A Hybrid Recommender System Using Rule-Based and Case-Based Reasoning

Shweta Tyagi and Kamal K. Bharadwaj

***Abstract*—Recommender systems are well known for their wide spread use in e-commerce, where they utilize information about user's interests to generate a list of recommendations. To enhance the recommendation quality, the recommendation techniques have sometimes been combined in hybrid recommenders. In this paper, we propose a weighted hybrid recommender system that integrates multiple recommendation algorithms together to improve recommendation performance. In the proposed approach, firstly users are classified by applying clustering technique on ratings data. Subsequently, rule-based reasoning (RBR) and case-based reasoning (CBR) are employed separately to choose classes (neighborhoods) of an active user and then collaborative filtering (CF) is applied on these neighborhoods to produce recommendation lists. These two techniques are respectively called RCF (combination of RBR and CF) and CCF (combination of CBR and CF). The proposed weighted hybrid recommender system (WRCCF) combines RCF and CCF schemes. Experimental results reveal that the proposed WRCCF consistently outperforms Pearson CF (PCF), RCF, and CCF in terms of prediction and classification accuracy.**

***Index Terms*—Hybrid recommender system, collaborative filtering, clustering, case-based reasoning, rule-based reasoning.**

I. Introduction

At present, in E-commerce, recommender systems (RSs) are broadly used for information filtering process to deliver personalized information by predicting user's preferences to particular items [1]. Although a lot of techniques have been developed recently, collaborative filtering (CF) has been known to be the most promising recommendation techniques [2], [3]. Cross-genre or 'outside the box' recommendation ability is the main power of this technique [1], [4]. It has been used in a variety of applications such as recommending web pages, books, movies, tapes and products.

Typically, CF explores similar users by recognizing commonalities between the user and his neighbors on the basis of their previously expressed preferences and then accordingly suggests new items or products based on inter -users comparison [1]. In practice, there are two main classes of CF: the memory-based CF and the model-based CF [2]. The memory-based CF uses the entire RS database to make recommendations, while model-based CF learns a model offline from the data which is then used for online recommendations. Although memory-based algorithms are simple and provide high accuracy recommendations but these are computationally expensive as the size of the input data set increases. On the other hand, model-based algorithms reduce the online processing cost but there are tradeoffs between scalability and prediction performance. In this paper, we propose a method which combines two model-based CF algorithms by a weighted scheme to improve the quality of recommendation as well as coverage of CF.

The rest of the paper is organized as follows. In the next section, we provide a brief overview of several methods to improve the performance of CF recommendation technique shown by previous research. In Section 3, the proposed weighted hybrid movie RS is presented. The details of the experimental evaluation and results are given in section 4. Finally, we conclude the paper and outline some future research directions in section 5.

II. Background

More recently, a number of machine learning techniques and hybrid filtering techniques have been implemented to achieve quality recommendations and to handle the problems of pure CF. Sparsity, scalability, neighbor transitivity, and accuracy are the main problems of CF [1]. To handle the problems of CF, other recommendation techniques such as *content-based filtering* [1], [5] and *knowledge-based filtering* [1], [4] have been combined with CF by using hybrid algorithms. Moreover, several data mining or machine learning algorithms including Bayesian belief nets (*BNs*) [6], clustering techniques [7], and latent semantic analysis [8] have been employed for building a model in CF techniques. These algorithms have been combined with CF to solve the problems of CF. In this work, we introduce a weighted hybrid scheme to combine two model-based CF algorithms. To learn the models, we used knowledge-based techniques: rule-based reasoning (RBR) and case-based reasoning (CBR) individually for the two model-based CF algorithms.

The RBR system learns general knowledge from user's information space, represents it in terms of rules, and answers new problem by reasoning with generalized knowledge [9]. There are only few research groups, which are exploring the application of RBR concepts and techniques to CF RSs [10], [11].

CBR is a relatively recent problem solving technique which solves new problems by adapting previously successful solutions to similar problems. In CBR, a "new problem" is compared with cases in the casebase (case library)

Manuscript received April 27, 2012; revised June 4, 2012.

