the subjective and objective information to generate recommendations. The processing of opinion merged is more natural for the consumer decision process.

Second, we present a new idea by applying the fuzzy linguistic model. Use of linguistic terms to present human beings' mind is a better way to understand the users' preference.

This paper is organized in the following sections. First, this study will formally define the problem in Section 2 and propose the algorithms in Section 3. Then, we evaluate the effectiveness of the proposed methods in Section 4. Finally, conclusions and valuable discussions are stated in Section 5.

II. RELATED WORK

In a recent survey of state-of-the-art recommender systems they can be classified into collaborative, content-based and hybrid approaches. The classification is dependent on how recommendations are made.

Collaborative filtering is widely used and is the preferred method for personal recommendation. Recommendations are made for items that people with similar tastes and preferences have liked in the past. Many systems, such as that of Amazon.com [13], Sarwar [14], Hofmann [11], and GroupLens [16], have adopted this technique.

CF algorithms can be divided into two main categories [1]: User-based and Item-based. The former combines the similar users' previous preferences to make rating predications. The later is to compute the similarity between items, and then selects the most similar one.

The basic purpose for the CF algorithm is to generate recommendations from the experiences of past similar users. Most CF-based algorithms recommend items for users based on the nearest-neighborhood method [7, 10, 11]. A typical nearest-neighborhood procedure can be separated into three steps. The first step is to determine a neighborhood for the active user or item through the similarity value, which is usually defined by the Pearson correlations. Then, a prediction is calculated from a weighted combination of selected neighbors' ratings for the active user or given item. Finally, a descending sorted list is made from these predications. Recommendations are generated by choosing the top N items on this list.

Yager gives a methodology for using fuzzy set methods to represent the content knowledge in a content-based recommender system[18]. He assumes the availability of a representation scheme for each object that allows the development of an appropriate tool to calculate the similarity relationship for the set of objects. A different approach is to use fuzzy values to represent the attributes of an item. The proposed recommendation strategies are purely content-based. Zenebe followed the concepts of Yager to propose a new approach which uses items features such as background data and user feedback as input [22].

III. PROBLEM STATEMENT AND DEFINITIONS

A. Problem Description

Let $U = \{u_1, u_2, \dots, u_m\}$ and $I = \{i_1, i_2, \dots, i_n\}$ denote all users and the set of all distinct items, respectively. A preference function, $P_{u_i}(i_p)$, represents user u_i 's preference for the item i_p . The active user is defined as u_a and the domain expert can be a subjective user denoted us. The goal of this study is to propose new algorithms which aggregate both the subjective and the objective information to make prediction for unrated items. After having the predicted information, the top- N recommendations will be derived for the active user.

B. Problem Definitions

1) User's Preference Representation Using Fuzzy Set

As stated previously, it is nature for users to assess their preference function based on words rather than numbers [2, 4, 22]. The preference function can be defined by a linguistic term. The semantic meaning of each term can be quantified by fuzzy numbers.

The preference function illustrates user u_i 's preference for the items i_p . The number of users is m and the number of items is n . The preference function $P_{u_i}(i_p)$ is determined as follows:

$$P_{u_i}(i_p) = \langle q_{ip}^1, q_{ip}^2, q_{ip}^3, q_{ip}^4, q_{ip}^5 \rangle, \quad (1)$$

$$q_{ip}^k \in [0,1], \quad 1 \leq k \leq 5, \quad 1 \leq i \leq m, \quad 1 \leq p \leq n$$

In Eq. (1), $\langle q_{ip}^k \rangle$ denotes 5-tuples used for the user u_i preference degree on item i_p by mapping the linguistic terms listed in Table 1. As shown in Table 1, the linguistic terms "highly recommend", "very like", "like", "somewhat like", "no comment", "somewhat dislike", "dislike", "very dislike" and "hate" are used to represent the degree of user's preference in this study.

TABLE I. THE MAPPING OF LINGUISTIC TERMS AND 5-TOUPLES.

