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Collaborative Filtering: Techniques and Applications

Najdt Mustafa[1], Ashraf Osman Ibrahim[2,*], Ali Ahmed[3], Afnizanfaizal Abdullah[4]
[1]Department of information system, Alneelain University, Khartoum, Sudan.
[2]Faculty of computer and technology, Alzaiem Alazhari University, Khartoum North 13311, Sudan
[3]Karary University, Omderman 12304, Sudan.
[4]Universiti Teknologi Malaysia, 81310 Skudai Johor, Malaysia.
njdt.kashef@neelain.edu.sd, ashrafosman2@gmail.com, alikaray@gmail.com, afnizanfaizal@utm.my

Abstract— **During the last decade a huge amount of data have been shown and introduced in the Internet. Recommender systems are thus predicting the rating that a user would give to an item. Collaborative filtering (CF) techniques are the most popular and widely used by recommender systems technique, which utilize similar neighbors to generate recommendations. This paper provides the concepts, methods, applications and evaluations of the CF based on the literature review. The paper also highlights the discussion of the types of the recommender systems as general and types of CF such as; memory based, model based and hybrid model. In addition, this paper discusses how to choose an appropriate type of CF. The evaluation methods of the CF systems are also provided throughout the paper.**

Keywords— Collaborative filtering; recommender systems; memory based; model based; hybrid model ; Evaluation Metrics.

I. Introduction

Recommender systems are considered as devices and programing engineering organization that is utilized for generating advantages suggestion to the users, as well as to help them in the procedure of decision making [1].One of the common recommender systems techniques is collaborative filtering (CF). The basic idea of CF is the extraction of information about the old behavior or opinions to user that exist in society, any elements where expected that the current user of the system are likely to have willingness to be selected, or similar to his taste [2]. The CF methodology takes a matrix which is given to the user only by estimating the inputs and a similar forecast for the following types of output. The work of CF is to give estimates of the current number of active user input and distinguish other users. Then, it achieves comparison process to get to the nearest person for the current user active friendly for any similar preferences with the current active user preferences [2].

Nowadays, Collaborative flirting can be classified into three fundamental categories as shown in Figure 1.There is a strong body of research that has been conducted in these three main techniques model-based, memory based and hybrid based methods [3]. In memory based model, the system tries to find users who resemble the current active user preferences and is used to predict the current active user preferences. That is, memory-based method is an effective way and easy to implement, which is used: neighborhood-based CF, item-based, user-based and top-N. With regard to the concept of the model based, there is a version to build a model based on the evaluation data or some of the extraction of information from the dataset and used to build a model to make recommendations without the need of using the data set at a time. While hybrid based is a mix between the two previous methods, it takes advantages of the features of memory and avoid disadvantages of the features of the model[3]. The application of the CF is used in numerous studies handling the collaborative filtering in many fields such as e-commerce, marketing , e-learning , social networking sites as well as in the marketing of books, movies and music, newspaper, TV programs , and service centers that include travel, tourism, Customer Relationship Management, learning machine, and networks offers services.

This paper gives an overview of the recommender system as well as to demonstrate the use of the collaborative filtering algorithm. Moreover, a different model of CF algorithms has been discussed and that some of the most important scientific papers published in this area have been reviewed.

The rest of this paper is organized as follows. Section 2 outlines the recommender systems techniques. Section 3 provides an overview of collaborative filtering approaches. The memory based classification is presented in Section 4. Section 5 presents the hybrid based collaborative filtering models. Section 6 highlights the enhancement of the collaborative filtering methods. Several issues, characteristics and challenges of the collaborative filtering are reviewed in Section 7. Section 8 provides an evaluation metrics of the collaborative filtering systems. Discussion and conclusion of current open research issues are provided in Sections 8 and 9 respectively.

II. Recommender Systems Techniques

Several methods have been suggested for use in recommender systems. Some investigations categorise recommender systems in view of their method with recommendation in three types: content-based, collaborative, and hybrid methodologies contrasted to their counterparts which have been classified into four classes : Content based Filtering (CBF), knowledge based (KBF), Collaborative filtering (CF) and Hybrid filtering (HF) [4].