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and one or more similar cases are *retrieved*. A solution to the problem suggested by these matching cases is then *reused* and tested for success. Unless the retrieved case is a close match the solution will probably have to be *revised* producing a new case that can be *retained* [12]. CBR have been used by researchers in the context of CF to solve the problems of CF [13], [14], [15].

In the present work, we are combining RBR and CBR with CF separately. Additionally, we employ a weighted hybrid algorithm to join the recommendations made by two aforementioned techniques. Our approach differs from most of the earlier hybrid methods. The proposed algorithm does not use predefined weightage of different methods and does not depend on any feedback system. In our algorithm, weightages of items predicted by different methods may differ for each user and is dependent on user's current profile.

III. Proposed Hybrid Recommendation Framework

The proposed hybrid RS first of all produces recommendations by applying two model-based CF techniques. The system takes the benefit of k-means clustering algorithm to classify users into different clusters. These clusters are used as a basis to select a neighborhood (nbd) of an active user. Consequently, for the process of nbd selection, proposed system utilizes two knowledge-based techniques: RBR and CBR separately. For this purpose users information is represented by user profile vector (UPV). Thus for each user u_a, we have a corresponding profile vector as given below.

$$UPV(u_a) = \langle D_{a,1}, D_{a,2}, D_{a,3}, D_{a,4}, G_{a,1}, G_{a,2}, \ldots, G_{a,18} \rangle, \quad (1)$$

where $D_{a,1}, D_{a,2}, D_{a,3}$ *and* $D_{a,4}$ are representing the demographic information such as age, gender, occupation and location respectively and $G_{a,1}, G_{a,2}, \ldots, G_{a,18}$ are denoting genre interestingness measure (GIM) [16] of the user u_a in 18 genres.

A. Applying RBR for Nbd Selection

RBR system represents knowledge of the system in terms of a bunch of rules (facts). These rules are in the form of *IF THEN* rules such as:

IF some condition THEN some action.

If the 'condition' is satisfied, the rule will take the 'action' [9]. In our system the condition part of the rule is composed of features of UPV and the action part decides the cluster based on these features. The rules are produced by applying C5 method [17] on training users. These rules are employed to classify active user. For this purpose, a *matching rule* is selected in the set of few representative rules (rulebase) extracted from the set of training users. Any rule matching the attributes of the active user is taken as the *matching rule*. This *matching rule* suggests the cluster (nbd) of the active user.

B. Applying CBR for Nbd Selection

In this alternate nbd selection procedure, the CBR technology is employed. The set of training users form the casebase for this process. Therefore, the users (cases) in the casebase are represented by their rating vectors along with $UPVs$. Further, for active user (u_a), the retrieval step searches the casebase to select a set R of top most similar cases. Subsequently, a class (cluster) with high score is retrieved from the casebase. The cases in the retrieved class form the nbd of the active user and the score of a class C is computed using following expression:

$$score(C) = \sum_{u_b \in R} \begin{cases} similarity(u_a, u_b), \; if \; Class(u_b) = C, \\ 0, \qquad otherwise. \end{cases} \quad (2)$$

The similarity between active user and source user can usually be calculated using various similarity functions. For computing similarity between two users, u_a and u_b, the following formula is used as suggested in [18]:

$$similarity(u_a, u_b) = \frac{1}{\sqrt{\sum_{j \in Q} fd(a_j, b_j)}}, \quad (3)$$

where Q is the set of predictor features from UPV (age, gender, occupation, location and GIM in 18 genres) and fd stands for feature dissimilarity, which can be computed as:

$$fd(x,y) = \begin{cases} (x-y)^2 \; if \; feature's \; values \; are \; numeric, \\ 0 \qquad if \; values \; are \; same \\ 1 \qquad otherwise \end{cases} \quad (4)$$

We consider a weighting factor [19] to devalue similarity weights that are based on a small number of co-rated items,

$$similarity'(u_a, u_b) = \frac{Min(|T_a \cap T_b|, \delta)}{\delta} similarity(u_a, u_b), \quad (5)$$

where T_a and T_b are the sets of items rated by users u_a and u_b respectively and $|T_a \cap T_b|$ is the number of items rated in common by the users. This weighting factor bounds the similarity to the interval [1]. If the number of co-rated items is smaller than δ, the similarity of these users will be devalued. This change avoids overestimating the similarities of users who have high profile similarity, but not rated items in common. This should be noted that the feature values are normalized to ensure they lie between 0 and 1, before computing the similarity.