Linguistic term	5-tuples
highly recommend	$\langle 1, 0, 0, 0, 0 \rangle$
very like	$\langle 0.8, 0.2, 0, 0, 0 \rangle$
like	$\langle 0.3, 0.6, 0.1, 0, 0 \rangle$
somewhat like	$\langle 0.1, 0.5, 0.4, 0, 0 \rangle$
no comment	$\langle 0, 0.25, 0.5, 0.25, 0 \rangle$
somewhat dislike	$\langle 0, 0, 0.2, 0.6, 0.2 \rangle$
dislike	$\langle 0, 0, 0.1, 0.7, 0.2 \rangle$
very dislike	$\langle 0, 0, 0, 0.2, 0.8 \rangle$
hate	$\langle 0, 0, 0, 0, 1 \rangle$
NULL	$\langle 0, 0, 0, 0, 0 \rangle$

For example:

If user u_a likes item 1 very much, we may set $P_{u_a}(i_1) = \text{"very like"} = \langle 0.8, 0.2, 0, 0, 0 \rangle$. In other words, $P_{u_a}(i_2)$ will be NULL if user u_a does not provide rating for item 2.

2) Similarity Measure

The user's preference function is expressed by a fuzzy number. The Euclidean fuzzy near compactness is widely used to assess the distance of similarity between two fuzzy numbers. While the Euclidean near compactness is close to 1, the degree of similarity becomes higher.

The preference function of user u_i and u_j can be expressed as $P_{u_i}(i_p) = \langle q_{ip}^1, q_{ip}^2, q_{ip}^3, q_{ip}^4, q_{ip}^5 \rangle$ and $P_{u_j}(i_p) = \langle q_{jp}^1, q_{jp}^2, q_{jp}^3, q_{jp}^4, q_{jp}^5 \rangle$

The similarity $S_{u_i, u_j}(i_p)$ between u_i and u_j for the item i_p is defined as Eq. (2).

$$S_{u_i, u_j}(i_p) = 1 - \frac{1}{\sqrt{5}} \left(\sum_{k=1}^5 (q_{ip}^k - q_{jp}^k)^2 \right)^{1/2} \quad (2)$$

For example: if user u_a likes item 1 very much, we may set $P_{u_1}(i_1) = \text{"very like"} = \langle 0.8, 0.2, 0, 0, 0 \rangle$. In other words, $P_{u_2}(i_1) = \text{"like"} = \langle 0.3, 0.6, 0.1, 0, 0 \rangle$

$$S_{u_1, u_2}(i_1) = 1 - \frac{1}{\sqrt{5}} \left(\sum_{j=1}^5 (0.8 - 0.3)^2 + (0.2 - 0.6)^2 + (0 - 0.1)^2 + (0)^2 + (0)^2 \right)^{1/2} = 0.71$$

The average degree of similarity $S(u_i, u_j)$ between u_i and u_j is defined as

$$S(u_i, u_j) = \frac{\sum_{q=1}^{|Z|} S_{u_i, u_j}(i_q)}{|Z|}, \quad (3)$$

where Z is the set of items for which users u_i and u_j provide ratings simultaneously and $|Z|$ is the number of items.

3) Generate The Prediction for Unrated Item

Once the neighbors are found, we can combine the preference value of neighbors to compute a prediction value on unrated items for the active user. The influence of different neighbor will not be equal. The following weight function denotes the influence of user u_j on the active user u_a . It is expressed as:

$$w_{u_j, u_a} = \frac{S(u_j, u_a)}{\sum_N S(u_k, u_a)} \quad (4)$$

As shown Eq. (4), each neighbor should be weighted by the similarity value. The higher similarity value between a neighbor and the active user will cause the larger weight to account for the prediction value. Therefore, we can derive a weight vector W^a based on the normalized similarity from neighbors.

To generate the prediction for the active user's preference degree on item i_p , the process can be implemented through the composition matrix operation $W^a \circ E^a$. The matrix E^a , called evaluation matrix, contains the linguistic term of each neighbor's preference.

Let the number of neighbors be n . The prediction for the preference of u_a for item i_p is defined as follows:

$$\begin{aligned} Y^a &= W^a \circ E^a \\ &= [w_1^a \quad \dots \quad w_n^a] \circ \begin{bmatrix} P_{u_1}(i_p) \\ \vdots \\ P_{u_n}(i_p) \end{bmatrix} \\ &= [w_1^a \quad \dots \quad w_n^a] \circ \begin{bmatrix} q_{kp}^1 & q_{kp}^2 & q_{kp}^3 & q_{kp}^4 & q_{kp}^5 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ q_{kn}^1 & q_{kn}^2 & q_{kn}^3 & q_{kn}^4 & q_{kn}^5 \end{bmatrix} \\ &= [y_1^a \quad \dots \quad y_n^a] \end{aligned} \quad (5)$$

Where $y_j^a = (w_j^a \bullet q_{kp}^1) \oplus \dots \oplus (w_j^a \bullet q_{kn}^5)$ and " $\bullet$ ", " $\oplus$ " are defined as algebraic product ($a \bullet b = ab$), bounded sum ($a \oplus b = \min\{1, a + b\}$), respectively.

