IJICT International Journal of Information & Communication Technology

ITRC

Volume 2- Number 4- September 2010 (79-87)

Technical Note

Addressing the New User Cold-Start Problem in Recommender Systems Using Ordered Weighted Averaging Operator

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Received: August 11, 2010 - Accepted: September 26, 2010

***Abstract*—Recommender systems have become significant tools in electronic commerce, proposing effectively those items that best meet the preferences of users. A variety of techniques have been proposed for the recommender systems such as, collaborative filtering and content-based filtering. This study proposes a new hybrid recommender system that focuses on improving the performance under the *"new user cold-start"* condition where existence of users with no ratings or with only a small number of ratings is probable. In this method, the optimistic exponential type of ordered weighted averaging (OWA) operator is applied to fuse the output of five recommender system strategies. Experiments using MovieLens dataset show the superiority of the proposed hybrid approach in the cold-start conditions.**

Keywords- recommender system; collaborative filtering; content-based filtering; demographic- information; hybrid approach; OWA

I. INTRODUCTION

Recommender systems automatically recommend items of interest to their users based on some existing information such as user's preferences, preferences of other users and purchase history of each user [1]. With advancement of electronic commerce, recommender systems have been considered as critical tools for sales in online stores. With an accurate recommender system, online stores could increase their revenue by up-selling and cross-selling [2].

In the recommender system literature, there are many approaches that utilize various types of data and analysis techniques. One of the most successful methods is collaborative filtering (CF) which uses users' ratings on items [2]. Another successful method is content-based filtering (CBF) which uses content information of items to find the match between items and users [3]. Still another method is demographic-based method that uses the demographic information, such as, age, gender and occupation, in the user profile to recommend items of interest to the users. Also, there is another approach which combines other methods to gain a more precise recommender system.

Cold-start problem is a popular and potential problem in the recommender systems. This problem refers to the significant degradation of recommendation quality when no or only a small number of purchasing records or ratings are available [2].

There are two kinds of cold-start problem: new user and new item. New user cold-start problem refers to existence of a user with a few ratings. The average number of purchases in every Internet store is usually limited for each user. Since there are a lot of new users or less-active users in every Internet shopping mall, the new user kind of cold-start problem is a very popular and serious issue in the recommender systems [2].On the other hand, new item cold-start problem refers to a new item which does not have many ratings [4]. This is an extreme kind of data sparseness that occurs when recommender systems can not recommend any promotions for items with no or very rare ratings data. In the literature, new item cold-start problem is also known as the early-rater problem [23]. Our solution is to address the user-side problems by proposing a new hybrid recommender system.

Many hybrid approaches have been proposed in the literature to circumvent this problem. Most of these approached combine the content information and rating data (CF) [2]. As a result, the current literature requires an applicable and comprehensive algorithm with a high performance in cold-start condition so that companies would be able to recommend items more accurately.

In this study, we propose the optimistic exponential type of ordered weighted averaging (OWA) operator as a hybrid recommender system. When we have a user with a small number of ratings (new user cold-start problem), CF and CBF methods cannot work well, because they do not have enough information (there are a small number of purchasing records or ratings) In such a situation, the OWA operator uses the demographic information for recommendation to solve the problem. Using all the existing information for each user, this approach aims at proposing an accurate recommendation. We combine the user ratings, content information and demographic information together to alleviate the user-side cold start problem. Although, there are some other research that combine this information to conquer the cold start problem, to the best of our knowledge, recommender system literature does not contain any reference to the optimistic exponential type of OWA. Our experiment results confirm that we can overcome the cold start problem efficiently.

The remaining of the paper is organized as follows. In section II, we review the recommender systems. Then the optimistic OWA and the proposed approach are discussed in details in section III. After that, the proposed approach is tested on a real dataset and experimental results are discussed. Finally, section V concludes the paper.

II. RECOMMENDER SYSTEMS

In the recommender systems, we want to predict the customer rating on some products that he has not rated before. Formal definition of recommender systems can be considered as follows:

$G = \{g_1, g_2, g_3, g_4, \ldots\ldots\}$

$U = \{u_1, u_2, u_3, u_4, \ldots\ldots\}$

Where, G is the item set and U is the set of all users.

