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Cold-start Problem in Collaborative Recommender Systems: Efficient Methods Based on Ask-to-rate Technique

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To develop a recommender system, the collaborative filtering is the best known approach, which considers the ratings of users who have similar rating profiles or rating patterns. Consistently, it is able to compute the similarity of users when there are enough ratings expressed by users. Therefore, a major challenge of the collaborative filtering approach can be how to make recommendations for a new user, that is called cold-start user problem. To solve this problem, there have been proposed a few efficient methods based on ask-to-rate technique in which the profile of a new user is made by integrating information gained from a quick interview. This paper is a review of these proposed methods and how to use the ask-to-rate technique. Consequently, they are categorized into non-adaptive and adaptive methods. Then, each category is analyzed and their methods are compared.

Keywords: recommender systems, collaborative filtering, new user, user cold-start

1. Introduction

The idea of personalizing searching engines, intelligent software agents and recommender systems is taken into consideration by users who ask for help in sorting, classifying, personalizing, filtering and sharing a large amount of information. One of the common recommender techniques is Collaborative Filtering (CF) [1-3] which offers preferred items to a user based on the items previously rated by their collaboration. The essential supposition is that, if users X and Y assign a similar rate to n items or have a similar behavior, they will rate or behave other items similarly [4]. Therefore, a major challenge of CF technique can be how to make recommendations for a new user who has recently entered the system; that is called cold-start user problem. In other words, the system must attempt to gather information about the new user before being able to fully use the system.

To solve the cold-start user problem, a few efficient methods have been proposed based on ask-to-rate technique [5], in which a new user is asked to rate the selected items until having a sufficient number of rated items. The methods can be categorized to two non-adaptive and adaptive methods depending on whether the presented items are similar to "all" new users or not. In this paper, both non-adaptive and adaptive methods are explained and their efficient methods are reviewed.

The rest of this paper is organized as follows. The recommender systems are introduced in Section 2. The concept of CF recommender systems is described in Section 3. A comprehensive survey of ask-to-rate technique and some of the efficient methods are discussed in Section 4. Finally, in Section 5, the related methods are discussed and conclusion of this work is presented.

2. Recommender Systems

Recommender systems are a subset of information filtering systems which are used as efficient tools for overcoming information overloading, inspecting a large set of information and selecting information related to each user. The issue of recommendation and rating prediction implies items like movie, music, book, etc. or social factors like people or groups that have not been seen by users yet. When recommender systems are able to predict ratings for items that have not been observed yet, the item(s) can be recommended to a target user. A target user is a user for whom the recommendations are made. A movie recommender system, for example, might memorize explicit or implicit user ratings to recommend new movies to the same user, based on the ones that s/he has already seen.

Thus, how would the recommendation be produced? There is a taxonomy provided by [6] with five different techniques including collaborative filtering, content-based, demographic [7, 8], utility-based [9] and knowledge-based ones. There is another category to overcome limitations of the mentioned methods by combining techniques, which tries to use advantages of one technique to fix disadvantages of others. Several ways have been proposed for their combination to come up with a new hybrid system (see [6] for precise descriptions, where seven categories of hybrid system are presented). CF systems are described here since repeating the detailed explanation of other categories in this paper might be redundant. The interested authors could refer to original articles [1, 6, 10].

3. Collaborative Filtering Recommender Systems

Collaborative filtering recommender systems are one of the biggest sub-domains of information retrieval. The basic concentration of these systems is on finding users with similar interests to the target user and aggregating their opinions to make a recommendation. So, it calculates similarity between users instead of the content of items. Under the existing amount of information, both users and website owners receive benefit from CF systems; thus, users are able to come across preferred items; moreover, the profit from e-commerce websites potentially go up because of persuading the user to buy more related products or accessories.

Researchers have already classified many algorithms for collaborative recommendation including the *memory-based* or *model-based* CF [11]. Also, for taking advantages and alleviating certain drawbacks of two algorithms, some studies have suggested *hybrid algorithms* [6, 12]. This section focuses on a common memory-based CF algorithm, named *user-based kNN* (k-Nearest Neighbors) [2].

