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Multi-objective optimization for long tail recommendation

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ABSTRACT

Recommender systems are tools to suggest items to target users. Accuracy-focused recommender systems tend to recommend popular items, while suggesting items with few ratings (long tail items) is also of great importance in practice. Recommending long tail items may cause an accuracy loss of recommendation results. Thus, it is necessary to have a recommendation framework that recommends unpopular items meanwhile minimizing the accuracy loss. In this paper, we formulate a multi-objective framework for long tail items recommendation. Under this framework, two contradictory objective functions are designed to describe the abilities of recommender system to recommend accurate and unpopular items, respectively. To optimize these two objective functions, a novel multi-objective evolutionary algorithm is proposed. This multi-objective evolutionary algorithm aims to find a set of tradeoff solutions by optimizing two objective functions simultaneously. Experiments show that the proposed framework is effective to suggest accurate and novel items. The proposed recommendation algorithm could suggest many high-quality recommendation lists for the target user based on the concept of Pareto dominance in one run.

1. Introduction

Social media information increases at an unprecedented rate. It becomes increasingly difficult for users to filter abundant information and discover their interested products from the billions of ones. The task of recommender systems (RSs) is to alleviate information overload and generate connections between users and items that users may be interested in. Recommender systems take personalization into account and provide different recommendation results for different users based on the personal demographic features and social information of users [1]. Recommender systems are ubiquitous in e-commerce websites, such as Amazon, Movielens, Netflix [2–4]. Due to the demand of recommendation online, RSs have been applied on diverse topics, such as movies, music, books and location [5], among others [1]. Recent surveys of recommender systems are found in [1,6–8].

The traditional task of recommendation techniques is maximizing the accuracy as much as possible to match the need of users by recommending items with high ratings to users [9,10]. [11] indicates that accuracy-based recommendation methods always suggest items with exceptional similarity, which is unconscionable. Accuracy-based recommendation methods focus on mainstream items, i.e., popular items, which may be known to users and easily be found without recommender systems [12], such that just recommending popular items has very little value for the users. As a result, many researchers pay attention to recommending long tail items or unpopular items [13,14]. Recommending unpopular items by giving up on accuracy is also meaningless. A good recommendation list should not only contain popular items, but also collect the long tail items [11], which is an apparent trade-off between these two objectives.

Various techniques which not only take accuracy into account but also recommend long tail items have been proposed. [12] proposed a general recommendation optimization framework, in which recommending long tail as an inequality constraint is added to previous recommendation algorithm. [15] proposed a graph-based recommendation approach to find a trade-off among accuracy, diversity, similarity and long tail. [16] noted that long tail recommendation is closely related to the objective of novelty or diversity. [17] proposed a hybrid algorithm by combining accuracy- and novelty-focused algorithms using weighted linear aggregation. In this hybrid algorithm, a parameter is used to find a balance between these two objectives and this algorithm is proposed for unary data. [18] proposed a hybrid recommendation algorithm that combines some existing algorithms, in which multi-objectives evolutionary algorithm is used to find several hybridization parameters of different algorithms. [19] introduced a methodology to evaluate the algorithms in terms of novel item retrieval and formulate the trade-off between novel item retrieval and accuracy as a binary optimization problem, in which a parameter is used to control the

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trade-off. Most of hybrid algorithms mentioned above are a combination of different functions by hybridization parameters. Though their computation complexity may be lower, it is difficult to determine parameters and those parameters should be found by trial and error. Those parameters are user-adjusted, so that it just could search in a small regions of search space. Recommendation results are in a small regions of objective space and the best solution is hard to get.

In this paper, we model the long tail recommendation as a multi-objective optimization problem (MOP). Two contradictory objective functions are proposed to quantify these two objectives in this paper. These two objective functions are used to find the balance of recommending popular items and long tail items. Optimizing the first one objective function tends to improve recommendation accuracy and optimizing the second one objective function tends to increase recommendation novelty. The proposed multi-objective long tail recommendation framework (called MORS) consists of two phases. First, traditional accuracy-focused recommendation technique is used to get the unknown ratings. Second, MORS optimizes two conflicting objective functions simultaneously by a novel multi-objective evolutionary algorithm (MOEA) and returns a set of recommendation solutions that are optimal in terms of these two optimization objectives.

