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A Sequential Ranking Approach for Improving Recommendation Diversity

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ABSTRACT

Nowadays it is becoming very critical to find the relevant information in online information system. Recommended systems are introduced to deal with the problem of decision making from large amount of information. Recommended systems are used widely in e-commerce applications, as in Amazon and Netflix, and in social networking sites like Face book etc. There are a lot of techniques for making recommendations. In this paper we have focused on techniques to improve aggregate diversity while maintaining accuracy to improve the recommendations by taking movie databases. The diversity increases with the recommended techniques employing various real-world data sets.

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I. INTRODUCTION

The growth of the Internet has made it much more difficult to effectively extract useful information from all the available online information [1]. This problem is not only wide. Recommendation technology help users to deal with these information systems, and are used for research studies and also in many e-commerce applications like flipkart ,myntra , e-bay and in social networking sites like face book etc

Recommender systems are a subclass of information filtering systems that predict the 'rating' or 'preference' that user would give to an item such as music, books, or movies or social element e.g. people or groups they had not yet considered, using a model built from the characteristics of an item or the user's social environment.Since large amount of data is added to information system day by day these recommendations help users to choose new items which were best and suitable for their requirements.

Recommender systems predict the ratings of unknown items for each user using other users ratings, and recommend top *N* items with the highest predicted ratings. There are many studies on developing algorithms to improve rating predictions the quality of recommender system is evaluated in many dimensions, and not only the accurate recommendations are sufficient to find most relevant items for users individually. The importance of *diversity in recommendations* has been investigated several studies. It increases sales by recommending items and it allows users to make decisions such as which item to buy The goal of recommender systems is to provide a user with highly distinct and diverse recommendations to give more options for users to getrecommended such items. There is an inverse relationship between accuracy and diversity. Diversity should be increased by having minimal loss in accuracy [1]. Recommendation can not only be given to single product, it also allows recommending collection of products [2] [3].

In contrast to individual diversity, which has been explored in a number of papers, some recent studies started examining the impact of recommender systems on sales diversity by considering *aggregate diversity* of recommendations across all users. Where aggregate diversity is retrieved to recommendation list across all users.

II. LITERATURE SURVEY

Recommendation engine understand user's needs and provides good recommendationslist in which items in the top are highly relevant to user's needs. User's preferences are analyzed by RS and it constructs a relationship model between items and users. User's interests are input to RS whereas output will be list of recommendations. In order to provide users with different recommendations which are related to their requirement there have been many techniques.This section briefly describes about various recommendation techniques to improve diversity while maintaining certain level of accurate recommendations.

1. Neighbourhood Based CF Technique

There exist multiple variations of neighborhood-based CF techniques [5] [6]. 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 user's using a cosine similarity metric. Based on the similarity calculation, set of nearest neighbours of user u is obtained. A neighborhood-based CF technique can be user-based or item-based, depending on whether the similarity is calculated between users or items. In this paper, we used both user-based and item-based approaches for rating estimation

2. Item Popularity Ranking

Standard ranking approach [4] ranks item from high predicted rating to lowest onesThis ranking approach ranks items directly based on their popularity, from lowest to highest, here the popularity is represented by the number of known ratings that each item has. The item popularity-based ranking approach can increase recommendation diversity; however, recommendation accuracy drops. Besides the diversity gain, such a accuracy loss would not be acceptable in most real-life personalization applications. Therefore, we introduce a general technique to parameterize recommendation ranking approaches, which allows achieving diversity gains while controlling accuracy losses.

3. Parameterized Ranking

All ranking approaches proposed in this paper are parameterized with "ranking threshold" *TR*[*TH*, *T*max] where *T*max is the largest possible rating to allow user to choose a certain level of accurate recommendations. Given any ranking function *rank*X(*i*), ranking threshold *TR* is used for creating the parameterized version of this ranking function. The 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 *TR* get ranked ahead of all items that are below *TR*. Thus, increasing the ranking threshold *TR*[*TH*, *T*max] towards *T*max would enable choosing the most highly predicted items resulting in more accuracy and less diversity.