Memory-based algorithms are essentially heuristics as in *the user-based kNN* system which calculates the prediction of a target item based on statistical techniques in order to find users with similar tastes as follows:

- First, the similarity, $sim(u_t, u_i)$, between target user, u_t, and all other users, u_i, who have rated target item, a_t, is computed by different measures such as Pearson's Correlation (shown in Equation (1)), Cosine measure, a recent measure like proximity-impact-popularity [13] and so on, which reflects distance, correlation or weight between two users.

$$sim(u_t, u_i) = \frac{\sum_{m=1}^{h} (r_{u_t,a_m} - \overline{r_{u_t}}) \cdot (r_{u_i,a_m} - \overline{r_{u_i}})}{\sqrt{\sum_{m=1}^{h} (r_{u_t,a_m} - \overline{r_{u_t}})^2} \cdot \sqrt{\sum_{m=1}^{h} (r_{u_i,a_m} - \overline{r_{u_i}})^2}} \quad (1)$$

  where $r_{u,a}$ is rating of item a by user u, $\overline{r_u}$ is mean of rating by users u_t or u_i for all the co-rated items and h is the number of items co-rated by both users. The similarity ranging is between -1 (the least similar users to target user) and 1 (the users most similar to the target user).

- Second, prediction for a target item by a target user can be calculated using at most k nearest neighbors, who have also rated the target item, found from the former step as Equation (2).

$$prediction(u_t, a_t) = \frac{\sum_{h=1}^{k} (r_{u_h,a_t} - \overline{r_{u_h}}) \cdot sim(u_t, u_h)}{\sum_{h=1}^{k} |sim(u_t, u_h)|} + \overline{r_{u_t}} \quad (2)$$

  where $\overline{r_{u_t}}$ and $\overline{r_{u_h}}$ are mean of ratings for the target user and user h on all other rated items and $sim(u_t, u_h)$ is similarity between the target user and user h.

One of the advantages of memory-based CF algorithms is their intuitive idea that makes it easy to comprehend and the results are conveniently explainable. Furthermore, the main strength of pure CF systems is that the new data can be added increasingly and without difficulty since they do not require any tagging of the items' content, like content-based filtering, and recommendations are made only using the rating data. Hence, this approach is suitable for any domain, especially in domains the contents of which are either rare (like restaurants) or accruing contents are difficult (like movies or music).

Collaborative systems have their own limitations like cold-start problem [5, 14-16], scalability [17] and sparsity [4]. As an important problem, the *cold-start user problem* occurs when a user, who is new to the recommender system, enters the system and there are no ratings by the user. The user-based CF cannot compute similarity between new and other users [14-16, 18, 19] Hence, it is difficult to make recommendations.

To solve this problem, there have been different techniques. The ask-to-rate technique [5, 14, 16, 18, 19] is the most direct way for obtaining some information about the new user and for learning the user's preferences. The next section explains the ask-to-rate technique.

4. Asking for Explicit Ratings

The most direct way to cope with cold-start user problem and make a rapid profile of a new user is to ask for explicit ratings by presenting items to the user. It can elicit initial information about the new user with a quick and short interview. After presenting some items to the new user,

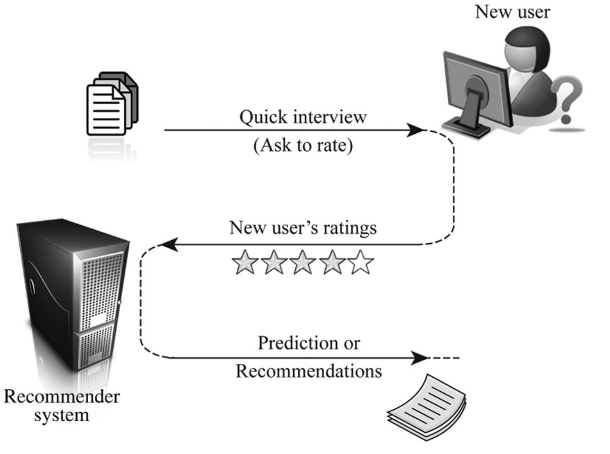

Figure 1. The new user prompting process.

this process is completed and, whereas in user-item matrix the row of a new user is not empty, the new user enters the normal phase of recommender system. The CF system should use these ratings to compute similarity between new and other users. Whereby, s/he gets precise recommended items, shown in Figure 1.

