Contribution to Collaborative Filtering Based on Soft Computing to Enhance Recommender System for e-Commerce

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Abstract: Recommender Systems (RSs) are used by an ever-increasing number of e-commerce sites to recommend items of interest to the users based on their preferences. Collaborative filtering is one of the most regularly used techniques in RSs that help the users to catch the items of interest from a massive numbers of available items. This technique is based on the idea that a set of like-mind users can help each other to find valuable information. The major challenge in recommender systems is that the user ratings or grades are very often uncertain or vague because it is based on user's tastes, opinions, and perceptions. Fuzzy sets appear to be a proper paradigm to handle the uncertainty and fuzziness of human decision making activities and to successfully model the normal sophistication of human behavior. Because of these motives, this paper adopts type-2 fuzzy linguistic approach to efficiently describe the user ratings and weights to precisely rank the relevant items to a user. The proposed method permits users to express their ratings in qualitative form, converts such preferences to their corresponding quantitative form using the concept of type-2 fuzzy logic, maps the values that represent the preferences with the retrieved items from the database, and finally recommends products that best satisfy the consumer's likings. Empirical evaluations show that the proposed technique is feasible and effective.

Key words: Collaborative filtering, multicriteria decision making, type-2 fuzzy linguistic, recommender systems.

1. Introduction

Now, with the rapid growth of the Internet, the explosive evolution and variety of information available on the Web and the accessibility of a large amount of products for sale in e-commerce sites, have led to information overload problem; consumers have to spend more time glancing the Net in order to find the information needed, and it has also become very difficult for customers to attain the most suitable choices from the massive variety of products leading them to make poor decisions. So, developers found a solution in Recommender Systems (RS). RSs have proven in recent years to be a valuable means for coping with the information overload problem and to provide recommendations of products likely to interest a user [1]. This technique is generally used in e-commerce to advise items that a customer is assembly going to buy [1]. For another point of view, RS is a platform that can be used to diminish the searching cost of customers and improve customer's loyalty.

The orientation toward the presentation of personalized item-subsets differentiates RS conceptually from similar processes such as internet filtering [2], with the RS drawing on a number of user-specific explanations in order to make personalized recommendations. Since their inception, the use of RS has extended quickly with existing applications that recommend movies, web-pages, news articles, medical treatments, music, and other products [3], [4]. Prevalent purchasing sites such as Amazon (www.amazon.com) and eBay (www.ebay.com) exemplify some of the businesses that have joined recommendations into their shopping experience. Recommender systems used in e-commerce are targeted marketing methods, which rely on historical experiences to increase the sales of products.

One of the major problems of RSs is the problem of the system's stability compared to the user's profile dynamicity (Dynamicity vs. Plasticity Problem) [1]. This problem comes from the system's inability to track the user's behavioral evolution, because in RSs once a user's profile has been established, it is difficult to change it. The other relevant challenges are the sparsity and first rate problems. The sparsity problem refers to the number of recommendations made by customers. This problem occurs when the number of items rated is small compared to the total number of items. First rate problem refers to a product that can be the subject of a recommendation only if another user has earlier rated it [3].

RSs are built generally based on two different types of methods that are Content Based Filtering (CBF) and Collaborative Filtering (CF) [1]. The CBF approach creates content recommendations based on the characteristics of users or items. This system does not need data of other users and able to recommend an item to users with unique taste, i.e., CBF is able to recommend new and unpopular item to each user. But the main disadvantage of CBF is hard for the system to adapt to changes in the user's preferences [5].While the CF method just use the evaluations made by users on the items to guess the unknown ratings of new user-item pair.

Collaborative Filtering has some advantages such as it does not want a description of items in terms of features, but it is based only on the judgment of participating users' community. CF can recommend items based on quality or experience and can provide unexpected recommendations, i.e. it can recommend items that are relevant to the user, but do not contain content from the user's profile. Because of these reasons, CF system has been used fairly successfully to build recommender systems in various domains [6]-[8]. To improve the recommendation quality, scholars are conducted toward hybridization between CF and a CBF to enhance the CF accuracy in recommender systems in order to deal with the sparsity and scalability problems [1].

With the hot development of Web2.0, many CF algorithms are designed to integrate social or trust information. The more widely used techniques are [1], [6], [9]: memory (user)-based, and model(item)-based. These techniques use a calculation of similarities between individuals (memory-based) or items (model-based). Memory-based schemes calculate locality formations using the user-item matrix, which covers the ratings of items by user. Nevertheless, users have no obligation to provide their opinion on all items. In the model-based CF algorithm, a set of items ranked by the active user is used to compute similarities between these items and a target item to select the most similar items. The sparsity is more problematic for memory-based collaborative methods, because it may not be feasible to obtain sufficient ratings from users of a system. Model-based methods decrease the faults derived from sparsity; nevertheless it still needs to have a certain smallest number of ratings in order to build an estimation model of ratings.

In CF, the most common representation of preferences is under the form of utilities, i.e. quantitative votes (ratings) provided by users about the items. The recommender estimates the votes of the users on the items they have not seen. However, choosing a rating is no easy task for any user; the rating scale is usually reduced and the rating values given by the users may be influenced by many factors [2], [5]. Based on the drawbacks resulting from the use of votes to express user preferences, many systems propose to exchange utility functions by preference relations. In this case, the user is not inquired to vote for resources but to express a qualitative interest about the resources he/she has already seen[3], [4]. Moreover, most recommender system techniques entail user explicit expression of personal preferences for items (need user interaction). Nevertheless, methods have been built for obtaining ratings implicitly in order to add more ratings and reduce sparsity [10]. However, even with the use of up-to-date methods (including data mining methods), sparsity still remains a critical drawback for recommender systems due to the extensive number of items available.

