Solution for Ordered Weighted Averaging Operator for Making in the Interaction multi-Criteria Decision in User-Based Collaborative Filtering Recommender System

Tri Minh Huynh, Vu The Tran, Hung Huu Huynh, and Hiep Xuan Huynh

***Abstract*—In the recommender system, the most important is the decision-making solution to consulte for user. Depending on the type and size of data stored, decision-making will always be improved to produce the best possible result. The main task in implementing the model is to use methods to find the most valuable product or service for the user. In this paper, we propose a new approach to building a multi-user based collaborative filtering model using the interaction multi-criteria decision with ordered weighted averaging operator. This model demonstrates the synergy and interplay between user criteria for decision making. The model was evaluated through experimentation with the multirecsys tool on three datasets: MovieLense 100K, MSWeb and Jester5k. The experiment illustrated the model comparison with some other interactive multi-criteria counseling methods that have been reserched on both sparse datasets and thick datasets. In addition, the model is compared and evaluated with item-base collaborative filtering model using the interaction multi-criteria decision with ordered weighted averaging operator on both types of datasets. Consultancy results of the proposed model are quite effective compared to some traditional consulting models and some models with other operator. This counseling model can be applied well in a variety of contexts, especially in the case of sparse data that will result in improved counseling. In addition, with the above method, the user-base model is always more efficient than item-base on all datasets.**

***Index Terms*—User-base, item-base, collaborative filtering recommender system, the interaction multi-criteria decision, ordered weighted averaging operator.**

I. Introduction

The Multi-Criteria Recommender System [1]-[4] is increasingly being researched and developed by scientists to serve better the need about finding diverse information of users. Often, almost all events occurring in the human world are essentially multi-criteria. Consultation will not be appropriate if the decision is only based on the evaluation of a particular criterion. The multi-criteria counseling system is based on the evaluation of multiple criteria rather than on a criterion for determining the outcome of counseling because there are always interrelations, influences and interactions among the criteria and from that make the real decision.

The counseling system is based on assessing many of the criteria for making decisions that suggest that users have long been interested in research. For example, the counseling system evaluates the many factors that influence the destination to suggest that the traveler chooses according to his preferences [5]; The system relies on image-specific features or demographic features [6] to advise users seeking demographic information and lots of other model [7]-[10]. In this paper, we propose a new approach to building a user-based collaborative filtering model using the interaction multi-criteria decision with ordered weighted averaging operator. This model is also built on the basis of a combination of traditional consulting techniques and the analysis of user evaluation data on products in archival data. Model identifies key users (which are key criteria). Rely on these criteria to make a counseling decision. The model assign the weights for these user criteria according with the proposed method. Based on the weights and ratings of this user for each product performing the mathematical operations for the consultancy rankings. The results of the proposed model are reliable, responsive to user requirements and can be effectively applied to different datasets. The proposed model seem always better than other models. Particularly, the experimental results on datasets (too sparse) which number of users is much larger than number of items show better than results on dataset (too thick) which number of items is much larger than number of users and the experimental results of proposed model is always better than the current IBCF model [3], [11].

The paper is organized into five sections. The first part introduces an overview of the multi-criteria consulting system, some current approaches. The second part presents multi-criteria and some decision-making operations for the consulting model. The third part presents the multi-criteria decision-making model with ordered weighted interactions, model implementation steps. The fourth part presents some experiments to evaluate the model through the multirecsys tool. The last part is the conclusion.

II. Proposed Model and Operation Are User for Decision Making

A. Recommender Model with Traditional Average Operations: Arithmetic Mean (MA), Geometric Mean (GM) and Hamornic Mean (HM)

The matrix A $(m \times n)$ consists of m rows $u_1, u_2, \dots, u_m$ and n columns $i_1, i_2, \dots, i_n$. Each row of u_p $(p{:}\,1..m)$ with each column i_q $(q{:}\,1..n)$ determines the value r_{pq} as Table I. Each row is a criterion. The single criterion model shown on matrix A with the function $\hat{r}(u, i)$ is determined based on a

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single row called a single criterion model. In contrast, for $\hat{r}(u,i)$, each $\hat{r}_q$ value is determined based on the set R_q ={ $r_{1q}, r_{2q}, \dots, r_{mq}$ } $(q{:}\,1..n)$ where r_{pq} is the value corresponding to u_p $(p{:}\,1..m)$ and i_q, this is a multi-criteria model with the criterias are rows.

