C^2DR: Robust Cross-Domain Recommendation based on Causal Disentanglement

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ABSTRACT

Cross-domain recommendation aims to leverage heterogeneous information to transfers knowledge from a data-sufficient domain (source domain) to a data-scarce domain (target domain). Existing approaches mainly ignore the modeling of users' domain specific preferences on items. We argue that incorporating domain-specific preferences from the source domain will introduce irrelevant information that fails to the target domain. Additionally, directly combining domain-shared and domain-specific information may hinder the target domain's performance. To this end, we propose C^2DR, a novel approach that disentangles domain-shared and domain-specific preferences from a causal perspective. Specifically, we formulate a causal graph to capture the critical causal relationships based on the underlying recommendation process, explicitly identifying domain-shared and domain-specific information as causal irrelevant variables. Then, we introduce disentanglement regularization terms to learn distinct representations of the causal variables that obey the independence constraints in the causal graph. Remarkably, our proposed method enables effective intervention and transfer of domain-shared information, thereby improving the robustness of the recommendation model. We evaluate the efficacy of C^2DR through extensive experiments on three real-world datasets, demonstrating significant improvements over state-of-the-art baselines. The code is available at: https://github.com/KongMLin/C2DR.

CCS CONCEPTS

• **Information systems → Recommender systems**.

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KEYWORDS

Cross-Domain Recommendation; Knowledge Transfer ; Causal Disentanglement

1 INTRODUCTION

Personalized recommendation systems play a crucial role in the evolution of various online applications, including e-commerce [13], search engines [19] and conversational systems [6]. Numerous recommender models have been developed based on the use of rich information captured from historical user interactions [5]. However, the scarcity of user-item interaction records often poses a challenge in accurately identifying user preferences [11]. Additionally, traditional recommendation systems encounter difficulties for new users who have no any prior interaction history, giving rise to the prevalent cold-start problem [2]. With users increasingly participating in multiple domains, there is a potential to utilize information from different domains to alleviate the challenges of data sparsity and cold start [3]. This insight has led to the development of the Cross-Domain Recommendation (CDR).

In the CDR family, previous works can be divided into two main branches based on their approaches to transferring knowledge between domains. (1) Transfer Learning-based approaches focus on leveraging the knowledge learned in the source domain to improve recommendation performance in the target domain [8, 24]. In particular, feature-based transfer learning [7, 36] transfers useful features by mapping or sharing the feature space between the two domains. Model-based transfer learning [1] is initially trained in the source domain and then fine-tuned or adapted to the target domain using shared information (e.g., overloaded users or items). (2) Shared representation learning-based approaches aim to learn a common latent space that captures the intrinsic relationships between users and items across domains. Typically, matrix factorization-based methods [14] factorize the interaction matrices of the user-item
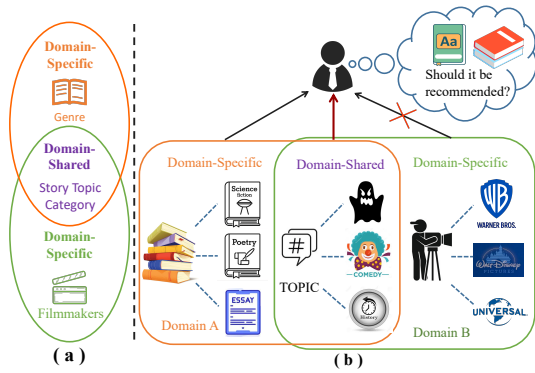
Figure 1: (a): An example of user preferences in Book and Film domain. (b): C^2DR **utilizes disentangled domain-shared information and domain-specific factors for recommendations.**

from the source and target domains into a shared low-dimensional latent space. Some works [10, 12] utilize deep neural networks to learn complex, non-linear representations of users and items across domains. They can automatically extract and transfer high-level features, such as item content or user behavior patterns, from the source to the target domain.

