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Performance Evaluation of Ranking-Based Techniques

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Abstract
Recent years and many techniques have been proposed to improve the recommendation quality. However, in most cases, new techniques are designed to improve the accuracy of recommendations, whereas the recommendation diversity has often been overlooked. In particular, we showed that, while ranking recommendations according to the predicted rating values (which is a de facto ranking standard in recommender systems) provides good predictive accuracy, it tends to perform poorly with respect to recommendation diversity. Therefore, in this paper, we proposed a number of recommendation ranking techniques that can provide significant improvements in recommendation diversity with only a small amount of accuracy loss. In addition, these ranking techniques offer flexibility to system designers, since they are parameterizable and can be used in conjunction with different rating prediction algorithms (i.e., they do not require the designer to use only some specific algorithm). They are also based on scalable sorting based heuristics and, thus, are extremely efficient. We provide a comprehensive empirical evaluation of the proposed techniques and obtain consistent and robust diversity improvements across multiple real-world datasets and using different rating prediction techniques. This work gives rise to several interesting directions for future research. In particular, additional important item ranking criteria should be explored for potential diversity improvements. This may include consumer-oriented or manufacturer oriented ranking mechanisms, depending on the given application domain, as well as external factors, such as social networks. Also, as mentioned earlier, optimization-based approaches could be used to achieve further improvements in recommendation diversity, although these improvements may come with a (possibly significant). Increase in computational complexity. Moreover, because of the inherent tradeoff between the accuracy and diversity metrics, an interesting research direction would be to develop a new measure that captures both of these aspects in a single metric.

Keywords
Recommender Systems, Recommendation Diversity, Ranking Functions, Performance Evaluation Metrics, Collaborative Filtering