TABLE I: MULTI-CRITERIA MODEL WITH ARITHMETIC MEAN, GEOMETRIC MEAN, HAMORNIC MEAN ON A(4×3)

	i_1	i_2	i_3
u_1	?	1	3
u_2	3	?	1
u_3	3	4	1
u_4	4	2	?
$\hat{r}_{AM}$	3.33	3.00	1.66
$\hat{r}_{HM}$	3.30	2.00	1.44
$\hat{r}_{GM}$	3.27	1.71	1.229

For example, for Table I, the functions $\hat{r}_{AM}, \hat{r}_{HM}, \hat{r}_{GM}$ are defined by the four criteria u_1, u_2, u_3, u_m with the set on the criteria $(r_{1q}, r_{2q}, \dots, r_{mq})$. The operations are defined [12], [13]:

- *AM:* $\hat{r} = \frac{1}{m}\sum_{j=1}^{m} r_{jq}$
- *GM:* $\hat{r} = \sqrt[m]{r_{1q} * r_{2q} * \dots * r_{2mq}}$
- *HM:* $\hat{r} = \frac{m}{\frac{1}{r_{1q}}+\frac{1}{r_{2q}}+\dots+\frac{1}{r_{mq}}} = \frac{m}{\sum_{i=1}^{m}(\frac{1}{r_{iq}})}$

  $r_{pq} > 0 \ (p{:}\,1..m, q{:}\,1..n)$

  $min(r_{1q}, r_{2q}, \dots, r_{mq}) < \hat{r}_q < m * min(r_{1q}, r_{2q}, \dots, r_{mq})$

B. Ordered Weighted Averaging operator-OWA

With the set: $(r_{1q}, r_{2q}, \dots, r_{mq})$ in the rows in Table II, the orderd weighted average [14] per column q, $q{:}\,1..n$ is defined as follows:

$$\hat{\boldsymbol{r}}(\boldsymbol{r_{1q}}, \boldsymbol{r_{2q}}, \dots, \boldsymbol{r_{mq}}) = \sum_{j=1}^{m'} \boldsymbol{w_j} * \boldsymbol{r'_{jq}} \qquad (1)$$

With m' is the number $r_{pq} > 0 \ (p{:}\,1..m)$, $\sum_{j=1}^{m} w_j = 1$ and w_j is the weight at row j and is the ordered permutation decreasing gradual of the weights. r'_{pq} is the permutation of r_{pq} at column q and it is weighted descending order w_j, $r'_{1q} \le r'_{2q} \le \dots \le r'_{mq}$.

TABLE II: MULTI-CRITERIA MODEL WITH ORDERED WEIGHTED AVERAGING OPERATOR ON A(4×3)

	i_1	i_2	i_3	w
u_1	?	1	3	0.17
u_2	3	?	1	0.12
u_3	3	4	1	0.03
u_4	4	2	?	0.22
$\hat{r}$	1.33	1.25	0.95	

$\hat{r}_1 = 0.22 * 4 + 0.12 * 3 + 0.03 * 3 = 1.33.$

III. COLLABORATIVE FILLTERING RECOMMENDATION BASED ON THE INTERACTION MULTI-CRITERIA DECISION WITH ORDERED WEIGHTED AVERAGING OPERATOR

A. Proposed Model

On the data set M contains user's the evaluation information for the products shown in Table III with m rows are m user $u_1, u_2, \dots, u_m$ and n columns are n products $i_1, i_2, \dots, i_n$. Each user u_p $(p{:}\,1..m)$ defines an evaluation value (u_p, i_q) for product i_q $(q{:}\,1..n)$. This value is in the range of 1 to 5. If u_p has not evaluated the product i_q then (u_p, i_q)="?". The proposed model selects the user-based collaborative filtering model with k nearest neighbors (kNN). In Table I. (k = 3), 3 users u_2, u_4, u_6 are nearest neighbors to u_a consulted users based on the similarity (or distance) between u_a and each user in the system according to pearson correlation. Each user in kNN is weighted separately as shown in 3.2. The Pearson measure [15] between u_x and u_y $(x, y{:}\,1..m)$ is defined:

$$sim_{pearson}(u_x, u_y) = \frac{\sum_{i \in I_{u_x,u_y}} (r_{u_x i} - \bar{r}_{u_x})(r_{u_y i} - \bar{r}_{u_y})}{\sqrt{\sum_{i \in I_{u_x,u_y}} (r_{u_x i} - \bar{r}_{u_x})^2}\sqrt{\sum_{i \in I_{u_x,u_y}} (r_{u_y i} - \bar{r}_{u_y})^2}} \qquad (2)$$

I_u is the set of data items evaluated by u_x, $\bar{r}_{u_x}$ is the average rating evaluation of u_x on all data items, $\bar{r}_{u_y}$ is the average rating evaluation of u_y on all data items. Then, the distance between two users is (1-*r*).

B. Indentify the Weight and Results of the Consultancy

Let U_k be the set of nearest neighbors to u_a. Depending on the context, determine the appropriate weight for best advice. Here we determine the weights of the users in the set U_k is the distance value between each user and the consulted user (u_a). For each r_{aj} $(j{:}\,1..n)$ not evaluated by the consulted user u_a for products, such as $r_{a1}, r_{a8}, r_{a52}, \dots$ in Table III, we define the mean values $\hat{r}_{aj}$ in these products according to the proposed method (formula 1) to advise the user u_a. The method is as follows:

For m' is the number of users $u_t(t{:}\,1..k) \in U_k$ rated for product i_j $(j{:}\,1..n)$ (m'<= k, here k = 3), the user has not evaluated for that product with the value "?". Determine the orderly weighted average of m' users per product by formula (4), with each item j having the m' value r_{tj} to be calculated on average. After defining $\hat{r}_{aj}$ values, rank these values in descending order, selecting the products corresponding to the high to low values to suggest to the user. Suppose we choose two products to introduce to the user u_a when the two products selected are i_1 and i_{52}; $\hat{r}_{a1} = 2.81$ *and* $\hat{r}_{a52} = 2.7$.

TABLE III: PROPOSED MODEL

	i_1	i_2	…	i_8	…	i_{52}	…	i_n	w
u_1	?	1	…	1	…	?	…	3	
u_2	5	4	…	4	…	5	…	2	0.34
…	…	…	…	…	…	…	…	…	…
u_4	3	2	…	2	…	4	…	2	0.25
u_x	?	1	…	1	…	3	…	1	
…			…		…		…	…	…
u_6	3	0	…	0	…	0	…	1	0.12
u_y	4	?	…	?	...	3	…	?	
…	…	…	…	…	...	…	…	…	…
u_m	4	2	…	4	…		…	?	
u_a	?	2	…	?	…	?	...	3	
$\hat{r}$	2.81	-	…	1.86	…	2.7	…	-	

IV. EXPERIMENT

A. Datasets Used for Experiments

The data set used for experimentation on the proposed model is the MovieLens 100K movie and the Jester5k joke book, which is available at http://grouplens.org/datasets. Movielens archive of 100,000 reviews performed by 943 users on a total of 1,682 films, each rated at least 20 movies and rated from 1 (bad) to 5 (good). The MSWeb was generated by sampling and processing the logs of www.microsoft.com in one week timeframe, episode stores information about the 98.653 rating made by 32.710 users on the number of 285 website (Vroot) with value of TRUE/1. These are two datasets which is too sparse but on MovieLens 100K number of items is much larger than number of users and opposite on MSWeb. Jester5k episode stores information about the 500,000 rating made by 5,000 users on the number of 100 jokes, with values from -10 to 10. Each user evaluates at least 36 jokes. This is dataset which is too thick.