In the literature, most of the studies use user-item ratings matrix with single ratings. However, keeping ratings in multiple aspects (criteria) of items give more information about the user's preferences [11]-[13]. Therefore, taking the broad benefits of the multicriteria ratings in personalization applications to improve the quality of the recommendation is one of the motivations behind this work. However, the information about ratings and weights provided by the user is usually incomplete because that the increasing complexity of the socio-economic environment makes it less possible for the user to consider all relevant aspects of a problem. How to utilize the fuzzy decision matrix to find the most desirable alternative(s) is an interesting and important issue, which is worth paying attention to [14], [15].

Despite being effectively used in many domain areas, high order fuzzy logic is not widely employed in recommendation systems. However, they can help to minimize, or even solve, typical drawbacks of such systems. Fuzzy logic provides high-value properties to recover items stored in a database and, as a consequence, to provide recommendations for users, because fuzzy sets have the ability to manage concepts such as similarity, preference and uncertainty in a unified way and they also have the aptitude to perform rough reasoning. Thanks to such advantages, particularly for uncertainty, fuzzy logic can help to minimize the sparsity problem, which is the main drawback current recommender systems suffer from [9].

In this article, we investigate the recommendation problem in which all the information provided by the user whether ratings or attribute's weights are expressed as ratings matrix where each of the elements is characterized by interval type-2 fuzzy set (IT2FS). If we can use IT2FSs for handling fuzzy decision-making problems, then there is room for more flexibility due to the fact that IT2 FSs provide more flexibility to present uncertainties than traditional T1FSs [16]. Similar to the transition from ordinary sets to type-1 fuzzy sets (T1FSs) when the circumstances are so fuzzy that we have trouble determining the membership grade even as a crisp number in [0, 1], we use T2FSs.

The rest of the paper is organized as follows: Section 2 briefly discuses some of the research related to recommender systems. The proposed model is described in Section 3. The experimental result and evaluation of the proposed system are given in Section 4. Finally in Section 5 the conclusion and future research directions are presented.

2. Literature Review

Regardless of the existence of different methods, including data mining techniques, available to be used in recommender systems, such systems still contain numerous limitations. They are in a continuous need for personalization in order to make effective suggestions and to provide valuable information of items available [1]. A way to reach such personalization is by means of another data mining technique called classification based on association, which uses association rules in a prediction viewpoint. In spite of being generally the most efficient approach for recommender systems, model-based collaborative methods also present some shortcomings as well as content-based based methods. As a result, current approaches for recommender systems do not hire merely one type of method. Typically, current approaches are likely to employ concepts from both categories of methods in order to take benefit from the strengths of each of them [3], [12].

Although traditional CF models have been successful in many recommendation systems, they all have to face several critical problems: data sparsity, scalability, and cold-start. To alleviate the sparsity problem, many matrix factorization models are used, such as the Singular Value Decomposition (SVD) and Maximum Margin Matrix Factorization (MMMF) [1], [6]. These models reduce the dimensions of the user-item matrix and smoothing out the noise information, which is also helpful to algorithm scalability. The academics in [7] extend traditional clustering CF models by co-clustering both users and items into multiple subgroups, and use them to improve the performance of CF-based recommender systems. Using subgroups is a promising way to further improve the top-N recommendation performance for many popular CF methods.

Multi-Criteria recommender systems are gaining widespread attention from both research and industry. In [15] a hybrid methodological framework was proposed that combines techniques from the field of multiple criteria decision analysis and more specifically from the disaggregation-aggregation approach to model user's preferences, together with the CF technique from the field of recommender systems, to identify the most preferred unknown items for every user. Another related work in [12], where the authors presented the concept of preference lattice for user clustering. This lattice is instantiated through: (a) an aggregation function of the criteria, (b) using the total item ratings for the recommendation, rather than the rankings of each criterion, and (c) combining clustering with the CF. F. Ricci *et al.* [4] developed a recommender system for personalizing travel using case-based reasoning techniques. The recommendations are performed by ranking and aggregating elementary items (locations, activities, services) based on the user's preferences and a repository of past travels. Many other aggregation functions which would carry adaptability towards more relevant recommendations are often approved. Such functions can model various interactions between the inputs and mixed behavior [10].

There are some works that employed fuzzy logic for handling the graded/uncertain information in recommender system. For example, in [17] the authors suggested a conceptual framework for recommending one-and-only items. They used fuzzy logic, which allows reflecting the vague information in the domain. Furthermore, fuzzy near compactness (FNC) concept is employed to measure the similarity between consumer needs and product features in order to recommend ideal products to potential buyers. In [18] a fuzzy linguistic approach is proposed to capture the uncertainty in user preferences in a knowledge-based recommender system. In [9], the authors presented a fuzzy recommender system based on collaborative behavior of ants (FARS). FARS worked in two phases: modeling and recommendation. First, user's behaviors are modeled offline, and the results are used in second phase for online recommendation. This system utilizes both of ACO and fuzzy logic to prepare the high potential and suitable promoting recommendations for active user.

