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Multi-Criteria Decision Based Recommender System using Fuzzy Linguistics Model for E-Commerce

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ABSTRACT

Recommender systems have been explored, extreme in recent years, and are applied in a variety of applications. An increasing number of E-commerce sites on the Internet has caused the data overload. Mostly, users are permitted to provide overall ratings for experience items, but many online systems allow users to provide their evaluations on different standards. Various efforts have been gained in the past to design a recommendation system, centering on the ratings of a single standard. Nevertheless, investigation of the utility of multi criteria recommender systems in an online environment is nevertheless in its early childhood. In this paper, Author proposed multi-criteria recommendation system using fuzzy linguistic modeling. The proposed approach recommends the relevant item to the user with the help of Fuzzy Multi-criteria Decision Making approach.

Keywords : Recommendation system, Fuzzy linguistic, Fuzzy Multi- criteria Decision Making.

I. INTRODUCTION

Recommender system (RS) the most successful Web application helps in attenuate information overload available on large data spaces. With the arrival of numerous online products in the market the recommendation system is no further so new for customers as easily as for the researchers. Recommendation system solves the problem that how can the users acquire the right product quickly and accurately from the website.

Recommender systems are the technologies to filter the information utilized to suggest items to users that they might like or find interesting. There has been much research done in this field for developing new techniques to recommendation system over the last decade. It was issued as an independent area for research in the middle of 1990's when the researchers explicitly rely on the rating structure [1].

Recommendation systems typically of three types, it can be collaborative or content-based or hybrid filtering.

Content Based Methods: In content-based recommendation methods, the utility u(c,s) of item s for user c is estimated based on the utilities (c,si) s assigned by user c to items si∈S that are "similar" to item s. For example, in a movie recommendation application, in order to recommend movies to user c, the content-based recommender system tries to understand the commonalities among the movies user c has rated highly in the past (specific actors, directors, genres, subject matter, etc.). Then, only the movies that have a high degree of similarity to whatever user's preferences are would get recommended.

Collaborative Methods" Unlike content-based recommendation methods, collaborative recommender systems (or collaborative filtering systems) try to predict the utility of items for a particular user based on the items previously rated by other users. More formally, the utility u(c, s) of item s for user c is estimated based on the utilities u(cj, s) assigned to item s by those users cj∈C who are "similar"to user c. For example, in a movie recommendation application, in order to recommend movies to user c, the collaborative recommender system tries to find the "peers" of user c, i.e., other users that have similar tastes in movies (rate the same movies similarly). Then, only the movies that are most liked by the "peers" of user c would get recommended. There have been many collaborative systems developed in the academia and the industry. It can be argued that the Grundy system was the first recommender system, which proposed to use stereotypes as a mechanism for building models of users based on a limited amount of information on each individual user. Using stereotypes, the Grundy system would build individual user models and use them to recommend relevant books to each user. Later on, the Tapestry system relied on each user to identify like-minded users manually. Group Lens Video Recommender, and Ringo were the first systems to use collaborative filtering algorithms to automate prediction. Other examples of collaborative recommender systems include the book recommendation system from Amazon.com, the PHOAKS system that helps people find relevant information on the WWW, and the Jester system that recommends jokes.

Hybrid Methods : Several recommendation systems use a hybrid approach by combining collaborative and content based methods, which helps to avoid certain limitations of content-based and collaborative systems. Different ways to combine collaborative and content-based methods into a hybrid recommender system can be classified as follows: (1) implementing collaborative and content-based methods separately and combining their predictions, (2) incorporating some content-based characteristics into a collaborative approach, (3) incorporating some collaborative characteristics into a content-based approach, and (4) constructing a general unifying model that incorporates both content-based and collaborative characteristics..