B. Evaluation Recommendations

Method used to evaluate model is the Receiver Operating Characteristic (ROC) [15]-[18]. The method was developed for signal detection and goes back to the Swets model (van Rijsbergen 1979). The ROC-curve is a plot of the system's probability of detection (also called sensitivity or true positive rate TPR) by the probability of false alarm (also called false positive rate FPR). A possible way to compare the efficiency of two systems is by compar-ing the size of the area under the ROC-curve, where a bigger area indicates better performance. Four values contain the true-false positives/negatives, and they are as follows: True Positives (TP): These are recommended items that have been purchased and False Positives (FP): haven't been purchased. False Negatives (FN): These are not recommended items that have been purchased and True Negatives (TN) haven't been purchased. First, let's build the ROC curve. True Positive Rate (TPR): This is the percentage of purchased items that havebeen recommended. TPR=TP/(TP + FN). False Positive Rate (FPR): This is the percentage of not purchased items that havebeen recommended. FPR= FP/(FP + TN).

TABLE IV: FIVE MOVIES ARE CONSULTED ON 5 MODELS WITH MOVIELENSE

UBCF	*UBCF_OWA*
1.Titanic (1997) 2.Dante's Peak (1997) 3.Shadow Conspiracy (1997) 4.Air Force One (1997) 5.L.A. Confidential (1997)	1. Scream (1996) 2. Titanic (1997) 3. Air Force One (1997) 4. Liar Liar (1997) 5. Murder at 1600 (1997)

UBCF_AM	*UBCF_HM*	*UBCF_GM*
1. Rainmaker,The 1997 2. Midnight in the Garden of Good and Evil (1997) 3. Dante's Peak (1997) 4. G.I. Jane (1997) 5. Cop Land (1997)	1. Rainmaker,The 1997 2. Midnight in the Garden of Good and Evil (1997) 3. Dante's Peak(1997) 4. G.I. Jane (1997) 5. Cop Land (1997)	1. Dante's Peak 1997 2. Shadow Conspiracy1997 3. Titanic (1997) 4. Rosewood (1997) 5. L.A Confidential1 997

C. Experimental Tools

The model was experimented with by the Multicriteria Recommender System (multirecsys), which we built, developed and installed on R [www.r-project.org].

D. Scenario 1: Experimental Demonstration of the Results of the multi-Criteria Counseling Model with Order-Weighted Interactions (UBCF_OWA) and Comparison with Some Existing Models

We tested the proposed model of counseling (UBCF_OWA) on three datasets: Movielens100K (data too sparse, number of items is much larger than number of users); MSWeb (data too sparse, number of users is much larger than number of items) and Jester5k (data is too thick). On three these datasets, we compared the results of the counseling with the existing methods (UBCF, IBCF) [19]-[21], and compared with some other mathematical models such as UBCF_AM, UBCF_HM, UBCF_GM to evaluate the results of the proposed model. Experimental results with kNN=5, consultants on the Movielens100K and Jester5k show that the consultancy results have some differences but not much. Based on the ROC Curve found that UBCF_OWA is always better than other models. Particularly, the experimental results on the Movielens100K, MSWeb is better than on the Jester5k and the experimental results of proposed model is always better than the current IBCF model and some other current model.

TABLE V: FIVE COMICS ARE CONSULTED ON FIVE MODELS WITH JESTER5K

UBCF	*UBCF_OWA*	*UBCF_AM*	*UBCF_HM*	*UBCF_GM*
"j78"	"j78"	"j78"	"j78"	"j71"
"j71"	"j84"	"j84"	"j84"	"j72"
"j72"	"j71"	"j71"	"j71"	"j73"
"j73"	"j72"	"j72"	"j72"	"j74"
"j75"	"j73"	"j73"	"j73"	"j75"

MovieLense

Jester5k

MSWeb

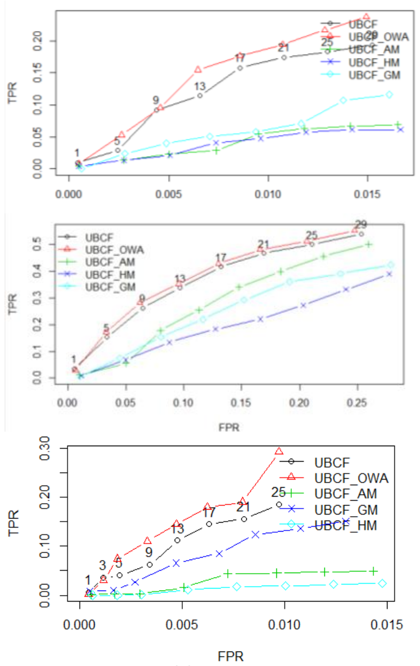


Fig. 1. Roc curve of five models.