4. Item Average Absolute Relative Ranking

This ranking technique ranks items according to an average of all known ratings for each item and is computed by the *rank*AvgRating. Similarly, the relationship between predicted rating values and item absolute (or relative) likeability, also suggests that the items with lower likeability, on average, are more likely to have lower predicted rating values likely representing less popular movies and, thus, could be recommended for better diversity. In the Item Absolute Likeability, i.e., ranks items according to how many users liked them i.e., rated the item above TH. In the Item Relative Likeability, i.e., ranks items according to the percentage of the users who liked an item among all users who rated it are computed by rankRelLike.

5. Item Rating Variance, Neighbour Rating Variance

In this ranking technique we give ranking for items according to each item's rating variance i.e., ranking items according to the rating variance of neighbors of a particular user for a particular item. In neighbor's rating variance the closest neighbors of user *u* among the users who rated the particular item *i*, denoted by *u'*, are chosen from the set of *U*(*i*)and is computed by *rank*NeighborVar.

6. Random Ranking Technique

This technique uses random uniform distribution, The more highly predicted items, on average, tend to be among the more popular items. While the proposed ranking approaches improve the diversity by considering alternative item ranking functions, such as item popularity, we found that reranking the candidate items at random can provide diversity improvements. Here, we defined the random ranking as uniform distribution function where Random (0,1) is a function that generates uniformly distributed random numbers in the [0, 1] interval.

III. PROPOSED SYSTEM

All the techniques described above resulted in maintaining accuracy but not reached to provide certain diversity gain. In this section we introduce new technique of sequential ranking which provides recommendation with diverse items

1. Sequential Item Likability

In this module we have ranking items according to an average of all known ratings for each item sequence and is computed by the *rankSeqR*ating. Similar movies which form item sequences and, thus, be recommended for better diversity.

$$\text{rank}(i) = \sum_{i \in j} |U_H(i), \text{where } U_H(i) = \{u \in U(i) | \ R(u,i) \geq T_H\}$$

2. Enhanced Sequential Ranking Approach

In the sequential ranking approach, once the user makes her choice, a new list of recommended items is presented. Thus, the recommendation process is a sequential process. Moreover, in many domains, user choices are sequential in nature. The main enhancement in using sequential ranking approach is that it is a novel approach to recommender systems based on a DP (Decision Process) model together with appropriate initialization and solution techniques and a novel predictive model that outperforms previous predictive models. Our first step is to construct a predictive model of user purchases, that is, a model that can predict what item the user will buy next. This model does not take into account its influence on the user, as it does not model the recommendation process and its effects. Nonetheless, we shall use a recommendation chain, with an appropriate formulation of the state space, as our model. This information corresponds to previous choices made by users in the form of a set of ordered sequences of selections. Thus, the set of states contains all possible sequences of user selections. Of course, this formulation leads to an unmanageable state space with the usual associated problems.

IV. RESULT& DISCUSSION

The concept of this paper is implemented and different results are shown below, The proposed paper is implemented in Java technology on a Pentium-IV PC with 20 GB hard-disk and 256 MB RAM with apache web server. The propose paper's concepts shows efficient results and has been efficiently tested on different Datasets. The Fig 1, Fig 2 shows the real time results compared with different number of neighbors.

Iterm Popularity	**Parameterized Ranking**	**Item Absolute Likeability**	**Item Relative Likeability**
Taxi Driver (1976) 5.0 Toy Story (1995) 4.533333333333333 Four Rooms (1995) 3.8666666666666667 Braveheart (1995) 3.5999999999999996 GoldenEye (1995) 3.533333333333333 Precision (Accuracy):0.03225806451612903 Diversity: 15.5	Toy Story (1995) 5 GoldenEye (1995) 5 Four Rooms (1995) 5 Get Shorty (1995) 5 Copycat (1995) 5 Precision (Accuracy):2.129032258064516 Diversity: 15.5	Fargo (1996) 5.0 Flipper (1996) 5.0 Lone Star (1996) 5.0 Sound of Music, The (1965) 5.0 Long Kiss Goodnight, The (1996) 5.0 Precision (Accuracy):0.7225806451612903 Diversity: 15.5	Fargo (1996) 5.0 Flipper (1996) 5.0 Lone Star (1996) 5.0 Long Kiss Goodnight, The (1996) 5.0 Ghost and the Darkness, The (1996) 5.0 Precision (Accuracy):0.23870967741935484 Diversity: 15.5

