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Explicitly Modeling Relationships between Domain-Specific and Domain-Invariant Interests for Cross-Domain Recommendation

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Abstract

This paper focuses on cross-domain recommendation (CDR) without auxiliary information. Existing works on CDR all ignore the bi-directional transformation relationships between users' domain-invariant interests and domain-specific interests. Moreover, they only rely on the sparse interactions as supervised signals for model training, which can not guarantee the generated representations are effective. In response to the limitation of these existing works, we propose a model named MRCDR which explicitly models relationships between domain-specific and domain-invariant interests for cross-domain recommendation. We project the domain-specific representations of users to a common space generating their domain-invariant representations. To remedy the problem of insufficient supervised signals, we propose two strategies that generate extra self-supervision signals to enhance model training. The aligned strategy tries to make the two domain-invariant representations an overlapped user to be consistent. The cycle strategy tries to make the reversely projected representation of the domain-invariant representation of a non-overlapped user to be consistent with its original domain-specific representation. We conduct extensive experiments on real-world datasets and the results show the effectiveness of our proposed model against the state-of-the-art methods.

Keywords: cross-domain recommendation, domain-specific and domain-invariant interests, neural networks, self-supervised learning

1 Introduction

In the era of information explosion, recommendation systems are becoming more and more important for users to quickly find their potential items of interest. However, there are two long-standing obstacles for traditional recommendation systems, i.e., data sparsity and cold-start problems since users tend to only interact with a small fraction of items of even no interaction at all. As more and more users begin to interact with more than one domain (e.g., music and book), it increases opportunities of leveraging information collected from other domains to alleviate the two problems. This idea leads to Cross-Domain Recommendation (CDR) which has attracted increasing attentions in recent years.

According to whether recommended items are from the same domain as users, cross-domain recommendation can be divided into two categories: the cold-start recommendation [1–4] and the collective recommendation [5–8]. Cold-start recommendation treat one domain as the source domain and the other domain as the target domain. The aim is to recommend items in the target domain to the users who only have interactions in the source domain and vice versa. For the collective recommendation, there is no distinction between the source domain and the target domain. The aim is to recommend users with items from the same domain, leveraging information from both domains and improving recommendation performance on both domains. In this paper, we only focus on the collective cross-domain recommendation.

Existing approaches can be mainly divided into two categories. The first category of approaches is based on a shared strategy. The most representative approach is the Collective Matrix Factorization (CMF) method proposed by Singh et al [5]. It collectively factorizes interaction matrices in each domain and shares representations of overlapping users across domains. Later researchers proposed deep learning-based methods [9, 10], the common of which is a shared module across domains to generate user representations. Zhao et al. proposed a Preference Propagation GraphNet (PPGN) [11] which constructs a shared graph to integrate user interactions in the two domains. The second category of approaches is based on a transfer strategy, that is, they first extract information in each domain and then transfer it between domains. Hu et al. first proposed a collaborative cross-network (CoNet) [6] which utilizes the dual transfer mechanism and becomes a framework that is widely extended by later researchers [8, 12]. However, both categories of approaches focus only on commonalities between domains and ignore differences between domains. To overcome this problem, researchers proposed that both users' domain-invariant interests and domain-specific interests should be modeled simultaneously. Specifically, Yan et al. proposed the DeepAPF [13] method that leverages an attentional network to learn non-uniform importance weights of users' domain-invariant and domain-specific representations. Xu et al. proposed the ReCDR [14] method which constructs both single-domain and cross-domain graphs to generate users' two kinds of representations.

Although effective, the existing methods still have several limitations. First, existing methods tend to generate the domain-specific and domain-invariant interest representations as two separate representations for each user. They ignore that there exist bi-directional transformation relationships between these two kinds of user interests. To be specific, domain-invariant interests can be seen as removing domain-related effects from domain-specific interests while domain-specific interests can be seen as injecting domain influences into domain-invariant interests. Second, the two generated user interest representations are optimized by gradient descent together with other model parameters. The sparsity of user interactions results in the number of supervised signals that can be used for model training limited, so it is impossible to guarantee the generated user representations are effective. Third, the structures and mechanisms of most of existing methods are designed mainly for overlapping users. However, in real scenarios, the overlapping degree between domains is typically small and the majority of users are non-overlapped [15, 16]. Therefore, these methods do not perform well in real-world settings.

Addressing the aforementioned limitations of existing methods faces three major challenges. **Challenge 1**: designing a representation generation mechanism that enables the generated representations to reflect the abovementioned bidirectional transformation relationships. **Challenge 2**: proposing effective strategies to remedy the problem of insufficient supervised signals. This will help in learning optimal user interest representations. **Challenge 3**: applying the proposed mechanism and strategies to both overlapping users and non-overlapping users to cope with the fact that non-overlapping users account for a large proportion in real datasets.

In response to the challenges, we propose a model named **MRCDR** to explicitly **M**odel **R**elationships between users' domain-specific and domain-invariant interests for **C**ross-**D**omain **R**ecommendation. To address **Challenge 1**, we first employ multilayer graph convolution operations on the user-item interaction graph in each domain to generate user domain-specific interest representations and item representations. We then explicitly project the domain-specific representations to a common space which can be seen as removing domain-related effects, hence generating user domain-invariant interest representations. We call this the forward projection process. To address **Challenge 2**, we propose an aligned strategy that generates extra constraints for model training. It tries to make the two projected domain-invariant representations in the common space of an overlapping user to be consistent. For making the strategy applicable for non-overlapping users (i.e., the **Challenge**

3), we further propose a cycle strategy to supplement the aligned strategy. The cycle strategy further consists of a backward projection process which is the inverse transformation of the forward process. This strategy tries to make the reversely projected domain-invariant representation of a non-overlapped user to be consistent with her original domain-specific representation. The two strategies jointly achieve the objective of utilizing both overlapped and non-overlapped users to generate extra self-supervision signals to enhance the model learning. They further alleviate the problem arising from the small degree of user overlapping of two domains. Finally, we fuse user domain-specific and domain-invariant representations by concatenation for recommendations. The contributions of our work are summarized as follows:

- The proposed MRCDR model is the first work that explicitly models the bi-directional transformation relationships between user domain-specific and domain-invariant interests in cross-domain recommendation.
- We propose two strategies that generate extra self-supervision signals to enhance model training. The two strategies, respectively, generate extra constraints from overlapping users and non-overlapping users, which alleviate the problem of insufficient supervised signals.
- We conduct extensive experiments on real-world Amazon and Douban datasets. Comprehensive results demonstrate that our method significantly outperforms the state-of-the-art CDR methods.

The remainder of this paper is organized as follows. After surveying related work in Section 2, we introduce notations and formulate the problem in Section 3. Section 4 will introduce our proposed MRCDR model in detail. Section 5 presents the experimental settings and experimental results. Finally, we conclude this paper in Section 6.

2 Related Work

In this section, based on whether recommended items are from the same domain as users, we broadly classify existing approaches on CDR into two categories: cold-start cross-domain recommendation and collective cross-domain recommendation.

2.1 Cold-Start Cross-Domain Recommendation

The cold-start recommendation aims to recommend a user in domain A with items from domain B or vice versa. As users have no historical interaction in the target domain, these users are referred to as cold-start users.