For example, Let the weight vector W be $[0.36 \ 0.33 \ 0.31]$ and the preference matrix of item i_p be expressed as:

$$E = \begin{bmatrix} 0.8 & 0.2 & 0 & 0 & 0 \\ 0.6 & 0.3 & 0.1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Finally, user u_a 's preference for item i_p can be conducted

$$\begin{aligned} Y &= W \circ E = [0.36 \quad 0.33 \quad 0.31] \circ \begin{bmatrix} 0.8 & 0.2 & 0 & 0 & 0 \\ 0.6 & 0.3 & 0.1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix} \\ &= [0.796 \ 0.171 \ 0.033 \ 0 \ 0] \end{aligned}$$

The proposed system will recommend item i_p for user u_a .

A defuzzification process is necessary in order to generate a ranked list of recommendations for the active user u_a . There are several defuzzification methods, such as center of gravity, center of sum, maximum method and so on. The most popular is the center of gravity method which can be defined as follows:

$$y^* = \frac{\sum_{i=1}^5 y_i^a \times (5 - i + 1)}{\sum_{i=1}^5 y_i^a} \quad (6)$$

If the defuzzification value y^* of the prediction for item i_p is larger than 4, the framework will put the item i_p into the recommendation list.

IV. SOLUTION FRAMEWORK

This section details the proposed algorithm which is similar in spirit to the classical memory-based CF approach. To model the users' perceptions of preference, the system defines nine linguistic terms shown in table 1 to represent the degrees of preference. Each user has his/her own perception of the approximate value of each linguistic term. The proposed framework is illustrated in Fig. 1.

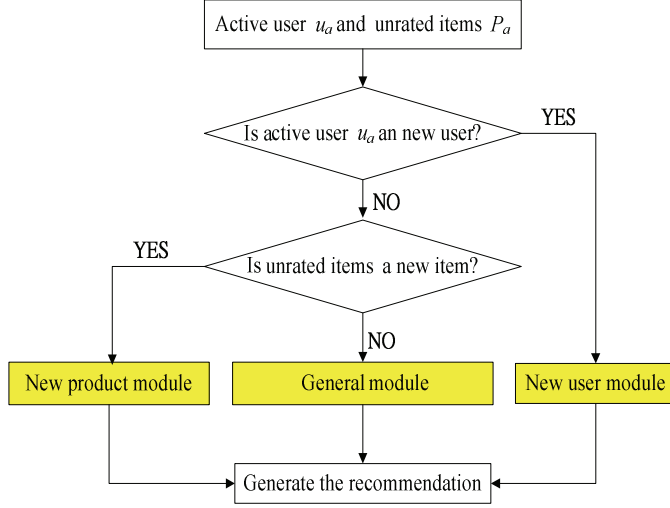


Figure 1 The flowchart of the proposed framework.

Fig. 1 shows the flowchart of the proposed framework. When the active user is an old user and the unrated item has been rated by other users, the framework will use the general module to make prediction. If the active user is an old user and the unrated item is new, the system will use the new item module. However, if the active user is a new user, the system will furnish the subjective information to make a prediction. We will explain each step in detail as follows.

A. New Product Module

New products are added regularly to recommender systems. When the new product launch, some domain experts will write the product review. For example, when a new movie launch, there are some film review written by famous film critic. To calculate the similarity between the active user and the subjective user, the result will demonstrate whether the active user like mainstream films. We compute the average similarity $S_{u_s, u_a}(i_q)$ between subjective user u_s and u_a for the item i_q based on Eqs. (2) and (3). Then the proposed algorithm will use Eqs. (4) and (5) to predict the value.

B. New User Module

For users that are new to the recommender system, information about their preferences is initially unknown. We can furnish the subjective user's information to the new user.

C. General Module

There are four steps in this module. The nearest-neighbor technique and user-based approach are applied to find the users similar to active user u_a . Neighborhood, $Neighbor(u_a)$, is a set of users who are similar to u_a . The aggregated

information from all neighbors' preference could be represented as the objective users' opinion. The proposed algorithm will make prediction based on the aggregation of objective and the subjective users' information.

