Ranking Based Approach To Maximize Utility Of Recommender Systems

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Abstract - E-commerce applications that sell products online need to recommend suitable products to customers to fasten their decision making. The recommender systems are required in order to help users and also the businesses alike. There were many algorithms that came into existence to built recommender systems. However they focused on recommendation accuracy. They did not concentrate much on recommendation quality like diversity of recommendations. This paper introduces many item ranking algorithms that can produce diverse recommendations. While generating recommendations transactions of all users are considered. A prototype application is built to test the efficiency of the proposed recommender system. The empirical results revealed that the proposed ranking-based techniques for diverse recommendations are effective and can be used in real world applications.

Index Terms –Recommendations, recommender system, ranking techniques, recommendation diversity, collaborative filtering

I. INTRODUCTION

As information added to World Wide Web is increased day by day [1]; recommender systems have become indispensable with respect to commercial online applications that sell products. While making purchasing decisions online, users have to surf lot of information in order to make decisions. To overcome these problem recommender systems came into existence. They help the customers to choose best products easily while helping the businesses to grow faster. Many existing recommender systems are available in literature. They are explored in [2], [3], [4], [5], and [6] and widely used in real time applications such as e-commerce portals such as Netflix and Amazon. Ratings are the basis for making recommender systems. Based on the existing items and their ratings, the recommender systems can predict the rating of items whose ratings are not known. They recommend top rated items to end users so as to enable them to make decisions quickly. However, the recommendations quality is essential and it has to be evaluated based on many dimensions. Accuracy alone is not sufficient to get most similar items [7], [8]. Recommendation diversity is also important in recommender systems. This problem is studied in [9], [10], [11], [12], [13], and [14]. The study revealed that user has to get diverse recommendations besides personalized recommendations. This is the motivation behind all such studies while making recommender systems. However, these studies measured recommendations from individual point of view known as individual diversity. Recent studies such as [10] and [11] recommender systems can make use of aggregate diversity across all users in order to improve recommender systems. As high individual diversity is not similar to high aggregate diversity, For instance the recommender system provides top 5 recommendations to five users. However, they are different for each user. Hence they are diverse in nature. Recommender systems with high aggregate diversity are very useful. They can be used in modern business applications as discussed in [10], [15], [11], [16]. Nevertheless, the impact of aggregate diversity approach in real time e-commerce applications has not been fully realized. Aggregate diversity in sales is reduced due to recommender systems in contrast to traditional belief as explored in [11]. This is based on the fact that idiosyncratic items. Examples of such things are Netflix Prize Competition as explored in [17] and [18]. Extreme results are to be avoided and safe recommendations are to be provided as proposed in [19]. The importance of aggregate recommendations is growing among the online business applications and hence the diversity.

Higher individual and aggregate diversity can be achieved at the expense of accuracy. In fact there is possible tradeoff between the diversity and accuracy leading to less personalized recommendations as explored in [9], [20] and [12]. By using highly idiosyncratic items of users it is possible to achieve higher level of diversity. Using Movie Lens dataset two extreme cases were considered which illustrates tradeoff between diversity and accuracy. This is shown in table 1.

Quality Metric: Top-1 recommendation of:	Accuracy	Diversity
Popular Item (item with the largest number of known ratings)	82%	49 distinct items
"Long-Tail" Item (item with the smallest number of known ratings)	68%	695 distinct items

Table 1 – Tradeoff between diversity and accuracy

From the results in the table 1, it is understood that obtaining higher diversity is possible by recommending less popular items at the cost of higher recommendation accuracy. In contrast to this, the proposed techniques consider some additional factors in order to provide diverse recommendations while maintaining comparable accuracy of recommendations. Empirical results revealed that the diversity is achieved with some loss of accuracy. However, the results are comparably accurate. The advantages of the proposed ranking techniques include efficiency, parameterizable, and flexible. The ranking approaches proposed in this paper do not need demographics of users or content features of items. Thus it can be adapted to wide variety of systems where recommendations are required.

The rest of this paper is organized as follows. Section II reviews literature. Section 3 describes the proposed techniques. Section 4 discusses the experiments and results while section 5 concludes that paper.

II. RELATED WORK

Based on the approach followed, recommendations are divided into three types namely collaborative, content-based and hybrid [2], [21]. Content based recommender systems are based on the users' previous behavior. Whereas the collaborative recommender systems consider recommending items preferred by other users as well. The hybrid approaches combine the features of both. Other classification pertaining to recommender systems divide them into two categories namely model based and heuristic based [2], [22]. The latter depends on activities of previous users while the former is based on the neighborhood approach as explored in [22], [23], [24], and [5]. The model based techniques are explored in [25], [26], [22], [26], [27], and [28]. In real world applications, recommender systems perform two activities. The first activity is finding ratings of unrated items. Finding user's utility maximizing items is important here. The ranking techniques proposed in this paper improve diversity of recommendations. CF techniques are combined with the ranking techniques for rating prediction.

