A NOVEL CUMMULATIVE PROPOSAL RANGE USING RECOMMENDATION ALGORITHM

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Abstract - Recommender systems are there to help user and business by giving the personalized information instead of global information. There is a growing awareness of the importance of aggregate diversity in recommender systems and also there has been significant amount of work done on improving individual diversity. Recommender systems are becoming increasingly important to individual users and businesses for providing personalized recommendations. There were many algorithms were proposed to describe the recommender system but all techniques are described only about recommendation accuracy rather than recommendation quality, such as diversity of recommendation. It is necessary to maintain the diversity of recommendations in the proposal system and to explore a number of items ranking techniques that can generate recommendations that have substantially higher aggregate diversity across all users while maintaining comparable levels of recommendation accuracy. Recommendation algorithm shows the diversity gains of the proposed techniques using several real-world rating datasets and different rating prediction algorithms. Ranking approaches are designed to improve the recommendation diversity in the task of finding the best items for each user.

Key words: ***Recommender systems, recommendation diversity, ranking functions, performance evaluation metrics, collaborative filtering.***

1. INTRODUCTION

Recommender systems are there to help user and business by giving the personalized information instead of global information. Recommender systems are usually classified into three categories: content-based, collaborative, and hybrid approaches. Content based recommender systems recommend items similar to the ones the user preferred in the past. Collaborative filtering recommender systems recommend items that users with similar preferences have liked in the past. Finally, hybrid approaches can combine content-based and collaborative methods in several different ways. A neighborhood-based CF technique can be user-based or item-based, depending on whether the similarity is calculated between users or items, 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.

Recommendation algorithm used both user-based and item-based approaches for rating estimation. 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. Over the last 10- 15 years, recommender systems technologies have been introduced to help people deal with these vast amounts of information, 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. In particular, the importance of diverse recommendations has been previously emphasized in several studies. 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. 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 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).

2. RECOMMENDATION ALGORITHM

There exist multiple variations of neighborhood-based CF techniques. 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. 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 $R(u', i)$ Here $R(u)$ represents the average rating of user u. A neighborhood-based CF technique can be user-based or item-based, depending on whether the similarity is calculated between users or items, 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. In our experiments we used both user-based and item-based approaches for rating estimation.

2.1 OVERVIEW

In real world settings, recommender systems 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 are designed to improve the recommendation diversity in the second task of finding the best items for each user. Overview of each technique, 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 items i 2 I by user u 2 U is often defined as R: U*I tends to 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 notation to represent a known rating (i.e., the actual rating that user u gave to item i), and the R notation to represent an unknown rating (i.e., the system-predicted rating for item i that user u has not rated before). Traditional recommender systems adopt the standard ranking approach that ranks the candidate items according to their predicted rating values and, thus, recommends to users the top most highly predicted items. Quality of recommendations can be evaluated along a number of dimensions and recommendation systems provide highly personalized items. Ranking approaches that can improve recommendation diversity and performance using rating prediction technique in conjunction with recommendation ranking function.

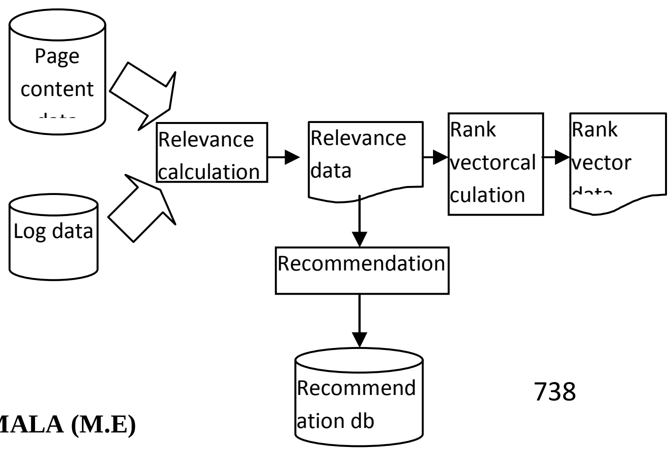

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Figure 2.1 System Architecture

3. RELATED WORKS

3.1 RECOMMENDATION TECHNIQUE

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3.2 TOP-K QUERY PROCESSING

Top-k queries, produce results that are ordered on some computed score. A top- k query over defined subsystems returns the objects with the least aggregated scores. A top-k query returns the subsets of most relevant results instead of all results to minimize the cost metric that is associated with the retrieval of all results and maximize the quality of the result set, such that the ser is not overwhelmed with irrelevant results. the proposed ranking techniques provide a flexible solution to improving recommendation diversity because they are applied after the unknown item ratings have been estimated and, thus, can achieve diversity gains in conjunction with a number of different rating prediction techniques.