In retrospect, the aforementioned technical frameworks have demonstrated promising results within their respective branches. It becomes evident that existing approaches often place excessive emphasis on the assumption of domain in-variance [1, 2], presuming that the data distribution remains unchanged in each domain. However, this assumption can be problematic, as the characteristics and distributions of user/item data can vary significantly across domains. Consequently, blindly transferring knowledge without accounting for these differences can result in transferring the irrelevant information. Motivated by recent progress [27], we further consider a challenging question in CDR: What information should be transferred? We recognize that user preferences are expressed through distinct behaviors in different domains, transferring **domain-shared information** can yield positive effects for other domains, while transferring **domain-specific information** may introduce negative transfer issues. To illustrate this point, we provide a toy example in Figure 1, consisting of two domains: "Film" and "Book," each containing several **domain-shared information** and **domain-specific information**. Intuitively, shared user preferences such as "Story Topic" and "Category" are domain-invariant. This suggests that a user's taste in these preferences is likely to be similar and stable across multiple domains. On the other hand, specific user preferences such as "Filmmakers" and "Literary Genre" provide precise intra-domain information that does not contribute to other domains. Therefore, the optimal approach is to capture and transfer the most relevant factors, specifically the **domain-shared information**, to boost recommendations in other domains.

In this paper, we explore the disentanglement of domain information from a fundamental perspective — causality, which has received little scrutiny in recommender systems. We try to elucidate how domain-share and domain-specific information serves as causal variables to influence the effects observed across and within individual domains. To achieve this, we propose an innovative

causal-based framework called C^2DR for robust cross-domain recommendation. Our approach begins by constructing a causal graph that provides insights into the important causal connections that identified casual variables affect the recommendation outcomes. Furthermore, we develop multiple encoders to learn causal representations for specific items, as well as users' domain-specific interests within each domain and the domain-shared information across domains. To disentangle these causal representations, C^2DR employs a domain classifier with a gradient reverse layer (GRL) to extract domain-shared information and reweight the representation space, allowing the separation of a user's domain-specific interests within each domain. Ultimately, C^2DR ensures that the gradients of individual domain loss functions, regarding the representation of domain-shared information, are mutually orthogonal. This orthogonal property facilitates effective intervention and transfer of the causal variables, thereby enhancing the recommendation system's resilience to fluctuations in user behavior or preferences.

2 RELATED WORK

2.1 Cross-Domain Recommendation

Cross-domain recommendation (CDR) addresses data sparsity by leveraging overlapping user or item information from source domains [34]. This enhances performance in the target domain even with limited data. CDR methods can be broadly categorized into three groups: **Collective Matrix Decomposition:** JCSL[18] employs a similarity matrix based on clustering and overlapping users for regularization. **Embedding and Mapping:** EMCDR [24] combines matrix factorization and Bayesian personalized ranking using a nonlinear mapping function based on a multi-layer perceptron. SSCDR[8] exploits overlapping users and items from the source domain to train the mapping function. **Deep Knowledge Transfer:** CSN [15] combines feature maps in a high-dimensional space for bidirectional knowledge transfer. CoNet [7]introduces cross-connection units and a shared transfer matrix for fine-grained and sparse knowledge transfer, though it can lead to negative transfers. A recent approach, MADD [31], presents the domain disentanglement framework, using the attention mechanism to disentangle raw user embeddings into domain-invariant and domain-specific features, but is sensitive to training strategies.