The main contributions of this work can be summarized as follows:

- We propose a multi-objective recommendation framework to recommend long tail items. In our framework, recommendation accuracy and novelty are considered simultaneously.
- Two objective functions are proposed to reflect the abilities of recommendation techniques to recommend popular and long tail items, respectively.
- Based on recommendation problem and objective functions, we redefine genetic representation and genetic operators to design a novel multi-objective evolutionary algorithm. This new designed multi-objective evolutionary algorithm is adopted to optimize these two objective functions above to find a trade-off between recommending popular and unpopular items.
- MORS can return multiple optimal tradeoff solutions for one target user in only one run, while other recommender systems just give one solution. In this way, MORS provides multiple solutions to decision makers. Decision makers must use some other information or subjective preference to decide which of these solutions to keep. Experiments show that MORS also can return some candidate solutions which are better than those generated by traditional algorithms.

This paper is organized as follows. Section 2 gives the related background, including the definition of recommender systems, recommendation techniques, the long tail recommendation and the introduction to multi-objective optimization. The MORS is described in detail in Section 3. Section 4 shows extensive experiments to validate the effectiveness of MORS. Section 5 concludes the paper.

2. Related background

2.1. Problem description

Recommender systems are techniques to predict the preferences of users and recommend items to users that they may be satisfied with. In the standard setting of RSs, there are a set of users U, a set of items I and an U-I matrix R that consists of ratings of users on items. The ratings are used to described how the target user like items. The ratings in matrix R can be expressed either explicitly, such as using non-negative integers or real numbers within a certain range, or implicitly, such as by binary ratings. Because of the data sparsity problem in recommender systems, there are few ratings in R. There are two kinds of the most important recommendation problems [20,21] named as *best item* and *top-N* recommendation problems. The first recommendation problem can be defined as: Given users set U, items set I and ratings matrix R, compute the unknown ratings in R and suggest to every user an unrated item whose rating has the highest value. In the second recommendation problem, the task of recommender systems is to provide the target user with a list of N top ranked items [22]. In this paper, our work pursues the top-N recommendation task.

2.2. Recommendation techniques

Numerous recommendation techniques have been proposed in recent years. The most widely used taxonomy provided by Burke [23] distinguishes different recommendation techniques into:

- *Demographic*: Demographic recommendation recommends items preferred by users that have similar demographic profiles with the target user.
- *Content-based (CB)* [24]: Content-based recommendation suggests items whose content is similar to the content of what the target users preferred in the past.
- *Collaborative filtering (CF)* [25]: Collaborative filtering approaches are categorized as *memory-based* and *model-based*. The memory-based CF recommend items that were preferred by users with similar tastes to the target user (user-based collaborative filtering), or that are similar to what the target user preferred in the past (item-based collaborative filtering). Model-based CF recommend items based on the models that have been trained as the input [26,27], which are superior to memory-based collaborative filtering methods for recommending items, alleviating data sparsity problem and allowing incorporation of additional different sources of information [27].
- *Knowledge-based* [28]: Knowledge-based recommendation gives recommendation on the basis of specific domain knowledge to meet the users preferences.
- *Hybrid algorithms* [23,29]: To gain better performance and smoothen disadvantages of individual technique above, recommendation techniques combining two or more recommendation methods are proposed by several researchers.

Beyond traditional recommendation methods above, others techniques also have been proposed for recommender systems, for example Restricted Boltzmann Machines (RBM) [30], deep learning [31], Tensor Factorization and Factorization Machines [32], and so on.

2.3. Long tail recommendation

The terminology long tail is first introduced by Anderson in [33]. According to Anderson's description, the long tail within recommendation represents items with very few ratings, i.e., items with low popularity. The long tail phenomenon in the dataset MovieLens 1 million is illustrated in Fig. 1. As shown in Fig. 1, most of items just receive few ratings from users and a small number of items are rated by lots of users, which makes it hard to suggest items from the long tail.

The ability to recommend long tail items can be used to judge the practical performance of recommender systems. It has high value to recommend items from the long tail. For users, the long tail recommendation could recommend items that meet the interest of them and surprise them simultaneously. For the providers,