The embedding and mapping framework is the most important framework for this recommendation problem which was first proposed by Man et al. [1]. Their proposed EMCDR model first learns latent representations of users/items in each domain and then learns a mapping function across domains utilizing the representations of overlapping users. For a cold-start user, her representation can be obtained by mapping her representation from the source domain to the target domain. Following this framework, several EMCDR-based approaches have emerged. Zhu et al. [17] proposed a DCDCSR model which took into account rating sparsity degrees of individual users/items when generating latent representations. Wang et al. [2] propose a CDLFM model which first calculates similarities among users' rating behaviors and embedded the similarity values into the matrix factorization process. Fu et al. [3] proposed an RC-DFM model which fuses review text and item contents with ratings to generate more semantic representations. Bi et al. [18, 19] proposed to construct a heterogeneous information network and took into consideration the interaction sequence information to learn effective representations. Wang et al. [4] aligned the representations of overlapping users in low-dimensional space.

2.2 Collective Cross-Domain Recommendation

For collective recommendation methods, there is generally no distinction between source and target domains. The goal of these methods is to improve the recommendation performance on both domains simultaneously. We further divide these methods into two subcategories: traditional methods and deep learning-based methods.

2.2.1 Traditional methods

Matrix Factorization (MF) is one of the most commonly used methods in the traditional cross-domain recommendation. Singh et al. [5] proposed a collective matrix factorization (CMF) model which collectively factorized several matrices with shared latent representations of common entities. Pan et al. [20] proposed to factorize the data matrices into three parts: a user-specific latent feature matrix, an item-specific latent feature matrix, and a data-dependent core matrix that captures data-dependent effect. Li et al. proposed that users and items share cluster-level rating patterns in different domains. They proposed a codebook transfer model (CBT) Li et al. [21] which tri-factorizes the rating matrix into a "codebook" which comprises the representatives of all the user/item clusters and two cluster indicator matrices. Gao et al. [22] further proposed CLFM which partitions the latent rating pattern into a shared common part and a domain-specific part to capture both shared common cluster-level rating patterns and domain-specific rating patterns. Hu et al. [23] proposed a CDTF model which takes into consideration the full triadic relation user-item-domain to reveal the user preference on items within various domains in depth. More recently, Song et al. [24] propose to exploit the aspect factors extracted from the review text to improve the performance of CDR. The RB-JTF method is proposed to transfer knowledge by sharing user latent factors and transferring aspect latent factors.

2.2.2 Deep learning-based methods

With the emergence and success of deep learning, more and more studies begin to apply deep learning to cross-domain recommendation tasks.

Hu et al. [6] proposed a collaborative cross-network (CoNet) that enabled dual knowledge transfer across domains by introducing cross-connections from one base network to another and vice versa. Following a similar framework, Li et al. [12] proposed a Deep Dual Transfer Cross-Domain Recommendation (DDTCDR) model which develops a latent orthogonal mapping to extract user preference over multiple domains. Liu et al. [7] proposed the ACDN model that parameters characterize the personal aesthetic preferences from product photos. Liu et al. [8] proposed a Bi-direction Transfer learning method for cross-domain recommendation by using Graph Collaborative Filtering network as the base model (BiTGCF). Li et al. [25] further applied the dual learning mechanism to the cross-domain click-through rate prediction task. Zhao et al. [11] proposed a Preference Propagation GraphNet (PPGN) which constructs a cross-domain preference matrix to model the interactions of different domains as a whole. Yuan et al. [26] proposed a deep Domain Adaptation Recommendation (DARec) model which learns representations of shared patterns and transfers them between two domains via a deep neural network.

Zhu et al. [27] proposed a Dual-Target Cross-Domain Recommendation (DTCDR) model which designs an embedding-sharing strategy to combine and share the embeddings of overlapping users across domains. They further proposed a graphical and attentional framework called GA-DTCDR [28] in which they constructed two separate heterogeneous graphs based on the rating and content information to generate more representative user and item embeddings. Zhao et al. [29] proposed a cross-domain recommendation framework via aspect transfer network (CATN) to capture users' multi-faced and fine-grained preferences.

The MRCDR model we proposed in this paper falls into the deep learning-based collective cross-domain recommendation method.

3 Preliminaries

In this section, we introduce notations and formulate the cross-domain recommendation problem of this paper.

3.1 Notations

Let D^A and D^B denote two different domains that share partially overlapped users. The user sets can be denoted as $\mathcal{U}^A = \{\mathcal{U}_c, \mathcal{U}_d^A\}$ and $\mathcal{U}^B = \{\mathcal{U}_c, \mathcal{U}_d^B\}$ where $\mathcal{U}_c$ is the set of overlapped users while $\mathcal{U}_d^A$ and $\mathcal{U}_d^B$ are non-overlapped user sets of each domain. $\mathcal{I}^A$ and $\mathcal{I}^B$ are disjoint item sets that indicate that the two domains have no item in common. Two binary matrices $\mathbf{R}^A \in \mathbb{R}^{|\mathcal{U}^A| \times |\mathcal{I}^A|}$ and $\mathbf{R}^B \in \mathbb{R}^{|\mathcal{U}^B| \times |\mathcal{I}^B|}$ represent interactions between users and items in each domain, where $|\mathcal{U}^A|$, $|\mathcal{I}^A|$, $|\mathcal{U}^B|$, and $|\mathcal{I}^B|$ denote the number of users and items in domain A and domain B, respectively. $R_{u,i} = 1$ denotes user u has interacted with item i and $R_{u,i} = 0$ represents there is no observed interaction between user u and item i.

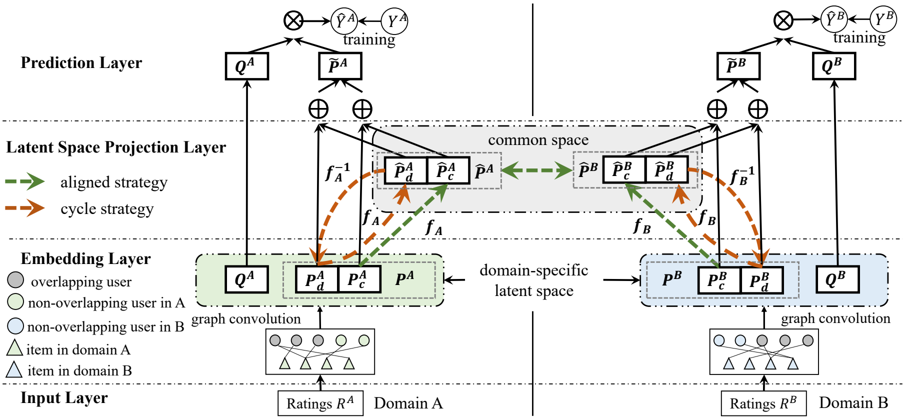


Fig. 1 The architecture of our proposed MRCDR model for cross-domain recommendation.

3.2 Problem Formulation

Given two observed domains D^A and D^B including interaction matrices $\mathbf{R}^A$ and $\mathbf{R}^B$, user sets $\mathcal{U}^A$ and $\mathcal{U}^B$, item sets $\mathcal{I}^A$ and $\mathcal{I}^B$, we aim to make recommendations for all users in both domains. To be more specific, we recommend items that users have not interacted with but may have interests, that is, we generate a set of items $\mathcal{I}_{u_1} \subseteq \mathcal{I}^A$ for user $u_1 \in \mathcal{U}^A$ and $\mathcal{I}_{u_2} \subseteq \mathcal{I}^B$ for user $u_2 \in \mathcal{U}^B$ leveraging information from both domains.

