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Recommender Systems based on Multi- Attribute Decision Making

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Abstract: User based collaborative filtering systems suggest interesting items to a user relying on similar-minded people called neighbors. The selection and weighting of these neighbors characteristics the different recommendation approaches. While standard strategies perform a neighbor selection based on user similarities. The paper built an evaluation model of user interest based on resource multi-attributes, proposes a modified Pearson-Compatibility multi-attribute group decision-making algorithm, and introduces an algorithm to solve the recommendation problem of k-neighbor similar users. Here this study addresses the issues on preference differences of similar users.

Keywords: Recommender system, Collaborative Filtering, Multi –criteria Decision Making

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I. INTRODUCTION

Recommender systems (RSs) are applications that provide personalized advice to users about products or services they might be interested in. Recommender systems are playing a major role in the digital and social networking revolution and becoming a part of everyday life. Recommender system provides advice to user about items they wish to purchase or examine. Recommendations made by such system can help users navigate through large information spaces of product descriptions, new articles or other items. The main task of a recommender system is to locate items, information sources and people related to the interest and preferences of a single person or a group of people. They have become fundamental applications in electronic commerce and information access, providing suggestions that effectively prune large information spaces so that users are directed toward those items that best meet their needs and preferences. A variety of techniques have been proposed for performing recommendation, including content-based, collaborative, knowledge-based and other techniques (1).

RSs work through two phases: prediction and recommendation. In the prediction phase, the rating of an item for a specific user is estimated through a utility function based on this user's past historical ratings, or the content of a particular item, or the user profile, etc. The recommendation phase takes place after predicting the ratings of all the candidate items for the user, where different strategies are used to choose the most suitable items to support the user's decision. However, a broad recommendation process includes both phases

A recommender system aims to generate meaningful recommendations to users for items or products that might interest them. In many markets, consumers face a price of products and information from which that can make choices. To alleviate this problem, many web sites attempt to help users by incorporating a recommender system that provides users with a list of items and/or web pages that are likely to interest them.

As one of the most successful approaches to building recommender systems, collaborative filtering (CF) uses the known preferences of group of users to make recommendations or predictions of the unknown preferences for other users. The fundamental assumption of CF is that if users X and Y rate n items similarly, or have similar behaviors (e.g., buying, watching, and listening), and hence will rate or act on other items similarly.

User's interest in a product or service is affected by user topic preferences, content preferences, user habits, public evaluation and other factors, and that these factors are decided by the different attributes of items. For example, user liking a new movie may be caused by one or more attributes of the movie, such as the director, star, theme. Content, style, public comment etc. Thus, in the application of collaborative filtering algorithm, it is necessary to use a multi-attribute analysis model, in which the user rating to an item is based on a different perspective (attributes) to describe their interest preferences.

Based on our previous research, we propose that multi –attribute collaborative filtering can be treated as a group decision making process. By building the rating matrix of target items for the similar users, we remove the user who has a large attribute preference difference to target user from the nearest user set, and save the problem of recommendation deviation. In addition, we can analyze the user's interest performance from the view of item attributes and give the descriptions for the recommendation.Accordingly,this paper proposes a modified

Pearson-Compatibility multi-attribute group decision-making algorithm and introduces the algorithm to solve the recommendation problem of k-neighbor similar users.

II. RELATED WORKS

There are many types of Recommender systems, each one has its different approaches and can be used in different context according to needs. This section will introduce briefly the different approaches used in recommendation.

2.1Content Based Filtering (CBF)

This recommendation depends only user not the group of people. If the user preferred in past then the next time he will take the same item. A content-based recommender depends on learning method i.e user select the item according to the past experience.

Probabilistic methods in general and the naïve Bayes approach in particular generate a probabilistic model based on previously observed data. The naïve Bayes model estimates the a posteriori probability(c/d) of document d belonging to class c, based on the a prior probability P(c)for the class, the probability(d) of observing the document, and the probability P(d/c)of observing the document given the class as follows:

$$P(c/d) = \frac{P(c)\,P(d/c)}{P(d)}$$

In recommendation the naïve Bayes method is used to estimate the probability that a document (an item) is either relevant or irrelevant (class c), based on the in-formation available for each user, that is, documents already rated are used to build the P(d/c)probabilities. This approach has been used by many different authors (11)
Regarding the feature vector similarity, the most common measure is the cosine similarity, even though the standard dot product between two vectors has also been used (11):

$$sim_{dot}\,(di,dj) = \Sigma_k w_{ki} w_{kj}$$

$$sim_{cos}\,(di,dj) = \frac{sim_{dot}\,(di,dj)}{\sqrt{\Sigma_k w_{ki}^2}\sqrt{\Sigma_k w_{kj}^2}}$$

Where w_{ki} is the weight assigned (by any of the techniques mentioned before) to the feature k in document i .
In recommender systems items are suggested by decreasing order of similarity with the user, whose profile is represented in the same form of the documents (that is, in the space of features under consideration). The similarities are computed as the feature vector similarity between each (unrated or unobserved) document in the col-lection and the user's vector.