A. Literature survey

The recommendation system became an important field of research in the mid 1990's. Comparison and rating of the operation of different recommendation algorithms for Technology Enhanced Learning (TEL) with the use of data sets. This dataset can be placed in the sheath of the collaborative filtering system. It can be product review in case of content-based system [1]. After this a framework of a personalized learning recommender system (PLRS) proposed by Jie Lu, which help to determine the study materials which best fit his/her necessity. The PLRS creates a learning activity database once, by this student's personal information is obtained, which aids to identify the student's learning requirement and then use matching rules to get a recommendation of learning material for the scholar. The PLRS has several advantages, including like handling sparsity problem, preventing false positive errors and offering more accuracy in recommending the appropriate learning material [2].

G. Adomavicius, Y. Kwon defines the recommendation problem as a multi-criteria decision making (MCDM) problem and the category of multi-criteria rating recommenders ,which consist of two approaches – the similarity-based approach and the aggregation function-based approach – to incorporating and leveraging multi-criteria rating information in recommender systems and shows that multi-criteria ratings can be successfully improve recommendation accuracy, as compared to traditional single-rating recommendation techniques[6]. Chein-Shung proposed a system which integrates multi-criteria into the collaborative Filtering algorithm with the help of Genetic Algorithm for optimal feature weighting. In this the system consists of two parts. First, with the help of Genetic Algorithm the weight of each user toward each feature is computed and the provide recommendation by incorporating feature weight into the collaborative filtering. The proposed approach first uses the traditional user-based CF algorithm to compute the prediction for each single criterion and then aggregates the overall prediction based on the weighting values derived by Genetic Algorithm [8].

B. The Proposed Method

In our proposed system the above approaches extends with certain modification aiming to obtain more accurate result to improve the performance of multi-criteria recommendation system. In the proposed scheme:

- ✓ First, linguistic variables assigned by the users for each criteria are translated into fuzzy numbers and are represented in the fuzzy decision matrix.
- ✓ Second, we compute the average fuzzy scores and with the help of that, defuzzified values and normalized weight for each criteria are evaluated.
- ✓ Then total aggregated score for item against each criteria is computed.
- ✓ Finally calculated the overall ratings as final outcome.

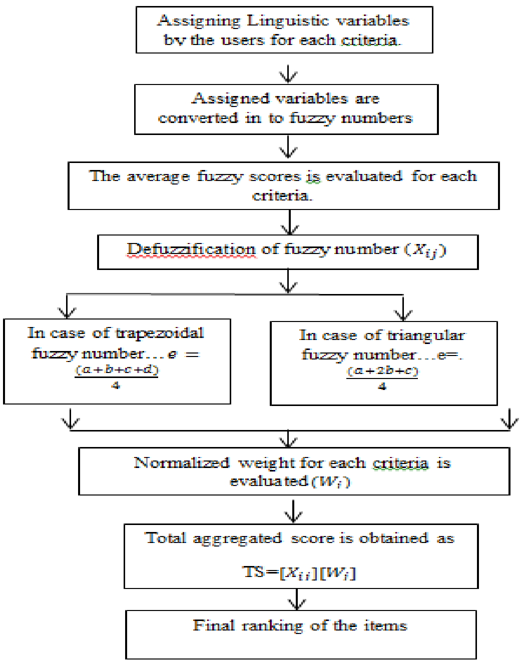

Figure 1. Flow Diagram of the proposed system

II. MULTICRITERIA RECOMMENDATION SYSTEM

Multi-criteria recommendation system is the technique that recommends user's preference for an item as a vector of ratings along several criteria. [4] In contrast, in a multi-criteria system, users can provide their ratings on multiple attributes of an item. For example, in a movie recommendation system the user overall rating shows the general interest of the user on that movie. However, in case of multi criteria recommendation system the ratings of a movie are such as for Actor, Actress, Director, and Music, provided by the user according to the preferences.