4 The Proposed MRCDR Model

In this section, we introduce our proposed MRCDR model. Fig. 1 shows its architecture which mainly includes the following four layers:

- **Input Layer.** The inputs of MRCDR are users' implicit feedbacks (i.e., whether they have interacted with the items) in both domains without requiring any additional auxiliary information.
- **Embedding Layer.** This layer aims to generate domain-specific representations for users and items based on interactions between them in each domain.
- **Latent Space Projection Layer.** This layer projects user domain-specific representations to a common space generating user domain-invariant representations. Two strategies (i.e., the aligned strategy and the cycle strategy) are proposed to generate extra self-supervision signals to enhance model training.
- **Prediction Layer.** This layer fuses user domain-specific and domain-invariant representations by concatenation. It applies a fully-connected neural network to generate the probability interaction score between a user-item pair.

4.1 Embedding Layer

This layer aims to generate effective domain-specific representations utilizing observed user-item interactions in each domain. Since operations are the same in both domains, for brevity, we omit superscripts that indicate domains.

Existing methods for recommendations mainly generate user/item representations by decomposing the interaction matrix $\mathbf{R}^{M\times N}$ into two matrices $\mathbf{U}^{M\times k}$ and $\mathbf{I}^{N\times k}$ [1, 5]. Each row in $\mathbf{U}, \mathbf{I}$ denotes the corresponding representation of a user/item. However, it is argued that these MF-based methods are not sufficient to yield optimal representations as they lack explicit modeling of the crucial collaborative signals which are only considered in the optimization objection. What's more, such methods can not capture complex non-linear interactions.

Recently, graph-structured data are proved to be beneficial to improve the recommendation performance [11, 30, 31]. To explicitly capture the behavioral similarity between users (or items), we first denote user-item interactions as a graph $G(V, E)$ in which a vertex $v \in V$ is a user/item and an edge $e_{ui} \in E$ indicates an observed interaction between user u and item i. Based on the interaction graph, the graph convolution operation can aggregate information from connected vertexes which is defined as follows.

$$\mathbf{p}_{v_i} = \sigma(\sum_{v_j \in N(v_i)} w_{v_i v_j} \mathbf{p}_{v_j} + b), \tag{1}$$

where $\mathbf{p}_{v_i}$ and $\mathbf{p}_{v_j}$ are the embeddings of vertex v_i and v_j. $N(v_i)$ denotes the set of vertexes that are connected to v_i. $w_{v_i v_j}$ and b are learnable parameters.

We further argue that there exists high-order connectivity information in the interaction graph, that is, users/items are not only affected by their directly connected neighbors but also neighbors of neighbors. Therefore, in our model, we stack L layers graph convolution networks to capture such high-order information which is formulated as follows.

$$\begin{aligned} \mathbf{p}^l_{v_i} &= \sigma(\sum_{v_j \in N(v_i)} w^l_{v_i v_j} \mathbf{p}^{l-1}_{v_j} + b^l), \\ l &= 1, 2, ..., L. \end{aligned} \tag{2}$$

When $l = 1$, $\mathbf{p}^0_{v_i}$,$\mathbf{p}^0_{v_j}$ are initial embeddings of vertexes v_i and v_j. To generate the initial embeddings, we first denote users and items by one-hot codings $\tilde{\mathbf{E}}_U, \tilde{\mathbf{E}}_I$ using IDs as there is no additional auxiliary information under the assumption of our question. We then transform $\tilde{\mathbf{E}}_U, \tilde{\mathbf{E}}_I$ into low-dimensional dense embeddings $\mathbf{E}_U = \tilde{\mathbf{E}}_U \mathbf{M}_U$ and $\mathbf{E}_I = \tilde{\mathbf{E}}_I \mathbf{M}_I$ where $\mathbf{M}_U$, $\mathbf{M}_I$ are transformation matrices. Rows in $\mathbf{E}_U$ and $\mathbf{E}_I$ are initial embeddings $\mathbf{p}^0_{v_i}$, $\mathbf{p}^0_{v_j}$.

The outputs in the last layer of all vertexes form matrices $\mathbf{P}$ and $\mathbf{Q}$ which are treated as domain-specific representations of users and items that contain user preferences and item attributes in a specific domain, respectively.

4.2 Latent Space Projection Layer

Besides interests affected by domain characteristics that are embedded in the domain-specific representations, we argue that there exist user domain-independent interests, such as preferences for color and genre. In cross-domain recommendations, it is essential to model both user domain-specific interests and domain-invariant interests effectively to achieve satisfactory results. We further propose that there exist bi-directional transformation relationships between domain-specific interests and domain-invariant interests. To be specific, domain-invariant interests can be seen as removing domain-related effects from domain-specific interests. On the contrary, domain-specific interests can be seen as injecting domain influences into domain-invariant interests.

To capture such relationships, it is important to enable the generated two kinds of user representations to be transformed to each other bi-directionally. Therefore, when generate user domain-invariant representations, instead of separately generating them, we design a forward projection process. It contains two projection functions $f_A(\cdot)$, $f_B(\cdot)$ to project user domain-specific representations $\mathbf{P}^A$, $\mathbf{P}^B$ to a common space. The functions of $f_A(\cdot)$, $f_B(\cdot)$ can be seen as removing domain-related effects from $\mathbf{P}^A$, $\mathbf{P}^B$ and generate domain-invariant representations $\hat{\mathbf{P}}^A$, $\hat{\mathbf{P}}^B$:

$$\hat{\mathbf{P}}^A = f_A(\mathbf{P}^A, \theta^A), \quad \hat{\mathbf{P}}^B = f_B(\mathbf{P}^B, \theta^B), \tag{3}$$

where θ^A and θ^B denote parameters in $f_A(\cdot)$ and $f_B(\cdot)$.

Once the representation generation process is proposed, it is important to optimize the projection functions (i.e., $f_A(\cdot)$, $f_B(\cdot)$) efficiently as they determine whether domain-specific representations are accurately projected to the common space and whether the generated domain-invariant representations are effective. For this purpose, we propose an *aligned strategy* and a *cycle strategy* to generate extra self-supervision signals to enhance model learning.

In the following, we will describe the aligned strategy and the cycle strategy in detail.

4.2.1 The aligned strategy

Under the scenarios of cross-domain recommendations, some users may have interactions in both domains who are called overlapping users. As the forward projection process projects user domain-specific representations to a common space, domain-invariant representations of corresponding overlapping users should be consistent since domain-invariant interests of the same user are fixed. Based on this, we propose the aligned strategy which generates extra self-supervision signals by forcing the distance between overlapping users' two domain-invariant representations to be as close as possible.

We first distinguish overlapped users $\mathcal{U}_c$ from the total user sets $\mathcal{U}^A, \mathcal{U}^B$. For each overlapped user $u_c \in \mathcal{U}_c$, her domain-specific representations in each domain are denoted as $\mathbf{p}_{u_c}^A \in \mathbf{P}^A$ and $\mathbf{p}_{u_c}^B \in \mathbf{P}^B$. After the forward projection process, the two resulting domain-invariant representations transformed by $f_A(\cdot)$ and $f_B(\cdot)$ are denoted as $\hat{\mathbf{p}}_{u_c}^A \in \hat{\mathbf{P}}^A$ and $\hat{\mathbf{p}}_{u_c}^B \in \hat{\mathbf{P}}^B$ (the formulas are shown in equation (3)). Then, we denote the generated extra self-supervision signals from the overlapped users $\mathcal{U}_c$ as $\mathcal{L}_c$, which is formulated as:

$$\mathcal{L}_c = \sum_{u_c \in \mathcal{U}_c} \|\hat{\mathbf{p}}_{u_c}^A - \hat{\mathbf{p}}_{u_c}^B\|_2, \tag{4}$$

where $\|\cdot\|_2$ is the $L2$ normalization. $\mathcal{L}_c$ can then perform as extra constrains for model training.