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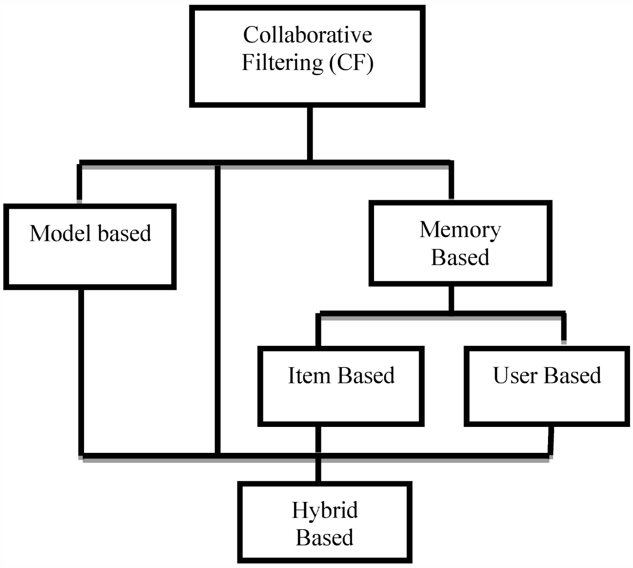

Fig. 1. Recommender collaborative flirting taxonomies [4]

A. Content based Filtering (CBF)

CBF approaches recommend items that are similar in content to the items that the user liked in the past or match to the attributes of the user [5]. In content based filtering method, each item is represented by a feature vector or an attribute profile. The feature holds numeric or nominal values representing certain aspects of the item such as colour, price, etc. A variety of (dis) similarity measures between the feature vectors may be used to calculate the similarity between two items. The Euclidean or cosine (dis) similarity algorithms can be used as in equations (1) and (2) [4].

$$\mathrm{dissim}(x, y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} = \|x - y\|_2 \qquad (1)$$

$$\mathrm{sim}(x, y) = \frac{\sum_{i=1}^{n} x_i * y_i}{\sqrt{\sum_{i=1}^{n} x_i^2}\sqrt{\sum_{i=1}^{n} y_i^2}} \qquad (2)$$

Where x and y are vectors of items with n elements in them, dissim (x,y) and sim(x,y) measure the distance apart and closeness respectively.

The (dis) similarity values are then used to obtain a ranked list of recommended items. These methods are depending on information retrieval, and they can provide recommendations in any domain.

In content based methods, when the items are represented as a set of features in a proper and clear way, then the system can work well. Content-based recommender systems make recommendations through content analysis of textual information, for example, documents, item descriptions, newsletters, URLs, web logs, profiles for users' needs, preferences, tastes, and find regularity in the content [6].

A. Knowledge based filtering (KBF)

Knowledge based filtering approaches are famous in the way that they have functional knowledge. These methods have knowledge with regard to how a certain item satisfies a certain user need, thus, one can think of the relationship between the need and possible recommendation. Knowledge-based approaches have similarly a detailed representation of the user's needs [10].

B. Hybrid filtering

Hybrid filtering refers to a combination of two or more approaches; the goal of this combination is to overcome the lacks of one approach with other one[11]. The combination of collaborative filtering approaches and content based produce isolated rank's lists of recommendations and combine them to develop the new recommendation result [12].

These hybrid approaches contain the content of the item, the ratings of users, content-based filtering, and demographic information. One famous example of these hybrid systems is weighted and switching. In a weighted hybrid system, the score of a recommended item can be computed from the available results based on available recommendation approaches. On the other hand, switching hybrid system uses some standards to switch among recommendation approaches. Collaborative filtering may be merged with other method trying to escape from the ramp-up issue[9]. Study [13]applied 'Selection agent', used hybrid of CF and content-based filtering. Another study such as in [6], also applied hybrid technique for recommendation and used more of the available information and thus has more precise recommendations.

Having demonstrated above paragraphs on recommender systems techniques can be used for many applications based on the application domain, which can determine the suitable technique. In this paper, we will focus on the CF algorithm.

III. Collaborative Filtering Approaches

Generally, CF approaches can be categorized into two categories: memory based and model based method. The memory based method requires all ratings, items and users to be stored in a memory. On the other hand, model based methods tend to create a summary of ratings patterns offline [14]-[15].

The Probabilistic CF methods are based on an underlying probabilistic model while non-probabilistic CF methods are not based on probabilistic model [3]. One of the well-known CF non-probabilistic is the nearest neighbor technique. Nearest neighbor techniques can be divided into two classes; item-based nearest neighbor and user-based nearest neighbor [4].