C. Ratings Prediction

For the prediction of ratings, the above discussed nbd selection procedures are followed by CF. These recommendation schemes are called RCF (combination of RBR and CF) and CCF (combination of CBR and CF). The proposed system generates a single list of recommendations by taking a weighted sum of predictions made by RCF and CCF techniques.

More formally, to understand the prediction procedure, CF RS [1] has a set of users $U = \{u_1, u_2, \ldots, u_m\}$ and a set of items $T = \{t_1, t_2, \ldots, t_n\}$ where each user u_i has rated a subset of items T_i. The rating of user u_i for item t_j is denoted by $r_{i,j}$. Consequently, to make a recommendation, RS predicts rating ($r'_{a,k}$) of item t_k seen by the users in the nbd set and not by the active user u_a [1,3].

$$r'_{a,k} = \bar{r}_a + z\sum_{u_l \in N} similarity(a,l) \times (r_{l,k} - \bar{r}_l), \qquad (6)$$

where z is multiplied as a normalizing factor and usually taken as $z = 1 \big/ \sum_{u_l \in N} |similarity(a,l)|$, N is the set of neighbors who have rated item t_k, $\bar{r}_a$ is the average rating of u_a, and, $similarity(a,l)$, is the similarity measure between users u_a and u_l. Many similarity functions are used for calculating $similarity(a,l)$ like Pearson correlation coefficient [3], cosine-based approach, and Euclidean distance function [1]. In the present work, we are employing the similarity function given in equation (5).

Our weighted scheme, WRCCF (weighted hybrid of RCF and CCF), predicts the rating by combining the two lists of recommendations produced by RCF and CCF methods. The proposed scheme determines the weightage of RCF (f_a) and the weightage of CCF (f'_a) techniques such that $f_a + f'_a = 1$. Subsequently, the WRCCF method predicts rating of any unseen item t_k for active user u_a by using following formula.

$$rw'_{a,k} = f_a \times rr'_{a,k} + f'_a \times rc'_{a,k} \qquad (7)$$

where $rw'_{a,k}$, $rr'_{a,k}$, and $rc'_{a,k}$ denotes the ratings predicted by WRCCF, RCF, and CCF methods respectively.

To determine weightage of each technique for active user u_a, we first select the set of items T_a' already seen by u_a. After that prediction is computed, by RCF and CCF techniques separately, for each item $t_p \in T_a'$. Further, by varying the values of f_a and f'_a, prediction for each training item t_p is calculated by using equation (7). Consequently, the values of f_a and f'_a are selected which minimizes the error of prediction made by WRCCF scheme.

IV. Experiments and Results

We performed the experimental evaluation of our algorithm on the most widely used MovieLens data set [20]. This data set consists of 100,000 ratings made by 943 users on 1682 movies. Ratings follow the 1(bad)-5(excellent) numerical scale. Each user in the data set has rated at least 20 movies and each movie has been rated by at least one user. The demographic detail (age, gender, occupation, and zip code) of each user and basic information (genre and release date) of each movie are also there in the data set.

A. Performance Measures

There are several metrics that have been proposed for assessing the accuracy [21] of CF methods. They are divided into two main categories: prediction accuracy metrics and classification accuracy metrics. In this paper, we use both accuracy metrics for measuring the performance of our system. Two metrics, the mean absolute error (MAE) and the root mean squared error (RMSE), are used to evaluate prediction accuracy of different RSs. Further, to measure classification accuracy, we employed the metrics: Precision, Recall and F1-measure. Along with accuracy, we also measured the prediction coverage of the system.