However, the degree of user overlapping is always limited in real scenarios and most users are non-overlapped. For non-overlapped users who make up the majority of datasets, as they exist in a single domain, they only have one domain-specific representation in a domain. Therefore, the aligned strategy is not applicable. Simply utilizing overlapped users to generate self-supervision signals is insufficient to optimize the projection functions effectively. We further propose a cycle strategy to generate extra self-supervision signals from non-overlapped users.

4.2.2 The cycle strategy

Through the forward projection process, user domain-specific representations are projected from domain-specific spaces to a common space. As the functionality of projection functions during this process can be seen as removing domain-dependent effects from domain-specific representations, the inverse functions can be viewed as injecting domain-related influence into domain-invariant representations. Based on the idea of back-projection [32, 33], we propose to generate self-supervision signals by making the reversely projected domain-invariant representations of non-overlapped users to be consistent with their original domain-specific representations.

Analogous to the forward projection process constituted by the projection functions, we call the process corresponding to the inverse projection functions backward projection process. Since the backward projection process and the forward projection process form a circle, this strategy is called the circle strategy.

The set of non-overlapped users can be denoted as $\mathcal{U}_d^A = \mathcal{U}^A - \mathcal{U}_c$ and $\mathcal{U}_d^B = \mathcal{U}^B - \mathcal{U}_c$. For each non-overlapped user $u_d \in \mathcal{U}_d^A$ or $\mathcal{U}_d^B$, she has a domain-specific representation $\mathbf{p}_{u_d}^A \in \mathbf{P}^A$ or $\mathbf{p}_{u_d}^B \in \mathbf{P}^B$. After the forward projection process, the resulting domain-invariant representation in the common space can be denoted as $\hat{\mathbf{p}}_{u_d}^A \in \hat{\mathbf{P}}^A$ or $\hat{\mathbf{p}}_{u_d}^B \in \hat{\mathbf{P}}^B$. Denoting the inverse functions of $f_A(\cdot)$, $f_B(\cdot)$ as $f_A^{-1}(\cdot)$, $f_B^{-1}(\cdot)$, we formulate the extra self-supervision signals generated from non-overlapped users $\mathcal{U}_d^A$ and $\mathcal{U}_d^B$ as $\mathcal{L}_d$:

$$\mathcal{L}_d = \sum_{u_d \in \mathcal{U}_d^A} \|\mathbf{p}_{u_d}^A - f_A^{-1}(\hat{\mathbf{p}}_{u_d}^A)\|_2 + \sum_{\bar{u}_d \in \mathcal{U}_d^B} \|\mathbf{p}_{\bar{u}_d}^B - f_B^{-1}(\hat{\mathbf{p}}_{\bar{u}_d}^B)\|_2. \tag{5}$$

Through $\mathcal{L}_d$, the cycle strategy enables non-overlapped users to generate self-supervision signals from their own representations in each domain. Together with the aligned strategy, these two strategies jointly achieve the objective of utilizing both overlapped and non-overlapped users to generate extra signals. They further alleviate the problem arising from the small degree of user overlapping.

The projection functions $f_A(\cdot)$, $f_B(\cdot)$ can be different structures with inverse transformation. In our experiments, we utilize linear mappings as the projection functions, We show that by this simple structure, the proposed MRCDR model obtains an extremely high performance. It should be noted that the focus of this paper is to propose a framework to model relationships between domain-specific and domain-invariant interests with two strategies to generate extra self-supervision signals. Therefore, we leave the research of more complex structures for future work.

4.3 Prediction Layer

We omit superscripts as predictions are performed in both domains in the same way. After *the latent space projection layer*, for both overlapped and non-overlapped users, we obtain domain-specific representations $\mathbf{P}$ and domain-invariant representations $\hat{\mathbf{P}}$. We fuse them by concatenation and get final user representations $\tilde{\mathbf{P}} = [\mathbf{P} \oplus \hat{\mathbf{P}}]$. With item representations $\mathbf{Q}$ from *the embedding layer*, our model turns to predict an interaction score $\hat{y}_{u,i}$ between a given pair of user and item (u, i) based on their corresponding representations $\mathbf{p}_u \in \tilde{\mathbf{P}}$ and $\mathbf{q}_i \in \mathbf{Q}$.

To be general, we denote the prediction process as $\hat{y}_{u,i} = h(\mathbf{p}_u, \mathbf{q}_i)$ where $h(\cdot)$ is the prediction function and can be multilayer perceptron or other more complicated structures. We adopt a simple but effective and widely-used method, i.e., inner-product. The formula is as follows:

$$\hat{y}_{u,i} = \sigma(\mathbf{p}_u^T \mathbf{q}_i), \tag{6}$$

where σ is the sigmoid function.

4.4 Model Training

With representations of users and items, we compute a score $\hat{y}_{u,i}$ of interactions between a user and item pair (u, i). We opt for the widely used BPR loss [34, 35] which is based on the assumption that observed interactions, which are more reflective of user's preferences, should be assigned higher prediction scores than unobserved ones. The formula is as follows.

$$\mathcal{L}_{BPR} = -\sum_{(u,i,j)\in\mathcal{T}} log\sigma(\hat{y}_{u,i} - \hat{y}_{u,j}), \tag{7}$$

where $\mathcal{T} = \{(u,i,j)|(u,i) \in \mathcal{T}^+, (u,j) \in \mathcal{T}^-\}$ is the training set. $\mathcal{T}^+$ denotes the set of observed interactions between users and items, while $\mathcal{T}^-$ is the sampled unobserved interaction set. σ is the sigmoid function.

As our goal is to simultaneously make recommendations for users in both domains, following previous works [6, 11, 27], our model can be simplified into a unified multi-task model. Therefore, the BPR loss is a joint loss on domain A and domain B:

$$\begin{aligned}\mathcal{L}_{BPR}^{all} &= \mathcal{L}_{BPR}^{A} + \mathcal{L}_{BPR}^{B} \\ &= -\sum_{(u,i,j)\in\mathcal{T}^A} log\sigma(\hat{y}_{u,i}^{A} - \hat{y}_{u,j}^{A}) - \sum_{(u,i,j)\in\mathcal{T}^B} log\sigma(\hat{y}_{u,i}^{B} - \hat{y}_{u,j}^{B})\end{aligned} \tag{8}$$

As mentioned above, we have proposed two strategies to generate self-supervision signals for enhancing model training. The formulas are shown in equation (4) and (5). Totally, the loss function $\mathcal{L}_{all}$ is formulated as:

$$\mathcal{L}_{all} = \mathcal{L}_{BPR}^{all} + \mu_c(\frac{1}{|\mathcal{U}_c|}\mathcal{L}_c) + \mu_d(\frac{1}{|\mathcal{U}_d^A| + |\mathcal{U}_d^B|}\mathcal{L}_d) + \lambda\|\Theta\|_2^2, \tag{9}$$

where $|\mathcal{U}_c|$ is the number of overlapped users and $|\mathcal{U}_d^A|+|\mathcal{U}_d^B|$ is the total number of non-overlapped users. The weights μ_c and μ_d control the contribution of $\mathcal{L}_c$ and $\mathcal{L}_d$, respectively. Θ is the parameter set and we conduct $L2$ regularization on Θ parameterized by λ to prevent overfitting.