A. model based CF

Model based CF methods anticipate the obscure ratings following learning a model from the underlying information using machine learning or statistical methods [5]. Model-based

CF methods, for instance, reliance networks, Bayesian and clustering model need to be recognized to tackle those shortcomings about memory-based CF approaches [14][15]. Model-based techniques consists of Bayesian classifiers [15], relapse based methods [16] and cluster-based CF [17] [18]. The concept of the model based CF versions is to build a model on the basis of the evaluation data, or is to build some of the extraction of information from the data collection and dataset that used and to make recommendations without having to use the dataset at a time.

B. memory based CF

Memory based CF methods aim to use previous data to predict the unknown rating depend on some heuristic [5], They are operating over the entire user database to predict the results. We can find that the commonly memory based methods are based on the concept of nearest neighbors, using a diversity of distance measures [8]. The process of the predicting ratings via referring to users which their ratings are similar to the queried user based on neighborhood-based methods, which are common memory-based CF approaches. With regard to the production of memory-based CF methods prediction, a sample of the user-item database is used. Each user belongs to a group of people that have similar interests. The memory based CF has some features such as clarify the results. In other words, memory based CF is regarded as an important aspect of recommendation systems, ease of use, facilitating new data easily, independence content of elements that are recommended to expand the scope of a good rating with the common elements. In addition, the disadvantages of memory based CF is the problems on points clear and slow. Also, the difficulty of development Particularly in the context of the actual systems that generates recommendations in real time on the basis of large datasets [3].

C. Memory vs Model Based

Collaborative filtering algorithms calculate similarities between neighbors in memory. This method is called memory based; the database of sections will be stacked in memory and used directly so as to generate a recommendation. In opposed to this strategy, there is the model based method, in which a model is adapted and used to calculate recommendation. In general, model based method produces a model offline, and recommendation takes place online, and virtually immediate [16]. Model Based algorithms gained a huge push in the research communities after those million dollar prize competition in 2006. Throughout those three years that were taken for the win of the competition, an ever increasing amount contender received model based as part of their strategy. Finally, the winning team alleged to have used a collection of over 100 different methodologies consists of a weighted ensemble; the major algorithms employed were Model Based Matrix factorization techniques [20].

IV. MEMORY BASED CLASSIFICATION

As we mentioned earlier, the memory based CF methods work based on the previous data and predict rating, the common memory based CF methods are based on the concept of nearest neighbors. Memory based CF methods mainly depend on user belongs of a group of people who have similar interests. CF approaches which follow the same ideas of the memory based divided into the following approach.

A. Item based

Item-based collaborative filtering is a kind of model based method for making recommendations. There are two phases in item based collaborative filtering. Firstly, find the similarities between items that are computed by using one of the number similarity measures. Secondly, assessed similarity values by using predict ratings for unknown item. Item-based nearest neighbor methods are transpose of the user-based nearest neighbor methods. However, it can create predictions depend on similarities among items[4].

The cosine based similarity method is common way to calculate similarity between items, as we can see in equation (3) [28, 32].

$$\mathrm{Itemsim}(i,j) = \frac{\sum_{u\in U_{i,j}}(R_{u,i}-\bar{R}_u)(R_{u,j}-\bar{R}_u)}{\sqrt{\sum_{u\in U_{i,j}}(R_{u,i}-\bar{R}_u)^2}\sqrt{\sum_{u\in U_{i,j}}(R_{u,j}-\bar{R}_u)^2}} \quad (3)$$

Where $R_{u,i}$ and $R_{u,j}$ represent the rating of user u on items i and j respectively, $\bar{R}_u$ is the mean of the uth user's ratings and $U_{i,j}$, represents all users who have rated items i and j. In addition, the prediction calculation for item based nearest neighbor method for user u and item j as in equation (4).

$$P_{item-based}(u_t,j) = \frac{\sum_{i\in R_{u_t}} \mathrm{Itemsim}\ (i,j) * R_{u_t,j}}{\sum_{i\in R_{u_t}} \mathrm{Itemsim}\ (i,j)} \quad (4)$$

B. User based

User-based collaborative filtering methods for determine the similarity of the user by analyzing the elements participated in the vote between the user and that of the user uses the similarities and predicted weight in order to assess the important rating of the user on the efficiency of the element. The Pearson correlation coefficient similarity is the most used to compute similarity methods as given in equation (5) [4].