With respect to Neighborhood-Based CF Technique there are many existing variations of these techniques as explored in [22], [5] and [29]. However, in this paper the similarity between the use and other users is computed as follows.

$$\mathcal{S}im(\mathcal{U},\mathcal{U}') = \frac{\sum_{i\in I(u,u')} R(u,\ i).R(u',i)}{\sqrt{\sum_{i\in I(u,u')} R(u,i)^2}\sqrt{\sum_{i\in I(u,u')} R(u',i)}^2}$$

With respect to matrix factorization CF technique, there were many such techniques came into existence [34], [35], [36]. They became popular of late in recommender systems [30], [31], [32], [33]. The following piece of code is used to estimate the rating of unknown items.

For each rating $\mathbf{R}(u,i)$

$$\mathbf{err} = \mathbf{R}(u,i) - P_u^T\ q_i$$

$$\mathcal{P}_{u=}\ \mathcal{P}^T\ +\ \theta(err\ \times\ q_i\ -\curlywedge \times\ \mathcal{P}_u$$

$$q_{u=}\ q^T\ +\ \theta(err\ \times\ \mathcal{P}_u\ -\curlywedge \times\ q_i$$

End For

With respect to accuracy of recommendations, many recommendation approaches came into existence over many years. They include decision support measures, and statistical accuracy metrics [7]. Mean Absolute Error (MAE) is an example for statistical accuracy metric while precision and recall are metrics for decision support. It has been suggested that usefulness of recommender systems is important besides their accuracy [7], [8].

With respect to diversity of recommendations, they are measured in two different ways. They are known as individual and aggregate. Many recent studies focused on individual diversity [9], [20], [12], [13]. Item novelty is another measure proposed by Zhang and Hurley [13] to know the additional diversity. In [20] diversity conscious algorithms were introduced to compensate the loss of accuracy caused by recommendation diversity. There were few studies that focused on aggregate diversity [10], [11]. There are many metrics to measure aggregate diversity. For instance percentage of items can be used to measure it. In this paper we focus on top – Nrecommendations with diversity. The measure we use in this paper is the total number of distinct items recommended. These recommendations are across all users. The proposed ranking approaches presented in this paper focus on improving recommendation diversity. However, this paper reveals that there is tradeoff between the diversity of recommendations and their accuracy.

III. RANKING APPROACHES FOR RECOMMENDATIONS

This section provides information about various ranking approaches that are used for generating recommendations.

Standard Approach

All recommender systems are supposed to predict the rating of items for which ratings have not been given. The perdition of rating to such items is the purpose of this approach which is widely used among the recommender systems. The ranking criterion used is as given below.

$$\boldsymbol{rank_{Standard}(i) = R^*(u,i)^{-1}}$$

Proposed Ranking Approach

The proposed approach is known as item-popularity based ranking. Based on the popularity of items, this approach determines ranks to items. It is achieved using the following equation.

$$\boldsymbol{rank_{Standard}(i) = |U(i)|, where\ U(i) = \{u \in U | \exists R(u,i)\}}$$

Item based CF is used with MovieLens data in order to compare both standard and proposed ranking approaches. The proposed approach increased recommendation diversity around 3.5 times at the cost of dropping accuracy of recommendations by 20%.

Controlling the Tradeoff

By parameterizing the proposed item-popularity based ranking approach the tradeoff between the diversity and accuracy of recommendations can be controlled. The parameter is known as "ranking threshold". Based on the threshold decisions are made whether to use proposed ranking approach and standard approach. Items which are above the ranking threshold are ranked using proposed approach tailored to use ranking threshold parameter while the items that are below threshold are ranked using standard ranking approach. The same is achieved using the equation given below.

$$rank_x(i,T_R) = \begin{cases} rank_x(i), & if\ R^*(u,i) \epsilon [T_R, T_{max}], \\ \square \\ \square \\ \propto_u + rank_{Standard}(i), & if\ R^*(u,i) \epsilon [T_H, T_R], \end{cases}$$

$$\text{Where } I_u^*(T_R) = \{i \epsilon I | R^*(u,i) \geq T_R\}, \propto_u = \max_{i \in I_u^*} rank_x(i).$$

As can be seen in the above equation there are two cases. The first case uses proposed approach while the second case uses standard approach.