5 Experiments

We conduct extensive experiments on real-world datasets to answer the following six key questions:

- **Q1:** How does our approach outperform the state-of-the-art single-domain and cross-domain recommendation models? (see Section 5.2.1)
- **Q2:** How do the utilization of cross-domain information, the proposed two strategies (i.e., the aligned strategy and the cycle strategy), and the graph convolution operation, contribute to performance improvement of our model? (see Section 5.2.2)
- **Q3:** Can our proposed model effectively alleviate the performance degradation caused by data sparsity? (see Section 5.2.3)
- **Q4:** How does the proportion of overlapped users affect the performance of our model? (see Section 5.2.4)
- **Q5:** How do hyper-parameters (e.g., the embedding size, the learning rate, the parameter λ, and the parameter μ_c and μ_d) affect the performance of our model? (see Section 5.2.5)

Table 1 Experimental datasets and tasks

Dataset	Domain	#Users	#Items	#Interaction	sparsity
Amazon	Book	8714	10027	346262	99.61%
	CD	6709	10522	165013	99.61%
	Movie	4994	6573	271975	99.17%
	Music	5297	5827	56621	99.82%
	Cell	10295	10000	82534	99.92%
	Cloth	10266	10000	66393	99.94%
Douban	Movie	12629	10000	4346588	96.56%
	Music	9161	10000	949959	98.96%
	Book	11961	10000	789097	99.34%

Task	Dataset	Domains	#Common Users
task 1	Amazon	Book-CD	220
task 2		Movie-Music	745
task 3		Cell-Cloth	1383
task 4	Douban	Movie-Book	2459
task 5		Music-Book	2179
task 6		Movie-Music	3708

5.1 Experimental Settings

5.1.1 Dataset

In our experiments, two real-world datasets are adopted to evaluate the performance of MRCDR and baselines. The first dataset, the **Amazon**[1] dataset, is the most widely used dataset for cross-domain recommendation studies. We choose 6 domains for evaluation, i.e., "Books", "CDs and Vinyl", "Movies and TV", "Digital Music", "Cell Phones and Accessories", and "Clothing, Shoes and Jewelry" (referred to as "Amazon-Book", "Amazon-CD", "Amazon-Movie", "Amazon-Music", "Amazon-Cell", and "Amazon-Cloth"). The ratings of $4-5$ are treated as positive samples and thus convert the problem into implicit feedback recommendations. We retain users and items with at least 20 interactions in "Amazon-Book" and "Amazon-Movie". For the remaining four domains, the number of interactions is set to 5. Specifically, we reserve 10000 items in the "Amazon-Cell" and "Amazon-Cloth" domains. It should be noticed that, due to space limitations, we can not conduct experiments on all the 24 domains. However, among the 3 tasks we construct, there are two tasks with relatively similar domains (i.e., "Amazon-Book$\leftrightarrow$Amazon-CD" and "Amazon-Movie$\leftrightarrow$Amazon-Music"), and a task with very different domains (i.e., "Amazon-Cell$\leftrightarrow$Amazon-Cloth"). This makes the experimental results of our model convincing.

The second dataset is the **Douban** dataset crawled from the Douban website[2]. Douban is a popular online social network where users give ratings

[1] http://jmcauley.ucsd.edu/data/amazon/
[2] https://www.douban.com

to three types of items: movie, music, and book and form three domains of data denoted as "Douban-Movie", "Douban-Music", and "Douban-Book". We select users/items with at least 10 interactions and reserve 10000 items in each domain. We have made the Douban dataset we used public[3] to facilitate subsequent cross-domain recommendation studies.

The detailed statistics of the two datasets and our defined tasks are summarized in Table 1.

5.1.2 Evaluation Metric

We follow the *leave-one-out* evaluation protocol which is a widely used raking-based evaluation strategy [27, 33]. For each user, we reserve one interaction as the test item and determine hyper-parameters by randomly sampling another interaction as the validation set. The performance of the models is measured by two typical evaluation metrics, i.e., *Hit Ratio (HR)* and *Normalized Discounted Cumulative Gain (NDCG)*. $HR@N$ measures whether the test item is contained by the top-N item ranking list:

$$HR@N = \frac{1}{|U_t|} \sum_{i \in U_t} \delta(p_i \leq top\ N), \tag{10}$$

where U_t is the set of the test users. p_i is the hit position of the test item for the user i and $\delta(\cdot)$ is the indicator function. $NDCG@N$ measures the specific ranking quality that assigns high scores to hit at top position ranks:

$$NDCG@N = \frac{1}{|U_t|} \sum_{i \in U_t} \frac{log2}{log(p_i + 1)}, \tag{11}$$

For both $HR@N$ and $NDCG@N$, a higher value indicates better performance. In the experiments, we empirically set N to 5 and 10.

5.1.3 Comparison Methods

We compare MRCDR[4] with both state-of-the-art single-domain and cross-domain recommendation methods:

(1) Single-domain recommendation models

NeuMF: *Neural Matrix Factorization* [36] combines the linearity of matrix factorization and non-linearity of Deep Neural Networks for modeling user-item latent interactions.

NGCF: *Neural Graph Collaborative Filtering* [35] model the user-item interactions as a bipartite graph structure and integrate this structure into the embedding process to model the high-order connectivity information.

(2) Cross-domain recommendation models

[3] https://github.com/zangtianzi/Douban_Dataset
[4] We will release the code in the future.

CMF: *Collective Matrix Factorization* [5] jointly factorizes matrices of individual domains. Latent factors of overlapped entities are shared across domains.

CoNet: *Collaborative Cross Network* [6] enables dual knowledge transfer by introducing cross-connections from one base network to another and vice versa.

PPGN: *Preference Propagation GraphNet* [11] constructs a cross-domain preference matrix to model the cross-domain interactions. A propagation layer is used to capture the high-order information transition over the joint graph.

DTCDR: *Dual-Target Cross-Domain Recommendation* [27] shares the knowledge of common users across domains. For a fair comparison, we also consider only implicit feedback from users in this model, not other auxiliary information.

BiTGCF: It is a bi-directional transfer learning model which uses graph collaborative filtering networks as the base model [8]. The feature propagation module borrows the idea from LightGCN to simplify the feature propagation model more reasonably.

ReCDR: *Relation Expansion based Cross-Domain Recommendation* [14] generate a whole cross-domain heterogeneous graph by connecting nodes having high embedding similarities. The cross-domain graph and single-domain graph are combined in the learning procedure.

Noted that we do not compare with the methods for cross-domain sequential recommendation [25, 37–39] and cold-start user recommendation [1–4, 15, 17], as our recommendation scenairos are different.

5.1.4 Experiment Setup

We implement MRCDR using Tensorflow and all experiments are conducted on an NVIDIA TITAN Xp GPU. In the embedding layer, we stack 2-layers graph convolution networks, which means that, for each user, we consider the information of neighbors within 2 hops. We chose the LeakyReLU activation function and the size of user/item representations is set to 64. We adopt the mini-batch gradient descent optimization method and set the batch size to 1024. For the loss function, the weight μ of $\mathcal{L}_c$ and $\mathcal{L}_d$ is set to 0.01 while λ is set to 0.001. We utilize Adam optimizer and set the learning rate to 0.001. For the baselines, we tune the parameters to get the best performance.

5.2 Experimental Results

5.2.1 Performance comparison

Due to space limitation, we only show experimental results on $HR@5$, $HR@10$, and $NDCG@10$ (Abbreviated as $H@5$, $H@10$, and $N@10$) in Table 2 and Table 3.

As we can see, in general, cross-domain recommendation methods perform better than single-domain recommendation methods (i.e., NeuMF) as

Table 2 Performance comparisons between MRCDR and baselines on the Amazon dataset. Best baselines are underlined. $\star$ indicates the statistical significance for $p \leq 0.01$ compared with the best baseline method based on the paired t-test.