I. Introduction

In the current age of information overload, it is becoming increasingly harder to find relevant content. This problem is not only widespread but also alarming [28]. Over the last 10-15 years, recommender systems technologies have been introduced to help people deal with these vast amounts of information [1, 7, 9, 30, 36, 39] and they have been widely used in research as well as e-commerce applications, such as the ones used by Amazon and Netflix. The most common formulation of the recommendation problem relies on the notion of ratings, i.e., recommender systems estimate ratings of items (or products) that are yet to be consumed by users, based on the ratings of items already consumed. Recommender systems typically try to predict the ratings of unknown items for each user, often using other users' ratings, and recommend top N items with the highest predicted ratings. Accordingly, there have been many studies on Developing new algorithms that can improve the predictive accuracy of recommendations. However, the quality of recommendations can be evaluated along a number of dimensions, and relying on the accuracy of recommendations alone may not be enough to find the most relevant items for each user [24, 32]. In particular, the importance of diverse recommendations has been previously emphasized in several studies [8, 10, 14, 33, 46]. These studies argue that one of the goals of recommender systems is to provide a user with highly idiosyncratic or personalized items, and more diverse recommendations result in more opportunities for users to get recommended such items. With this motivation, some studies proposed new recommendation methods that can increase the diversity of recommendation sets for a given individual user, often measured by an average dissimilarity between all pairs of recommended items, while maintaining an acceptable level of accuracy [8, 33, 46]. These studies measure recommendation diversity from an individual user's perspective (i.e., individual diversity). In contrast to individual diversity, which has been explored in a number of papers, some recent studies [10, 14], started examining the impact of recommender systems on sales diversity by considering aggregate diversity of recommendations across all users. Note that high individual diversity of recommendations does not necessarily imply high aggregate diversity. For example, if the system recommends to all users the same five best-selling items that are not similar to each other, the recommendation list for each user is diverse (i.e., high individual diversity), but only five distinct items are recommended to all users and purchased by them (i.e., resulting in low aggregate diversity or high sales concentration). While the benefits of recommender systems that provide higher aggregate diversity would be apparent to many users (because such systems focus on providing wider range of items in their recommendations and not mostly bestsellers, which users are often capable of discovering by themselves), such systems could be beneficial for some business models as well [10-11, 14, 20]. For example, it would be profitable to Netflix if the recommender systems can encourage users to rent "long-tail" type of movies (i.e., more obscure items that are located in the tail of the sales distribution [2]) because they are less costly to license and acquire from distributors than new release or highly-popular movies of big studios [20]. However, the impact of recommender systems on aggregate diversity in real-world e-commerce applications has not been well understood. For example, one study [10], using data from online clothing retailer, confirms the "long tail" phenomenon that refers to the increase in the tail of the sales distribution (i.e., the increase in aggregate diversity) attributable to the usage of the recommender system. On the other hand, another study [14], shows a contradictory finding that recommender systems actually can reduce the aggregate diversity in sales. This can be explained by the fact that the idiosyncratic items often have limited historical data and, thus, are more difficult to recommend to users; in contrast, popular items typically have more ratings and, therefore, can be recommended to more users. For example, in the context of Netflix Prize competition [6, 22], there is some evidence that, since recommender systems seek to find the common items (among thousands of possible movies) that two users have watched, these systems inherently tend to avoid extremes and recommend very relevant but safe recommendations to users. As seen from this recent debate, there is a growing awareness of the importance of aggregate diversity in recommender systems. Furthermore, while, as mentioned earlier, there has been significant amount of work done on improving individual diversity, the issue of aggregate diversity in recommender systems has been largely untouched. Therefore, in this paper, we focus on developing algorithmic techniques for improving aggregate diversity of recommendations (which we will simply refer to as diversity throughout the paper, unless explicitly specified otherwise), which can be intuitively measured by the number of distinct items recommended across all users. Higher diversity (both individual and aggregate), however, can come at the expense of accuracy. As known well, there is a tradeoff between accuracy and diversity because high accuracy may often be obtained by safely recommending to users the most popular items, which can clearly lead to the reduction in diversity, i.e., less personalized recommendations [8, 33, 46]. And conversely, higher diversity can be achieved by trying to uncover and recommend highly idiosyncratic or personalized items for each user, which often have less data and are inherently more difficult to predict, and, thus, may lead to a decrease in recommendation accuracy. Table 1 illustrates an example of accuracy and diversity tradeoff in two extreme cases where only popular items or long tail type items are recommended to users, using Movie Lens rating dataset. In this example, we used a popular recommendation technique, i.e., neighborhood-based Collaborative Filtering (CF) technique [9], to predict unknown ratings. Then, as candidate recommendations for each user, we considered only the items that were predicted above the pre-defined rating threshold to assure the acceptable level of accuracy, as is typically done in recommender systems. Among these candidate items for each user, we identified the item that was rated by most users (i.e., the item with the largest number of known ratings) as a popular item, and the item that was rated by least number of users (i.e., the item with the smallest number of known ratings) as a longtail item, if the system recommends each user the most popular item (among the ones that had a sufficiently high predicted rating), it is much more likely for many users to get the same recommendation (e.g., the bestselling item).