2.2 Causal Inference in Recommender System

Causal inference has gained significant attention in the construction of robust machine learning models, including its application to recommendation systems. A comprehensive framework for conducting causal analysis in recommendation systems is presented in [29]. Various specific applications within recommendation systems have utilized causal inference techniques. Schnabel [21] introduces the inverse propensity score (IPS) method to handle missing-at-random data. Wang et al. [26] propose the dual robust (DR) estimator and joint optimization method to address large variance in the IPS method. Causal inference techniques have also been used to mitigate bias in recommendation systems [25, 32]. Yuan et al. [30] tackle position bias in click-through rate (CTR) prediction using a multi-valued treatment approach. Sato et al. [20] discuss user self-selection bias and highlighted biased estimates even with varying sample sizes. Wei et al. [28] leverage counterfactual reasoning to

eliminate popularity bias. Another relevant work [27] uses general knowledge from multiple source domains to improve performance in the target domain. Building upon these findings, we further leverage the structure causal model to develop a robust cross-domain recommendation (CDR) approach.

3 PRELIMINARY

In this research work, we consider a generalized Cross-Domain Recommendation (CDR) scenario involving two domains that have a common set of users. The data from the source domain is denoted as $\mathcal{D}^B = (\mathcal{I}^B, \mathcal{U}^B, \mathcal{Y}^B)$, and the data from the target domain is denoted as $\mathcal{D}^A = (\mathcal{I}^A, \mathcal{U}^A, \mathcal{Y}^A)$. Here, $\mathcal{I}$, $\mathcal{U}$, and $\mathcal{Y}$ represent the item set, user set, and interaction set, respectively, for each domain. Specifically, we have $\mathcal{U}^A \subseteq \mathcal{U}^B$ and $I^B \cap I^A = \emptyset$. User input features are denoted as $f_u^A \in \mathcal{X}$ and $f_u^B \in \mathcal{X}$ for the target and source domains, respectively. Item input features are denoted as $f_i^A \in \mathcal{X}$ and $f_i^B \in \mathcal{X}$ in their respective domains, where $\mathcal{X}$ denotes the feature space. Given the observed interactions matrices $\mathcal{Y}^B \in \{0,1\}^{|\mathcal{I}^B| \times |\mathcal{U}^B|}$ and $\mathcal{Y}^A \in \{0,1\}^{|\mathcal{I}^A| \times |\mathcal{U}^A|}$ in both domains, where each element A_{ij}, B_{ij} indicates whether user $i \in U$ has interacted with item $j \in I$ in the interaction set $\mathcal{Y}$, the goal of our C^2DR model is to learn disentangled representations of domain-shared information X, domain-specific information $\mathcal{X}_*$, and item representations $\mathcal{I}_*$ in both domains, where $* \in \{A, B\}$ [1]. By transferring the domain-shared representations X, we aim to enhance the recommendation performance in both domains.

4 METHODOLOGY

In this section, we first detail the causal view of the cross-domain recommendation process, followed by its rationality for disentangling domain-specified and domain-shared information. Then, we introduce the proposed C^2DR framework.
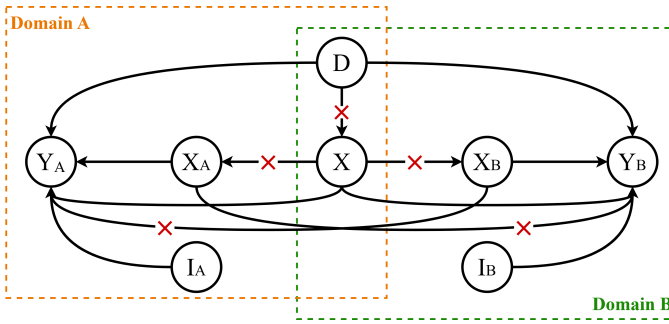
Figure 2: Cross domain recommendation casual graph. This cutting off of edges represents the elimination of causal relationships.