For each customer u_i, there is a binary set P_i that each of its pair (g_j, s_j) represents given rate s_j for the item g_j by customer u_i:

$$\forall u_i : \mathrm{Pi} = \{(g_1, s_1), (g_2, s_2), \ldots\ldots\}, \quad u_i \in U, g_i \in G, s_i \in S \qquad (1)$$

Where, S is a set of all possible rates in the system. A recommender system should predict s_i for (g_i, s_i) which has not been registered in the system yet.

Generally speaking, each recommender system contains three components [4]:

i. Background data: the information that exists in the system before the recommendation procedure begins.

ii. Input data: the information that is obtained through the communication between user and the system in order to generate a recommendation.

iii. Recommendation algorithm: an algorithm that applies background and input data to arrive at its recommendations.

Recommendation algorithm can use information about the users such as previous ratings, demographic information, specific inquiry patterns, to propose some relevant things to the users. Also, they can use the properties of items to prioritize such items to meet the user's preferences [24].

III. RELATED WORK

In previous studies, there have been numerous methods of product recommendation. According to the most well-known classified standard, the typical methods of recommender systems are sorted into collaborative filtering, content-based filtering and hybrid approach [5]. Also some previous studies have used demographic-based methods for the recommender system [6, 7].

A. *Collaborative Filtering*

Collaborative Filtering (CF) is one of the oldest, most mature and successful approaches for building recommender systems [25]. The critical step of collaborative filtering approach is finding customers with preferences similar to the preferences of the current customer [5]. Using other users' ratings on the items, this method finds similarities between users [2]. After this step, it presents recommendation for the current customer based on the preference of most similar ones. Some of the most important systems using this approach are Ringo and GroupLens [26]. The greatest strength of CF approach is the ability to filter any type of items, such as text, music, videos, and photos because in CF method domain knowledge is not needed. The filtering process is only based on previous ratings of a given target user and it is not necessarily required to analysis the actual content, itself [27]. CF methods suffer from the cold-start problem.

B. *Content-Based Filtering*

As the name suggests, using content information of previously rated items, content-based filtering (CBF) methods find the preference of current user about a new item without relying on the interests of other users. For example, keywords of previous purchased book of a user could be used to recommend some other similar books which have similar keywords [2]. One of the most important advantages of CBF method is that it allows the user to encounter new content that has not been rated before, since the system must be able to match the characteristics of an item against related features in the user's profile [28]. But, like the CF approaches, the CBF methods suffer from the new item type of cold-start problem.

C. Demographic-Based Method

This approach uses the demographic information of user's profile such as age, gender and education, to find the similar preference customers with the current customer to present the recommendation for him [2, 7]. In contrast the other methods, the main benefit of a demographic technique is that it may not require a history of user ratings of the type needed by CF and CBF approaches. Using these methods can alleviate the new user cold start problem, because they do not require any rated items for the current user to recommend a new item [4]. However, gathering this information is a difficult task because users are reluctant to give this type of data.

D. Hybrid Approach

To avoid disadvantages of existing approach besides combining advantages of them, some researchers have fused them and introduced the hybrid approach [5].

Generally, all the hybrid approaches can be classified into three categories [5]. In the first category, one approach provides some additional information for another one. In [8], CBF has been used to enhance existing user data which is used in CF method. Second method is presenting a framework which applies information of single approaches in a comprehensive approach.[9]. Finally, in the last type, the scores (or votes) of single recommendation approaches are fused to produce a single recommendation [4]. In [10] results of CBF and CF methods have been linearly fused. In [7], the results of single approaches, including CF, CBF and demographic have been considered as a set of votes which have been combined in a consensus scheme.

One of the most important problems of the recommender systems is cold start (new user) problem. In this state the system tries to generate predictions for new users who have not enough ratings yet. There are many proposed methods in the recommender systems literature for alleviating the cold-start problem. In [2] a new similarity measure has been introduced for collaborative filtering to alleviate this problem. In [1] using a hybrid approach collaborative filtering and users' information have been combined. In [17] some simple information is considered which are easily accessible for all users even new users. Also, many studies have presented hybrid approaches that combine both content information and CF method [18, 19, and 20].

As it was mentioned before, all the single approaches have some disadvantages and hybrid approaches have been proposed to conquer these disadvantages. In this paper, we introduce the optimistic exponential OWA approach as a hybrid approach to the recommender systems. This approach is classified in the third category of introduced hybrid categories.