One of the well-known methods in multi criteria decision making (MCDM) is technique for Order Preference by Similarly to Ideal Solution (TOPSIS) [14]. The basic concept of this method is that the selected alternative should have the shortest distance from the positive-ideal solution and the farthest distance from the negative-ideal solution. Fuzzy Technique for TOPSIS is one of the most commonly used approaches in solving numerous MCDM problems. Recently, fuzzy TOPSIS has been merged with interval type-2 fuzzy sets and subjective weights for criteria to handle the wide arrays of vagueness and uncertainty. However, the role of objective weights in this new interval type-2 fuzzy TOPSIS has given noticeably less attention. Scholars in [19] presented a new method for handling fuzzy multiple criteria hierarchical group decision-making problems based on arithmetic operations and fuzzy preference relations of IT2FSs.

Due to the two major challenges for the CF based recommender systems, which are the scalability and sparsity problems, the application of traditional fuzzy algorithm can confront some difficulties. From this point, our goal is to design an efficient CF algorithm that uses preferences of similar learners (neighbors) to predict the active learner's preferences, then, generating diversified recommendations that meet their needs according to his preferences membership degrees to improve their top-N recommendation performance. These membership values can be obtained in the CF phase by applying the type-2 fuzzy logic where all the information provided by the users is characterized by IT2FSs that are well suited to deal with imprecision and vagueness. Results revealed that such techniques can be applied effectively in recommender systems; minimizing the effects of typical drawbacks of the fuzzy –based CF that is less capable of handling the linguistic uncertainties.

3. Proposed Type-2 Fuzzy Recommender System

This part contains our novel CF algorithm that combines a model-based collaborative filtering algorithm with type-2 fuzzy logic one to alleviate the preferences' vagueness problem of recommender systems, model the variations in human decision making and subsequently enhance recommendation's quality and effectiveness. The schema of the proposed system is shown in Fig. 1. As the collaborative filtering approach was originally based on nearest neighbor algorithms, the recommended products will be the ones that have been liked by users with similar interests to the new user, who is commonly referred to as active user. We first use the T2 fuzzy rating and weighted arithmetic averaging operator to aggregate all individual T2 fuzzy decision matrices provided by the user, then we calculate the ranking value of each item's attribute or aspects and construct the ranking-value matrix of the collective T2 fuzzy decision matrix.

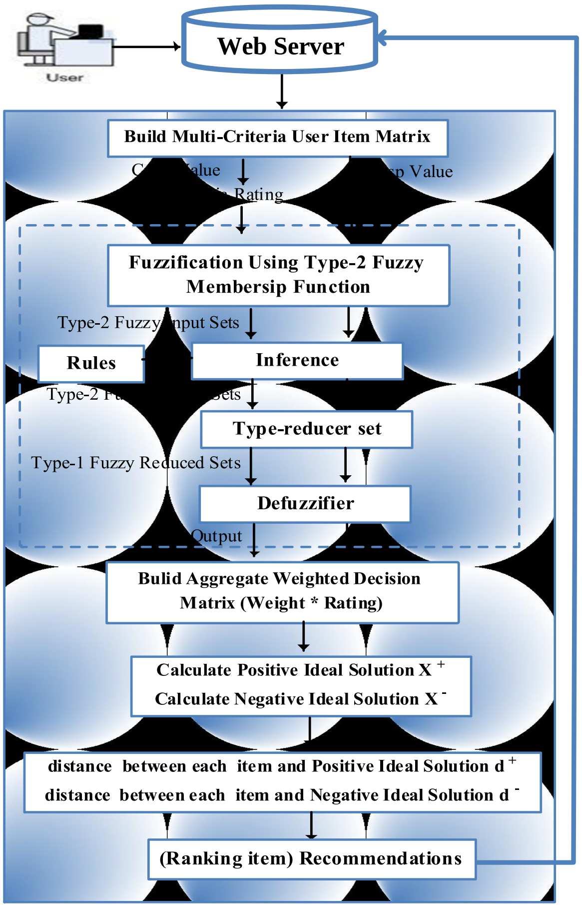


Fig. 1. The proposed type-2 fuzzy-based recommender system.

3.1. Build Multicriteria User Item Matrix

With a growing number of real-world applications, extending recommendation techniques to incorporate multi-criteria ratings has been regarded as one of the important issues for the next generation of recommender systems. Multicriteria ratings offer more information about user's preferences from different aspects of an item and lead to more accurate recommendation than a single-rating system [11]. In multicriteria recommender systems, the user-item ratings matrix contains user ratings on items in multiple aspects (criteria), weights for each criterion and then recommend to the users the items based on the multicriteria ratings provided by others users. For example, the single user rating for music gives the general user preference on that music. However, the multicriteria ratings of a music such as ratings for music, lyric and voice provide in-depth knowledge about the user preferences on that music. In a view to make the user task easier, it thus seems pertinent to investigate the use of preference relations for recommender systems [12].

One of the important steps in fuzzy recommender system is defining weights [15]. In general, weights can be divided into two types, which are subjective and objective. Subjective weight can be obtained based on information of the attributes from the decision makers through questionnaires, interviews or trade-off interrogation directly. This subjective weight can reveal the strength of decision makers' judgment. On the other hand, objective weight can be acquired from the objective information such as decision matrix through mathematics models. As discussed earlier, the information about attribute' weights is usually incomplete. In our work, how to apply the interval type-2 fuzzy decision matrix to find the most desirable alternative(s) is an interesting and important issue [16].