II. Existing System

Recommender systems are usually classified into three categories based on their approach to recommendation: content based, collaborative, and hybrid approaches [1,3]. Content based recommender systems recommend items similar to the ones the user preferred in the past. Collaborative Filtering (CF) recommender systems recommend items that users with similar preferences (i.e., "neighbors") have liked in the past. Finally, hybrid approaches can combine content-based and collaborative methods in several different ways. Recommender systems can also be classified based on the nature of their algorithmic technique into heuristic (or memory-based) and model based approaches [1, 9]. Heuristic techniques typically calculate recommendations based directly on the previous user activities (e.g., transactional data or rating values). One of the commonly used heuristic techniques is a neighborhood-based approach that finds nearest neighbors that have tastes similar to those of the target user [9, 13, 34, 36, 40]. In contrast, model-based techniques use previous user activities to first learn a predictive model, typically using some statistical or machine-learning methods, which is then used to make recommendations. Examples of such techniques include Bayesian clustering, aspect model, flexible mixture model, matrix factorization, and other methods [4-5, 9, 25, 44, 48]. In real world settings, recommender systems generally perform the following two tasks in order to provide recommendations to each user. First, the ratings of unrated items are estimated based on the available information (typically using known user ratings and possibly also information about item content or user demographics) using some recommendation algorithm. And second, the system finds items that maximize the user's utility based on the predicted ratings, and recommends them to the user. Ranking approaches proposed in this paper are designed to improve the recommendation diversity in the second task of finding the best items for each user. Because of the decomposition of rating estimation and recommendation ranking tasks, our proposed ranking approaches provide a flexible solution, as mentioned earlier: they do not introduce any new procedures into the recommendation process and also can be used in conjunction with any available rating estimation algorithm. In our experiments, to illustrate the broad applicability of the proposed recommendation ranking approaches, we used them in conjunction with the most popular and widely employed CF techniques for rating prediction: a heuristic neighborhood-based technique and a model based matrix factorization technique. Before we provide an overview of each technique, we introduce some notation and terminology related to recommendation problem. Let U be the set of users of a recommender system, and let I be the set of all possible items that can be recommended to users. Then, the utility function that represents the preference of item i□I by user u□U is often defined as R:U□I□Rating, where Rating typically represents some numeric scale used by the users to evaluate each item. Also, in order to distinguish between the actual ratings and the predictions of the recommender system, we use the R(u, i) notation to represent a known rating (i.e., the actual rating that user u gave to item i), and the R*(u, i) notation to represent an unknown rating (i.e., the system-predicted rating for item i that user u has not rated before). Neighborhood-based CF technique There exist multiple variations of neighborhood-based CF techniques [9, 36, 40]. In this paper, to estimate R*(u, i), i.e., the rating that user u would give to item i, we first compute the similarity between user u and other users u' using a cosine similarity Metric [9, 40]:

$$sim(u,u') = \frac{\sum_{i \in I(u,u')} R(u,i) \cdot R(u',i)}{\sqrt{\sum_{i \in I(u,u')} R(u,i)^2}\sqrt{\sum_{i \in I(u,u')} R(u',i)^2}},$$

where, I(u, u') represents the set of all items rated by both user u and user u'. Based on the similarity calculation, set N(u) of nearest neighbors of user u is obtained. The size of set N(u) can range anywhere from 1 to |U|-1, i.e., all other users in the dataset. Then, R*(u, i) is calculated as the adjusted weighted sum of all known ratings R(u', i), where, u' □ N(u) [13, 34]:

$$R^*(u,i) = \overline{R(u)} + \frac{\sum_{u' \in N(u)} sim(u,u') \cdot \left(R(u',i) - \overline{R(u')}\right)}{\sum_{u' \in N(u)} |\, sim(u,u') \,|}.$$

A neighborhood-based CF technique can be user-based or item-based, depending on whether the similarity is calculated between users or items. Formulae (1) and (2) represent the user-based approach, but they can be straightforwardly rewritten for the item-based approach because of the symmetry between users and items in all neighborhood-based CF calculations [40]. In our experiments we used both user-based and item-based approaches for rating estimation. Matrix factorization CF technique Matrix factorization techniques have been the mainstay of numerical linear algebra dating back to the 1970s [16, 21, 27] and have recently gained popularity in recommender systems applications because of their effectiveness in improving recommendation accuracy [41, 47]. Many variations of matrix factorization techniques have been developed to solve the problems of data sparsely, over fitting, and

