A Single-Step Approach to Recommendation Diversification

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ABSTRACT

This paper addresses recommendation diversification. Existing diversification methods have a difficulty in dealing with the accuracy-diversity tradeoff. We propose a novel method to simultaneously optimize the user preference and diversity of k-items to be recommended.

Keywords

Diversification, e-commerce, recommender system

1. INTRODUCTION

The recommender systems (*RS*) analyze each user's preference on items and suggest a set of personalized items that s/he is likely to prefer most [6][5]. In most cases, however, the recommended items are quite similar to one another, which is called a *monotony phenomenon* [2]. If the recommended items are all quite similar to those from a core set that the user has already purchased, they may not be attractive to her/him anymore. Therefore, it is important to take the *diversity* of a recommendation into account. A number of methods have been proposed for recommendation diversification [2][1].

To the best of our knowledge, most existing methods consider user preference and diversification independently: (1) constituting a *candidate list* with regard to a *user preference*, and then (2) making up a *recommendation list* by taking the *diversity* among the items into account [2][1][3]. However, such a *2-step approach* suffers from the difficulty in finding the optimal size (i.e., the number of included items) of a candidate list. If the size of a candidate list is small, most items in the candidate list may not be sufficiently diverse and thus the final recommendation list consists of such items similar to one another. Enlarging the size may result in the recommendation less relevant to a target user, since it considers only the diversity when making up the final recommendation list.

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Motivated by these problems, we propose a novel method to derive the final *recommendation list* in a *single step* where items are diverse as well as of high user preference.

2. PROPOSED METHOD

Given a target user, the recommendation in our work is formulated as the problem of finding a set of k unrated items maximizing the objective function that considers his preference on the items and their diversity at the same time. For predicting user preferences on unrated items, any *collaborative filtering* (*CF*) can be applied (we used the *user-based CF* [7] here). In order to measure diversity, we compute the *dissimilarities* of external features of items. For example, in the case of a movie, the external features of each item would be its genre, name of a director, title, and so on: Star Wars movie would be represented as {SF, Action, George Lucas, Star, Wars, ...}. *Jaccard coefficient* is employed to compute the similarity between two items, denoted as $J(I_i, I_j)$ where I_i and I_j stand for items i and j, respectively.

We define our objective function as shown in Equation (1). Given a set R consisting of k unrated items, the objective function $L(R)$ is expressed in the following, where $P(I_i)$ represents the predicted preference on I_i (normalized between 0 and 1), and diversity factor d, a tunable parameter (ranging from 0 to 1) that implies the degree of relative importance of diversity:

$$L(R) = \frac{1-d}{|R|} \sum_{I_i \in R} P(I_i) + \frac{d}{|R| \times |R-1|} \sum_{I_i \in R} \sum_{I_j \in R} (1 - J(I_i, I_j)) \tag{1}$$

The first term in the objective function corresponds to the average user preference of items in R; the second term does the average dissimilarity in R. The two terms are linearly combined by the diversity factor d.

However, optimizing Eq. (1) is practically infeasible since it is *NP-hard* to find the optimal set R of k items among n items. Moreover, the number of items, n, in online shops is very large in general. Therefore, we propose two strategies that can significantly reduce the number of possible item sets to be examined: (1) *item clustering* and (2) *approximation.* First, we cluster all the items with any distance-based clustering algorithms (we employ the well-known *k-medoid* algorithm here). Then, we find a set of k *clusters*, rather than k items, that make our objective function maximized, where (a) the user preference on a cluster is the average user preference on items included in the cluster and (b) the dissimilarity between two clusters is the average dissimilarity between all possible pairs of items in the two clusters. Finally, we choose one item having the highest user preference from each cluster to make up the final recommendation list of k items. Since n, the total number of items, is substituted with c, the total number of clusters ($c \ll n$), the number of comparisons with all possible solutions is significantly reduced from ${}_{\mathrm{n}}\mathrm{C}_{\mathrm{k}}$ to ${}_{\mathrm{c}}\mathrm{C}_{\mathrm{k}}$.