Input:

Set of items: I , Set of users: U , Subjective user: u_s , Active user: u_a
 Subjective users' preference, objective users' preference
 Active user's preference, Set of unrated items for u_a : P_a

Output: Top N recommendations

Method:

// Subjective module

for each $u \in U$

Use Eq. (3) to compute average degree of similarity $S(u, u_s)$

According to the average similarity $S(u, u_s)$, we rank all users into a rank list RL

// Objective module

Based on $S(u_a, u_s)$ and choose $k+v$ nearest neighbors from RL to $Neighbors$

for each $u \in Neighbors$

Use Eq. (3) to compute average degree of similarity $S(u, u_a)$

Select the best k nearest neighbors from $Neighbors$ to $Neighbor(u_a)$

Use Eq. (4) to compute the weight of influence in $Neighbor(u_a)$

Construct a weight vector W^a

Call Generate the predictions and recommendations procedure

■ Subjective Procedure:

The subjective procedure is a preprocessing phase, a special procedure in the proposed algorithm. This job is usually performed offline and the results are stored in a database. Let the subjective user be denoted by u_s . When we input one user's preference data, the system automatically computes the average similarity between this user and subjective user using Eq. (3). We will generate a ranking list which contains all users, based on the average similarity between each user and the subjective user.

■ Objective Procedure:

(1) Creating Possible Neighborhoods for an Active User u_a

According to the similarity between the active user and the subjective user $S(u_a, u_s)$, the system filters the nearest $k + v$ neighbors to a temporary buffer $Neighbors$. Eq. (3) will be used to compute the average degree of similarity of each user to the active user. Next, we choose the best k nearest neighbors to form $Neighbor(u_a)$. We use Eq. (4) to compute each user's weight of influence in $Neighbor(u_a)$ and then determine a weight vector W^a based on the normalized similarity of the neighbors.

(2) Compute the Influence for Each User in $Neighbor(u_a)$

Once the best k neighbors are found, we can aggregate the preference value of neighbors to compute a prediction value for unrated items for the active user. Evaluators may want to assign some level of importance when the top k users'

information is considered. The influence of different neighbors will not be equal. Therefore, we determine a weight vector W^a based on the normalized similarity of neighbors from Eq. (4). The evaluation matrix E^a contains a linguistic term for each neighbor's preference.

(3) Generate the Predictions and Recommendations Procedure

The process of generating a prediction for item i_p can be implemented through the composition matrix operation $W^a \circ E^a$. The result is a fuzzy vector giving user u_a preference for item i_p . The prediction for u_a 's preference for item i_p is defined as

$$Y^a = W^a \circ E^a.$$

The prediction y^* is a fuzzy number which should lead to defuzzification by Eq. (6). After predicting all the unrated items, the top N recommendations, a set of ordered items with a higher predicted value is identified.

V. EXPERIMENT EVALUATION

To evaluate the performance of the proposed model, we collected preference data about movies from IMDB. One hundred different movies from IMDB are collected for 618 users. Therefore, the dataset consisted of ratings from 618 users on 100 items. The subjective information is the film review from Yahoo! Movies. Four popular metrics are adopted to evaluate the effectiveness of recommendations in this study. Precision is defined as the ratio of relevant items selected to number items selected. It can be expressed as follow :

$$precision = \frac{\text{recommend items that are relevant}}{\text{total recommend items}} \quad (7)$$

Recall represents the probability that a relevant item will be selected. It can be expressed as follow :

$$recall = \frac{\text{relevant items that are recommended}}{\text{total known relevant items}} \quad (8)$$

F1 combines precision and recall into a single number. It can be expressed as follow :

$$F1 = \frac{2 \times precision \times recall}{(precision + recall)} \quad (9)$$

Mean absolute error (MAE) measures the average absolute deviation between a predicted rating and the true one. It can be expressed as follow :

$$E = \frac{\sum_{i=1}^N |p_i - r_i|}{N} \quad (10)$$

where N is the number of all items; p_i and r_i represent the predicted rating and the true rating, respectively.