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convergence speed, and they turned out to be a crucial component of many well-performing algorithms in the popular Netflix Prize1 competition [4-6, 15, 22, 29, 30]. We implemented the basic version of this technique, as presented in [15]. With the assumption that a user's rating for an item is composed of a sum of preferences about the various features of that item, this model is induced by Singular Value Decomposition (SVD) on the user-item ratings matrix. In particular, using K features (i.e., rank-K SVD), user u is associated with a user-factors vector pu (the user's preferences for K features), and item i is associated with an item-factors vector qi (the item's importance weights for K features). The preference of how much user u likes item i, denoted by R*(u, i), is predicted by taking an inner product of the two vectors, i.e.,

$$R^*(u,i) = p_u^T q_i \, .$$

III. Proposed Work

Typical recommender systems predict unknown ratings based on known ratings, using any traditional recommendation technique such as neighborhood-based or matrix factorization CF techniques, discussed in Section II. Then, the predicted ratings are used to support the user's decision-making. In particular, each user u gets recommended a list of top-N items, LN(u), selected according to some ranking criterion. More formally, item ix is ranked ahead of item iy (i.e., ix □ iy) if rank(ix) < rank(iy), where rank: I □ □ is a function representing the ranking criterion. The vast majority of current recommender systems use the predicted rating value as the ranking criterion: The power of -1 in the above expression indicates that the items with highest-predicted (as opposed to lowest-predicted) ratings R*(u, i) are the ones being recommended to user. In the paper we refer to this as the standard ranking approach, and it shares the motivation with the widely used probability ranking principle in information retrieval literature that ranks the documents in order of decreasing probability of relevance [37]. Note that, by definition, recommending the most highly predicted items selected by the standard ranking approach is designed to help improve recommendation accuracy, but not recommendation diversity. Therefore, new ranking criteria are needed in order to achieve diversity improvement. Since recommending best-selling items to each user typically leads to diversity reduction, recommending less popular items intuitively should have an effect towards increasing recommendation diversity. And, as seen from the example in Table 1 (in Section I), this intuition has empirical support. Following this motivation, we explore the possibility to use item popularity as a recommendation ranking criterion, and in the next subsection we show how this approach can affect the recommendation quality in terms of accuracy and diversity. Item popularity-based ranking approach ranks items directly based on their popularity, from lowest to highest, where popularity is represented by the number of known ratings that each item has. More formally, item popularity-based ranking function can be written as follows:

$$rank_{\mathrm{ItemPop}}(i) = |U(i)|, \text{ where } U(i) = \{u \in U \mid \exists R(u,i)\}.$$

The power of -1 in the above expression indicates that the items with highest-predicted (as opposed to lowest-predicted) ratings R*(u, i) are the ones being recommended to user. In the paper we refer to this as the standard ranking approach, and it shares the motivation with the widely used probability ranking principle in information retrieval literature that ranks the documents in order of decreasing probability of relevance [37]. Note that, by definition, recommending the most highly predicted items selected by the standard ranking approach is designed to help improve recommendation accuracy, but not recommendation diversity. Therefore, new ranking criteria are needed in order to achieve diversity improvement. Since recommending best-selling items to each user typically leads to diversity reduction, recommending less popular items intuitively should have an effect towards increasing recommendation diversity. this intuition has empirical support. Following this motivation, we explore the possibility to use item popularity as a recommendation ranking criterion, and in the next subsection we show how this approach can affect the recommendation quality in terms of accuracy and diversity. The item popularity-based ranking approach as well as all other ranking approaches proposed in this paper are parameterized with "ranking threshold" $T_R[T_H, T_{max}]$ (where, T_{max} is the largest possible rating on the rating scale, e.g., T_{max}=5) to allow user the ability to choose a certain level of recommendation accuracy. In particular, given any ranking function $rank_X(i)$, ranking threshold TR is used for creating the parameterized version of this ranking function, $rank_X(i, T_R)$, which is formally defined as:

$$rank_X(i,T_R) = \begin{cases} rank_X(i), & \text{if } R^*(u,i) \in [T_R, T_{\max}] \\ \alpha_u + rank_{\mathrm{Standard}}(i), & \text{if } R^*(u,i) \in [T_H, T_R) \end{cases}$$

$$\text{where } I_u^*(T_R) = \{i \in I \mid R^*(u,i) \geq T_R\}, \alpha_u = \max_{i \in I_u^*(T_R)} rank_X(i).$$