The user-item interaction information can be either explicit or implicit. Our system depends on explicit method in which the users consciously expressing their preferences for items, e.g., discrete ratings for movies. In formal, multicriteria user-item ratings matrix is a matrix of size $M \times N$,where the element R_{itj} (i=1, 2,..., m; t =1, 2,..., k ; j=1, 2,..., n) is the rating assigned to alternative item I_i by the user U_j under criterion C_t. W_{tj} is the weight given to criteria C_t by user U_j, m is the total number of item, n being the total number of users, and k is the total number of criteria[14].

$$\begin{array}{cc} & \begin{array}{cccccc} & C_1 & C_2 & C_3 & \cdots & C_t \\ \textit{Items} & W_1 & W_2 & W_3 & \cdots & W_t \end{array} \\ \hline U_1 & \begin{pmatrix} I_1 & R_{11} & R_{12} & R_{13} & \cdots & R_{1t} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ I_m & R_{m1} & R_{m2} & R_{m3} & \cdots & R_{mt} \end{pmatrix} \end{array} \quad (1)$$

Usually in a quantitative setting, the information is expressed in terms of numerical values. The ratings scale normally range from 1 to 5, where 1 denotes the greatest dislike to the item and 5 denotes the greatest like to the item. Here, the linguistic assessment is used instead of numerical value representation. Instead of specifying numerical scale while collecting feedback, the linguistic terms are used to collect. Due to the subjective, imprecise and vague of user preference data, the fuzzy linguistic approach is adopted to represent the user's preferences. In addition, Fuzzy Multicriteria Decision Making (FMCDM) approach is chosen to rank items for a user based on the user-item ratings matrix in collaborative recommendation context. The decision objective is to select the most appropriate items for a user from n different items in the database.

3.2. Fuzzifying Multi Criteria User-Item Matrix

After user ratings on items in multiple aspects (criteria) and weights for different criteria in the form of preference rating matrix; user' ratings and weights are fuzzified using type-2 Triangular Fuzzy Number (TFN), provided to determine the degree of membership in the user preference fuzzy set. The users find it easy to express their preferences on item for different criteria using natural language terms rather than numerical values. The type-2 membership function to evaluate the user preference of an item Ii with respect to the criteria Ct is denoted by $\mu_{TFN}^{Ct}(I_i)$. So, the rating element in the matrix is denoted as $R_{itj} = \mu_{TNF}^{Ct}(I_i)$.

A Fuzzy Logic System (FLS) can be defined as the nonlinear mapping of an input data set to a scalar output data set [2]. Fuzzy sets have attracted growing attention and interest in modern information technology, production technique, decision making, pattern recognition, and diagnostics and data analysis among others. When a problem has dynamic behavior, fuzzy logic is a suitable tool that deals with such problem. Here, the customer supplies his tastes, preferences and opinions in qualitative form; the system in turn transforms the needs to their respective quantitative forms using the concept of type-2 fuzzy logic. This computation eventually produces a TFN which represents an aggregate of the consumer's needs.

A type-2 (T2) FS is characterized by a fuzzy membership function, i.e., the membership value (or membership grade), for each element of this set is a FS in [0, 1], unlike a type-1 FS where the membership grade is a crisp number in [0, 1]. The membership functions of T2 FSs are three dimensional and include a footprint of uncertainty (FOU), which provide additional degrees of freedom that make it possible to directly model and handle uncertainties [20].

Table 1. Linguistic Set and TFN

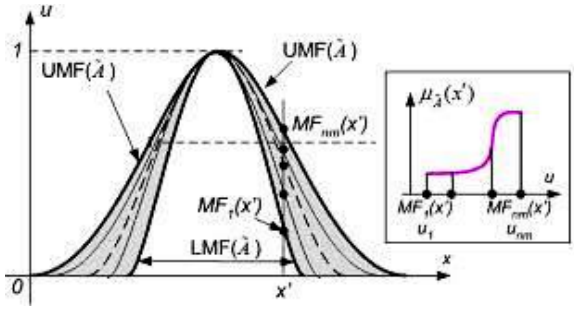
No.	Linguistic Term	TFN
1	Very unlikely (VUL)	(0, 1, 2)
2	Unlikely (UL)	(1, 2, 3)
3	Medium (M)	(2, 3, 4)
4	Likely (L)	(3, 4, 5)
5	Very likely (VL)	(4, 5, 6)

Unfortunately, T2FS is highly complicated computations, thereby difficult to use in real life applications. Thus, some scholars developed with the new concepts of interval T2FS (IT2FS) that make computations more manageable [21]. In the new concepts, there are upper membership function and lower membership function that represented by T1FS membership function. The area between these two functions is footprint of uncertainty, which is used to characterize T2FS as shown in Fig. 2. Some authors have also applied the IT2FS theory to the field of decision making [19]. In this work, we exploit type
all variables (ratings and weights) that is defined as [22]:

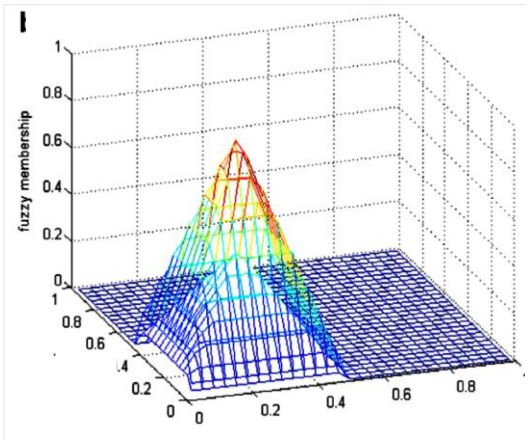
$$LMF = \begin{cases} h(x+a)/a, & \text{if } -a \le x \le 0 \\ h(a-x)/a, & \text{if } \quad 0 \le x \le a \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

$$UMF = \begin{cases} h(x+b)/b, & \text{if } -b \le x \le 0 \\ h(b-x)/b, & \text{if } \quad 0 \le x \le b \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

where $0 \le a \le b$ and $0 \le h \le 1$. All of MF' parameters are numerically specified based on the experiences. In our case five linguistic sets presented in Table 1 are used to enable users express their opinion for each criteria and weight: Very unlikely (VUL), Unlikely (UL), Medium (M), Likely (L), and Very likely (VL).



(a)



(b)

Fig. 2. (a) Interval type-2 FMF, (b) UMF and LMF representing the FOU.

In formal, a T2FS in the universal set X, denoted as $\tilde{A}$ can be characterized by a T2 FMF $\mu_{\tilde{A}}(x,u)$ as [22]:

$$\tilde{A} = \int_{x\in X} \mu_{\tilde{A}}(x) \big/ x = \int_{x\in X} \left(\int_{u\in J_x} f_x(u)/u \right) \Big/ x \quad J_x \subseteq [0,1] \tag{4}$$

where $f_x(u)$ is the secondary membership function and J_x is the primary membership of x which is the domain of the secondary membership function. The FOU of $\tilde{A}$ can be expressed by the union of all the primary memberships as

$$FOU(\tilde{A}) = \bigcup_{\vee x\in X} J_x = \{(x,u) : u \in J_x \subseteq [0,1]\} \tag{5}$$

the upper membership function (UMF) and lower membership function (LMF) of $\tilde{A}$ are two T1 fuzzy membership functions that bound the FOU. IT2FSs are specific T2FS whose secondary membership functions are interval sets expressed as:

$$\tilde{A} = \int_{x\in X} \left(\int_{u\in j_x} 1/u \right) \Big/ x \tag{6}$$

$$J_x = \left\{ (x,u) : u \in \left[\underline{\mu}_{\tilde{A}}(x), \overline{\mu}_{\tilde{A}}(x) \right] \right\} \tag{7}$$

$$FOU(\tilde{A}) = \bigcup_{\vee x\in X} \left[\underline{\mu}_{\tilde{A}}(x), \overline{\mu}_{\tilde{A}}(x) \right] \tag{8}$$

as a result, IT2FSs requires only simple interval arithmetic for computing. A type-2 FLS is characterized by

IF–THEN rules, where their antecedent or consequent sets are now of type-2. Type-2 FLSs, can be used when the circumstances are too uncertain to determine exact membership grades. Here, a Sugeno (TSK) Fuzzy model is utilized, which is a special group of rule-based model with fuzzy antecedents and functional consequents. In our proposal, we use the TSK rules to obtain the type-2 fuzzy rating $\tilde{R}_{ij}$ by pooling all criteria C_t for each item i and user j; examples of these rules are:

If C_1 is VUL and C_2 is VUL and C_3 is VUL and C_4 is VUL. **Then** $\tilde{R}_{11} = \frac{1}{4}\sum_{t=1}^{k} C_t$.

If C_1 is UL and C_2 is UL and C_3 is VUL and C_4 is L. **Then** $\tilde{R}_{12} = \frac{1}{4}\sum_{t=1}^{4} C_t$, and so on.

In the same way, we use the TSK rules to obtain the type-2 fuzzy weights $\tilde{W}_j$ by pooling the weight of all criteria W_j for each user j; examples of these rules are:

If W_1 is UL and W_2 is VUL and W_3 is VUL and W_4 is VUL. **Then** $\tilde{W}_1 = \frac{1}{4}\sum_{j=1}^{4} W_j$

If W_1 is UL and W_2 is L and W_3 is VUL and W_4 is VL**. Then** $\tilde{W}_1 = \frac{1}{4}\sum_{j=1}^{4} W_j$,and so on

In the type-2 FLS, the inference engine combines rules and gives a mapping from input type-2 fuzzy sets to output type-2 fuzzy sets. It is necessary to compute the $\bigcup$ join (unions) and the meet $\bigcap$ (intersections). So any rule $R^l, l = 1,\ldots M$ and M is the number of rules, can be written as:

$$\mu_{R^l}(x, y) = \mu_{A^l \to O^l}(x, y) = \left[\prod_{i=1}^{p} \mu_{x_i}(x_i)\right] \tag{9}$$

where $x_i(i = 1, 2, \ldots\ldots, p)$ are the labels of the fuzzy sets describing the inputs A^l for each rule and $y_j \in Y$ represents the output. Each rule R^l determines a type-2 fuzzy set μ_{B^l} such that:

$$\mu_{B^l}(y) = \bigcup_{x \in X} \left[\mu_{\tilde{A}_x}(x) \bigcap \mu_{R^l}(x, y)\right] \tag{10}$$