Neigh Rating Variance	**Random Ranking**	**Sequential Ranking**
20,000 Leagues Under the Sea (1954) 5.0 Seven (Se7en) (1995) 3.3789904302724816 Taxi Driver (1976) 3.3392757801041824 Toy Story (1995) 2.9169406092483015 Richard III (1995) 2.5002348079271157 Precision(Accuracy):0.0064516129032258064 Diversity: 15.5	Taxi Driver (1976) 5.0 Four Rooms (1995) 4.655172413793103 GoldenEye (1995) 4.051724137931034 Copycat (1995) 3.3620689655172415 Toy Story (1995) 2.844827586206897 Precision(Accuracy):0.01935483870967742 Diversity: 15.5	Alien (1979) 5.0 Return of the Pink Panther, The (1974) 4.532100360953392 Star Trek: First Contact (1996) 4.5139139201437075 Toy Story (1995) 4.449643934319526 Return of the Jedi (1983) 4.300907402054105 Precision(Accuracy):0.2592592592592592 4 Diversity: 27.0

fig1: when N=25, the accuracy and diversity

Iterm Popularity	Parameterized Ranking	Item Absolute Likeability	Item Relative Likeability
Taxi Driver (1976) 5.0 Toy Story (1995) 4.871794871794871 20,000 Leagues Under the Sea (1954) 4.743589743589744 Four Rooms (1995) 4.615384615384616 GoldenEye (1995) 3.782051282051282 Precision(Accuracy):0.043478260869565216 Diversity: 16.1	Toy Story (1995) 5 GoldenEye (1995) 5 Four Rooms (1995) 5 Get Shorty (1995) 5 Copycat (1995) 5 Precision (Accuracy):2.4037267080745344 Diversity: 16.1	Love Bug, The (1969) 5.0 Bedknobs and Broomsticks (1971) 5.0 Sound of Music, The (1965) 5.0 Ghost and the Darkness, The (1996) 5.0 Fish Called Wanda, A (1988) 5.0 Precision (Accuracy):0.7142857142857143 Diversity: 16.1	Love Bug, The (1969) 5.0 Bedknobs and Broomsticks (1971) 5.0 Ghost and the Darkness, The (1996) 5.0 Fish Called Wanda, A (1988) 5.0 Cinema Paradiso (1988) 5.0 Precision (Accuracy):0.19254658385093168 Diversity: 16.1

Neigh Rating Variance	Random Ranking	Sequential Ranking
20,000 Leagues Under the Sea (1954) 5.0 Seven (Se7en) (1995) 3.2269276502332387 Birdcage, The (1996) 2.4991892768349366 Taxi Driver (1976) 2.290923503765359 Toy Story (1995) 1.9568540852726346 Precision(Accuracy):0.006211180124223602 Diversity: 16.1	Taxi Driver (1976) 5.0 Toy Story (1995) 4.12280701754386 Four Rooms (1995) 4.12280701754386 GoldenEye (1995) 3.4210526315789473 Copycat (1995) 3.245614035087719 Precision(Accuracy):0.018633540372670808 Diversity: 16.1	Aristocats, The (1970) 5.0 Kolya (1996) 4.9625411860234 Army of Darkness (1993) 3.63940820712115 Star Trek: First Contact (1996) 3.2951016802025688 Independence Day (ID4) (1996) 3.0916406350112884 Precision(Accuracy):0.08571428571428572 Diversity: 35.0

fig2: when N=35, the accuracy and diversity

V. CONCLUSION

In recent years Recommender systems have made significant progress; many techniques havebeen proposed to improve the performance of recommendations in recommended systems. In many cases techniques were improved in order to increase recommendation accuracy but increment of diversity is left untouched. We showed that in many techniques, while ranking recommendations according to the predicted rating values recommender systems provides good predictive accuracy, but performs poorly with recommendation diversity. Therefore, in this paper, we proposed a sequential ranking recommendation ranking technique that can improve recommendation diversity with only a small amount of accuracy loss. That is to overcome trade off accuracy and diversity[7].In addition, this ranking technique offer flexibility to system designers, since they are parameterizable and randomized can be used in conjunction with different rating prediction algorithms (i.e., they do not require the designer to use only some specific algorithm). More-over, recommendations can be done based on reviews or suggestions of customer or manufacturer of products. They are also based on scalable sorting based heuristics and, thus, are extremely efficient.

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