IV. PROPOSED METHOD

Generally speaking, recommendation is a binary classification problem which distinguishes preferred items and non-preferred items for a specific user. Considering $(g_j, s_{i,j})$ a specific member of Pi in (1), we can define the problem which recommender systems aim at solving as follows [11]:

$$(g_j, s_{i,j}) = \begin{cases} 1 & \text{when customer } u_i \text{ accept with item j} \\ 0 & \text{otherwise} \end{cases}$$

If customer u_i accepts an item, the item is labeled as 1, and otherwise its label is 0.

In this paper, we propose a new method to deal with the cold start problem effectively. The proposed method can give reasonable and appropriate recommendation even we have a new customer without any rate. As fig. 1 illustrates, in the proposed method, we apply five different classification strategies, and then the returned results of the underlying classifiers are fused using Optimistic exponential OWA operator. Strategy 1 uses the previous ratings of each customer to find the similar customers. Strategy 2 applies the content information of previous purchases. Strategy 3 uses demographic information and previous ratings. Also, strategy 4 uses the demographic information. Finally, strategy 5 applies both content information of previous purchases and previous ratings of each customer. As we will show later, this method works better than each other strategies, especially when we face the cold start problem.

In the following sections, we first explain five used strategies, and then the proposed approach will be presented.

A. First Strategy: CF Method

This method works based on the CF method. In this strategy the distance between two customers u_i and u_j who have rated item set $\{g_1, g_2, \ldots, g_m\}$ is calculated as follows:

$$\mathrm{Di,j} = \frac{\sqrt{(p_{i1}-p_{j1})^2+(p_{i2}-p_{j2})^2+\ldots+(p_{im}-p_{jm})^2}}{m} \quad (2)$$

Where p_{ik} is the rate of the customer i to the kth item; also m is the number of common items between customers i and j.

B. *Second Strategy: CBF Method*

This strategy works based on CBF method; it predicts using the similarity between current item and customer's previous items.

C. *Third Strategy: CF & Demographic-Based Filtering*

This strategy is similar to the first strategy, but there is a difference. This strategy not only compares the previous ratings of other customers by the current customer, but also uses their demographic characteristics as extra knowledge. In fact, if customer u_i and customer u_j have rated $g_1, g_2 \dots g_m$ items, the distance between two customers is computed as follows:

$$D_{i,j} = \frac{\sqrt{(p_{i1}-p_{j1})^2+(p_{i2}-p_{j2})^2+\dots+(p_{im}-p_{jm})^2}}{m} + \sqrt{(a_1-b_1)^2+(a_2-b_2)^2+\cdots(a_n-b_n)^2}$$

Where $a_1, a_2 \dots a_n$ are the demographic characteristics of customer u_i and the similarly $b_1, b_2, \dots, b_n$ are demographic characteristics of customer u_j and p_{ij} is same as (2).

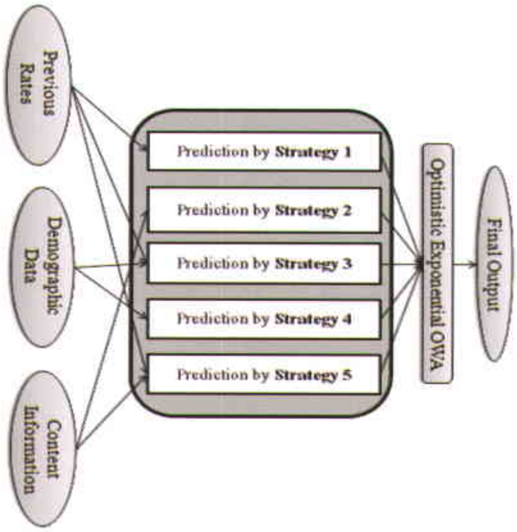

Figure 1. Overview of the proposed hybrid approach for the recommender systems

D. *Fourth Strategy: Demographic-Based Filtering*

As mentioned before, it works based on the demographic features of customers.

E. *Fifth Strategy: CF and CBF*

The fifth strategy is a hybrid approach based on the first and second strategies. Considering the result of CF method as 'outp_cf' and the result of CBF as 'outp_cbf', then the output of fifth strategy is calculated as follows:

outp_st5 = (outp_cbf + outp_cf) / 2

Note that the labels of the instances in all of above strategies are identified by k-nearest neighbor algorithm [17] (KNN). Also Euclidean distance has been used as the similarity measure for the KNN to detect the similarity between customers or between items.