IV. EXPERIMENTS AND RESULTS

The proposed recommender system with ranking approaches is built as a web based prototype application suing Java Enterprise Edition technologies such as Servlets and JSP (Java Server Pages). The algorithms are built using Java language. The environment used to run application includesa PC with 2 GB RAM and Dual Core processor. The data used for experiments MovieLens, and Yahoo! and Netflix Movies ratings. Information about these datasets is given in table 2.

	Movies Lens	Netflix	Yahoo! Movies
Number of users	2,830	3,333	1,349
Number of Movies	1,919	2,092	721
Number of ratings	775,176	10,67,999	53,622
Data Sparsity	14.32%	15.32%	5.51%
Avg# of common movies between two users	64.6	57.3	4.1
Avg# of common users between two movies	85.1	99.5	6.5
Avg# of users per movies	404.0	510.5	74.4
Avg# of movies per users	274.1	320.4	39.8

Table 2 –InformationaboutMoving Rating Data Sets

As seen in table 2, the summary of information about the datasets used for experiments is presented in table 2. The difference between the performance of standard ranking approach and proposed approach without considering ranking threshold parameter are presented in fig. 1.

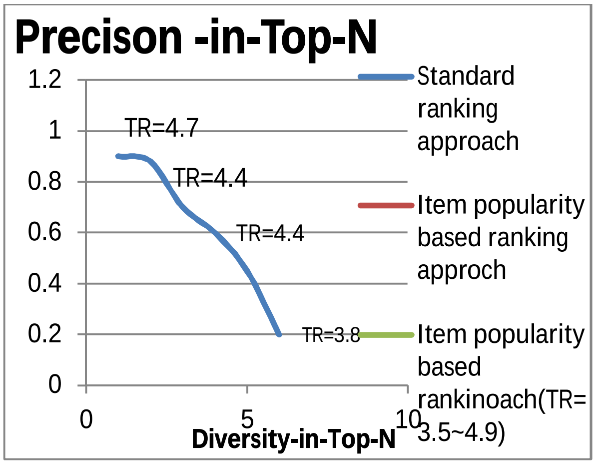

Fig. 1 – Difference between the performance of standard and proposed ranking approaches

Performance of Proposed Ranking Approach with Parameters

The performance of proposed ranking approaches is studied with the datasets described earlier. These ranking approaches take "ranking threshold" as a parameter to control the tradeoff between the diversity and accuracy of recommendations. Fig. 2 shows the performance of the proposed ranking approaches when executed with different parameters at runtime.

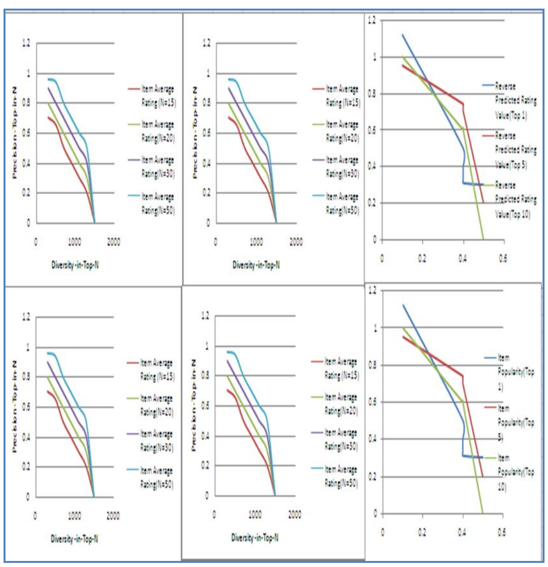

Fig. 2 – Performance of proposed ranking approaches with different parameters

As can be seen in fig. 2, it is evident that the tradeoff between the diversity and accuracy were controlled effectively. For instance in fig. 2 (c) the diversity of the recommendations was improved from 133 to 311 with only 1% loss in recommendation accuracy.

V. CONCLUSIONS AND FUTURE WORK

Recommendations in e-commerce applications bestow advantages to customers and also businesses as they can help customers to take quick decisions. The existing techniques used in recommender systems focused on accuracy of recommendations while giving less importance to aggregate diversity of recommendations. In this paper, we particularly focused on aggregate recommendations in order to improve diversity in recommendations. We achieved it using various recommendation techniques with less amount of loss of accuracy. We could control the tradeoff between the accuracy of diversity of recommendations. Moreover the proposed ranking approaches have flexibility to system designers as they can be tuned with runtime parameter for ranking threshold. This work in this paper could give many directions for future research in this area. They include finding additional ranking criteria; ranking mechanisms that are manufacturer – oriented and consumer-oriented [18]. The tradeoff between the diversity and accuracy is a problem to be solved. However, this paper has given solution to this by using ranking threshold as runtime parameter. The experimental results revealed that the proposed ranking algorithms are useful in making diverse recommendations while reducing the loss of accuracy of the recommendations.

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