4.1 Causal Look at CDR

Causal Graph. The causal graph is a directed acyclic graph denoted as $G = V, E$, where V represents the set of variables, and E denotes the causal relations among variables [17]. In the causal graph, a

capital letter (e.g., X) signifies a variable, while a lowercase letter (e.g., x) represents its observed value. An edge in the graph indicates that the ancestor node is a cause (X_A), and the successor node is an effect (Y_A). To begin, we abstract the causal graph of most existing cross-domain recommendation models, as illustrated in Figure 2. In this representation, (D) corresponds to the domain indicator, which is modeled as a binary variable in our task. (X) represents the embedding of the domain-shared interest (e.g., a user who enjoys love stories tends to watch romantic movies). (X_A) signifies the embedding of the user's domain-specific interest in domain A (e.g., a user who appreciates horror movies may also read a significant amount of poetry). (I_A) denotes the embedding of a specific item in domain A. Finally, (Y_A) represents the ranking score in domain A. It is important to note that the example provided here for domain A holds true for domain B as well.

Causal Relationships. Let us now elucidate the causal relationships within the causal graph, where the paths $\{D, X_A, X, I_A\} \rightarrow Y_A$ represent the direct effects of the domain indicator, user-related factors (i.e., domain-shared interest and user's domain-specific interest), and item on the ranking score. Specifically, among the variables D, X_A, X, I_A, the domain-shared information X should be independent of the domain-specific information X_A. Considering that the domain-shared information X represents high-level preferences that remain constant across domains, X should be independent of the domain indicator D. Moreover, it is crucial to avoid transferring domain-specific information to different domains (e.g., $X_B \rightarrow Y_A$), as such transfers may result in negative effects on the recommendation process and impair accurate estimation of the ranking score. To summarize the causal relationships in the causal graph, we have the following key operations:

Domain-shared information extraction: We ensure that the domain-shared interest representations, denoted by X, remain independent of the domain indicator D. This independence indicates that the distribution of domain-shared interest representations does not change with different domains, i.e., $P(X|D = 0) = P(X|D = 1)$. By cutting off the causal relation $D \rightarrow X$, we achieve statistical independence between X and D (i.e., $D \perp X$).

Domain-specific information extraction: We disentangle the user's domain-shared interest representations (X) from their domain-specific interests in a particular domain (X_A). Similarly, we disentangle X from the domain-specific interests in other domains (X_B). This disentanglement allows us to achieve statistical independence between X and X_A, as well as between X and X_B. By cutting off the causal relations $X \rightarrow X_A$ and $X \rightarrow X_B$, we ensure the independence of these variables (i.e., $X_A \perp X_B, X \perp X_B, X \perp X_A$).

Domain irrelevant information control: To maintain the accuracy of the recommendation process, we control the transfer of domain-specific information from one domain to another. We want to avoid negative transfer effects on the recommendation process. Therefore, we enforce the independence between the domain-specific interest in one domain (X_B) and the ranking score in another domain (Y_A). By cutting off the causal relation $X_B \rightarrow Y_A$, we prevent unwanted interference and maintain the integrity of the recommendation process (i.e., $X_B \perp Y_A$).

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[1]To simplify the notation, we use $*$ to indicate the operations performed in both domain A and B.

By incorporating these causal operations into the causal graph, we aim to disentangle the different factors that influence cross-domain recommendation. This disentanglement allows us to enhance the transferability of the recommendation system, improve the accuracy of ranking score estimation, and mitigate negative transfer effects. Ultimately, our approach leads to a more accurate and robust recommendation system that can adapt to various domains and provide reliable recommendations to users.

4.2 C^2DR framework

Figure 3 provides a high-level overview of C^2DR, which follows the causal graph in Figure 2 to learn the causal representation of the user's domain-specific interests within each domain and their domain-shared interests across domains. The framework consists of multiple steps. Firstly, it trains multiple encoders to acquire representations for causal variables while employing a domain classifier to extract domain-shared information. Secondly, C^2DR incorporates multiple objectives and learns a weight vector, enabling the independent treatment of causal variables ($X_A \perp X_B, X \perp X_B, X \perp X_A$). Lastly, C^2DR employs an orthogonalization constraint to mitigate negative transfer of domain-irrelevant information.