$$\mathrm{Usersim}(u_t,u) = \frac{\sum_{u\in I_{u,u_t}}(R_{u,i}-\bar{R}_u)(R_{u_t,i}-\bar{R}_{u_t})}{\sqrt{\sum_{u\in I_{u,u_t}}(R_{u,i}-\bar{R}_u)^2}\sqrt{\sum_{u\in I_{u,u_t}}(R_{u_t,i}-\bar{R}_{u_t})^2}} \quad (5)$$

The equation (6) will be used to predict t u rating for item j [23].

$$P_{item-based}(u_t,j) = \bar{A}_{u_t} + \frac{\sum(R_{u_n,i}-\bar{R}_{u_n}) * \mathrm{sim}(u_t u_n)}{\sum_{u_n\in N_{u_t}}|\mathrm{sim}(u_t u_n)|} \quad (6)$$

C. Item vs userbased

From the previous sections, we can conclude that the types of memory based collaborative filtering methods which based on which dimension of the user-item rating matrix are used to find similarities. Each one of the two types of memory based collaborative filtering methods has its own behavior and formulas. Item based methods search for item rated similarly by various users and follow the assumption that if many users rate two items similarly. On the other hand, user based methods will search for like-minded individuals and follow the assumption that similar users like similar items [16].

V. HYBRID BASED COLLABORATIVE FILTERING

Hybrid based collaborative filtering models considered as a third type of the collaborative filtering which combine collaborative filtering techniques with each other to make predictions or recommendations. The hybrid based collaborative filtering is mainly the result of hybridization or combination of memory and model based CF. It is a mixture between the two previous methods, so it takes the advantage of the features of Memory and avoids disadvantages and that it takes the advantage of the features of the Model.

VI. ENHANCE THE COLLABORATIVE FILTERING APPROACH

Although collaborative filtering methods underpinned success in many domains of application, more improvements (enhancement) are still needed as there were several works aimed at enhancing the CF method. The study in [17] suggested a hybrid technique that considers customers' purchase sequences over time. This method enhances the quality of recommendations to provide recommendations based on customer groups[18]. The authors introduced a state-of-the-art and taxonomy of intelligent recommender agents on the internet on different systems of recommendations system. In study [19], machine learning techniques used as a valuable tool for achievement an objective understanding of how values are embedded in technologies are presented.

Another study as in [20] presented a novel method to non-local adaptive nonparametric filtering to image modeling. However, a study [22] presented an enhanced CF method by using a genetic algorithm for obtaining optimal similarity functions to obtain better quality and quicker results as a hybrid method. Also,[21] introduced collaborative filtering method to enhance the recommendation quality derived from user-created tags to overcome some of the limitations in CF systems.

VII. CHARACTERISTICS AND CHALLENGES OF CF

There are challenging environments especially in E-commerce recommendation methods for large online companies like eBay and Amazon. Commonly, a recommender system provides fast and accurate recommendations that will attract the interest of customers and bring benefits to companies. For CF methods, producing high quality predictions or recommendations based on how well they address the challenges, which are characteristics of CF tasks as well.

A. Scalability

Traditional CF methods will suffer serious scalability problems if numbers of existing users and items grow tremendously. For instance, with tens of millions of customers (M) and millions of distinct catalog items (N), a CF algorithm with the complexity of O(n) is already too large. Furthermore, many systems need to react immediately to online requirements and make recommendations for all users regardless of their purchases and ratings history, which demand a high scalability of a CF system [3].

B. Synonymy

The synonym is a tendency of a number of the same or very similar items to have different names or entries. Many recommender systems are incapable to discover this latent association and thus treat these products differently. For instance, the seemingly different items "children movie" and "children film" as they are, in fact, the same item, yet the memory-based CF methods would find no match between them to calculate similarity. The prevalence of synonyms reduces the recommendation performance of CF approaches [3].

C. Data scatter

In fact, numerous commercial recommender systems are used to evaluate very large product sets. The user item matrix used for CF approach will thus be very sparse and that performances of the predictions or recommendations of the CF systems are challenged [3].

D. Gray Sheep

The users whose opinions do not consistently agree or disagree with any group of people and therefore do not benefit from CF[23]. On the other hand, the opposite group whose idiosyncratic tastes make recommendations nearly impossible had known as black sheep. Even though this is a failure of the recommender system, non-electronic recommenders also have great problems in these cases, therefore, black sheep is an acceptable failure [3].

E. Shilling Attacks

In cases where anyone can provide recommendations, people may give tons of positive recommendations for their own materials and negative recommendations for their competitors. It is desirable for CF methods to introduce precautions that discourage this kind of phenomenon [3].

