A Multi-Criteria Item-based Collaborative Filtering Framework

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***Abstract*—Collaborative filtering methods are utilized to provide personalized recommendations for users in order to alleviate information overload problem in different domains. Traditional collaborative filtering methods operate on a user-item matrix in which each user reveal her admiration about an item based on a single criterion. However, recent studies indicate that recommender systems depending on multi-criteria can improve accuracy level of referrals. Since multi-criteria rating-based collaborative filtering systems consider users in multi-aspects of items, they are more successful at forming correlation-based user neighborhoods. Although, proposed multi-criteria user-based collaborative filtering algorithms' accuracy results are very promising, they have online scalability issues. In this paper, we propose an item-based multi-criteria collaborative filtering framework. In order to determine appropriate neighbor selection method, we compare traditional correlation approaches with multi-dimensional distance metrics. Also, we investigate accuracy performance of statistical regression-based predictions. According to real data-based experiments, it is possible to produce more accurate recommendations by utilizing multi-criteria item-based collaborative filtering algorithm instead of a single criterion rating-based algorithm.**

Keywords- Collaborative filtering, multi-criteria rating, item-based, accuracy, scalability.

I. INTRODUCTION

Depending on developments in the Internet technologies, people face with a new kind of a problem which is information overload. Due to their needs, people get used to utilize resources provided by web-based applications. However, the rapid growth of information in web leads new problems in particularly decision making process. Therefore, researchers develop recommender systems which can help people during selection process of the most related information [1]. Collaborative filtering (CF) is one of the most popular recommender systems and it is employed in online applications, e.g., e-commerce, e-learning, and social networks [1].

CF performs on a user-item matrix holding huge amount of users' preferences on several items. There are two main approaches of CF algorithms, i.e, memory- and model-based CF. Former one utilizes the entire user-item database to generate a prediction [2]. These systems depends on user correlations which are generally estimated by using Pearson correlation coefficient (PCC) [3]. Memory-based CF algorithms are successful at providing accurate referrals. On the other hand, since these type of CF methods form online neighborhoods of users, they have scalability problems. In order to overcome such problem of CF systems, researchers introduce model-based CF approaches. The model building process is performed by different machine learning algorithms such as Bayesian network [2], clustering [4], and dimension reduction [5]. In addition, Sarwar et al. [6] propose a method which depends on item correlations and according to the introduced algorithm, it is possible to improve online performance of CF systems with a decent accuracy result. A comprehensive survey about traditional CF methdos can be found in [7].

The majority of traditional CF systems operate on 2D user preference data in which each user reveal her admiration about an item according to a single criterion. However, users might consider more than one criterion in order to rate a single item. For example, before revealing her admiration about a movie, a user might consider success of director and acting, effectiveness of visuals, and expressiveness of the story of the movie. Thus, overall rating for the movie is composed of four different rating given for each criterion. Adomavicius and Kwon [8] introduce that finding the actual correlations between users is more likely if multi-criteria ratings are employed. In their study, the Adomavicius and Kwon [8] deeply analyze extending of memory-based collaborative filtering algorithm to incorporate and leverage multi-criteria ratings.

Although existing works introduce the way of proposing recommendations by utilizing multi-criteria ratings, the methods are in the class of memory-based CF. Thus, they have scalability issues and their online performance is need to be improved. In the previous study that we inspire, Adomavicius and Kwon [8] mention that it is possible to transform the item-based CF algorithm into a new form which can handle the multi-criteria ratings. However, the authors do not analyze the new method with respect to the most suitable similarity measure and the optimum size of item neighborhoods. Therefore, in this study, we introduce the new framework for extending the traditional item-based CF algorithm to utilize the advantages of multi-criteria rating systems.

Main contributions of the paper are listed below:

- In order to provide item-based recommendations from multi-criteria ratings, an item-based CF framework is proposed.
- The most appropriate neighborhood forming approach is determined.
- Accuracy performance of statistical regression-based

predictions is investigated.

The rest of the paper is organized as follows. In the next section, a brief literature summary about multi-criteria rating-based recommender systems is given. Traditional item-based CF algorithm is explained in Section 3. The item-based framework for multi-criteria CF is introduced in the following section. Experimental outcomes are presented in Section 5 and finally, the conclusions about the paper is given in the last section.