2.2Collaborative filtering(CF) or Rating –based recommenders

In collaborative filtering, the user will be recommended items that people with similar tastes and preferences liked in the past. Collaborative filtering recommendation is probably the most familiar, most widely implemented and most mature of the technologies. Collaborative recommender system aggregate ratings or recommendations of objects, recognize commonalities between users on the basis of their rating, and generate new recommendations based on inter-user comparisons. These methods have the interesting property that no item descriptions are needed to provide recommendations, since the methods merely exploit information about past ratings. Compared to CBF approaches, CF also has the salient advantage that a user may benefit from other people's experience, thereby being exposed to potentially novel recommendations beyond her own experience (Adomavicius and Tuzhilin, 2005). A typical user profile in a collaborative system consists of a vector if items and their ratings, continuously augmented as the user interact with the system over time. Some systems used time-based discounting of ratings to account for drift in user interests (10).

In general,CF approaches are commonly classified into two main categories: model based and memory based .Model based approaches build statistical models of user/item rating patterns to provide automatic rating predictions.

Memory based approaches, on the other hand make rating predictions based on the entire collection. These approaches can be user and item based strategies. **User based** strategies are built on the principle that a particular user's rating records are not equally useful to all other users as input for providing personal item suggestions. Central aspects to these algorithms are thus a) how to identify which neighbors form the best basis to generate item recommendations for the target user, and b) how to properly make use of the information provided by them. Typically, neighborhood identification is based on selecting those users who are more similar to the target user according to a similarity metric (1). The similarity between two users is generally computed by a) finding a set of items that both users have interacted with, and b) examining to what degree the users displayed similar behaviors (e.g. rating, browsing and purchasing patterns) on these items. It is also common practice to set a maximum number of neighbors (or a minimum similarity threshold) to restrict the neighborhood size either for computational efficiency, or in order to avoid noisy users who are not similar enough. Once the target user's neighbors are selected, the more similar a neighbor is to the user, the more her preferences are taken into account as input to produce recommendations. For instance, a common user-based approach consists of predicting the relevance of an item for the target user by a linear combination of her neighbors‟ ratings, weighted by the similarity between the target user and such neighbors.

Item-based strategies, on the other hand, recognise patterns of similarity between the items themselves, instead of between user choices like user-based approaches do. In general item-based recommenders look at each item on the target user's list of chosen/rated items, and find other items that seem to be "similar" to that item. The item similarity is usually defined in terms of rating correlations between users, although cosine-based or probability-based similarities have also been proposed (11).

The greatest strength of collaborative techniques is that they are completely independent of any machine-readable representation of the objects being recommended, and work well for complex objects such as music and movies where variations in taste are responsible for much of the variation in preferences. Schafer, call this "people-to-people correlation
In collaborative filtering process as computing the expected value of a user prediction, given his/her ratings on other items. The item-based approach looks into the set of items the target user has rated and computes how similar they are to the target item i and then selects k most similar items {i1,i2,……,ik }. At the same time their corresponding similarities {si1,si2,…..,sik }are also computed. Once the most similar items are found, the prediction is then computed by taking a weighted average of the target user's ratings on these similar items.