MovieLense

Jester5k

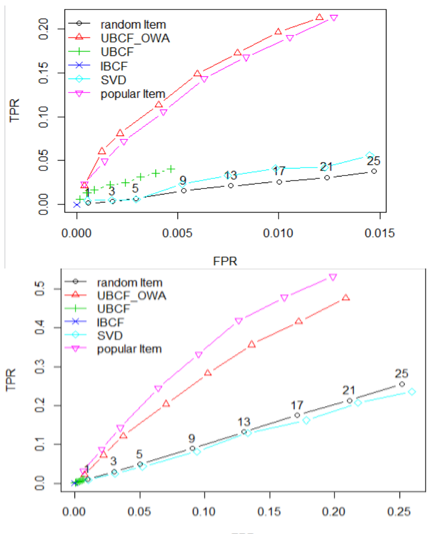
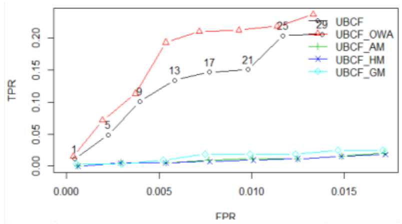


Fig. 2. ROC curve of UBCF_OWA model and other current models.

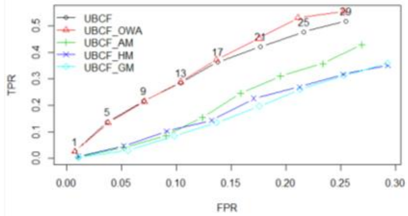
In Fig. 2, the result of UBCF_OWA model is alway better than RANDOM ITEM model, UBCF model, IBCF model, SVD model and very similar to POPULAR ITEM model.

E. Scenario 2: Experiment to Evaluate the Proposed Model with Different kNN Values on Three Datasets: Movielens100K, Jester5k and MSWeb

MovieLense



Jester5k



MSWeb

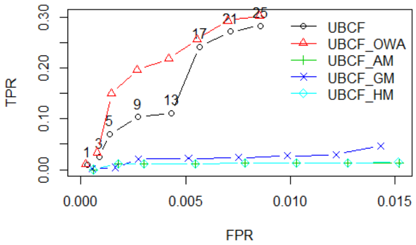
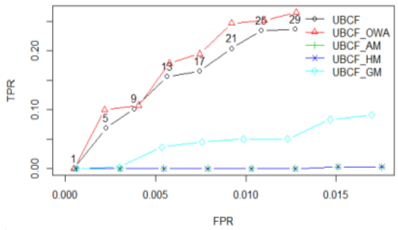
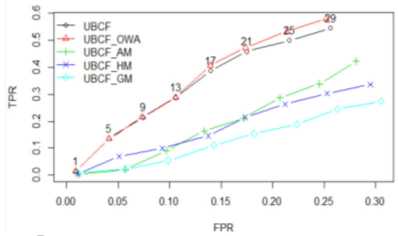


Fig. 3. ROC curve in five models with *k*=15.

MovieLense



Jester5k



MSWeb

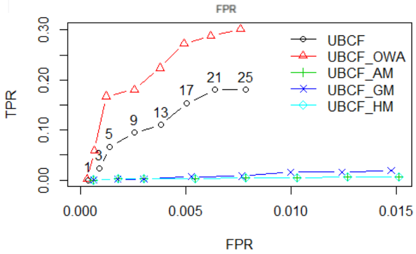
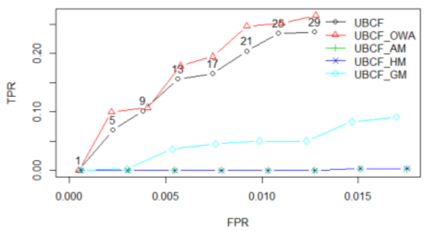
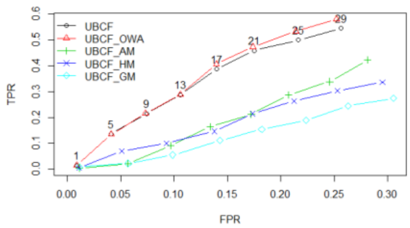


Fig. 4. ROC curve in five models with *k*=25.

