Diversified Sequential Recommendation via Evolutionary Multi-Objective Transfer Optimization

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***Abstract*—Sequential Recommendation (SR) intends to model user interests based on historical behavior sequences and suggest the next item. Most existing sequential models primarily focus on learning users' preferences on the relevance objective of the target item. However, the investigation of personalized preferences on the diversity objective of SR results is usually ignored. Evolutionary algorithms have amply demonstrated effectiveness in solving multi-objective problems but encounter efficiency bottlenecks when applied to multi-objective recommendation tasks due to the limited scalability at the user level. To address the problem, this study proposes to facilitate diversified SR via a multi-objective transfer optimization algorithm, in which each optimization task corresponds to the recommendation for a target user. With the optimization knowledge of user preference transferred within and across tasks, the diversified SR of a set of users can synchronously proceed. The novelty of our proposed algorithm is fully utilizing the outstanding global search capability of evolutionary multi-objective optimization without hindering the efficiency of sequential models.**

***Index Terms*—diversified recommendation, sequential recommendation, evolutionary multi-objective transfer optimization**

I. Introduction

Recommender systems have been widely deployed to many online services for addressing information overload. Conventional recommendation approaches, e.g., collaborative filtering-based methods [1] and matrix factorization-based methods [2], assume that user preferences are intrinsic and static. They generally ignore the dynamic and evolving characteristics of user behavior. Sequential Recommendation (SR) has been proposed to model these characteristics by exploiting user's sequential behavior patterns to predict potential items of interest [3]. Real-world recommendations generally involve different evaluation objectives. However, most existing sequential models have not been properly designed in terms of item diversification, which serves as an essential metric in evaluating practical recommender systems. Due to the conflicting nature of the preference-relevant and the diversity objectives, it is challenging to reach a balance between them.

Evolutionary multi-objective optimization has been introduced as an effective paradigm in resolving the trade-offs among contradictory objectives of multi-objective recommendation [4], [5]. Multi-Objective Evolutionary Algorithm (MOEA) is able to produce several Pareto-optimal recommendation lists via population-based search [6]. However, conducting a thorough recommendation comes at a significant cost in terms of efficiency, where MOEAs are criticized for the heavy computation burden involved in the population-based optimization process. The use of certain MOEA for diverse recommendations is limited to small systems and cannot scale with increased users or items.

To alleviate the curse of dimensionality problem in applying evolutionary multi-objective optimization for diversified SR, this paper proposes an Evolutionary Transfer Optimization (ETO) based recommendation method, in which the optimization knowledge can be sequentially transferred within a recommendation task, as well as efficiently shared across users with similar preferences. In this way, a scalable group of users can receive recommendations with a diversified list of items, thus improving the efficiency of recommendations at both the user and objective levels.

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II. Proposed Method

A. Preliminary of ETO

ETO has recently emerged as a paradigm that integrates evolutionary solvers with knowledge transfer across related domains to achieve better optimization performance [7]. Multitask optimization and sequential/dynamic optimization are typical research topics that involve the ETO paradigm to improve problem-solving efficiency. However, in the literature, none or very few methodologies have investigated ETO in recommender systems. In this paper, an instantiation of this broad idea is presented to introduce both intra-task sequential knowledge transfer and inter-task cross knowledge transfer into the development of diversified SR.

B. Problem Formulation and Chromosome Representation

$\{\mathbf{S}^{(u)}\}_{u=1}^{U}$ denotes the interaction history of U users in $\mathcal{U}$. Given user $u \in \mathcal{U}$, $\mathbf{S}^{(u)} = [i_1^{(u)}, i_2^{(u)}, \cdots, i_t^{(u)}, \cdots, i_{T_u}^{(u)}]$ denotes a chronological ordered sequence of items interacted with u, where T_u is the number of observed interactions. Herein, we focus on the recommendation task that predicts the subsequent item list user u may be interested in. A recommendation list with k-number of items is represented as a chromosome which is encoded as a sequence $\mathrm{x} = (x_1, \ldots, x_i, \ldots, x_k)$, where $x_i \in [1, N]$ is an integer gene that

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denotes the corresponding item ID. Each list contains the top k items searched with trade-offs between the preference-relevant and the diversity objectives. The diversity property is hard to define on a single item, thus the diversity objective is measured by maximizing the dissimilarity of all pairs of items, which is formulated as: $max\ f_D(\mathrm{x}, t) = \frac{2}{k(k-1)} \sum_{i,j \in \mathrm{x}, i \neq j} (1 - d(x_i, x_j))$, where $d(x_i, x_j)$ is the cosine dissimilarity between two different item vectors within the list.