Simply put, items that are predicted above ranking threshold TR are ranked according to $rank_X(i)$, while items that are below TR are ranked according to the standard ranking approach rank Standard(i). In addition, all items that are above T_R get ranked ahead of all items that are below T_R (as ensured by α_u in the above formal definition). Thus, increasing the ranking threshold $T_R[T_H, T_{max}]$ towards Tmax would enable choosing the most highly predicted items resulting in more accuracy and less diversity (becoming increasingly similar to the standard ranking approach); in contrast, decreasing the ranking threshold T_R□$[T_H, T_{max}]$ towards TH would make $rank_X(i, T_R)$ increasingly more similar to the pure ranking function $rank_X(i)$, resulting in more diversity with some accuracy loss. Therefore, choosing different T_R values in-between the extremes allows the user to set the desired balance between accuracy and diversity. In particular, as fig. 1 shows, the recommendation accuracy of item popularity-based ranking approach could be improved by increasing the ranking threshold. For example, the item popularity-based ranking approach with ranking threshold 4.4 could minimize the accuracy loss to 1.32%, but still could obtain 83% diversity gain (from 385 to 703), compared to the standard ranking approach. An even higher threshold 4.7 still makes it possible to achieve 20% diversity gain (from 385 to 462) with only 0.06% of accuracy loss. Also note that, even when there are less than N items above the ranking threshold TR, by definition, all the items. above TR are recommended to a user, and the remaining top-N items are selected according to the standard ranking approach. This ensures that all the ranking approaches proposed in this paper provide the same exact number of recommendations as their corresponding baseline techniques (the ones using the standard ranking approach), which is very important from the experimental analysis point of view as well in order to have a fair performance comparison of different ranking techniques.

IV. Results

In order to implement these three algorithms on the basis on time complexity and space complexity.