	Metric	NeuMF	NGCF	CMF	CoNet	PPGN	DTCDR	BiTGCF	ReCDR	MRCDR	Improv.
Book-CD	H@5	0.5188	0.6488	0.5793	0.5845	0.6611	0.6452	0.6947	0.7205	**0.8029***	**11.44%**
	H@10	0.6979	0.7968	0.7553	0.7700	0.8129	0.8007	0.8165	0.8348	**0.9042***	**8.31%**
	N@10	0.4522	0.5029	0.4687	0.4637	0.5354	0.5258	0.5781	0.6017	**0.6792***	**12.88%**
	H@5	0.4779	0.6102	0.5824	0.5484	0.6486	0.6239	0.6869	0.7033	**0.7974***	**13.38%**
	H@10	0.6143	0.7871	0.7262	0.6698	0.7968	0.7827	0.8073	0.8196	**0.8863***	**8.14%**
	N@10	0.3890	0.4954	0.4744	0.4769	0.5138	0.4931	0.5583	0.5769	**0.6679***	**15.77%**
Movie-Music	H@5	0.4980	0.5534	0.4988	0.5639	0.5670	0.4072	0.4969	0.5978	**0.6527***	**3.28%**
	H@10	0.6399	0.6573	0.6419	0.7128	0.6710	0.6013	0.6327	0.7306	**0.7801***	**6.78%**
	N@10	0.4004	0.4461	0.4123	0.4591	0.4684	0.3084	0.4034	0.4877	**0.5409***	**10.91%**
	H@5	0.5191	0.5368	0.5032	0.5619	0.5535	0.5788	0.6483	0.6695	**0.7640***	**14.12%**
	H@10	0.6581	0.6775	0.6476	0.6932	0.6934	0.7734	0.7782	0.7963	**0.8570***	**7.62%**
	N@10	0.4331	0.4357	0.4155	0.4748	0.4578	0.4692	0.5543	0.5824	**0.6625***	**13.75%**
Cell-Cloth	H@5	0.4666	0.5508	0.4590	0.5073	0.5785	0.4879	0.5938	0.6217	**0.6725***	**8.17%**
	H@10	0.5795	0.6847	0.5874	0.6683	0.7081	0.6213	0.7207	0.7428	**0.8005***	**7.77%**
	N@10	0.3798	0.4463	0.3786	0.4106	0.4538	0.3952	0.4823	0.5094	**0.5578***	**9.50%**
	H@5	0.4471	0.4937	0.3346	0.5411	0.5413	0.4688	0.5634	0.5893	**0.6241***	**5.91%**
	H@10	0.5615	0.6308	0.4381	0.6776	0.6802	0.5892	0.6825	0.6985	**0.7563***	**8.27%**
	N@10	0.3483	0.3812	0.2834	0.3989	0.4497	0.3441	0.4693	0.4814	**0.5165***	**7.29%**

they utilize information from other domains. Benefiting from the effectiveness of graph convolution operation, NGCF gets excellent performance even better than some cross-domain recommendation methods (i.e., CMF and DeepAPF). Moreover, the graph convolution-based methods (i.e., NGCF, PPGN, BiTGCF, and ReCDR) generally obtain competitive performance, which demonstrates the effectiveness of graph convolution operations in capturing high-order complex dependencies between users/items and generating effective representations. The deep dual knowledge transfer-based methods (i.e., CoNet, DDTCDR, and BiTGCF) generally perform well which shows the rationality of dual knowledge transfer. Benefiting from both the advantages of graph convolution operation and dual knowledge transfer, BiTGCF obtains the best performance among them. However, BiTGCF does not explicitly model users' domain-invariant and domain-specific interests. It also only depends on overlapping users to perform knowledge transfer between domains. When compared with our proposed model, the performance of BiTGCF decreases by an average of 14.23%, 10.65%, and 14.82% on $HR@5, HR@10$, and $NDCG@10$, respectively. ReCDR obtains the best performance among the baselines in all the cases. It further verifies the effectiveness of graph convolution operations in generating effective representations. Its excellent performance also benefits from effective modeling of both user domain-invariant interests in a cross-domain graph and user domain-specific interests in single-domain graphs.

Our proposed MRCDR model gets the best performance in all tasks on all matrices which extremely demonstrates the validity of our design. We see the average improvement on the Amazon dataset is 9.38%, 7.82%, and 11.68%

Table 3 Performance comparisons between MRCDR and baselines on the Douban dataset. Best baselines are underlined. $\star$ indicates the statistical significance for $p \leq 0.01$ compared with the best baseline method based on the paired t-test.

	Metric	NeuMF	NGCF	CMF	CoNet	PPGN	DTCDR	BiTGCF	ReCDR	MRCDR	Improv.
Movie-Book	H@5	0.4458	0.5285	0.4399	0.4892	0.5639	0.5231	0.5524	0.5699	**0.5865***	**2.91%**
	H@10	0.6092	0.6940	0.5947	0.6525	0.7128	0.6768	0.7133	0.7203	**0.7513***	**2.23%**
	N@10	0.3652	0.4277	0.3545	0.3836	0.4591	0.4217	0.4476	0.4615	**0.4772***	**3.40%**
	H@5	0.4999	0.5277	0.4488	0.5216	0.5619	0.5182	0.5796	0.6027	**0.6577***	**9.13%**
	H@10	0.6481	0.6696	0.5950	0.6417	0.6932	0.6693	0.7171	0.7387	**0.7910***	**7.08%**
	N@10	0.4138	0.4223	0.3729	0.4092	0.4748	0.4209	0.4763	0.5008	**0.5492***	**15.31%**
Music-Book	H@5	0.4980	0.5534	0.4988	0.5639	0.5670	0.5703	0.5982	0.6127	**0.6527***	**6.53%**
	H@10	0.6399	0.6573	0.6419	0.7128	0.6710	0.7024	0.7220	0.7443	**0.7801***	**4.81%**
	N@10	0.4004	0.4461	0.4123	0.4591	0.4684	0.4697	0.4986	0.5201	**0.5409***	**4.00%**
	H@5	0.5191	0.5368	0.5032	0.5619	0.5535	0.5523	0.5809	0.6017	**0.6648***	**10.49%**
	H@10	0.6581	0.6775	0.6476	0.6932	0.6934	0.6891	0.7075	0.7243	**0.7868***	**8.63%**
	N@10	0.4331	0.4357	0.4155	0.4748	0.4578	0.4465	0.5012	0.5186	**0.5537***	**6.77%**
Movie-Music	H@5	0.4779	0.5624	0.4509	0.5641	0.5658	0.5638	0.5882	0.6033	**0.6431***	**6.60%**
	H@10	0.6381	0.7334	0.6126	0.7429	0.7267	0.7304	0.7507	0.7689	**0.8089***	**5.20%**
	N@10	0.3965	0.4583	0.3691	0.4604	0.4573	0.4598	0.4763	0.4825	**0.5176***	**7.27%**
	H@5	0.5007	0.5556	0.4948	0.5432	0.5395	0.5267	0.5641	0.5890	**0.6398***	**8.62%**
	H@10	0.6597	0.6866	0.6393	0.6868	0.6852	0.6711	0.7088	0.7197	**0.7745***	**7.61%**
	N@10	0.4133	0.4457	0.4044	0.4502	0.4413	0.4325	0.4665	0.4844	**0.5219***	**7.74%**

while on the Douban dataset is 7.38%, 5.93%, and 7.42% on HR@5, HR@10, and $NDCG$@10, respectively. To investigate the statistical significance of our proposed model, we perform paired t-test between MRCDR and the best baseline method (i.e., ReCDR). From the experiment, we conclude that not only does MRCDR outperform the other methods by a large margin, but also the margin is statistically significant.