F. *OWA Technique*

In this study, we use the optimistic exponential type of ordered weighted averaging (OWA) operator to fuse the output of each learned classifier, which is proposed by Filev and Yager [12]. OWA were introduced by Yager [13] (cf. also Yager and Kacprzyk [14]) and are defined as follows: The OWA operator of dimension n is a mapping such as:

F: $R^n \rightarrow R$ and is given by

$$OWA(a_1, a_2, \dots\dots, a_n) = \sum_{i=1}^{n} w_i b_i$$

Where b_i is the i^{th} largest element among a_i's. The weights are non-negative ($w_i \geq 0$) and their sum equals to one ($\sum_{i=1}^{n} w_i = 1$).

The OWA operators include many of the well-known operators such as the maximum, the minimum, the k-order statistics, the median and the arithmetic mean. Also they have a compensatory behavior [15]. Based on this property the aggregation done by an OWA operator always is between the maximum and the minimum. It can be seen as a parameterized way to go from the min to the max. In [13] a degree of maxness (initially called orness) was introduced as follow:

$$Maxness\,(w_1, w_2, \dots\dots, w_n) = \frac{\sum_{i=1}^{n}(n-i)w_i}{n-1}$$

A simple class of OWA operators as exponential class was introduced to generate the OWA weights satisfying a given degree of maxness. The optimistic and pessimistic exponential OWA operators were correspondingly introduced as follows [12]:

Optimistic:

$$w_i = \alpha \times (1-\alpha)^{i-1}, \forall\, i \neq n;\; w_n = (1-\alpha)^{n-1} \quad (3)$$

Pessimistic:

$$w_1 = \alpha^{n-1};\; w_i = (1-\alpha) \times \alpha^{n-i}, i \neq 1 \quad (4)$$

Where parameter α belongs to the unit interval [0 1] and is related to orness value regarding the n.

In this paper, we have used the optimistic exponential kind of OWA as the hybrid approach. After constructing the classifiers, their outputs for each test instance are used as inputs for OWA algorithm. Finally, the fused result of this algorithm for each instance is used as the final output of the recommender systems. If the predicted label of item x for the user y is 1, x will recommend to y, otherwise it will not recommend.

OWA method has been proved to be very useful, because of its versatility [15]. This method is very simple, quick and powerful which has been successfully applied in several applications, such as aggregation of web search engines [15], churn management systems [29], risk analysis [30] and protein secondary structure classifiers fusion [31]. This method can be used in any recommendation system and is context-independent. It does not need any additional information such as ontology and knowledge about the context. Also, it does not need many features unlike the feature combination methods. In addition, compared to the other weighted methods, optimistic exponential OWA has had better performance in many applications [15, 29 and 31].

Considering above properties, OWA seems to be a promising method to combine the demographic information with the other existing information in the cold-start condition more efficiently in comparison to the other methodologies. So, in this paper we have used this method as a new hybrid approach to alleviate the user-side cold-start problem.

V. METHODOLOGY

A. Dataset

To evaluate the proposed method, the two MovieLens datasets, available on the web site http://www.grouplens.org/, was used. The first data set consists of 100,000 ratings from 943 users on 1682 movies. The second dataset contains 1,000,209 anonymous ratings of approximately 3,900 movies made by 6,040 users. In the first implementation of this study, all ratings of first dataset have been used and for the second implementation, about 200,000 ratings of second dataset have been applied. For both datasets, the ratings are on a numeric five-point scale [1, 2, 3, 4, 5]. We have considered rate 1 and 2 as label 0 and rate 3, 4 and 5 as label 1 in this classification problem. Also, age, gender and occupation have been used as the demographic data.

B. Making Cold-start Condition

To evaluate the proposed approach in the cold-start conditions (new users), we have partitioned data as training data and testing data as follows: the first MovieLens dataset has been sorted based on user id, and the train data has been constructed by ratings of users 1 to 641 and test data by users 642 to 943. So, all the users in the train data set are different from the users in the test data and all the users in the test data are new users. The number of users in the training set is 641 and in the test data is 302. Also, the number of ratings in the training set is about 70,000 and in the test data is about 30,000. We have assigned the first rating of users 642 to 943 into the instances 1 to 302 of the test data, as the same, we have assigned the second rating of user 642 to 943 into the instances 303 to 604 the test data and we continued this way to the end. So, first we meet 302 new users, next we meet 302 users that has only 1 rating in his history until we finally meet the final rating of the final user which is rating 685 of user 655 (fig. 2). The final user is user 655 because the number of user's ratings is different in this data set. We have applied this strategy for the second dataset. Among 1228 users in the second dataset, 897 belong to the training data and others belong to testing data. The number of ratings in the training set of second dataset is about 140,000 and in the testing data is about 60,000.