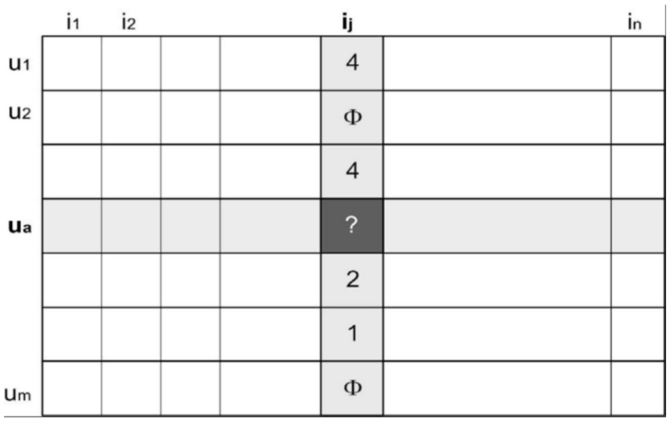

Fig.4.1 User × Item matrix for the Collaborative Filtering

As shown in Figure.1, the sum of ratings gathered from users can be represented as a user × Item matrix, with an entry r_{ul} representing either the rating user *u* gave to item *I*, if he rated it, or *null* otherwise

A user's comment on a certain item is usually an integration of multi –attribute comments made from different angles(6).Suppose an item is shown as follows:

$$P=\{a_1,a_2,a_3,\ldots..a_n\}$$

Based on the revised rating model ,the paper establish the user rating matrix. Suppose the user set is denoted as U $=\{U_1,U_2\ldots\ldots U_p\}$ and the user U_j rating for item P_i is denoted as $A(U_j,P_i)$:

$$\begin{array}{cc} & \text{Item} \\ \text{User} & \begin{bmatrix} r11 & \cdots & r1n \\ \vdots & \ddots & \vdots \\ rm1 & \cdots & rmn \end{bmatrix} \end{array}$$

Figure1 User X Item Matrix (mxn)

The rating matrix of an item is mainly acquired with the approaches of Web semantic digging and fuzzy mathematics [6].

Utility-based and knowledge-based recommenders do not attempt to build long-term generalizations about their users, but rather base their advice on an evaluation of the match between a user's need and the set of options available. Utility-based recommenders make suggestions based on a computation of the utility of each object for the user. Of course, the central problem is how to create a utility function for each user. Tête-à-Tête and the e-commerce site PersonaLogic2 each have different techniques for arriving at a user-specific utility function and applying it to the objects under consideration. The user profile therefore is the utility function that the system has derived for the user, and the system employs constraint satisfaction techniques to locate the best match. The benefit of utility-based recommendation is that it can factor non-product attributes, such as vendor reliability and product availability, into the utility computation, making it possible for example to trade off price against delivery schedule for a user who has an immediate need
(2).

2.3 Case Based Reasoning(CBR)

The main idea of CBR is to solve new problems by adapting the solutions given for old ones. When we apply CBR to recommender systems, the importance of the recommendation process lays with the case base representation. We propose, as a representation, a list of experiences (cases) of the user in certain items. Experiences are represented by means of objective attributes describing the item (case definition) and subjective attributes describing implicit or explicit interests of the user in this item (case solution).Assuming that the user's interest in a new item is similar to the user' s interest in Similar past experience, when a new item comes up, the recommender system predicts the user's interest in the new item based on interest attributes of similar experience.

2.4 Hybrid Recommender Systems

Hybrid recommender system combines two or more recommendation techniques to gain better performance. If it combines both techniques, it is called hybrid system. Such hybrid could offer good performance even with little or no user data. Several recommendation systems use hybrid approach by combining different recommendation techniques, which helps to avoid certain limitations of recommendation techniques (3).

Table 1 Hybridization Methods

In (3) a detailed taxonomy of hybrid recommender systems is pre-sented, classifying existing approaches into the following types:
1 **Cascade**: the recommendation is performed as a sequential process in such a way that one recommender refines the recommendations given by the other.
2 **Feature augmentation**: the output from one recommender is used as an additional input feature for other recommender.
3 **Feature combination**: the features used by different recommenders are integrated and combined into a single data source, which is exploited by a single recommender.
4 **Meta-level**: the model generated by one of the recommenders is used as the input for other recommender. As stated in (Burke, 2002): "this differs from feature augmentation: in an augmentation hybrid, we use a learned model to generate features for input to a second algorithm; in a meta-level hybrid, the entire model becomes the input."
5 **Mixed**: recommendations from several recommenders are available, and are presented together at the same time by means of certain ranking or combination strategy.
6 **Weighted**: the scores provided by the recommenders are aggregated using a linear combination or a voting scheme.
7 **Switching**: a special case of the previous type considering binary weights, in such a way that one recommender is turned on and the others are turned off.