Here in, we used interval type-2 fuzzy sets and intersection under product t-norm, so the result of the input and antecedent operations, which are contained in the firing set $\prod_{i=1}^{p} \mu_{x_i}$ is an interval type-1set. Finally, the type-reducer generates a type-1 fuzzy set output, which is then converted in a numeric output through running the defuzzifier. This type-1 fuzzy set is also an interval set, for the case of our FLS we used center of sets (COS) type reduction, Y_{COS} which is expressed as [11]:

$$Y_{cos}(x) = \left[c_l(\tilde{A})\ c_r(\tilde{A})\right] \tag{11}$$

$$c_l(\tilde{A}) = \frac{\int_{-\infty}^{C_l} x\bar{\mu}(x)dx + \int_{C_l}^{\infty} x\underline{\mu}(x)dx}{\int_{-\infty}^{C_l} \bar{\mu}(x)dx + \int_{C_l}^{\infty} \underline{\mu}(x)dx} = \frac{\sum_{i=1}^{M} \mu_l^i c_l^i}{\sum_{i=1}^{M} \mu_l^i} \tag{12}$$

$$c_r(\tilde{A}) = \frac{\int_{-\infty}^{C_r} x\underline{\mu}(x)dx + \int_{C_r}^{\infty} x\bar{\mu}(x)dx}{\int_{-\infty}^{C_r} \underline{\mu}(x)dx + \int_{C_r}^{\infty} \bar{\mu}(x)dx} = \frac{\sum_{i=1}^{M} \mu_r^i c_r^i}{\sum_{i=1}^{M} \mu_r^i} \tag{13}$$

M presents the number of rules. From the type-reducer we obtain an interval set, Y_{COS} , to defuzzify it we use the average of $c_l(\tilde{A})$ and $c_r(\tilde{A})$ so the defuzzified output of an interval singleton type-2 FLS is calculated as [14].

$$y = \frac{c_l(\tilde{A}) + c_r(\tilde{A})}{2} \tag{14}$$

3.3. Build Aggregate Weighted in Decision Matrix

After obtaining T2 fuzzy rating $\tilde{R}_{ij}$ and the T2 fuzzy weight $\tilde{W}_j$, each pooled $\tilde{R}_{ij}$ is weighted by $\tilde{W}_j$ with respect to each user to obtain the overall type-2 fuzzy index F_{ij} of alternatives by which the ranking of all the given alternatives can be found. This paper utilizes the fuzzy multiplication operator $\otimes$ to aggregate the user's assessment, so that the aggregation of the different ratings is given by:

$$F_{ij} = \left(\tilde{R}_{ij} \otimes \tilde{W}_j\right) \tag{15}$$

3.4. Calculate the Ideal Solution

The proposed system exploits the same idea of order of preference by similarity to ideal solution (TOPSIS) for best items selection. As mentioned earlier TOPSIS is based on the concept that the chosen alternative should have the shortest geometric distance from the positive ideal solution and the longest geometric distance from the negative ideal solution [23]. In general, a positive ideal solution maximizes the benefit criteria and minimizes the cost criteria, whereas a negative ideal solution maximizes the cost criteria and minimizes the benefit criteria. We get the positive ideal solution X^+ that represents the maximum of F_{ij} for each user and the negative ideal solution X^- that represents the minimum of F_{ij} for each user [23].

$$\begin{aligned} X^+ &= \left(u_1^+, u_2^+, u_3^+, \ldots . u_j^+\right). . , \\ &= \max\left\{F_{11}, F_{12}, F_{21}, F_{22}, \ldots\ldots . F_{ij}\right\} \end{aligned} \tag{16}$$

$$\begin{aligned} X^- &= \left(u_1^-, u_2^-, u_3^-, \ldots\ldots\ldots, u_j^-\right) \\ &= \min\left\{F_{11}, F_{12}, F_{21}, F_{22}, \ldots\ldots . F_{ij}\right\} \end{aligned} \tag{17}$$

3.5. Calculate the Distance between Each Alternative Item and the Ideal Solution

From equations (16) and (17), the distance $d^+(I_i)$ between each alternative item I_i and the positive ideal solution X^+ is calculated and we also calculate the distance $d^-(I_i)$ between each alternative I_i and the negative ideal solution X^- respectively,

$$d^+(I_i) = \sqrt{\sum_{j=1}^{n}\left(F_{ij} - u_j^+\right)^2} \tag{18}$$

$$d^-(I_i) = \sqrt{\sum_{j=1}^{n}\left(F_{ij} - u_j^-\right)^2} \tag{19}$$

3.6. Ranking Item (Recommendations)

By using equation (18), (19) we able to calculate the ranking value for each alternative item I_i denote by $T(I_i)$

$$T(I_i) = \frac{d^-(I_i)}{d^+(I_i) + d^-(I_i)} \tag{20}$$

finally, sort the values of $T(I_i)$ in descending sequence. The list of recommendations to be generated is chosen by selecting the Top-N items with the highest scores. The larger value of $T(I_i)$ the higher preference of the alternative I_i.

4. Experimental Results

To evaluate the accuracy of the proposed method, we conduct a set of experiments and compare the proposed method with traditional fuzzy recommendation algorithm. Our experiments were implemented using MatLab 2009b. All the experiments were based on a PC with Windows XP Professional, with Intel Pentium (R) Core(TM) 2 CPU, 2.13GHz and 2GB RAM. The dataset details, experimental setup, and evaluation metrics are represented below.