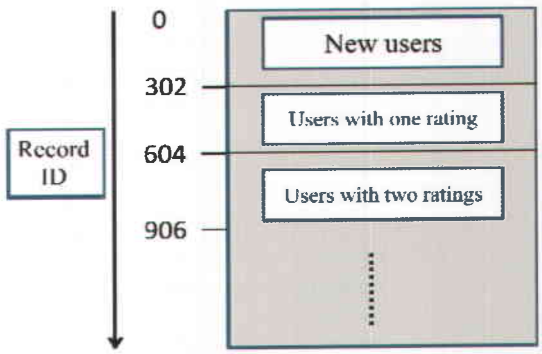

Figure 2. Test data in the first dataset

C. Result

We have used the precision as the performance measure, which is frequently used in data mining research and is defined by [16]:

$$Precision = \frac{True\ Classified}{Classified}$$

Where $True\ Classified$ is the number of instances that have been classified correctly and $Classified$ is the total number of instances which have been classified till now.

Here, for both used datasets, we have used an optimistic exponential OWA technique with $\alpha = 0.5$ which was simply obtained by a try-and-error algorithm. Also, the sensitivity of optimistic exponential OWA to this parameter has been discussed.

To evaluate the proposed hybrid recommender system, we have compared it with the results of five input strategies and two other hybrid methods including majority voting (MV) [7] and weighted majority voting (WMV) [21].

In the MV method the label of the current instance will be the most voted label among the returned results of the underlying classifiers. Also, in the WMV method, each classifier has a weight based on its expertness. The final result is the weighted average of the returned results of the underlying classifiers.

Fig. 3 shows the precision of five input classifiers and also three ensemble classifiers on the first dataset. As it can be seen in the beginning of Fig. 3, strategy1, strategy2 and strategy5 could not classify any instances of the new users (instances 1 to 302), and their precision till instance 302 equals 0. Also for the first 302 instance strategy3, strategy4 and ensemble method have same precision, because all of these strategies use the demographic information for new user and there is no additional information for him. Thereafter, it can be seen that strategy1, strategy2 and strategy5 which use previous ratings of the current user in their methods can classify the instances and increase their precision. Also the OWA operator has highest precision in comparison with all of the other strategies especially when the number of ratings for each user is lower than 20. Thereafter strategy1, strategy2 and strategy5 have had enough ratings for each user and could predict the user's preferences with a reasonable precision. So they decrease their distance from the ensemble methods. Strategy3 and strategy4 have almost a fix precision from the first instance to the final because they use the demographic information. strategy1 which needs to have enough joint ratings between the users has lower precision in contrast to strategy2, because strategy 2 needs only previous ratings of the current user who has not enough joint ratings by other users. Strategy 5 has a good precision and higher than all the other input strategies.

In the first dataset, the distance between the precision of OWA and two other hybrid methods, MV and WMV is significant and OWA could keep this distance from the beginning to the end. Fig. 4 depicts the comparison of these ensemble methods.

Table I illustrates the final precision of each method on the first dataset. Table II depicts the precision of each strategy after it has predicted the i^{th} rating of all users in the testing data ($i = 1,2,\ldots\ldots,10$) that is called the i^{th} stage for the first dataset. We have chosen 10 stages because till this stage each user has a limited ratings and cold-starting problem occurs. As it has been bolded in the table II, in all stages, OWA operator has the best precision. It shows that using OWA operator we can conquer to the cold-start problem efficiently. When we do not have any rate for a new user we can predict its rate for an item with %66.23 precision and having only one rate for a user, the performance of prediction is about %74.0.

To investigate the sensitivity of optimistic exponential OWA to the parameter α in (3), we have computed the performance of this algorithm for different values of α on the first dataset. We have changed this parameter from 0.3 to 0.7 increasing by 0.02 for the nine stages: 2, 3,…., 10. Fig.5 shows the results of these experiments. The horizontal line is the result of MV approach which has had the best result among all approaches in theses nine stages without considering the result of OWA technique.

From fig. 5 it can be seen, for all investigated values of parameter α, the performance of OWA is better than all other experimented approaches.