II. Related Work

The studies in multi-criteria rating-based recommender systems is started by an application paper in which Plantie et al. [9] introduce an application for automation of the information and evaluation phases in movie recommender system. In [10], Naak et al. develop a research paper management system utilizing a multi-criteria recommendation approach. Their special intention is allowing researchers to denote their interest in specific parts of articles. Besides, movie and research paper recommendations, there are studies also related to tourism domain. Bitonto et al. [11] develop a mobile cultural heritage recommender system. In their application, they employ an improved CF method. In another study, Fuchs and Zanker contribute the aspects on a major tourism platform, TripAdvisor.

In order to utilize in restaurant recommendations, Vilas et al. [12] present a multi-criteria algorithm. Manouselis and Costopoulou [13] classify multi-criteria recommender systems based on existing taxonomies and categories. They also identify a set of dimension in order to perform classification. Adomavicius and Kwon [8] deeply analyze the memory-based CF algorithms with respect to multi-criteria ratings. They compare the success of utilizing correlation-based similarity and employing distance between criteria. According to experimental results of their study, distance-based similarity computation introduce good accuracy results, and it is also possible that employing linear regression is an appropriate method if multi-criteria ratings are in usage. Li et al. [14] propose a novel approach to improve CF algorithms by using contextual information of a user along with the multi-criteria ratings.

With the aim of improving prediction accuracy of recommendations, Lakiotaki et al. [15] develop a recommender system based on multiple criteria analysis. The authors mention that their experimantal outcomes are better than the results of multiple rating CF methods. Besides traditional memory-based CF method, researchers also propose new versions of existing single-rating CF algorithms, Zhang et al. [16] propose two multi-criteria probabilistic latent semantic analysis algorithms extended from the single-rating version and in the first one multi-criteria ratings distribution is assumed to be mixture of the multi-variate Gaussian distribution and in the second one, they assume the mixture of the linear Gaussian regression model as the underlying distribution of multi-criteria ratings of each user. Liu et al. [17] are motivated on the basic assumption that not all the criteria in a multi-criteria rating domain have the same affect in order to dominate users' decision. Thus, in their work, the authors try to determine each users' the most dominant criterion. In order to model users in a multi-criteria recommender systems, Lakiotaki et al. [18] introduce recommender systems framework which profile users into groups and after that they employ multiple-criteria decision-analysis before applying a CF algorithm. Single rating-based hybrid CF methods are proposed in literature. Since these methods cannot be directly apply multi-criteria rating domain, Shambour and Lu [19] propose a hybrid multi-criteria CF approach. With the goal of improving accuracy level of multi-criteria CF methods, Jannach et.al [20] present new methods to leverage information derived from multi-dimensional ratings. They utilize Support Vector regression to determine the importance of the individual criteria ratings. Besides memory-based studies authors also introduce model-based approaches for multi-criteria recommender systems [21], [22].

III. Traditional Item-based CF Algorithm

Before introducing multi-criteria item-based CF framework, a brief information about traditional item-based CF algorithm is needed. Therefore, in this section, we explain the item-based CF algorithm proposed by Sarwar et al. [6]. In a single rating-based CF system, the collected user data is utilized to predict a rating by employing a function given in below [8]:

$$R : Users \times Items \rightarrow R_0 \tag{1}$$

where R_0 is the set of possible overall ratings.

In order to accomplish the task of the prediction function, the main process of a item-based CF algorithm is forming each item's neighborhood. Sarwar et al. [6] propose that adjusted cosine-based similarity (ACS) is an appropriate measure for estimating item distances. ACS is modified version of classical cosine similarity and Sarwar et. al [6] present it as in Eq 2.