MovieLense



Jester5k



MSWeb

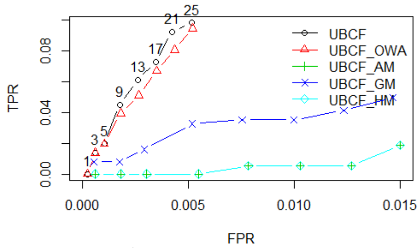


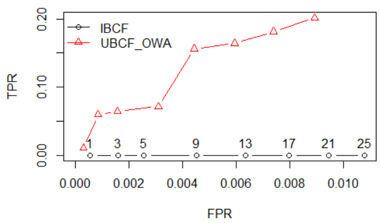
Fig. 5. ROC curve in five models with *k*=35.

Experimental results show that UBCF_OWA's results are always better than the other models on all datasets. Thereby, UBCF_OWA also demonstrates good performance on the too sparse datasets.

F. Scenario 3: Experiment to Evaluate the Proposed Model (User-Base) with the Item-Base Model Is Available Current on Movielens 100K (Number of Users Is Much Larger than Number of Items) and MSWeb (Number of Items Is Much Larger than Number of Users)

Experimental results show that UBCF_OWA's results are always better than the current IBCF models [7] on all datasets and has more effect on datasets which is too sparse and number of items is much larger than number of users.

MovieLense



MSWeb

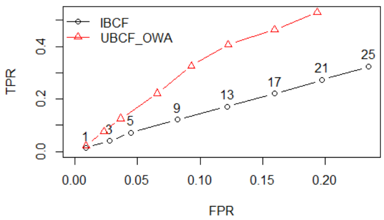
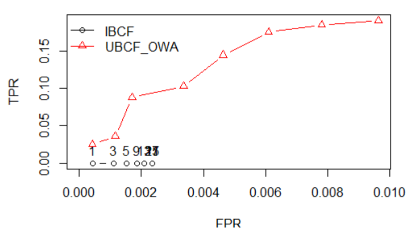


Fig. 6. ROC curve in two models with *k*=5.

MovieLense



MSWeb

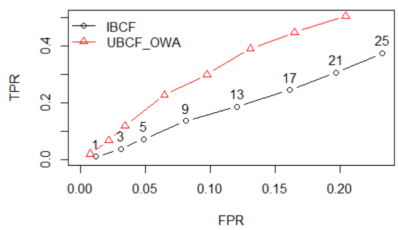


Fig. 7. ROC curve in two models with *k*=15.

MovieLense

MSWeb

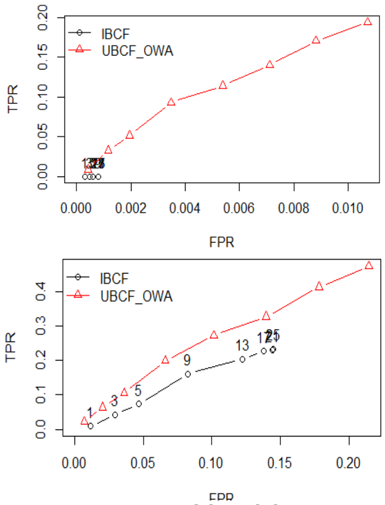


Fig. 8. ROC curve in two models with k=35.

V. Conclusions

The collaborative filtering recommender system based on the interaction multi-criteria decision with ordered weighted averaging operator can be well suited to suggestive systems based on the interaction, the interrelationships between the criteria. In many ways, we determine the weight accordingly. This gives the consultant decision to match the requirements of the coursed user. This model shows the coherence, interactions between the criteria, improvement of the consultant results with discrete information, lack of information and mutation of data. The paper provides a method of counseling with the weighting of criteria and prioritizing values for decision making. The proposed model can be applied on a variety of datasets and the results will be reliable, especially on sparse dataset. Although the execution time is longer as lost time to make weighted values and ordered rankings, weighting and the mean, but the results are more responsive. In the coming time, we will continue to research and improve the algorithm more to shorten the time of consulting and will continue to experiment on many other data sets to evaluate and improve the proposed model better.

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