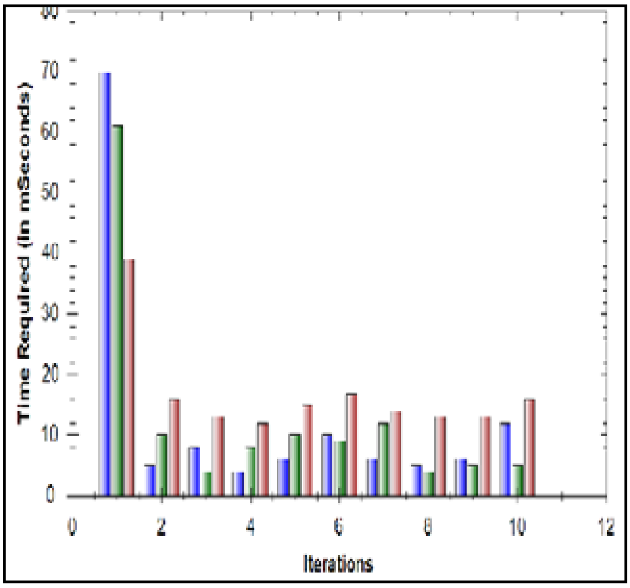

Fig. 1: Bar Chart on Basis on Time Complexity

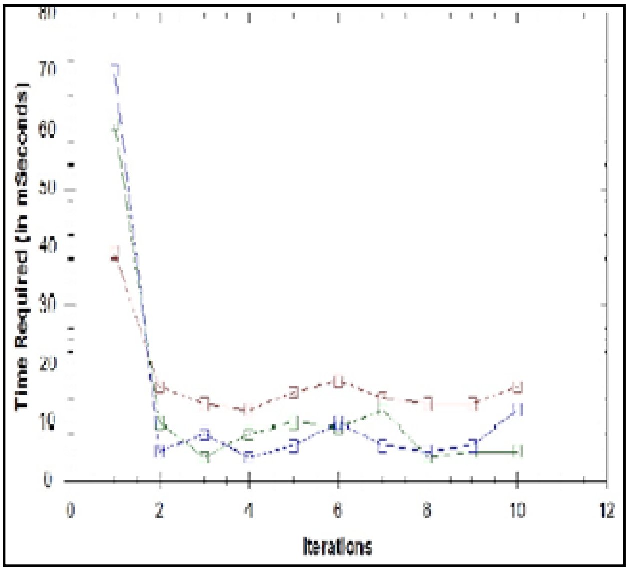

Fig. 2: Line Chart on Basis on Time Complexity

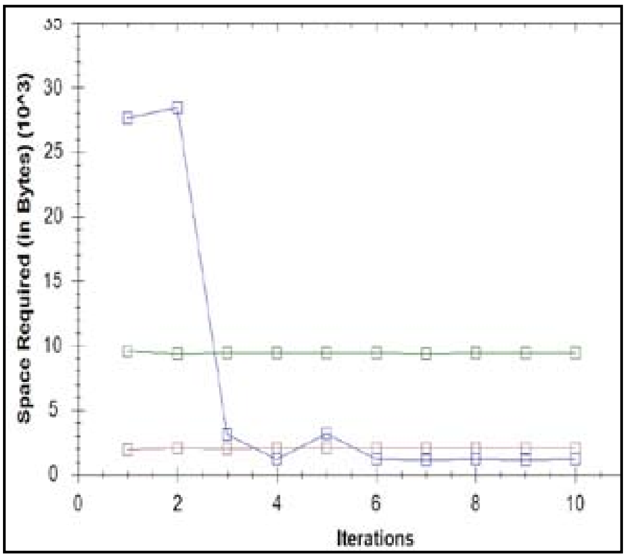

Fig. 3: Line Chart on Basis on Space Complexity

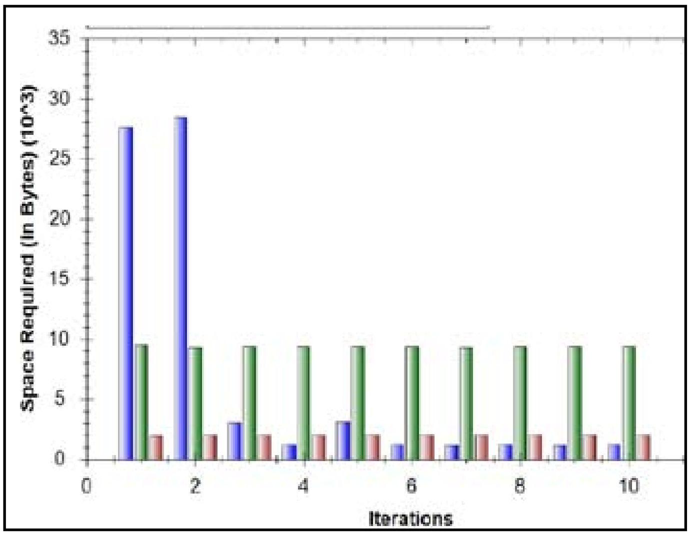

Fig. 4: Bar Chart on Basis on Space Complexity

V. Conclusions

Recommender systems are becoming increasingly important to individual users and businesses for providing personalized recommendations. However, while the majority of algorithms proposed in recommender systems literature have focused on improving recommendation accuracy (as exemplified by the recent Netflix Prize competition), other important aspects of recommendation quality, such as the diversity of recommendations, have often been overlooked. In this paper, we introduce and explore a number of item ranking techniques that can generate recommendations that have substantially higher aggregate diversity across all users while maintaining comparable levels of recommendation accuracy. Comprehensive empirical evaluation consistently shows the diversity gains of the proposed techniques using several real-world rating datasets and different rating prediction algorithms.

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