B. Design of Experiments

To perform the experiments, we randomly choose 450 users out of 943 users of MovieLens dataset. For this dataset of 450 users, four random samples of 50 active users are selected and remaining 400 users are considered as training users. Such kind of random sample selection was intended for the execution of four-folds cross validation. These samples will be referred to as sample 1, sample 2, …, and sample 4. During the testing phase, each active user's ratings are divided randomly into two disjoint sets, training ratings (60%) and test ratings (40%). The training ratings are used to compute the *UPV* of active user as a part of online processing whereas the test ratings are treated as unseen ratings that the system would attempt to predict. In our experimental study, we have considered four approaches: (1) PCF (Pearson CF), (2) RCF, (3) CCF, and (4) WRCCF. In all the experiments discussed above we keep *nbd* set size of thirty five users. The value of parameter δ is selected as thirty for our experiments.

C. Results

The two metrics MAE and RMSE are evaluated for comparing the predictive accuracy of our experiments. The coverage of the system is also analyzed and results are summarized in Table I. For a good performance, MAE and RMSE should be low and coverage should be high. The results show that the total MAE of RCF and CCF is always smaller than the corresponding value for PCF. Further the MAE of WRCCF is found minimum when compared with other approaches. The results of RMSE also show that the WRCCF outperforms the other three techniques and the coverage for WRCCF has the highest value in comparison to all other approaches.

TABLE I: Comparison of MAE, RMSE and Coverage of Proposed Schemes WRCCF with RCF, CCF, and PCF.

Prediction Accuracy		Algorithms			
		PCF	RCF	CCF	WRCCF
Sample 1	MAE	0.867615	0.834288	0.816468	0.809524
	RMSE	1.031720	1.014642	1.005709	1.005270
	Coverage	61.71983	92.66245	97.95974	98.67580
Sample 2	MAE	0.797042	0.758278	0.767523	0.755524
	RMSE	0.975996	0.934633	0.941695	0.930901
	Coverage	70.91187	90.95254	97.96190	98.41258
Sample 3	MAE	0.857382	0.827753	0.819207	0.808791
	RMSE	1.052662	1.023310	1.016965	1.015245
	Coverage	68.20880	90.01883	98.16295	98.68122
Sample 4	MAE	0.844226	0.826442	0.806730	0.805079
	RMSE	1.032777	1.012951	0.992679	0.992098
	Coverage	64.93650	91.44590	98.21554	99.04462

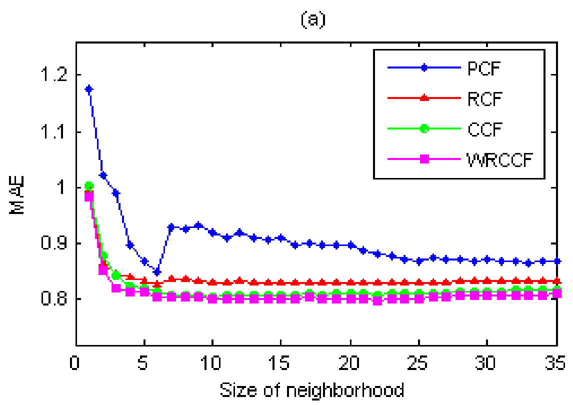
The classification accuracy of each of the different techniques is compared by computing precision, recall and F1 measure. A higher value of these measures implies better performance. Table II presents the results corresponding to different recommendation techniques. The proposed WRCCF scheme performs better for almost all samples. There are some exceptions noticed for samples 2, and 3. For sample 2, CCF has higher precision and RCF has higher recall. Moreover, precision of RCF is found higher for sample 3. The results also show that the performance of two schemes RCF and CCF fell between those of the PCF scheme and the WRCCF scheme for almost all samples. The PCF scheme performed poorly in all experiments. It is also observed that the value of F1 measure of WRCCF scheme is maximum for all the samples.

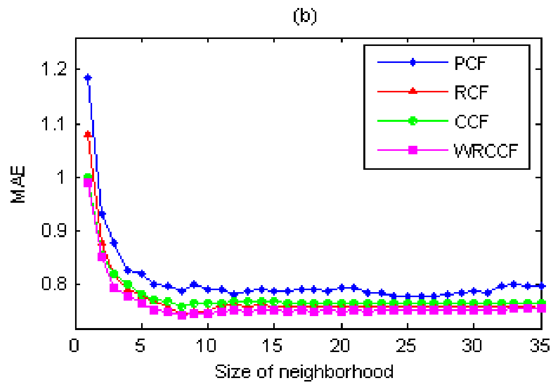
TABLE II: COMPARISON OF PRECISION, RECALL AND F1 MEASURE OF PROPOSED SCHEME WRCCF WITH RCF, CCF, AND PCF.