5.2.2 Ablation study

To further validate the effectiveness of our design, we perform ablation studies and propose four variants of MRCDR: (1) MRCDR-gcn is a variant without the graph convolution operation in the embedding layer and randomly initializes a vector as the representation for each user and item. (2) MRCDR-cycle is a variant without the cycle strategy which only leverages the extra signals generated from overlapping users to enhance the training of the model. (3) MRCDR-align is a variant without the aligned strategy which is realized by setting $\mu_c = 0$. (4) MRCDR-ssl is a variant without the two self-supervised learning based strategies.

As we can see from Table 4, after removing the graph convolution operation, MRCDR-gcn gets a significant performance decrease. The performance (i.e., MRCDR vs MRCDR-gcn) is reduced by an average of 35.44%, 23.58%, and 38.77% on HR@5, HR@10, NDCG@10, respectively. This verifies the importance of graph convolution operations in generating effective embeddings which is consistent with the conclusion from Table **??**. Removing the aligned strategy from the complete model (i.e., MRCDR vs MRCDR-align) results in

Table 4 Results of ablation study on the Amazon dataset.

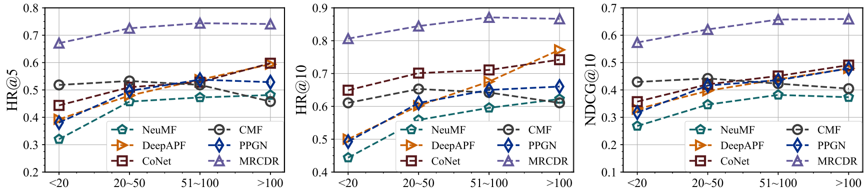
Metric	**HR@5**	**HR@10**	**NDCG@10**	**HR@5**	**HR@10**	**NDCG@10**
Variants	Amazon-Movie			Amazon-Music		
MRCDR-gcn	0.4002	0.5568	0.3274	0.5802	0.7103	0.4992
MRCDR-align	0.5384	0.6960	0.4410	0.7223	0.8236	0.6110
MRCDR-cycle	0.5588	0.7104	0.4577	0.7402	0.8444	0.6334
MRCDR-ssl	0.4124	0.5631	0.3328	0.6027	0.7375	0.5385
MRCDR	**0.5824**	**0.7264**	**0.4783**	**0.7640**	**0.8670**	**0.6625**

performance reduction by an average of 5.23%, 3.40%, and 6.55% on HR@5, HR@10, NDCG@10, respectively. Removing the cycle strategy (i.e., MRCDR vs MRCDR-cycle) results in performance reduction by an average of 2.88%, 1.75%, and 3.88%. This shows the effectiveness of the cycle strategy that acts as a supplement to make up for the insufficient number of overlapping users. When we remove both the aligned strategy and the cycle strategy (i.e., MRCDR-ssl), the performance degradation is significant. The performance of MRCDR-ssl is reduced by an average of 28.55%, 17.16%, and 32.97%. This suggests that at least one of the two strategies should be retained in order to ensure that the model learns relatively effective representations of user interests and thus achieves satisfactory performance. Our proposed MRCDR model outperforms all the variants, which can be concluded that all of our designs including the graph convolution operation and two strategies are effective in improving the accuracy of recommendation.

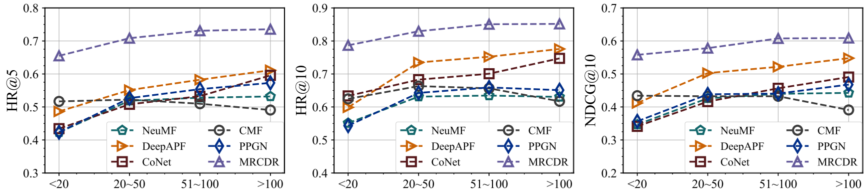
5.2.3 Data sparsity problem

In this experiment, we explore whether our proposed MRCDR model can effectively alleviate the data sparsity problem. Specifically, we divided users into four groups based on the number of interactions: fewer than 20 interactions, more than 20 interactions and less than 50 interactions, more than 51 interactions and less than 100 interactions, and more than 100 interactions. We take the "Douban-Music↔Douban-Book" task as an example. The proportion of users in each group is 33.63%, 51.88%, 11.24%, and 3.25% for the Music domain while 50.92%, 35.32%, 8.52%, 5.24% for the Book domain. Experimental results are drawn in Fig. 2.

From the results, we can see that, in general, the increase in the number of interactions leads to the improvement of recommendation performance. Compared with other methods, NeuMF performs significantly worse when the data is sparse which shows the inferiority of single-domain recommendation methods in the case of sparse data. Another important observation is that while some of the cross-domain recommendation models (e.g., DeepAPF and CoNet) perform satisfactorily when the number of user interactions exceeds one hundred, our proposed model achieves good results even when the number of user interactions is small. For the first two groups of users, the improvement is



(a) Performance on the Douban-Music.



(b) Performance on the Douban-Book.

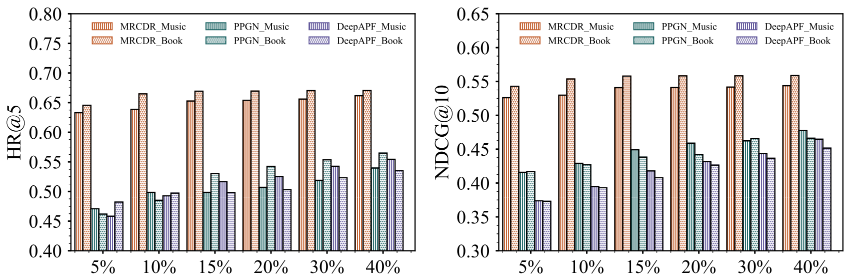
Fig. 2 Performance of MRCDR and baselines on user groups with different number of interactions.

more evident and meaningful. Since most users have few interaction records in real scenarios (i.e., about 80% users have fewer than 50 interactions.), the MRCDR model has more practical application significance.

5.2.4 Effects of the proportion of overlapped users

In this experiment, we investigate how the proportion of overlapped users affects the performance of MRCDR and the other two baselines (i.e., PPGN and DeepAPF) on the "Douban-Music↔Douban-Book" task and present the results in Fig. 3.

As we can see, under all six experimental settings, our proposed MRCDR model outperforms the other two baselines. As the proportion of overlapped users increases, the performance of PPGN and DeepAPF obviously improves. This is because these two methods all treat overlapped users as bridges to link two domains and share information across domains. A larger proportion of overlapped users enable them to learn more information from another domain. The performance of MRCDR is stable under different experimental settings, which indicates that our model can learn the information of overlapped users and non-overlapped users evenly. When the proportion of overlapped users is small (i.e., 5%), MRCDR will learn more information from non-overlapped users according to the cycle strategy. As the proportion of overlapped users increases, the aligned strategy begins to play a more and more important role. Such an observation is consistent with the conclusion from the ablation study which demonstrates the effectiveness of our design that simultaneously utilizes overlapped and non-overlapped users in generating self-supervision signals.



(a) (b)

Fig. 3 The effects of proportion of overlapped users on the "Douban-Music↔Douban-Book" task.