$$sim_{ij} = \frac{\sum_{u \in U} (r_{ui} - \overline{r_u})(r_{uj} - \overline{r_u})}{\sqrt{\sum_{u \in NN} (r_{ui} - \overline{r_u})^2} \sqrt{\sum_{u \in U} (r_{uj} - \overline{r_u})^2}}, \tag{2}$$

where r_{ui} and r_{uj} are the ratings of user u for item i, U shows users having ratings for both items i and j, and $\overline{r_u}$ is mean ratings of user u. After similarities are computed, service provider first forms nearest neighbors (NN) of item i, then calculates prediction (p_{aq}) for an active user (a) for a target item (q) as follows [8]:

$$p_{aq} = \frac{\sum_{i \in NN} (r_{ai} \times sim_{qi})}{\sum_{i \in NN} sim_{qi}}. \tag{3}$$

IV. Multi-criteria Item-based CF Framework

Traditional single rating-based CF systems request an overall rating from users in order to collect their preferences. However, multi-criteria rating-based methods provide to user the way of evaluating different aspects of an item during revealing their inclinations. In a multi-criteria rating-based CF system, since there is more than one criterion, traditional prediction function is modified as follows:

$$R : Users \times Items \rightarrow R_0 \times R_1 \ldots \times R_c \tag{4}$$

where R_0 is the set of possible overall ratings and R_i indicates the possible rating for each criterion i and c shows the number of criteria.

As previously mentioned, Adomavicius and Kwon [8] discuss similarity and aggregation function-based approaches in their work. In this study, we follow the same methodology with [8], thus, firstly we try to find the most appropriate method of estimating similarity between items. Since Adomavicius and Kwon [8] compare aggregating traditional similarities from each individual criteria with calculating similarity using multi-dimensional distance metrics, we follow the same methodology.

In the first group, it is possible to compute correlations between items according to each criterion. Consider that two items i and j has the rating vectors v_i and v_j and each rating in the vectors are in the form of $(r_0, r_1, \ldots, r_c)$. Then, similarities between two item vectors can be computed by estimating average of the similarities between each criterion as given Eq. 5.

$$sim_{avg}(i,j) = \frac{\sum_{s=0}^{c} sim_s(i,j)}{c+1} \tag{5}$$

or, it is possible to assign the minimum similarity value as the correlation between item i and j as presented in Eq. 6.

$$sim_{min}(i,j) = \underset{s=0,\ldots,c}{min}\; sim_s(i,j) \tag{6}$$

According to Adomavicius and Kwon [8], multi-criteria rating domain can be considered as multi-dimensional space. Therefore, each rating value indicates a coordinate on that c+1 dimensional space. Eventually, it is possible to compute distance between item vectors by using distance measures and the resulted distance can be converted to a similarity value. In [8], the authors evaluate the performance of Manhattan distance, Euclidean distance, and Chebyshev distance. Thus, in order to find the most appropriate distance metric we employ the same measures for estimating item distances and definitions of each measure are given below:

- Manhattan Distance:

$$dis(i,j) = \sum_{s=0}^{c} abs(r_i - r_j) \tag{7}$$

- Euclidean Distance:

$$dis(i,j) = \sqrt{\sum_{s=0}^{c} abs(r_i - r_j)^2} \tag{8}$$

- Chebyshev Distance:

$$dis(i,j) = \underset{s=0,\ldots,c}{max}\; abs(r_i - r_j) \tag{9}$$

After computing item distances, now, it is required to convert distance values to similarities. Since distance and similarity are inversely related, the conversion can be performed as given below: [8]:

$$sim(i,j) = \frac{1}{1 + dis(i,j)} \tag{10}$$

Adomavicius and Kwon [8] address a new approach in order to provide predictions that is different from traditional CF methods. The main intuition behind the authors' approach depends on the assumption that multi-criteria ratings represent user preferences for different components of an item and the overall rating is dependent of other ratings given for each criterion. Therefore, it is possible to find an aggregation function to determine overall rating. The aggregation function can be presented as below:

$$r_0 = f(r_1, \ldots, r_c) \tag{11}$$

The main step of aggregation-based recommendations is learning the aggregation function. In order to determine the function, linear regression technique can be employed. In linear regression, the overall rating is estimated as presented in Eq. 12 [8].

$$r_0 = w_1 r_1 + w_2 r_2 + \ldots + w_c r_c \tag{12}$$

In the proposed multi-criteria item-based CF framework, we employ such aggregation function, thus, a prediction value is produced for each criterion and the linear regression-based function is used in order to estimate final overall rating.