The present user rating system, such as Movielens, only asks a user to make a synthetic rating for the movie he or she watched and give a quantitative scoring between 1 and 5.This approach is not accurate in identifying the similarity in the preference of two users. For example, if two users are interested in the same movie. When they rate it, they give it the same score. However, the angle of their preference for the movie are totally different. A user may like the star and the style. The other user prefers the theme and the content of the movie. Therefore, we propose to build a multi-attribute rating system to evaluate a product, i .e ,a product has many attributes. When evaluating the product ,a user mainly gives the preference rating of each product attribute(8).

2.5 Multi-Attributes Decision Making(MADM)

Called also Multi-Criteria Decision Analysis (MCDA) is a discipline, which consists on making choice of the best alternative among a finite set of decision alternatives in terms of multiple usually conflicting criteria (called also attributes). The objective of MCDM is to assist a decision maker in choosing the best alternatives when multiple criteria conflict and compete with each other.

The method ,on which we rested on ,is an objective weight determination method, which is refer to as Correlation Coefficient (CC) and Standard Deviation(SD) integrated approach for determining the weights of attributes, to provide decision supports to MADM problems (9).

III. METHODS

3.1Extracting the Decision Matrix

An MCRS problem can be easily expressed in matrix format. A decision matrix A is an (m x k)matrix in which element xij indicates the performance of item I when it is evaluated in items of decision criterion Cj, (for i=1,2,3…m,, and j-1,2,3…..k).Let $u_1,\ldots.u_N$ be N users who have evaluated m items based on k criteria. As each item is evaluated by different users according the k attributes, the performance valve x_{ij} is the average of all rating's values given to the item I according to attribute j by user who voted for.

$$X_{ij} = \frac{\Sigma_l (r_{li})_j}{N}$$

$(r_{li})_j$:The rating given by user 1 to item I according attribute j.

2 Computing Attributes' Weights

Lets m decision alternatives $I_1, \ldots, I_m$ to be evaluated in terms of k attributes $C_1, \ldots, C_k$ which forms a decision matrix denoted by $X=(x_{ij})_{m,k}$, where xij is the performance value of I_i with respect to C_j. Let $W= (w_1,\ldots,w_k)$ be a normalized weights' matrix in such way that $\Sigma w_j=1$ where w_j is the weight of the attribute C_j.

The overall assessment value of each item is computed as follows

$$d_i = \Sigma_{j=1}^{k} x_{ij} w_j \ .i =1,\ldots.m$$

The bigger the overall assessment value, the better the decision alternative. The best item is the one with the biggest overall assessment value.

By removing criteria Cj from the set of criteria, we define the overall assessment value of each item as:

$$d_{ij} = \sum_{\substack{l=1 \\ l\neq j}}^{k} x_{il} w_l \ .i =1,\ldots..m$$

The coefficient correlation (CC) between the values of Cj and the above overall assessment values can be expressed by:

$$R_j = \frac{\sum_{i=1}^{m} (x_{ij} - \bar{x}_j)(d_{ij} - \bar{d}_j)}{\sum_{i=1}^{m} (x_{ij} - \bar{x}_j)^2 \sum_{i=1}^{m} (d_{ij} - \bar{d}_j)^2}$$

Where $\bar{x}_j$and $\bar{d}_j$are respectively the mean values of x_{ij} and d_{ij}, for i=1,…,m.

If Rj is high enough and close to one then the criteria Cj has little effect on decision recommendation. If Rj is very low then Cj has a significant impact on decision recommendation and items ranking. So, the criteria Cj should be given a very important weight. Based on the above steps, the weight of an attribute is computed as(7):

$$w_j = \frac{\sigma_j \cdot \sqrt{1-R_j}}{\varepsilon_{i=1}^{k} \sigma_{i\sqrt{1-R_i}}} \qquad ,j=1,\ldots k$$

Where the SD is calculated by:

$$\sigma_j = \sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(z_{ij} - \bar{z}_j\right)^2} \qquad .j=1,\ldots..k$$

IV. SELECTION OF THE NEAREST NEIGHBOR OF TARGET USER

User based collaborative filtering systems suggest interesting items to a user relying on similar minded people called neighbors. The selection and weighting of these neighbors characterize the different recommendation approaches. While standard strategies perform a neighbor selection based on user similarities, trust aware recommendation algorithms rely on other aspects indicative of user trust and reliability.

We define the target user as the online user which requires evaluations and preliminary recommendations. The set of nearest neighbors is composed of users who have the most similar interest and preference to item with the target user.