The system must be cautious about presenting informative items that gather useful information before a new user is allowed to normally use the system. If the ratings are obtained by a well-designed selection strategy compared with a strategy in which the users self-select the items to rate, the recommendation accuracy can be improved.

Generally, techniques should not appear severe to the new users and they must move toward minimizing user effort and maximizing recommendation accuracy. Of interest in [14, 18], evaluation of elicitation methods on user effort and accuracy metrics is shown in Table 1. The methods are mentioned in the following section. This paper provides an overview of the efficient methods based on the ask-to-rate technique. Reasonably, they are categorized to non-adaptive and adaptive methods, based on how the next items are selected.

Methods	User Effort	Recommendation Accuracy
IGCN	⋆⋆⋆⋆	⋆⋆⋆⋆⋆
(Log pop)×Ent	⋆⋆⋆	⋆⋆⋆⋆⋆
Entropy0	⋆⋆⋆⋆⋆	⋆⋆⋆⋆
HELF	⋆⋆⋆	⋆⋆⋆⋆
Popularity	⋆⋆⋆⋆⋆	⋆⋆⋆
Item-Item	⋆⋆⋆⋆⋆	⋆⋆
Entropy	⋆	⋆⋆
Random	⋆	⋆⋆

Table 1. The Evaluation of elicitation strategies in [14, 18] over both online and offline experiments on user effort and accuracy metrics, (⋆⋆⋆⋆⋆: best, ⋆: worst).

4.1. Non-adaptive methods

Using non-adaptive techniques makes it possible to present the same items to "all" new users regardless of changes in knowledge of the user being interviewed. In most of these methods, computation is based on information theory for the new user's problem. The advantage of these methods is that order only needs to be calculated once, although these techniques provide little information. Some of the techniques are classified as non-personalised methods in [16].

Various strategies have been proposed for non-adaptive methods such as Variance and Entropy strategies [19]; Random, Popularity, Pure entropy and Balanced strategies [14]; Entropy0, HELF strategies [18]; and Greedy strategy and the Other People's Greedy and Variations strategies [16]. Details of each non-adaptive strategy are:

1. *Active WebMuseum* is the first CF recommender system which uses the ask-to-rate technique [19]. This web-based virtual museum has a dynamic topology in which art paintings are personalized and ordered by museum visitors' taste and preferences. This paper proposes *Entropy* and *Variance* methods to present sequence of items to be rated by new users. These methods are the statistical analysis of distribution of item ratings given by other users in the dataset. According to Equation (3) the variance of the target item a_t is computed.

$$Variance(a_t) = \frac{\sum\limits_{u \in U_{a_t}} (r_{u,a_t} - \overline{r_{a_t}})^2}{|U_{a_t}|} \tag{3}$$

   where U_{a_t} is all users which have rated items a_t, r_{u,a_t} is rating of item a_t by user u and $\overline{r_{a_t}}$ is mean of a_t's rating. Experiments use *random strategy* (select items to present without prior planning) as a baseline measure and point out that these two methods generate more accurate predictions for new users than random strategy.

2. In 2002, MovieLens research group extended the aforesaid idea in web personalization [14]. In this research, some strategies were proposed which contained use of information theory and aggregated statistics to learn about new users. These strategies focused on the issue of which items to be presented to the new user during an initial interview. Different strategies have been tested through offline and online experiments to select movies that have used MovieLens dataset. Their evaluation considered *user effort* and *recommendation accuracy* related to the user experience. All the proposed methods have been measured based on rating prediction accuracy – *MAE* (*Mean Absolute Error*) evaluation metric. These methods are as follows:

   - *Random strategy*: selects the items randomly. It learns about new user preferences in terms of all available items. Random strategy is a baseline strategy which is used for comparison. The analysis of the rating matrix is not intelligent and the results of online and offline experiments point out that it needs much more user effort and that accuracy of predictions is unfavorable. If the distribution of ratings is not uniform, the user will probably not have any opinion about presented items.
   - *Popularity strategy*: It has been suggested to take an item's popularity into account, i.e. how many users have rated an item. The items are ordered by the number of ratings that they have been given by all users and present some of the most popular items to the new user. According to Equation (4), popularity of item a_t is computed, where r_{at} shows its rating.

$$Popularity(a_t) = |r_{a_t}| \tag{4}$$

     Implementation of this method is easy and its computation is inexpensive. It has accomplished the important goal of minimizing user effort. However, ratings may be uninformative since most users like popular items. Moreover, the popularity measure suffers from prefix bias – it is derived from popular items which receive ratings increasingly but not from unpopular items. This problem causes unequal distribution of ratings in the dataset.
   - *Pure entropy*: Another low complexity method for item selection is entropy, which was proposed by [19] and was re-presented in [14]. The entropy on a target item $H(a_t)$ is dispersion of the item ratings in the rating matrix. Using pseudocode in Figure 2. Then, some not-yet-rated items with the highest score are presented. This method provides a lot of information for each rating; but, some information is not informative for the system and sometimes it selects unknown items since this method does not take frequency into account. In offline experiment, Entropy, like Random strategy, needs

extreme user effort and performs extremely poorly on accuracy. It has not been evaluated in the online experiment. Hence, in terms of accuracy and user effort, Entropy and Random methods lag behind all the methods mentioned in [14].

```
Function Entropy (a_t)
entropy (a_t) = 0
for each item a_t in dataset
 for i as each of the possible rating values   // in movielens i = 1...5
   if a_t's rating= i
      value[i]+= 1             // rating frequencies
 end for
 proportion_i =value[i]/total number of users who rate a_t
 entropy(a_t)+=proportion_i*Math.log(proportion_i, 2)
end for each
entropy(a_t) = −entropy(a_t)
End
```

Figure 2. Pseudocode of entropy approach.

- *Balanced strategy*: The logarithmic of possibility with which the user has rated the item (popularity score) is multiplied by entropy, that is *(log popularity) *entropy* and some items are presented in a descending order. This method combines advantages of two components, has the best accuracy toward other methods proposed in [14] and needs medial user effort.

3. In 2008, idea of ask-to-rate by MovieLens research group was further extended in [18] to improve order of items and more precisely elicit opinion of new users at registration time. This paper was a winner in Yahoo! Research Best Paper Award [20]. They proposed an offline simulation framework and an online experiment with real users of the MovieLens live recommender system. Three new information theoretic strategies were presented: Entropy0, HELF and IGCN. Details of the two non-adaptive strategies include:

- *Entropy0 (Entropy Considering Missing Values)*: In [14], missing ratings (non-ratings) were ignored in entropy's calculation. Entropy0 was proposed to handle the problem of an item with the missing evaluation as all missing evaluations were filled with a separate category like "0" whereas "1-5" was the usual scale. A weighted entropy formulation was used as Equation (5):

$$Entropy0(a_t) = -\frac{1}{\sum_i w_i}\sum_{i=0}^{5} p_i w_i \log(p_i) \tag{5}$$

where $w = 0.5$ is the weight to identify missing values and $w_i = 1$ for $i = 1, 2, 3, 4, 5$ since this selection of weights provided the best results for the original experimentation. Note that, $w_0 = 0$ changed Entropy0 into the pure entropy measure. The Entropy0 method dominates one of the limitation of entropy and distinguishes between most unknown items (infrequently rated items) and frequently rated items. It is slightly more successful than Popularity method.