4.1. Data Set and Setup

In order to evaluate the proposed approach, a set of user submitted ratings are collected from the music recommender system developed for this experiment. During the user relevance feedback collection, the user is asked to provide their ratings on the heard music item in three aspects (quality of music, lyric, and voice) in a scale of 1 to 6.The developed system's database contains 1000 user ratings, provided by 150 users for 50 music items. The recommendation algorithms are evaluated over 500 ratings set, taken at randomly from a set of 1000 actual ratings. The average number of common users between two music items is 20. The average rating on each criterion is 3 approximately.

Since we have a large amount of data and to achieve reliable results, we have used 5-foldcross-validation technique. In this method, for each user, we have randomly divided the data set into 5 disjoint subsets. Using different random selection of the music items, 5 different runs are executed to avoid the sensitivity of sampling bias and the results are reported. In each subset, 80% of the data are used for training and 20% of data are used for testing recommendation. For each user, using the music items in the testing set, it generates Top-N recommendations and computes performance metrics. Moreover 5, 10, and 15 are used as values of variable number of items to be recommended (recommendation size).

4.2. Metrics

A number of metrics are available to evaluate the recommender system performance [24]. These include statistical accuracy metrics such as mean absolute error that determine the prediction accuracy of the algorithms, and recommendation accuracy metrics that determine how well the recommendation algorithm can predict items the user would rate highly. Statistical accuracy measures are found to be less appropriate when the user task is to find good items and when the granularity of true value is small because predicting the rating 4 as 5 or the rating 3 as 2 makes no difference to the user. Instead, the recommendation metrics (Precision, Recall, and F1-measure) are more appropriate [25]. To calculate these metrics, we need a contingency table to categorize the items with respect to the information needs as given in Fig. 3.

For the evaluation of recommender systems precision, recall, and F-measure are the widely used metrics to evaluate the quality of the recommendations [24].The F score can be interpreted as a weighted average of the precision and recall. F-measure is computed using the harmonic mean:

$$F_{ij} = \frac{2 \times P_{ij} \times L_{ij}}{P_{ij} + L_{ij}},$$

$$F = \sum_{i,j} \frac{n_i}{n} \max\left(\{F_{ij}\}\right) \tag{21}$$

P_{ij} (Precision) is the number of correct results divided by the number of all returned results and L_{ij}

(recall or sensitivity) is the number of correct results divided by the number of results that should have been returned for each cluster *j* and class *i*.

		Condition (as determined by "Gold standard")		
		Condition positive	Condition negative	
Test outcome	Test outcome positive	True positive	False positive (Type I error)	Precision = Σ True positive / Σ Test outcome positive
	Test outcome negative	False negative (Type II error)	True negative	Negative predictive value = Σ True negative / Σ Test outcome negative
		Sensitivity = Σ True positive / Σ Condition positive	Specificity = Σ True negative / Σ Condition negative	Accuracy = Σ True positive + Σ True negative / Σ Total population

Fig. 3. Performance evaluation matrices.

4.3. Results

The performance of traditional fuzzy based recommendation algorithm is compared with our approach using the precision, recall, and F1-measure. The average precision, recall and F1-measure of the users during Top-5 recommendations are shown in Table 2. These values reveal a good performance of the proposed approach.

Table 2. Average Percentage of Precision, Recall, and F-Measure

Recommendation Approaches	Precision %	Recall %	F-Measures %
Fuzzy –approach [6]	62.71	70.43	64.04
Proposed System	70.65	82.32	76.15

Moreover, it is found that the precision improvement is enhanced as the number of recommendation size increases as demonstrated in Table 3. Hence, it can be concluded that the proposed collaborative model has helped in improving the precision of the recommended results and generally provide a more accurate prediction than a type-1 fuzzy–based approach. This is because more uncertainty can be handled by using type-2 fuzzy set to represent user's ratings.

Table 3. Precision Table for Top-*N* Recommendation (%)

Recommendation Approaches	Top-5	Top-10	Top-15
Fuzzy –approach [6]	62.71	66.95	72.92
Proposed System	70.65	84.78	92.31
Improvement	**7.94**	**17.88**	**19.39**

5. Conclusion

Soft computing appears to be a suitable model to handle the uncertainty and fuzziness on user preference and to efficiently model the natural complexity of human behavior. To improve the recommendation quality, we are conducted toward hybridization between CF and type-2 fuzzy linguistic modeling to enhance the CF accuracy in recommender systems in order to deal with the sparsity and scalability problems. This paper adopts high order fuzzy linguistic approach to represent the user preferences in user-item ratings matrix and high order fuzzy multicriteria decision making method to rank the appropriate, relevant items to a user in a collaborative recommendation context. IT2FL is useful when we have to assess different qualitative concepts.

The suggested method makes predictions by using only the user-item interaction information. Furthermore, it can capture the hidden connections between users and items and have the ability to provide unexpected items, which are helpful to improve the diversity of recommendation. The experimental results show that the proposed approach gives better performance when compared with traditional fuzzy recommendation approaches in all the sensitive parameters. Our experimental results on a real-world data set confirm that the type-2 fuzzy multicriteria decision making approach has great potential in collaborative recommender systems and can be successfully used to build accurate and flexible recommender systems. Concerning the development of the current system, it is more natural to make preference predictions for a user via the correlated subgroups than the entire user-item matrix to achieve more the prediction accuracy.

