Abstract

Data sparsity is a well-known challenge in recommender systems. One way to alleviate this problem is to leverage knowledge from relevant domains.

Although several studies leverage side information (e.g., user reviews) for cross-domain recommendation, side information is not always available or easy to obtain in practice.

To this end, we propose cross-domain preference ranking (CPR) with a simple yet effective user transformation that leverages only user interactions with items in the source and target domains to transform the user representation.

Given the proposed user transformation, CPR not only successfully enhances recommendation performance for users having interactions with target-domain items but also yields superior performance for cold-start users in comparison with state-of-the-art cross-domain recommendation approaches.

Problem Definition

We consider the recommendation scenario involving two domains with disjoint item sets, namely, a source-domain item set and a target-domain item set (denoted as $I^S$ and $I^T$, respectively); there exists a set of users having interactions with items from both domains, namely shared users.

Formally, denote the set of users having interactions with items in $I^S$ ($I^T$) as $U^S$ ($U^T$, respectively) and the shared users as $U^{\text{shared}} = U^S \cap U^T$ and $U^{\text{shared}} \neq \emptyset$.

Let $I = I^S \cup I^T$ and $U = U^S \cup U^T$. The goal of the proposed CPR approach is to learn the representation matrix $\Theta \in \mathbb{R}^{(|U|+|I|) \times d}$ mapping each user and item to a $d$-dimensional embedding vector.

Proposed CPR Approach

Given a user $u$, let $I^S_u$ ($I^T_u$) denote the set of items in the source domain (target domain, respectively) that $u$ has interacted with.

To transfer knowledge from the source domain into the target domain, we bridge the non-overlapped $I^S$ and $I^T$ with the following user representation transformation: for each user $u \in U$, we have

$$\Theta_u = \Theta_u^{\text{shared}} + \tilde{a}_u^{I^S} + \tilde{a}_u^{I^T},$$

where $\Theta_u^{\text{shared}}$ denotes a learnable pseudo user representation for user $u$, $\tilde{a}_u^{I^S} = 1/|I^S_u| \sum_{i \in I^S_u} \Theta_i$, and $\tilde{a}_u^{I^T} = 1/|I^T_u| \sum_{i \in I^T_u} \Theta_i$.

With the above transformation, we formulate the maximum posterior estimator to derive our optimization criterion for CPR as

$$\text{CPR-OPT} := \max_{\Theta} \sum_{u \in U^T} \sum_{i \in I_u^T} \ln \sigma(\langle u, \Theta_i - \Theta_t \rangle)) - \lambda ||\Theta||^2,$$

where $\sigma(\cdot)$ denotes the sigmoid function, $\langle \cdot, \cdot \rangle$ denotes the inner product for two vectors, and $\lambda$ is a regularization parameter.

For more details, please refer to:

https://link.springer.com/chapter/10.1007/978-3-031-28238-6_35