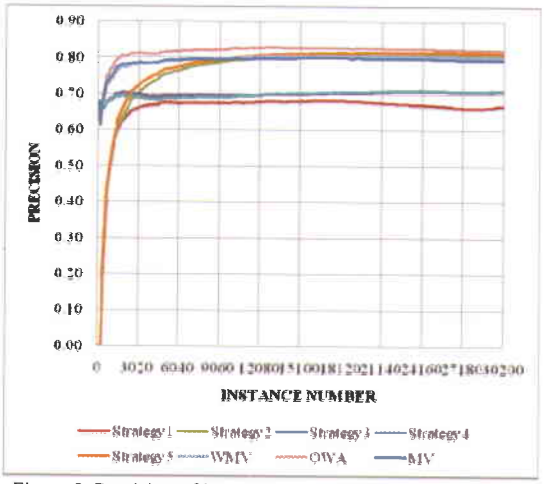

Figure 3. Precision of input strategies and hybrid methods on the first dataset

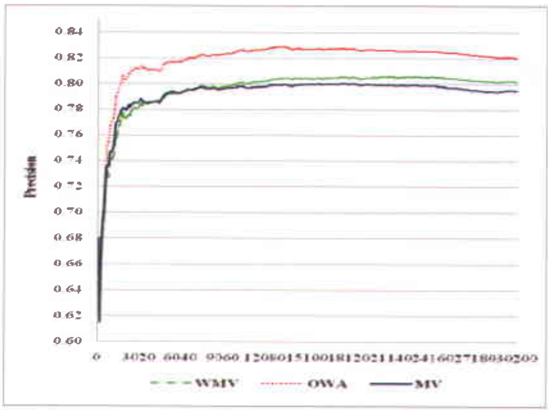

Figure 4. Precision of OWA and other hybrid methods on the first dataset

TABLE I. FINAL PRECISION OF EACH METHOD ON THE FIRST DATASET

Method	Final Precision
Strategy1	66.9
Strategy2	80.7
Strategy3	70.9
Strategy4	71.1
Strategy5	81.3
MV	79.5
WMV	80.1
OWA	**82**

Fig. 6 shows the precision of five input classifiers and also three ensemble classifiers on the second dataset. As it can be seen, the results of second implementation are similar to the first one.

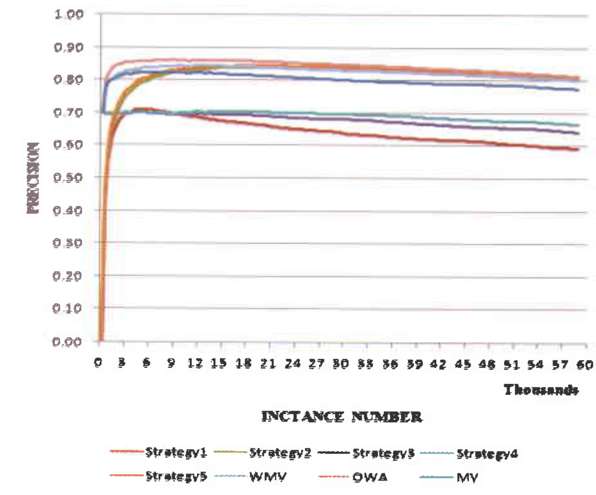

Figure 6. Precision of input strategies and hybrid methods on the second dataset

Similar to the first data set, in the second dataset the precision of OWA is significantly higher than the precision of two other hybrid methods, MV and WMV. Fig. 7 depicts the comparison of these ensemble methods in terms of precision.

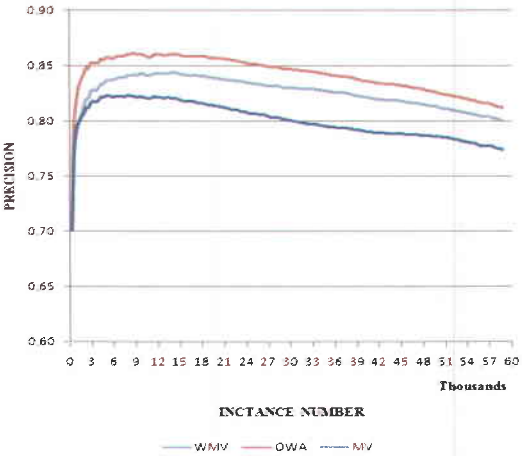

Figure 7. Precision of OWA and other hybrid methods on the second dataset

Table III illustrates the final precision of each method on the second dataset. As it shows, the proposed ensemble method in this paper could outperform the other single and hybrid methods significantly.