V. Experiments

In order to determine the most appropriate neighbor selection approach and method of producing predictions for multi-criteria item-based CF framework, we conducted real data-based experiments. In the experiments, we employed Yahoo!Movies (YM) data set collected by [20]. On the YM platform, each user can rate movies wit respect to 4 criteria, i.e, Story, Acting, Direction, and Visuals. The users also assign an overall rating for the movies. In the data set, 13-level rating scale (from A+ to F) is used. Since most of the data sets in recommender systems utilizes 5 star rating scale, we transform YM data set into such rating interval. During the experiments, we utilized two subset of YM data set. We firstly select a subset in which there are users and items having at least 20 ratings. On the other hand, in the second data set, users and items have at least 10 ratings. Detailed information about the data sets are given in Table I and it is possible to see a sample multi-criteria data set in Table II.

The main motivation of the paper is evaluating accuracy performance of the proposed framework. Therefore, mean absolute error (MAE) is utilized in order to measure accuracy in our experiments. MAE is one of the most popular statistical accuracy measure and widely used in CF. The lower the MAE values means more accurate prediction results.

In the experiments, 5-fold cross-validation methodology is preferred to use. Therefore, we divided YM20 and YM10 data sets into five subgroups uniformly randomly. In each iteration i, where $i = 1, 2, \ldots, 5$, corresponding subset was considered as the test users and the remaining ones were as the training users. We produced recommendations for each test user's rating items. During recommendation process, we replace target item's rating value with null.

TABLE I. DESCRIPTIONS OF DATA SETS

Name	User × Items	#Overall Ratings
YM20	429×491	18,504
YM10	$1,827 \times 1,471$	48,026

TABLE II. SAMPLE OF MULTI-CRITERIA RATING DATA SETS

	item1	**item2**	**item3**	**item4**
user1	$4_{4,3,5,4}$	$3_{2,3,3,4}$	$5_{5,5,5,5}$	$4_{5,2,4,5}$
user2	$2_{1,3,2,2}$	$3_{1,4,2,5}$	$4_{4,3,5,4}$	$5_{5,5,5,5}$
user3	$4_{4,3,5,4}$	$2_{3,1,2,2}$	$4_{4,4,4,4}$	$3_{4,2,5,3}$
user4	$3_{3,3,3,3}$	$3_{4,3,2,4}$	$4_{4,3,5,4}$	$2_{2,2,1,2}$

In the first group of experiments, we we tried to determine the most appropriate neighbor selection approach for multi-criteria item-based CF framework. During experiments, we firstly produced predictions by using only overall ratings. Thus, we got accuracy result of traditional item-based CF algorithm's for each data sets. After that, we continued with the experiments including the similarity-based approaches. In these experiments, we evaluated selection of both average and minimum similarity values' effect on accuracy in the proposed framework. In order to estimate item correlations, we employed PCC and ACS during the experiments. We also performed experiments for producing referrals by using multi-dimensional distance measure-based similarity estimation. Here, we utilized Euclidean, Manhattan, and Chebyshev distance metrics. During all experiments in the first group, we set number of neighbors (k) to 40. The results are presented in Table III for both data sets.

In Table III, it is possible to see accuracy performance of the traditional single rating item-based CF algorithm and different aspects of multi-criteria item-based CF framework. Traditional algorithm has MAE value similar with conventional CF approaches and since YM20 is more dense than YM10, the produced predictions from YM20 data set have less error than the ones obtained from YM10. According to outcomes presented in the Table II, it is not always improve traditional item-based algorithm's accuracy by utilizing multi-criteria ratings. If ACS is employed with selection average values of similarities between criteria vectors, accuracy worsens. On the other hand, classical similarity-based approach can be helpful for producing more accurate item-based referrals with multi-criteria ratings. The presented results show that the most significant gain is obtained if ACS with minimum value approach is utilized. If