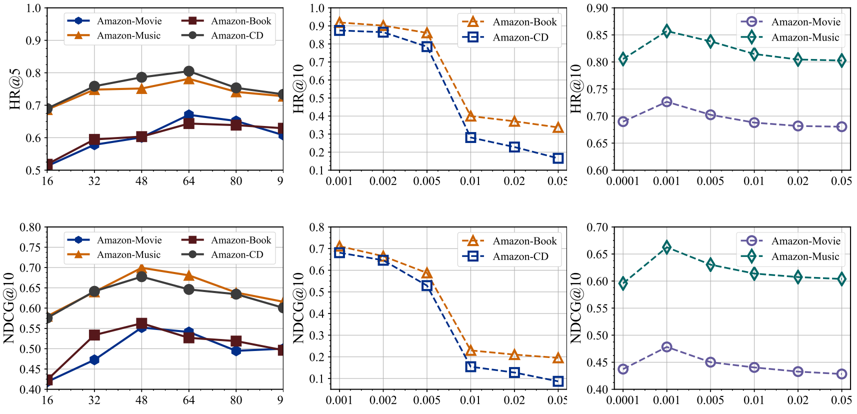
5.2.5 Effects of the hyperparameters

To demonstrate the stability and robustness of our proposed MRCDR model, in this section, we investigate the effects of hyperparameters.

Effects of the embedding size. We first investigate the effects of the embedding size (i.e., the length of the user/item representations). Taking two CDR tasks on the Amazon dataset as examples, we range the embedding size within $\{16, 32, 48, 64, 80, 96\}$ and plot the changes of $HR@5$ and $NDCG@10$ in Fig. 4(a). We can see that, in the beginning, as the embedding size increases, both $HR@5$ and $NDCG@10$ increase. This may be because a relatively large size improves the representation ability of embeddings. However, when the embedding size is larger than a threshold (64 for $HR@5$ and 48 for $NDCG@10$), both $HR@5$ and $NDCG@10$ begin to decline, which may be caused by the overfitting of the model. In our experiments, we set the embedding size to 64. Although the performance of MRCDR slightly fluctuates with different embedding sizes, it is still consistently better than other baselines, which demonstrates the robustness of our design.

Effects of the learning rate. We then investigate the effects of the learning rate. Taking the "Amazon-Book↔Amazon-CD" task as an example, we set the learning rate as $\{0.001, 0.002, 0.005, 0.01, 0.02, 0.05\}$, respectively, and plot the changes of $HR@10$ and $NDCG@10$ in Fig. 4(b). We can see that, in general, a small learning rate results in relatively better recommendation performance. The model performs best when the learning rate is set to 0.001. However, a smaller learning rate will lead to slower convergence of the model and longer training time. It is important to make a balance between model performance and training efficiency. In our experiments, we set the learning rate to 0.002.

Effects of the regularization parameter λ. We also investigate the effects of λ which controls the contribution of the parameter regularization term to the whole loss function. Taking the "Amazon-Book↔Amazon-CD" task as an example, we range λ within $\{0.0001, 0.001, 0.005, 0.01, 0.02, 0.05\}$ and show the experimental results in Fig. 4(c). We can see that at the beginning, with the



(a) Embedding size. (b) Learning rate. (c) λ.

Fig. 4 Effects of the hyperparameters.

increase of λ, the performance of the model increases. When λ is greater than 0.001, the accuracy of the model begins to decrease. This may be because a too-small λ makes the parameter regularization term have little influence on the model, so it cannot effectively prevent the over-fitting problem. In contrast, a too-large λ will lead to the under-fitting problem of the model. Therefore, in our experiments, λ is set to 0.001.

Table 5 Effects of different settings of μ_c and μ_d.

Parameter settings	HR@5	HR@10	NDCG@10	HR@5	HR@10	NDCG@10
$\mu_c = 0.01, \mu_d = 0.02$	0.7836	0.8770	0.6602	0.7785	0.8652	0.6585
$\mu_c = 0.01, \mu_d = 0.05$	0.7910	0.8899	0.6695	0.7868	0.8731	0.6633
$\mu_c = 0.02, \mu_d = 0.01$	0.7960	0.8967	0.6771	0.7898	0.8803	0.6642
$\mu_c = 0.05, \mu_d = 0.01$	0.7929	0.8894	0.6690	0.7501	0.8593	0.6292
$\mu_c = 0.01, \mu_d = 0.01$	**0.8029**	**0.9042**	**0.6792**	**0.7974**	**0.8863**	**0.6679**
$\mu_c = 0.02, \mu_d = 0.02$	0.7988	0.8968	0.6637	0.7889	0.8848	0.6564
$\mu_c = 0.05, \mu_d = 0.05$	0.7961	0.8917	0.6571	0.7858	0.8825	0.6508
$\mu_c = 0.1, \mu_d = 0.1$	0.7851	0.8824	0.6459	0.7784	0.8706	0.6381
$\mu_c = 0.2, \mu_d = 0.2$	0.7788	0.8811	0.6399	0.7672	0.8673	0.6358
$\mu_c = 0.5, \mu_d = 0.5$	0.7721	0.8798	0.6393	0.7619	0.8627	0.6308

Effects of the parameters μ_c and μ_d. We finally investigate the effects of μ_c and μ_d which determine the contribution of L_c and L_d to the whole loss function, respectively. The experimental results are shown in Table 5. From the results, we can see when $\mu_c = \mu_d = 0.01$, our model achieves the best performance on all three metrics. This shows that the generated extra self-supervision signals from overlapping users and non-overlapping users have equal importance. With the increase of μ_c or μ_d, the performance of the model begins to decline. When they are bigger than 0.05, the accuracy of the model decreases significantly. This may be because that μ_c and μ_d control the magnitudes of L_c and L_d. L_{BPR}, L_c, and L_d have different magnitudes. Therefore, in our experiments, we set $\mu_c = \mu_d = 0.01$ to represent the equally important influences of L_c and L_d, respectively.

6 Conclusion and Future Work

In this paper, we focus on the Cross-Domain Recommendation (CDR) problem in the case of partially overlapped users without requiring any auxiliary information. We propose a model named MRCDR that explicitly models the bi-directional transformation relationships between user domain-specific interests and domain-invariant interests. The domain-specific representations of users are projected to a common space to generate domain-invariant representations. To obtain more effective representations, an aligned strategy and a cycle strategy are proposed to generate self-supervision signals as extra constraints for model training. These two strategies alleviate the problem arising from the small degree of user overlapping of two domains.

Our proposed model can easily incorporate side information (e.g., comments, user profiles, and item attributes). Such information can help to generate more semantic representations of users and items, thus improving the recommendation performance of our proposed models. Our research explores the idea of generating extra self-supervision signals from both overlapping users and non-overlapping users. It effectively overcomes the inefficiency of most existing works in learning representations, which only leverage user-item interaction data as supervision signals. In the future, we will research more efficient projection functions, such as deep neural networks, to further improve the recommendation performance. We will also try to explore to generate more useful self-supervision signals for cross-domain recommendation.

7 Declarations

7.1 Ethical Approval and Consent to participate

Not applicable.

7.2 Human and Animal Ethics

Not applicable.

7.3 Consent for publication

All authors whose names appear on the submission

1) made substantial contributions to the conception or design of the work; or the acquisition, analysis, or interpretation of data; or the creation of new software used in the work;

2) drafted the work or revised it critically for important intellectual content;

3) approved the version to be published; and

4) agree to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

7.4 Availability of supporting data

The Amazon dataset used in this paper is downloaded from http://jmcauley.ucsd.edu/data/amazon/.

The Douban dataset used in this paper is crawled from the Douban website https://www.douban.com and is available at https://github.com/zangtianzi/Douban Dataset.

7.5 Competing Interests

The authors declare that they have no competing interests.

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7.7 Authors' contributions

Tianzi Zang designed this method and wrote the first draft of the manuscript. Yanmin Zhu sponsored the research. Ruohan Zhang conducted experiments and prepared Table 1-3. Jing Zhu performed the material preparation. Feilong Tang reviewed the manuscript. All authors commented on previous versions of the manuscript. All authors read and approved the final manuscript

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