TABLE III. FINAL PRECISION OF EACH METHOD ON THE SECOND DATASET

Method	Final Precision
Strategy1	59.36
Strategy2	80.64
Strategy3	64.31
Strategy4	66.57
Strategy5	81.01
MV	7747
WMV	80.07
OWA	**81.24**

Table IV depicts the precision of each strategy after it has predicted the i^{th} rating of all users in the testing data $(i = 1,2,\ldots\ldots,10)$ that is called the i^{th} stage for the second dataset.

From the empirical results, we can conclude that uniting the capability of input classifiers, the OWA has increased its performance compared to the other experimented algorithm. Also, our findings lead us to believe that using OWA technique could help to conquer the cold start problem efficiently.

Combining the strengths of several methods, OWA operator as a hybrid approach, could conquer the new user cold-start problem. When we have a new user and there is no history of user ratings, the OWA operator only uses the demographic information. It can be seen in the table IV that in the first stage the precision of OWA is equal to strategies 3 and 4. In this stage, the only existing information for the current user is his/her demographic information. So, using this information, OWA, strategy 3 and strategy 4 find most similar users and predict the new user's ratings for the current item and alleviate the user-side cold-start problem. But in the next stages of user-side cold-start problem, OWA has the best result among all. In the second stage, only one rating exists in the user's history. Using this history, the CF and CBF methods can use for recommendation. It is obvious that, the precision of CF and CBF in this situation are not very well. But, by combining the result of CF, CBF and demographic-based methods, OWA improves the precision. When number of ratings in the user's history increases, the CF and CBF have more knowledge and increase their precision. The precision of demographic-based method is almost fixed because its knowledge is fixed. By increasing the precision of CF and CBF approaches, the precision of OWA technique increases. After the first step, if we face a new item, as other users did not rate it, the CF method does not have any information. But, CF method can use the previous ratings of the current user and guess the user rating. In this situation, the OWA technique uses the outputs of CBF and demographic-based methods. All in a word, the OWA technique, combine the strengths of several methods and this characteristic leads to alleviate the cold-start problem.

TABLE II. PRECISION OF THE STRATEGIES IN EACH STAGE ON THE FIRST DATASET

Stage	Instance	Strategy1	Strategy2	Strategy3	Strategy4	Strategy5	MV	WMV	OWA
1	1-302	0	0	**66.23**	**66.23**	0	**66.23**	**66.23**	**66.23**
2	303-604	37.91	37.91	67.88	67.55	38.74	73.18	71.19	**74.34**
3	605-906	50.00	50.00	68.98	68.76	50.77	74.83	72.52	**76.93**
4	907-1208	56.04	56.29	69.29	68.87	57.28	75.99	73.43	**78.31**
5	1209-1510	60.07	60.93	70.20	69.47	62.78	77.62	74.90	**79.80**
6	1511- 1812	62.53	63.25	70.53	69.70	66.00	78.09	75.83	**80.57**
7	1813- 2114	63.91	65.61	70.25	69.39	68.26	78.15	75.78	**80.56**
8	2115- 2416	64.90	67.88	70.28	69.33	70.12	78.35	76.20	**80.96**
9	2417- 2718	65.71	69.02	70.16	69.24	71.19	78.44	76.53	**81.13**
10	1719- 3020	66.23	70.17	70.10	69.14	72.32	78.64	76.69	**81.23**

TABLE IV. PRECISION OF THE STRATEGIES IN EACH STAGE ON THE SECOND DATASET

Stage	Instance	Strategy1	Strategy2	Strategy3	Strategy4	Strategy5	MV	WMV	OWA
1	1-331	0	0	**70.09**	**70.09**	0	**70.09**	**70.09**	**70.09**
2	332- 662	40.48	42.75	69.49	69.49	43.96	77.19	76.89	**79.46**
3	663- 993	53.88	55.39	69.49	69.49	56.90	79.36	78.85	**81.77**
4	994- 1324	59.74	62.54	69.41	69.41	64.05	79.83	79.76	**83.01**
5	1325- 1655	63.32	66.22	69.37	69.37	67.98	80.30	80.48	**83.69**
6	1656- 1986	65.91	68.88	69.59	69.64	70.85	80.72	81.52	**84.34**
7	1987- 2317	67.54	71.30	69.79	69.87	73.11	81.27	82.00	**84.89**
8	2318- 2648	68.43	72.81	69.60	69.64	74.43	81.27	82.10	**84.78**
9	2649- 2979	69.39	74.35	69.82	69.92	75.83	81.71	82.68	**85.26**
10	2980- 3310	69.82	75.26	69.97	70.12	76.74	81.84	82.87	**85.32**