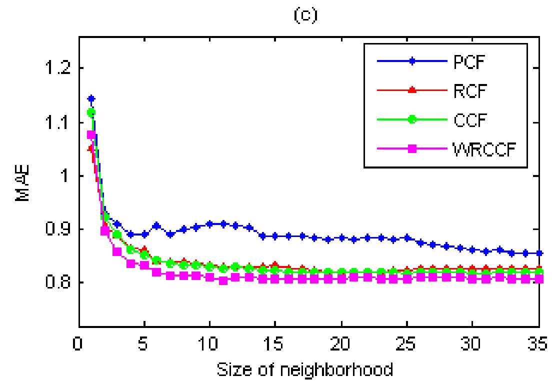
Classification Accuracy		Algorithms			
		PCF	RCF	CCF	WRCCF
Sample 1	Precision	70.51082	70.52870	70.92514	71.29361
	Recall	61.13604	74.44017	78.81799	79.33636
	F1-measure	61.21986	65.75075	68.99621	70.53080
Sample 2	Precision	69.70040	73.04519	73.12603	69.96863
	Recall	60.12049	81.76432	80.85177	75.02963
	F1-measure	60.67138	68.32222	71.17797	73.13401
Sample 3	Precision	71.67113	73.83323	73.81209	72.13468
	Recall	58.68255	62.51606	69.62117	70.28042
	F1-measure	58.58301	59.16901	62.93077	63.26116
Sample 4	Precision	71.34643	70.69598	70.04708	72.99667
	Recall	49.91126	58.17986	64.69395	66.45366
	F1-measure	51.54789	55.53926	59.76119	60.77925

The results shown in Table I and Table II demonstrate that the proposed approach WRCCF brings considerable improvement in the quality of recommendations in terms of prediction accuracy and classification accuracy. From the experiments, it is also clear that the performance of RCF and CCF lie in between PCF and WRCCF.

Additionally, to analyze the accuracy of the proposed approach we compared the MAE of all the experiments for each sample by varying the size of the nbd set. The graphs shown in Fig. 1, reveal that the MAE of our proposed approach is consistently lowest. The experimental results clearly indicate that the proposed WRCCF scheme outperforms PCF, RCF and CCF schemes.







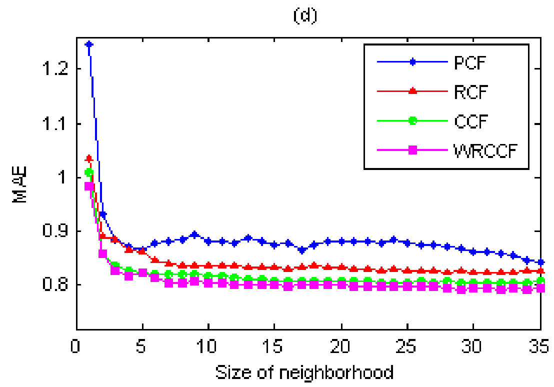


Fig. 1. MAE for: (a) active users of sample 1, (b) active users of sample 2, (c) active users of sample 3, and (c) active users of sample 4.

V. CONCLUSIONS

In this paper, we propose a weighted hybrid scheme, WRCCF, to improve the performance of CF based RSs. Our proposed scheme combines two model-based methods RCF and CCF by utilizing the techniques: clustering, RBR, and CBR. The effectiveness of proposed schemes are evaluated experimentally using MovieLens dataset and the results indicate that the proposed WRCCF scheme outperforms RCF, CCF and PCF schemes in terms of prediction and classification accuracy as well as coverage.

In the present work we have considered all the features equally important for CBR. By adding the feature importance factor to similarity measure, the accuracy of the RS can be improved further. Therefore, one of the possible extensions would be to take into consideration the weights of the features. The other promising direction for future work would be to incorporate trust and reputation mechanisms [22] into the proposed RS to further enhance its performance.

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