Second, we employ *Stepwise Forward Selection*, which approximates the optimal solution by inserting a cluster that maximizes the objective function at each step, eventually making up k clusters. At first, *SFS* compares every pair of clusters and chooses the pair with the highest score of the objective function. Then, it gradually inserts clusters one by one while maximizing the objective function until k clusters are found. It takes $\frac{c(c-1)}{2} + c(k-2)$ times to find the solution, which has the time complexity of $\mathrm{O}(c^2)$.

3. EXPERIMENTAL RESULTS

For evaluation, we used the MovieLens 1M dataset. We compared our method with two existing diversification methods, denoted as *TD* (*topic diversification*) [3] and *DRCF* (*diversification and refinement in collaborative filtering*) [1]. Both methods follow the traditional 2-step approach. In the second step, *TD* selects k items where the average dissimilarity of all pairs is maximized, while *DRCF* makes k clusters and selects the most preferred items from each cluster. We also implemented the graph-based recommendation method, proposed in [4], which does not consider diversification, as a baseline algorithm. The final k recommended items should be evaluated in terms of diversity and accuracy. We vary the value of k from 2 to 10 in an increment of 2. As accuracy metrics, we used the *precision*, *recall*, and *F-measure*. As a diversity metric, we used the *average dissimilarity*. We conducted sensitivity analysis, accuracy test, and diversity test.

First, Figure 1(a) shows the accuracy of our method with a varying number of clusters c. Our method provides the highest accuracy when c=20. Therefore, for the following experiments, we fixed the number of clusters, c, as 20. Figure 1(b) represents the accuracy results while varying the diversity factor d. Our method provides the highest accuracy when d is lower than 0.2. We thus fixed d as 0.2 hereafter. We also note that the results of *precision* and *recall* provided very similar tendencies with the above graphs in Figure 1.

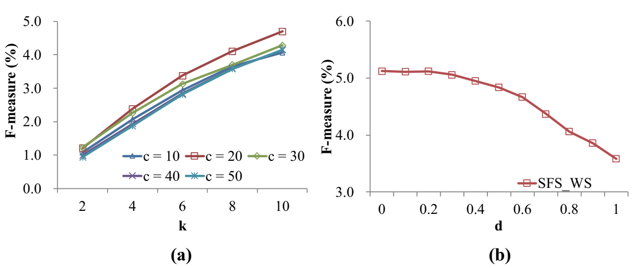

Figure 1: Sensitivity results.

Next, Figures 2(a), 2(b) and 2(c) report the accuracy results. Our proposed method outperforms all the existing methods in terms of *recall* and *F-measure*. In particular, our method improve up to 81.1% recall, 139.7% precision, and 87.2% F-measure, respectively, compared to those of *DRCF*. This is because our method considers both of preference and diversity simultaneously while the existing methods consider them independently. Figure 2(d) reports the diversity results. Our proposed method recommends more diverse items like this since it divides all the items into clusters with similar items while existing methods find preferred items first and consider diversification next among them. Moreover, depending on the business strategy, our method can provide more diversified recommendation to customers by increasing the diverse factor d.

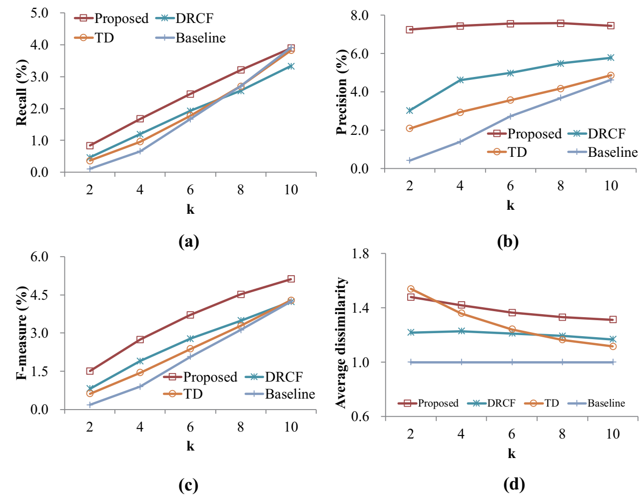

Figure 2: Accuracy and diversity results.

Regarding all the experimental results, we can conclude that the proposed method successfully resolves accuracy-diversity tradeoff.

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