Tiger: Transferable Interest Graph Embedding for Domain-Level Zero-Shot Recommendation

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ABSTRACT

Recommender systems play a significant role in online services and have attracted wide attention from both academia and industry. In this paper, we focus on an important, practical, but often overlooked task: domain-level zero-shot recommendation (DZSR). The challenge of DZSR mainly lies in the absence of collaborative behaviors in the target domain, which may be caused by various reasons, such as the domain being newly launched without existing user-item interactions, or users' behaviors being too sensitive to collect for training. To address this challenge, we propose a **T**ransferable **I**nterest **G**raph **E**mbedding technique for **R**ecommendations (Tiger). The key idea is to connect isolated collaborative filtering datasets with a knowledge graph tailored to recommendations, then propagate collaborative signals from public domains to the zero-shot target domain. The backbone of Tiger is the transferable interest extractor, which is a simple yet effective graph convolutional network (GCN) aggregating multiple hops of neighbors on a shared interest graph. We find that the bottom layers of GCN preserve more domain-specific information while the upper layers represent universal interest better. Thus, in Tiger, we discard the bottom layers of GCN to reconstruct user interest so that collaborative signals can be successfully propagated to other domains, and retain the bottom layers of GCN to include domain-specific information for items. Extensive experiments with four public datasets demonstrate that Tiger can effectively make recommendations for a zero-shot domain and outperform several alternative baselines.

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CCS CONCEPTS

• **Information systems** → **Personalization**; **Collaborative filtering**; **Content ranking**.

KEYWORDS

Recommender System, Knowledge Graph, Zero-shot Learning

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1 INTRODUCTION

Recommender systems play a critical role for online platforms in connecting users with their interested items. In the past decades, numerous methods have been proposed around how to leverage users' historical behaviors for better recommendations, such as collaborative filtering [13, 20], feature interactions [10, 29], sequential recommendations [15, 19], and multi-interest user modeling [21, 24]. However, the line of research on how to cold start a recommender system is almost blank. Different from user/item cold-start problems [1, 33, 50] which make recommendations for new users or items in a mature domain, recommender system cold-starting means the target domain is brand new without any user-item interactions. In this paper, we call the task of recommender system cold-starting as domain-level zero-shot recommendation.

The domain-level zero-shot recommendation (DZSR) is an important and practical task, typical applications of which include: (1) when an online service provider intends to launch a new domain

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