Table 1. Multi-criteria rating matrix

	Item i_1	Item i_2	Item i_3	Item i_4
User u_1	$5_{2,2,8,8}$	$7_{5,5,9,9}$	$5_{2,2,8,8}$	$7_{5,5,9,9}$
User u_2	$5_{8,8,2,2}$	$7_{9,9,5,5}$	$5_{8,8,2,2}$	$7_{9,9,5,5}$
User u_3	$5_{8,8,2,2}$	$7_{9,9,5,5}$	$5_{8,8,2,2}$	$7_{9,9,5,5}$
User u_4	$6_{3,3,9,9}$	$6_{4,4,8,8}$	$6_{3,3,9,9}$	$6_{4,4,8,8}$
User u_5	$6_{3,3,9,9}$	$6_{4,4,8,8}$	$6_{3,3,9,9}$	$6_{4,4,8,8}$

In Figure 2, there are five users $u_1, u_2, \ldots, u_5$ and four items $i_1, \ldots, i_4$. In a multi-criteria recommendation system the user gives a rating on multiple aspects $c_1, \ldots, c_2$ on a scale of 1 to 5.The overall rating are obtained by simply taking the average of multiple criteria ratings. It shows that user $u_1$is similar from the user u_2, but the user $u_3$have different preferences from user u_4. On the other hand, the single criteria ratings are not able to show accurate preferences of the user and lead to imprecise or incurred recommendation to the user for an item.

III. FUZZY LINGUISTIC MODELLING

Fuzzy logic is a form of multiple-valued logic which deals with values that is approximate rather than fixed and exact. Fuzzy logic variables are truth value that ranges in between 0 and 1 known as fuzzy set. A fuzzy set is defined by a function, called membership function. Fuzzy logic has been extended to deal with the concept of partial truth, where the truth value can range between completely true and completely false or completely 0 and completed a 1 (in mathematics usually take numerical values), in fuzzy logic applications, the non-numeric are often used to facilitate the expression of rules and facts. And these non-numeric values are linguistic variables such as age may have a value such as young or its antonym old. The membership function of a fuzzy set Z is defined as μ_Z and the membership value of x id denoted as $\mu_Z(x)$. Fuzzy set theory allows a continuous value for $\mu_Z(x)$ between 0 and 1 as given below:

$$\mu_Z(x)=\begin{cases} 1 \quad iff\ x \in Z \\ 0\ iff\ x \in Z \\ p \quad 0 < p <, iff\ x\ partially\ belong\ to\ Z \end{cases}$$

The membership function of a fuzzy set represents the degree of truth as an extension of valuation and in the case of linguistic terms, membership function is used to quantify these terms. Many things in this real world cannot be rated in quantitative form which is more inexact or approximate. The ratings are more inexact because the user may give different ratings for the same item at different time in different moods and situations. Thus, fuzzy linguistic variables are preferred in the proposed system instead of numerals.

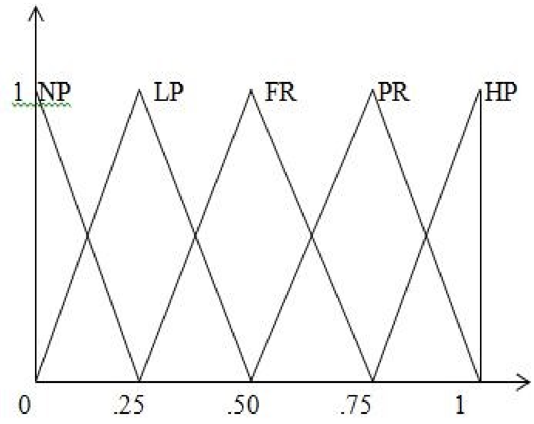

Figure 2. The Linguistic terms of fuzzy variables

IV. FUZZY MULTICRITERIA USER-ITEM RATING MATRIX

In the proposed system, the user, rate the item on multiple criteria like *actor, actress, director* for the movie recommendation. The rating is in the form of linguistic variables such as *Less preferred* or *Highly preferred.* Usually in quantitative system, the ratings are in the form of numerical values normally scaled from 0 to 1. But in our proposed system five linguistic terms are used to rate the item on multiple criteria such as *Not Preferred(**NP**), Less Preferred(**LP**), Fair(**FR**), Preferred(**PR**) and Highly Preferred(**HP**).*These user ratings are fuzzified using triangular membership functions. The triangular fuzzy numbers (TFN) associated with the