- *HELF* (*Harmonic mean of Entropy and Logarithm of Frequency*): This strategy is a hybrid of Popularity and Entropy strategies. It uses suitable feature of harmonic mean and logarithmic function. HELF combines harmonic mean of Popularity (rating-frequency of items) and Entropy scores of items; The combined measures are not correlated. HELF is defined as Equation (6):

$$HELF_{a_t} = \frac{2 * LF'_{a_t} * H'(a_t)}{LF'_{a_t} + H'(a_t)} \tag{6}$$

where $LF'_{a_t} = \log(|a_t|)/\log(|U|)$ is the normalized logarithm of the rating frequency of target item, and $H'(a_t) = H(a_t)/\log(5)$ is the normalized entropy of target item.

4. Other criteria were suggested in [16], which showed progression of methods for dealing with the new user. Below, details of some non-adaptive approaches called Greedy and Other People's Greedy and variations are explained.

- *Greedy strategy*: where the next item is chosen from those that the user can rate such that the prediction error for its test set is minimized. This method is not feasible in practice and requires knowing what each person can rate and the actual ratings. It is used as a baseline.

- *Other People's Greedy and Variations*, selected items will be presented to the new user from the top-n lists of other users' items obtained through a greedy method. It uses other people's opinions and selects items which reduce prediction error.

4.2. Adaptive methods

We define those approaches as *Adaptive* because selected items are consistent with "each" new user's opinions. For present items that best fit user's personal preferences the system should adapt to the earlier rates given by the new user. Thereupon, they rate items with personalized orderings and the interview process will be controlled more effectively than in non-adaptive approaches. Adaptive approaches take into account the user's historical ratings among initial interview and consider the system's changing profile of the new user; thereby, the number of items familiar to the new user is maximized. Dealing with the cold-start user problem by asking to rate, there are a few adaptive approaches for a personalized items' ordering, such as Item-item personalized [14]; IGCN [18]; naïve Bayes, perturbed Other People's Greedy and Variations [16] (which are classified as personalised methods in [16]) and clustering method [21]. The details of each strategy are:

Research Example	**Method**	**Pluses**	**Minuses**
Kohrs, A. Merialdo, B. (2001)	*Variance*	• The first statistical analysis of the item's ratings distribution toward solving user cold start problem	• Not adapted to a user's rating history
	Pure Entropy	• The first statistical analysis of the item's ratings distribution toward solving user cold start problem. • Using potential information of an item's ratings.	• Select unknown items. • Disregard item popularity and the rating frequencies • Not considered missing values. • Assign the most entropy value to the items with uniform rating distribution. • Not adapted to a user's rating history
Rashid, A.M. Albert, I. Cosley, D. Lam, S.K. McNee, S.M. Konstan, J.A. Riedl, J. (2002)	*Random*	• Used as a baseline. • Apply to all available items.	• Not apply intelligent analysis • Not adapted to a user's rating history
	Popularity	• Easy to compute • Easy to implementation • Most availability of users for rate items.	• Uninformative rating. • Increases Prefix bias • Causes unequal distribution of ratings in dataset • Not adapted to a user's rating history
	Balanced	• A combination of popularity and entropy's advantages.	• Poularity's dominance over multiply Pop by Ent. • Not adapted to a user's rating history
Rashid, A.M. Karypis, G. Riedl, J. (2008)	*Entropy0*	• Considering missing values • Distinguishes between most unknown items (infrequently rated items) and frequently rated items.	• Bias toward frequently rated items. • Not adapted to a user's rating history.
	HELF	• Using suitable feature of harmonic mean and logarithmic function • A combination of popularity and entropy's advantages.	• Not adapted to a user's rating history.
Crane, M. (2011)	*Greedy strategy*	• Used as a baseline. • Selecet items which reduced prediction error in test set.	• Cannot be applied in practice. • Not adapted to a user's rating history.
	Other people's greedy and variations	• Using other people's opinions. • Selecet items which reduced prediction error.	• Not adapted to a user's rating history.