C. Algorithm Overview

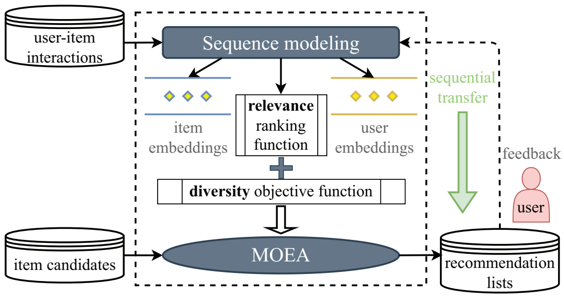

Fig. 1: Flowchart of intra-task sequential knowledge transfer.

The users are clustered based on the user embeddings obtained from the sequential preference model (e.g., GRU4Rec [3]). The procedure of the proposed intra-task sequential knowledge transfer is illustrated in Fig. 1. In particular, for each user, a set of non-dominated recommendation solutions is searched from the candidate item set by simultaneously optimizing the preference-relevant and the diversity objective functions. Then the obtained item list is recommended to user, new interactions are collected as feedback for updating the sequential model. Therefore, the optimization knowledge (i.e., objective-level preference and non-dominated solutions) of the solved multi-objective problem can be sequentially transferred to accelerate the convergence in subsequent search processes. Similar knowledge transfer paradigm can also be conducted across tasks within a cluster, which serves as the inter-task cross knowledge transfer of the proposed algorithm.

III. Preliminary Experiment

A. Dataset and Settings

The performance of the proposed method is preliminarily investigated on a publicly available dataset, *MovieLens-1M*. The dataset contains collected movie ratings, the ratings larger than 3 are kept as positive feedback. To conform to the setting of SR, we built the sequence by sorting the interactions based on the timestamps. For each user, the first 80% of interactions are used as training data, the remaining 20% are as testing data. During the test phase, our evaluation protocol randomly samples 98 unobserved items with 2 ground-truth items and ranks them together. The basic MOEA optimizer is NSGA-II. The population size is set to 100 and the maximum number of function evaluations for each task is $5,000$.

TABLE I: Metric Values Obtained by The Compared Methods.

Metrics	Compared Methods				
	BPRMF	GRU4Rec	GRU4Rec +ϵ-Greedy	GRU4Rec +MMR	GRU4Rec +ETO
Recall@5	0.1791	**0.1872**	0.1668	0.1724	0.1847
ILD@5	1.6212	1.5163	1.8409	1.7335	**1.8950**
$\mathbf{F_1}$@5	0.3226	0.3332	0.3059	0.3136	**0.3366**

B. Evaluation Metrics and Results

To evaluate the recommendation quality of different objectives, Recall and Intra-List Distance (ILD) are used as accuracy and diversity evaluation metrics, respectively. **Recall** measures whether the ground-truth item appears in the top-k recommendation list. The range of Recall@k is $[0, 1]$. **ILD** measures the diversity of recommendation lists as the average distance between pairs of items. The range of ILD@k is $[0, 2]$. Furthermore, $\mathbf{F_1}$**-score** is employed to quantify the effectiveness of each method in achieving the trade-off among conflicting objectives, which is defined as: $\mathbf{F_1} = \frac{2*\mathrm{Recall}*\mathrm{ILD}}{\mathrm{Recall}+\mathrm{ILD}}$. Table I shows the performance of compared baselines and our ETO method utilizing GRU4Rec for sequence modeling. The best performances are highlighted in bold, which basically verifies the superiority of the proposed algorithm.

IV. Conclusion and Future Work

This paper proposes to alleviate the efficiency barrier in applying evolutionary multi-objective optimization for diversified SR. ETO paradigm is introduced to facilitate knowledge transfer within and across multi-objective recommendation tasks. The proposed idea highlights the advantage of using evolutionary algorithms to solve multi-objective problems in diversified SR, while retaining the efficiency of the sequential model. The proposed algorithm serves as a starting point, thus more improvements and evaluations of the knowledge transfer method are needed. For future work, we aim to further refine this idea by using a centralized learning method in multi-objective SRs to facilitate large-scale optimizations.

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