References

[1] Prasad, R., & Kumari, V. (2012). A categorical review of recommender systems. *International Journal of Distributed and Parallel Systems*, *3(5)*, 73-83.

[2] Ojokoh, B., Omisore, M., Samuel, O., & Ogunniyi, T. (2012). A fuzzy logic based personalized recommender system. *International Journal of Computer Science and Information Technology & Security*, *2(5)*, 1008-1015.

[3] Zeng, Z. (2009). An intelligent e-commerce recommender system based on web mining. *International Journal of Business and Management*, *4(7)*, 10-14.

[4] Ricci, F., & Werthner, H. (2002). Case-based querying for travel planning recommendation. *Journal of Information Technology and Tourism*, *4(3)*, 215-226.

[5] Zenebe, A., & Norcio, A. F. (2009). Representation, similarity measures and aggregation methods using fuzzy sets for content-based recommender systems. *Fuzzy Sets and Systems*, *160(1)*, 76-94.

[6] Patil, S., Mane, Y., Dabre, K., Dewan, P., & Kalbande, D. (2012). An efficient recommender system using collaborative filtering methods with k-separability approach. *Proceedings of the International Conference on Emerging Trends in Engineering& Technology* (pp. 30-35).

[7] Xu, B., Bu, J., Chen, Ch., & Cai, D. (2012). An exploration of improving collaborative recommender systems via user-item subgroups. *Proceeding of The 21st International Conference on World Wide Web,* (pp. 21-30).

[8] Carbo, J., & Molina, J. M. (2004). Agent-based collaborative filtering based on fuzzy recommendations. *International Journal of Web Engineering and Technology*, *1(4)*, 414-426.

[9] Nadi, S., Saraee, M., Jazi, M., & Bagheri, A. (2011). FARS: fuzzy ant based recommender system for web users. *International Journal of Computer Science Issues*, *8(1)*, 203-209.

[10] Palanivel, K., & Sivakumar, R. (2010). A study on implicit feedback in multicriteria e-commerce recommender system. *Journal of Electronic Commerce Research*, *11(2)*, 140-156.

[11] Adomavicius, G., & Kwon, Y. (2007). New recommendation techniques for multi-criteria rating systems. *IEEE Trans*. *Intelligent Systems*, *22(3)*, 48-55.

[12] Liu, L., Mehandjiev, N., & Xu, D. (2011). Multi-criteria service recommendation based on user criteria preferences, *Proceedings of the 5th ACM Conference on Recommender Systems* (pp. 77-84).

[13] Adomavicius, G., Manouselis, N., & Kwon, Y. (2011). Multi-criteria recommender systems. *Recommender Systems Handbook* (pp. 769-803). Springer.

[14] Palanivel, K., & Sivakumar, R. (2010). Fuzzy multicriteria decision-making approach for collaborative recommender systems. *International Journal of Computer Theory and Engineering*, *2(1)*, 57-63.

[15] Lakiotaki, K., Matsatsinis, N. F., & Tsoukiàs, A. (2011). Multi-criteria user modeling in recommender

systems. *IEEE Transactions of Intelligent Systems*, *26(2)*, 64-76.
[16] Naim, S., & Hagras, H. (2012). A hybrid approach for multi-criteria group decision making based on interval type-2 fuzzy logic and intuitionistic fuzzy evaluation. *Proceedings of the IEEE International Conference on Fuzzy Systems* (pp. 1-8).
[17] Cornelis, C., Lu, J., Guo, X., & Zhang, G. (2007). One-and-only item recommendation with fuzzy logic techniques. *Journal of Information Sciences*, *177(22)*, 4906–4921.
[18] Martinez, L., Barranco, M., & Perez, L. (2008). A knowledge based recommender system with multi-granular linguistic information. *Journal of Computational Intelligence Systems, 1(3)*, 225-236.
[19] Jaffal, H., & Tao, C. (2008). Multiple attributes group decision making by type-2 fuzzy sets and systems. *Proceedings of the International Conference on Machine Learning* (pp. 3260–3265).
[20] Chen, Y., & Yao, L. (2009). Robust type-2 fuzzy control of an automatic guided vehicle for wall-following. *Proceedings of the International Conference of Soft Computing and Pattern Recognition* (pp. 172-177).
[21] Liang, Q., & Mendel, J. M. (2000). Interval type-2 fuzzy logic systems: theory and design. *IEEE Transactions on Fuzzy Systems*, *8(5),* 535–550.
[22] Jerry, M. (2007). Type-2 fuzzy sets and systems: an overview. *IEEE Computational Intelligence Magazine*, *2(1)*, 20-29.
[23] Jahanshahloo, G., Hosseinzadeh, F., & Izadikhah, M. (2006). Extension of the TOPSIS method for decision-making problems with fuzzy data. *Journal of Applied Mathematics and Computation 181*, 1544–1551.
[24] Manouselis, N., & Costopoulou, C. (2007). Analysis and classification of multi-criteria recommender systems. *Journal of World Wide Web*, *10(4)*, 415–441.
[25] Manouselis, N., & Costopoulou, C. (2007). Experimental analysis of design choices in multi-attribute utility collaborative filtering. *International Journal of Pattern Recognition and Artificial Intelligence*, *21(2)*, 311-331.

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