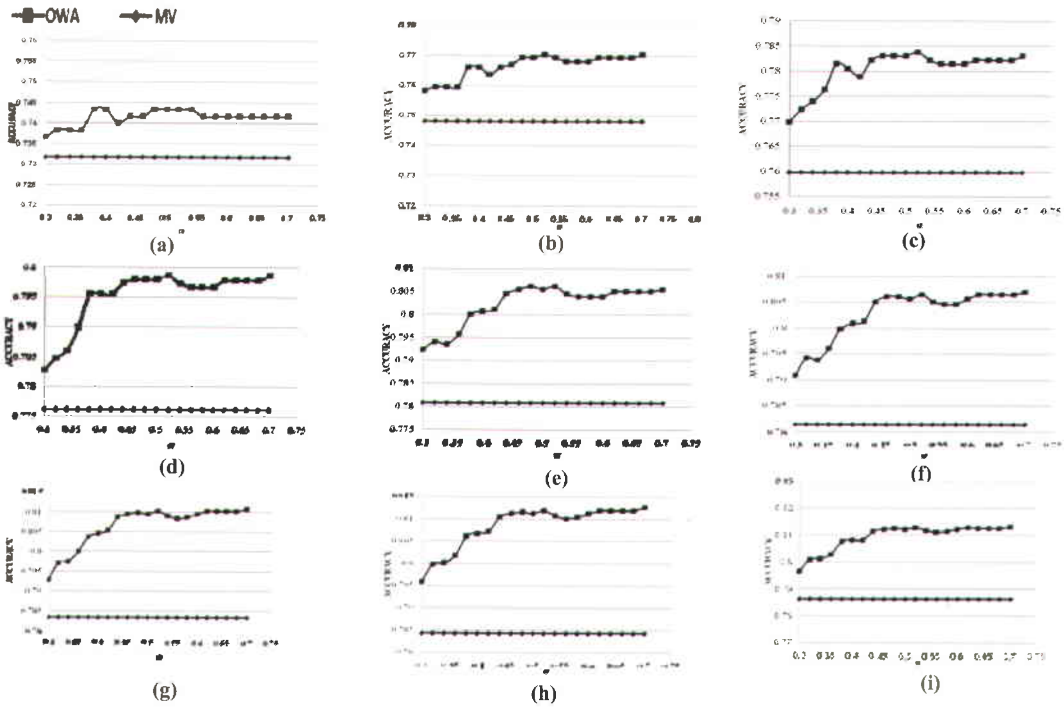

Figure 5. Sensitivity of OWA to the parameter α in: (a) stage 2, (b) stage 3, (c) stage 4, d) stage 5, e) stage 6, f) stage 7, g) stage 8, h) stage 9, i) stage 10

VI. CONCLUSIONS AND FUTURE WORK

In this paper we have proposed a hybrid approach in order to improve the prediction accuracy of the existing recommender systems in the cold-start (new user) condition. In the proposed approach, CF, CBF, demographic-based method, fusion of CF and demographic and fusion of CF and CBF classifiers have been used as the input strategies. For each instance, the results of these learned classifiers are fused by the optimistic exponential class of OWA technique. We have tested our hybrid approach by applying it to the MovieLens dataset. Experiment results show the superiority of our proposed approach compared to other well-known recommender systems. Also, our findings lead us to believe that our approach could help to overcome the cold start problem efficiently.

In order to give more robustness to our hybrid method, the fusion technique may be developed. It can be improved by giving dynamicity to α, the currently static parameter in (3). During the training phase it may be tuned instead of static setting. Also, we want to test the proposed approach in other popular problems of recommender systems, such as, sparsity problems [4].

As another future work, one of the most important issues which has not been considered in this work is related to changing users' characteristics over time. User's interests may change cause of a lot of reasons such as changing his\her demographic information. Detecting these changes and handling them can improve recommender system performance.

VII. REFERENCES

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