Traditionally, researchers use k-Nearest Neighbor(KNN)algorithm and Pearson correlation based similarity formula to do cluster analysis on the target user and similar user set with different group standards can be obtained. In the process of collaborative filtering recommendation with group decision making method, we consider the characteristics of the target user preference and search the similar user sets.

Step 1. Search the user set which has similar interest distribution with target user U_T, i.e., to obtain the intersection set of the interest distribution of all users and the target user. Two users can rate the same attributes in a number of categories and have similar interest weights.

This approach can be applied to obtain the initial Nearest Neighbor set:

$IU = \{(U_1,\Omega_1), (U_2,\Omega_2), (U_3,\Omega_3) \ldots, (Uw,\Omega w)\}$

Where w is the number of users totally in the initial Nearest Neighbor set. U_k denotes the k^{th} user whose interest set is S_k. Ω_k denotes the interest intersection between user U_k and the target user U_T.

Step 2. Use Pearson correlation-based similarity formula to calculate the similarity between target user U_T and a random user U_k. When the degree of similarity reaches the threshold, u_k can be divided into S_{UT} which is the similar user set of U_T. Finally, $S_{uT}= \{u_1, u_2, \ldots u_s\}$ is obtained, i.e.,similar users meet the threshold. The set of the interest intersection between the target user u_T and s similar users that meet the threshold is $Se_{uT}= \Omega_1 \cup \Omega_2 \cup \Omega_3 \ldots\ldots \cup \Omega s$(6,).

Collaborative Filtering Recommendation Algorithm Based on Multi-attribute Decision making

4.1 Group Decision making Model of Personalized Recommendation

After acquiring a similar user set Su_T, we need predict and recommend the items that target user U_T has not commented yet. Suppose the item set is source $=\{P_1,P_2,P_3,\ldots..P_n\}$ and $P_k(k=1,2,3\ldots.n)$ is the item that the target user has not commented yet. The traditional collaborative filtering recommendation algorithm is applied to calculate the overall evaluation.

value of the item A(UT , Pk) given by similar users and then obtain the initial recommended source $S_{Initial}$. Suppose a random item $Pk \in S_{Initial}$ has n attributes denoted as a set $Spk= \{a_1,a_2\ldots\ldots a_n\}$,the set satisfies the condition $Spk \subseteq SeuT$. The comment matrix is denoted as $A1,A2,A3,\ldots Ap$, which means similar users in SuT commend Pk. We suppose p users are similar with the target user and have made comments to the item. The algorithm proposed in this paper requires that $p >= 3$. When $p <3$, refer to the article [liu].

A recommendation model can be transferred to group decision-making model in order to solve a problem. However, the traditional group decision-making algorithm still need be improved when applied since there exists differences between similar users and decision-making expert. The differences mainly exist in the following aspects:

1. It is hard to use the weight vectors to measure the influence of similar users in the recommendation processes mainly because of the complexity of user preferences. According to the traditional method, two users have a high similarity in their interest preferences. However, it is hard to identify the deviation existing in the preferences of the two users on a specific item.
2. There are a large number of incomplete values in user comment information because some users may make no comments on the unfamiliar attributes to ensure the accuracy of evaluations. In this situation, the application of some traditional group decision-making algorithms, such as weighted average method or weighted least squared logarithm method may result in a great deviation of the final result.

To solve the two problems mentioned above, this paper makes improvements in group decision-making compatibility test algorithm and builds a collaborative correction algorithm based on Pearson-Compatibility mode(6)l

4.2 Collaborative Correction Algorithm Based On Pearson-Compatibility

Pearson Compatibility model could be used to simulate the process of experts doing group discussions and finally making group decision. The model mainly consist of two indicator calculation formulae: Pearson similarity calculation and Compatibility test. Pearson similarity calculation formula is mainly used to calculate the information reservation degree user rating matrix after the matrix has been revised. The mainly function of Pearson-Compatibility model is to build the associations between two variational indicators. Based on this association ,Compatibility correction algorithm will choose the best revised matrix in each iteration process, which could make the user matrix's unanimous and most similar to the true value.(6)

V. CONCLUSION

We have proposed a theoretical framework for neighbor selection and weighting in user based CF systems, based on a performance prediction approach.in this paper we have extanded the concept of mono-criterion rating to multi-criteria ones to meet the requirements of more practical recommendation systems. We proposed an approach for selection of relevant items in a RS based on multi-criteria. This method proposes a correlation coefficient and standard deviation integrated approach for determining weight of criteria in multi-criteria recommender systems.

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