Table 2. Classification of asking to rate, non-adaptive approaches

- *Item-item personalized*, where items are proposed until the user gives at least one rating; then, similarity between the items will be computed using a recommender system based on some similarity measures and some items that the user would be most likely to *buy* (or see in movie domain) will be presented. Whenever the user gives more ratings, the list of similar movies will be updated. Evaluation of strategy over both experiments on their metrics points out that it provides the best user effort like Popularity and Entropy0 strategies and the worst accuracy like Entropy and Random strategies since the approach tends not to identify items that the user will *like* [14]
- *IGCN* (*Information Gain through Clustered Neighbors*): Toward achieving an adaptive designed selection strategy, at first, [18] considered using decision trees. Initially, the users are clustered to groups and then a decision tree algorithm such as ID3 is used to come across the right cluster for the target user and learn user profile. This approach takes into account the items that are rated by a user so far. The goal of target user is to follow a route through the decision tree from the root node (with the highest information gain) to the leaf node (which infers the user's true class or neighborhood).

  However, the authors refuse to consider this ideal decision tree scenario because it may not be practically feasible with most members of a recommender system; instead, they have proposed a two-phase algorithm named IGCN. Before starting the first step, user clusters are created using bisecting k-mean approach and the information gain (IG) of items is computed. In the first phase called non-personalized step, the user gives several ratings to the items that are ordered by their information gain scores, to build an initial profile until the user has rated at least some threshold numbers of items. In the second phase, named personalized step, toward creating an affluent profile, information gain of the items is computed using only the best neighbors of the target user as long as the best neighbors have no changes. IGCN requires assuming a predefined clustering of users. The 20 days online experiment performed on 468 users presented that IGCN approach offers greater accuracy than all other proposed information theoretic measures in [18].
- *Naïve Bayes*: This method is a variant of Popularity method which is personalized. When a user is capable, or incapable, of rating an item, it uses naïve bays probability in which the user is capable of rating other items. The selecting items to be presented are the highest probable items which are able to be rated.
- *Perturbed Other People's Greedy and Variations*: This method combines naïve bayes probability and Other People's Greedy method to generate a list of personalized items. It utilizes advantages of both by selecting items which the user is able to rate and the amount by which the item cuts down on prediction error.
- In [21], the authors extended the item-item method to create a personalized methodology for dealing with the new user problem using ask-to-rate technique.
- *Clustering*: This proposed strategy enjoys item (in this paper, items were news articles) and user clustering information. This approach uses W-kmeans clustering algorithm, to choose which items to select next for rating by the user. The authors have demonstrated that it performs better than all of the common strategies like Random, Popularity, Pure Entropy, Balanced and Item-Item personalized and minimizes user effort

A brief comparison of the classification of methods to alleviate user cold-start problem by asking to rate, and their advantages and disadvantages are depicted in Table 3.

5. Conclusion

In summary, the objective of a recommender system typically is to recommend items that best fit users' personal preferences. Collaborative filtering systems generate recommendation based on user-user similarity. A new user encounters a serious problem in the collaborative filtering approach. Since the system does not have any data about the new user preferences, it could not provide any personalized recommendation for him/her. It has to acquire some data

Research Example	Method	Pluses	Minuses
Rashid, A. M. Albert, I. Cosley, D. Lam, S. K. McNee, S. M. Konstan, J. A. Riedl, J. (2002)	*Item-Item personalized*	• The first adaptive method. • Adapting to a user's rating history.	• Inattention to user's interests in items. • Providing uninformative rating
Rashid, A. M. Karypis, G. Riedl, J. (2008)	*IGCN*	• Adapting to a user's rating history.	• Requires assuming a predefined clustering of the users
Crane, M. (2011)	*Naïve Bayes*	• Considering the ability of a user for ratings.	• Poor performance compared to the simplest approach (Random).
	Perturbed other people's greedy and variations	• Reduce prediction error compared to	• Poor performance compared to other people's greedy method.

Table 3. Classification of asking to rate, Adaptive approaches.

about the new user. In this paper we have reviewed several methods for dealing with the new user problem via ask-to-rate technique. The methods are categorized into two, non-adaptive and adaptive categories.

Although a few efficient methods to solve the cold start new user problem have been proposed, it is still not a stone in the corner. During the items selection, the new incoming ratings of other users are not considered. Therefore, a future direction can be developing a new method, which will adapt to the earlier ratings given by other users.

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