In this experiment we evaluate the effect of neighbor size with the proposed algorithms. It is useful to select a subset of users to use in computing prediction instead of the entire user database. We compare the accuracy of the proposed algorithms based on two kinds of datasets, rich and sparse. The results are shown in Figs. 2, 3, 4. In these figure, the x -axis and y -axis represent the size of the neighborhood and the measures of accuracy, respectively. The size of the neighborhood will be 5, 10, 15, 20, 25 or 30. An examination of the results in these figures indicates that the best performance will be met when the size of the neighborhood is fifteen.

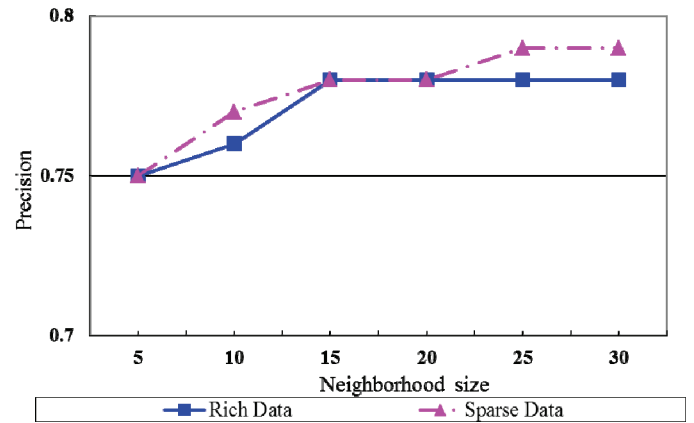


Figure 2 Precision for the proposed algorithms as neighborhood size grows.

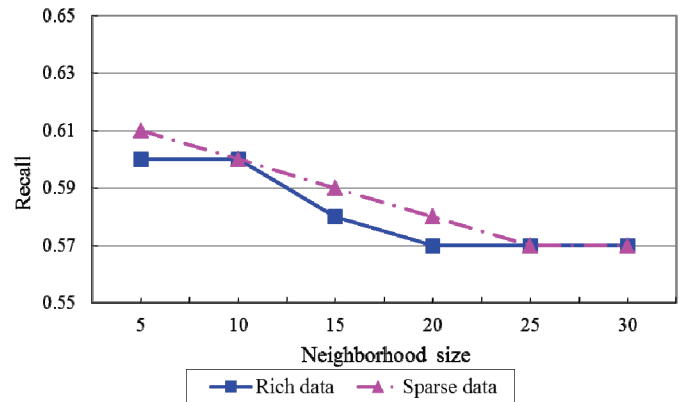


Figure 3 Recall for the proposed algorithms as neighborhood size grows.

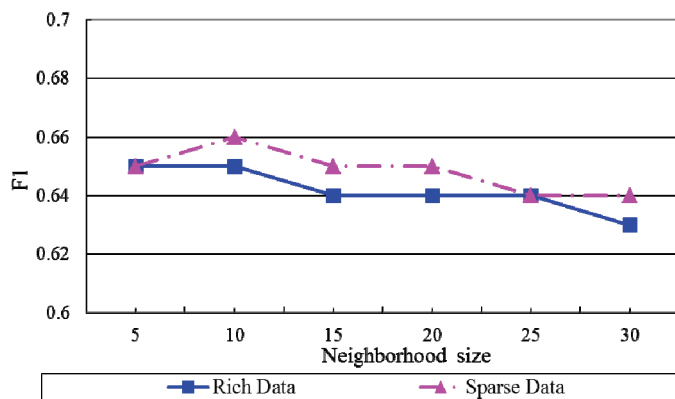


Fig. 4 F1 for the proposed algorithms as neighborhood size grows

There is no significant difference in the accuracy of the proposed algorithm between the sparse and rich dataset, as illustrated in Figs. 2, 3 and 4. When the users' preferences are insufficient (sparse dataset), most recommender systems suffer from neighbor forming bias so that those neighbors are not really similar to the active user. However, the accuracy of the proposed algorithm is not influenced by the sparsity problem. We also observe that the subjective module plays an important role. This is because the subjective user's information is always sufficient. The similarity between the subjective user and active user is always reliable.

VI. CONCLUSION

Traditional CF methods suffer from some limitations which are new user, new item and sparsity. This study proposes a novel CF framework based on fuzzy set theory. The proposed algorithm which combines the subjective and objective information can overcome the limitations. Experimental results show that the proposed method not only can provide reasonable recommendations as traditional CF methods, but also can solve the traditional limitations.

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