Table 2. Fuzzy multi-criteria user item rating matrix

	Item i_1 $C_1C_2C_3$	Item $i_2C_1C_2C_3$	Item $i_3C_1C_2C_3$	Item $i_4C_1C_2C_3$
User u_1	(0.75,1,1) (0,0.25,0.50) (0.25,0.50,0.75)	(0.75,1,1) (0.50,0.75,1) (0,0.25,0.50)	(0.50,0.75,1) (0.25,0.50,0.75) (0,0,0.25)	(0,0,0.25) (0.75,1,1) (0,0.25,0.50)
User u_2	(0.25,0.50,0.75) (0,0.25,0.50) (0,0,0.25)	(0,0.25,0.50) (0,0.25,0.50) (0,0.25,0.50)	(0.75,1,1) (0,0.25,0.50) (0.25,0.50,0.75)	(0.75,1,1) (0,0.25,0.50) (0,0,0.25)
User u_3	(0.50,0.75,1) (0.25,0.50,0.75) (0,0,0.25)	(0.50,0.75,1) (0.25,0.50,0.75) (0.25,0.50,0.75)	(0.25,0.50,0.75) (0.50,0.75,1) (0.75,1,1)	(0.50,0.75,1) (0.75,1,1) (0,0,0.25)
User u_4	(0,0,0.25) (0.25,0.50,0.75) (0,0.25,0.50)	(0,0.25,0.50) (0,0,0.25) (0.25,0.50,0.75)	(0,0,0.25) (0,0,0.25) (0,0.25,0.50)	(0.25,0.50,0.75) (0.50,0.75,1) (0.75,1,1)
User u_5	(0,0.25,0.50) (0,0.25,0.50) (0.25,0.50,0.75)	(0.25,0.50,0.75) (0.50,0.75,1) (0.75,1,1)	(0,0.25,0.50) (0,0,0.25) (0.75,1,1)	(0.25,0.50,0.75) (0.25,0.50,0.75) (0.50,0.75,1)

corresponding the linguistic variables are shown in Table 1. and graphically represented in Figure 2.

Table 3. Linguistic variables and their corresponding Triangular Fuzzy Numbers (TFN)

Linguistic variables	TFN
Not Preferred (NP)	(0,0,0.25)
Less Preferred (LP)	(0,0.25,0.50)
Fair (FR)	(0.25,0.50,0.75)
Preferred (PR)	(0.50,0.75,1)
Highly Preferred (HP)	(0.75,1,1)

The user-item rating matrix consists of n users $U_1, U_2, U_3, \dots, U_n$ in rows and m items $I_1, I_2, I_{3,\dots\dots}, I_m$ in columns. The user gives the rating for an item I_j is defined as multi-criteria ration on criteria $c_1, c_2, c_{3,\dots,} c_k$.

The membership function to calculate the user choice of an item I_j on the bases of criteria C_t where t=1,…,k is denoted by μ_Z^{Ct} (I_j) and the rating of each element in the matrix is denoted as R_{ijt}=μ_Z^{Ct} (I_j). In our system, the multiple criteria for a movie recommendation system are Actor, Actress, Music defined as C_K, where k=3, A fuzzy multi-criteria user item ratings matrix is shown in the Table 2.