4. STANDARD RANKING APPROACH

Distinctive recommender systems predict ratings for the new item, ratings based on known ratings, using any conventional proposal technique such as neighborhood based or matrix factorization CF techniques that predicted ratings are used to help the user's view of making. In particular, each user u gets recommended a list of top-N items, LN selected according to some ranking criterion. More properly, item ix is ranked in advance of item iy [i.e., ix iy] if rank ix < rank iy , where rank: I! IR is a function representing the ranking criterion. The vast greater parts of in progress recommender systems use the predicted mark value as the ranking criterion:

Rank standard(i) = R*(u,i)-1

The power of 1 in the above expression indicates that the items with highest predicted [as opposed to lowest predicted] ratings R are the ones being recommended to user. 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. Recommending the most highly predicted items selected by the standard ranking approach is designed to help get better advice accuracy, but not proposal diversity. Therefore, new statuses criterions are considered necessary in organize to accomplish diversity improvement. Since recommending preeminent advertising bits and pieces to each user normally leads to diversity diminution, recommending less trendy matter intuitively should have a consequence toward increasing recommendation diversity. The power of 1 in the above expression indicates that the items with highest predicted [as opposed to lowest predicted] ratings R are the ones being recommended to user. 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 [20]. Recommending the most highly predicted items selected by the standard ranking approach is designed to help get better advice accuracy, but not proposal diversity. Therefore, new statuses criterions are considered necessary in organize to accomplish diversity improvement. Since recommending preeminent advertising bits and pieces to each user normally leads to diversity diminution, recommending less trendy matter intuitively should have a consequence toward increasing recommendation diversity.

5. RECOMMENDATION ACCURACY

Several technique are try to measure the recommendation accuracy. The performance of the system and rating of the specified item for example the item should be good for all users. The rating must be used displayed as star values. This star value denotes the item is good one and liked by the user. The goal of the recommended system is to produce best N items liked by the user.

Recommendation system is fulfilling only after achieving the recommendation accuracy and recommendation diversity in equal way.

6.DIVERSITY OF RECOMMENDATION ALGORITHM

Recommendation diversity is calculating in dual way. Individual and Aggregate Individual diversity is one which is used to produce the unique item to the user, unique item is accurately relevant to the search for people, but user is not satisfies with the single item even the result is suitable for user. User always goes for comparison so individual diversity is not suitable for recommender system so recommender system go for aggregate diversity. Aggregate diversity is just opposite to the individual diversity, because individual diversity of the recommender system is produced unique results, but aggregate diversity of the recommender system produces multiple results. The result should be relevant to the search for the people. The goal the technique is to provide multiple results for the same user ass of accuracy is a major failure. Our goal is to provide item with recommendation diversity with our affecting accuracy. Various metrics are the two measures diversity group (Aggregate) considering the percentage of the item the performance of the recommender system based on top N product in the list.

7. ITEM POPULARITY BASED APPROACH

Item popularity related ranking approach position items in a straight line based on their status, from buck to peak, where popularity is represented by the number of predictable ratings that each piece have. More legitimately, item popularity related position function can be written as follows:

$$\text{Rank item popularity (i)} = |\,U\ (i)\,|$$

Accuracy is not enough for the item each and every items should have both accuracy and diversity (quality).

U- Uses of the recommender system, I-Set of all available items- List of Items.

The performance of the item-popularity- based ranking approach with the standard ranking approach using data set and item-based CF, present this comparison using the accuracy-diversity. In particular, the results demonstrate that, as compared to the normal ranking approach, the item popularity related ranking approach amplified proposal diversity; however, recommendation accuracy drop from 89 to 59 percent. Here, regardless of the important diversity expand such a noteworthy accuracy defeat [30 percent] would not be good enough in most general life personalization applications.

8. CONCLUSION

Recommender systems have made significant progress in 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, it 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, this project 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).

9. FUTURE ENHANCEMENT

Exploration of recommendation diversity when recommending item bundles or sequences instead of group of items also constitutes interesting topics for future research.

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