VIII. EVALUATION METRICS

The evaluation of any outcome of any model is an important issue; therefore, the recommender systems or CF systems need these measures to evaluate the performance. There are different types of the evaluation metrics used in CF systems as they depend on the application of the CF algorithms. In this section, we introduce the commonly used metrics such as; Mean Absolute Error (MAE), Normalized Mean Absolute Error (NMAE), Root Mean Squared Error (RMSE) and ROC sensitivity or area under the ROC Curve (AUC). The equations (7), (8), (9) and (10) illustrate the formulas of the above metrics in CF fields [14].

$$\mathrm{MAE} = \frac{\sum_{\{i,j\}} |p_{ij} - r_{ij}|}{n} \qquad (7)$$

Where n is the total number of ratings is over all users, p_{ij} is the predicted rating for user i on item j, and r_{ij} is the actual rating.

$$\text{NMAE} = \frac{\text{MAE}}{r_{max} - r_{min}} \quad (8)$$

Where r_{max} and r_{min} are the upper and lower bounds of the ratings.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{\{i,j\}}\left(p_{i,j} - r_{i,j}\right)^2} \qquad (9)$$

Where n the total number of ratings is over all users, p_{ij} is the predicted rating for user i on item j, and r_{ij} is the actual rating again.

$$\text{AUC} = \frac{s_0 - n_0(n_0+1)/2}{n_0 n_1} \qquad (10)$$

Where n_0 and n_1 are the numbers of negative and positive examples respectively, $s_0 = \Sigma r_i$, where r_i is the rank of its positive example in the ranked list.

IX. Discussion

The collaborative system intervene in many areas and it has been used in various aspects of e-commerce, marketing , e-learning , social networking sites as well as in the marketing of books, movies and music, and service centers such as travel, tourism and ad networks offers services. A study [24] suggested a recommendation system cooperative in music and Memory based was used to help the listener to choose morphological songs that suit them according to previous evaluations of the songs. When the listening is being evaluated, the system generates profile file for each listener recorder, and saves previous evaluations for them to be used as Public Profile to show the song, which is expected to gain admiration.

In study [25], the authors used a Memory-based CF and Pearson that are based on an artificial immune network. As far as study [26]] is concerned, the memory based CF has been applied to movies. As for study [22], the authors as well used the memory based in Movie lens, Film Affinity and Netflix dataset. Another study [27] applied the memory based in mobile music to rapidly growing mobile music market .The study [28] provides an application of collaborative filtering techniques to movie search for better ranking and browsing. Also, the literature on CF methods appears to indicate that there are several studies that have been used model-based CF, for instance, the study [23] used the model-based on online newspaper. In addition, study[29] used neighborhood models in e-commerce and this methodology is one of the memory based recommendations. With regard to a study [30],that has been applied on e-commerce to support product recommendation, it, yet, used hybrid based method. The authors in study [31] used a collaborative filtering method and hybrid as well to apply e-learning and personalization on it since two popular collaborative filtering methods; a memory-based by using the Pearson correlation and a matrix factorization method which using SVD. The study [32] also used a collaborative filtering approach to personalization in e-learning . As far as the study[33] is concerned, learning machine was being implemented and that it used hybrid a CF algorithm with two learning machine processes, Self-Organizing Map (SOM), Case Based Reasoning. There are many studies that used hybrid based method, for instance, a study [34] used hybrid based in Social Network, whereas a study [35]used a hybrid content based and item based collaborative filtering approach as they have been implemented in TV programs. A study [17] used a hybrid recommendation method and KNN method on Customer Relationship Management (CRM). A study[36] used the same approach on artificial intelligence networks. There are many studies appear to enhance Collaborative Filtering, for example, study [37] which developed personalized ranking, while [38]used of social network information and Pearson’s correlations to enhance collaborative filtering performance.

X. Conclusion

Collaborative filtering techniques emphasize the success of using recommender systems methodology in different areas of research. In this paper, we introduced the main recommender systems techniques. Then, the main categories of collaborative filtering techniques have been introduced which include; memory-based, model based, and hybrid CF method that combine CF with other recommender system methods. Moreover, some examples of mentioned CF techniques have been provided. The paper as well highlights some suggestions to enhance CF method and using the enhancement in different application applying CF method. The evaluation measures have been discussed as well. This study appears to suggest and/or indicate that the more distant future may belong to other algorithms, it improves the recommender system.

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