TABLE III. MAE VALUES OF SINGLE RATING AND MULTI-CRITERIA RATING ITEM-BASED CF

Recommendation Approach				**YM10**	**YM20**
Traditional Item-based CF				0.7714	0.7323
Multi-criteria Item-based CF	**Similarity**	**PCC**	**Avg**	0.7670	0.7789
			Min	0.7670	0.7445
		ACS	**Avg**	0.7953	0.7911
			Min	0.7475	0.7273
	Distance	**Euclidean**		**0.7293**	**0.6322**
		Manhattan		0.7328	0.6798
		Chebyshev		0.7335	0.6493

accuracy performance of multi-dimensional distance metrics-based similarity estimation method is analyzed, it is shown that all measures are helpful for improving accuracy results. Although, it is possible to utilize one of the distance metrics in multi-criteria item-based CF systems, the best accuracy performance is acquired by employing Euclidean distance for both data sets. Again, the result for YM20 is more accurate than YM10 due to difference between rating densities.

One of the important parameters effecting accuracy of item-based CF systems is value of (k). In literature, there are studies presenting the most appropriate k value for single rating-based CF systems. However, a certain k value for multi-criteria rating item-based CF systems. Therefore, in the second group of experiments, we tries various k values both data sets. We employed Euclidean distance as similarity measure and followed the same experimental methodology. We produced predictions for both data sets. The MAE outcomes are presented in Fig. 1.

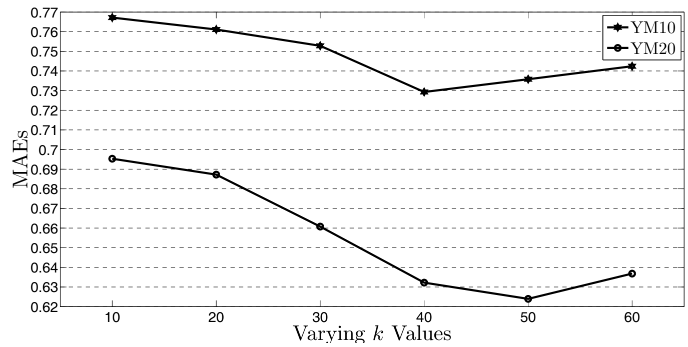

Fig. 1. Effect of k values on prediction accuracy

In Fig. 1, it is seen that parameter k has an important effect on accuracy performance. Furthermore, optimum k value can take different value according to data set. In our experiment, the most optimum results of k are 40 and 50 form YM10 and YM20, respectively. Therefore, in further implementation multi-criteria item-based CF systems, these optimum values can be utilized.

Up to now, we evaluated accuracy performance of traditional similarity-based multi-criteria ratings in item-based CF framework. According to experiment results, we selected Euclidean distance for both data set and the appropriate k values and the results indicates that, it is possible to improve accuracy of traditional item-based CF systems by using multi-criteria ratings. Moreover, since criteria similarities can be estimated off-line, scalability of existing multi-criteria rating-based CF systems can be enhanced.

In the last group of experiments, we tried to find effect of linear regression-based multi-criteria rating CF algorithm' success on item-based multi-criteria rating CF systems. As early mentioned, we employed the regression method provided by Adomavicius and Kwon [8] and we performed experiments for both data sets. The outcomes of the experiments indicates that, MAE values of regression-based method are 0.7402 and 0.6726 for YM10 and YM20 data sets, respectively. Since we can obtain more accurate results by using Euclidean distance measure-based similarity method as presented in Table III and Fig. 1, we can conclude that regression-based recommendation method cannot produce more accurate predictions than similarity-based approach for multi-criteria item-based CF systems.

VI. Conclusions and Future Works

In this work, we propose a multi-criteria item-based collaborative filtering framework. In order to determine appropriate neighbor selection method, we compare traditional correlation approaches with multi-dimensional distance metrics. Also, we investigate accuracy performance of statistical regression-based predictions. According to real data-based experiments, it is possible to produce more accurate recommendations by utilizing multi-criteria item-based collaborative filtering algorithm instead of a single criterion rating-based algorithm. In addition, since criteria similarities can be computed off-line, scalability of multi-criteria rating-based CF methods be improved.

In future, we will evaluate different neighbor selection approaches such as clustering or entropy-based methods in order to improve multi-criteria rating-based CF systems.

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