V. FUZZY MULTICRITERIA DECISION MAKING

This section consists of measuring the possibility of accurate result by using defuzzification of fuzzy numbers and calculating the normalized weight. As user ratings are inexact or approximate, the fuzzy linguistic approach is used to rate the user choices. After this defuzzification and normalized weights are used to to rank items for users on the basis of the rating given by the user in the user-item rating matrix. The main objective is to select the most suitable or appropriate item from m different items on the basis of k multi-criteria $(c_1, c_2, c_{3,\dots,} c_k)$. Let R_{itj} be the rating assigned to alternative item I_j by the U_i users on the C_t criterion. Then, the average of fuzzy numbers of the different rating will be:

$$R_{itj} = \frac{1}{p} \otimes (R_{it1} \oplus R_{it2} \oplus \dots R_{itp}) \text{……………..(1)}$$

p=1,2,3…..p.

Table 4. The Average fuzzy scores matix

	Item i_1	Item i_2	Item i_3	Item i_4
C_1	0.3,0.35,0.7	0.3,0.55,0.75	0.3,0.5,0.7	0.35,0.55,0.75
C_2	0.1,0.35,0.6	0.25,0.45,0.7	0.15,0.3,0.55	0.45,0.7,0.85
C_3	0.1,0.25,0.5	0.25,0.5,0.7	0.35,0.55,0.7	0.25,0.4,0.6

The average fuzzy score matrix for each criteria is obtained and shown in the Table III, after this defuzzified value for each criteria is obtained by the following equation for triangular fuzzy numbers:

$$e = \frac{(a+2b+c)}{4} \text{……………………………..(2)}$$

The crisp score (defuzzified value) for each item is obtained and are represented in the matrix X_{ij} where i is the number of items and j is the number of criteria. Normalized weight for each criteria is obtained by dividing the defuzzified score of each criteria by the total of all the criteria and stored in a matrix W_j as shown in the matrix.

$$\begin{array}{c} \\ C_1 \\ C_2 \\ C_3 \end{array} \begin{array}{c} \begin{array}{cccc} I_1 & I_2 & I_3 & I_4 \end{array} \\ \begin{bmatrix} 0.45 & 0.533 & 0.5 & 0.55 \\ 0.35 & 0.466 & 0.33 & 0.66 \\ 0.283 & 0.483 & 0.53 & 0.416 \end{bmatrix} \end{array} \quad \begin{array}{c} W_j \\ \begin{bmatrix} 0.33 \\ 0.33 \\ 0.33 \end{bmatrix} \end{array}$$

With the help of defuzzified value X_{ij} and the normalized weight for each criteria W_j , total aggregated score (TS) for items against each criteria is obtained by simply using an additive method that is: TS=$[X_{ij}][W_j]$………………….……..……………(3)

Total score for item (I_1) is obtained as(0.45 × 0.33)+(0.35 × 0.33)+(0.283 × 0.33)= 0.35739. Similarly, Total score for item(I_2)(I_3)(I_4) for a particular user is obtained, and the final ranking of the items are given the table 5.

Table 5. Final score and ranking of the items

Items	I_1	I_2	I_3	I_4
Final Scores	0.35739	0.48906	0.4488	0.53658
Rank	4	2	3	1

VI. RESULT AND DISCUSSION

The result of an experimental evaluation of multi-criteria recommendation system and the proposed multi-criteria recommendation system using fuzzy linguistic modeling are presented. The performance of multi-criteria recommendation is compared with fuzzy multi-criteria decision making and results of fuzzy multi-criteria decision making is more accurate and precise. In this the ranking of items for a particular user are as, $I_1 < I_2, I_2 > I_3$, $I_2 < I_4$. So, the results show that, I_4, is the most suitable item for the user.

VII. CONCLUSION AND FUTURE

This paper presents a multi-criteria recommendation system using fuzzy based approach. The performance of multi-criteria recommendation is compared with fuzzy multi-criteria decision making approach and the results shows that the fuzzy multi-criteria decision making is more accurate and precise. In the future, work can be done with fuzzy hybrid approaches to achieve more accuracy of the recommendation system.

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