4.2.1 Causal representation learning. As introduced above, we utilize multiple encoders to learn causal embedding for various user interests across domains. Specifically, we consider the user's domain-shared interest $X \in \mathbb{R}^{|\mathcal{U}| \times d}$, which represents their interests that are common across different domains. Additionally, we examine the user's domain-specific interests in each domain, denoted as $X_A \in \mathbb{R}^{|\mathcal{U}| \times d}$ and $X_B \in \mathbb{R}^{|\mathcal{U}| \times d}$ for domains A and B, respectively. Furthermore, we incorporate item representations $I_A \in \mathbb{R}^{|\mathcal{I}^A| \times d}$ and $I_B \in \mathbb{R}^{|\mathcal{I}^B| \times d}$ for domain A and domain B, where $|\mathcal{I}^A|$ and $|\mathcal{I}^B|$ represent the number of items in each domain. To obtain these embedding, we employ the following operations:

User Domain-Shared Interest: We use an encoder $X = F(emb(f_u^A \oplus f_u^B); \theta_s)$ to capture the user's domain-shared interest X. This encoder takes as input the concatenation of the domain-specific user features f_u^A and f_u^B, and applies the embedding operation $emb(\cdot)$ to obtain the embedded representation. The encoder is parameterized by θ_s.

User Domain-Specific Interests: Similarly, we use the encoder $X_* = F(emb(f_u^A \oplus f_u^B); \theta_*)$ to capture the user's domain-specific interests in each domain. The encoder is parameterized by θ_*.

Item Representations: The encoder $I_* = F(emb(f_i^*); \phi_*)$ is employed to capture the representation of items in each domain. This encoder takes the item features f_i^* as input and applies the embedding operation $emb_i(\cdot)$.

The function $F(\cdot)$ represents the information encoder, which can be implemented using various existing structures such as attention mechanisms [16] and graph neural networks [12]. These structures are utilized to capture users' personalized interaction information effectively. The embedding operation $emb(\cdot)$ is responsible for embedding the input features. Based on the learned representation for domain-shared information, we calculate the predicted user-item interaction result $\hat{y_s}^*$ in each domain as follows:

$$\hat{y_s}^* = Sigmoid(\mathcal{H}(X \oplus I_*; \psi_*)), \tag{1}$$

where $\oplus$ denotes the aggregation operation, $\mathcal{H}(\cdot; \psi_*)$ represents a ranking model that is implemented using a multi-layer MLP parameterized by ψ_*. Similarly, the predicted user-item interaction result $\hat{y}^*$ based on the learned representation for domain-specific information can be calculated as follows:

$$\hat{y}^* = Sigmoid(\mathcal{H}(X_* \oplus I_*; \psi_*)). \tag{2}$$

Consequently, trainable parameter set $\theta_s, \theta_*, \phi_*, \psi_*$ can be trained using supervised learning to recover the historical interactions in each domain. We use a binary cross-entropy (BCE) loss [34] to train our model:

$$\mathcal{L}_{BCE} = \sum_{* \in \{A,B\}} \sum_{\bar{y}^* \in \{\hat{y}^*, \hat{y_s}^*\}} -y^* \log \bar{y}^* - (1 - y^*) \log (1 - \bar{y}^*), \tag{3}$$

where $*$ indicates the operations performed in both domain A and B. $\bar{y}$ represents either $\hat{y_s}^*$ or $\hat{y}^*$, and y^* represents the user-item ground-truth matching score in each domain.

Note that the above training strategy has shown promise in capturing relationships within a single-domain scenario, but it faces challenges in explicitly separating domain-shared and domain-specific information in a cross-domain setting. This observation motivates us to develop a more effective training strategy for disentangling causal representations and extracting meaningful representations of user interests across different domains.

4.2.2 Causal representation disentanglement. Following the causal relationship described in subsection 4.1, it is crucial to ensure that the user's domain-shared interest representation (X) contains domain-invariant information that does not reveal specific domain information. For example, the semantic topic "Romantic" can be associated with both the "Movie" and "Film" domains. To achieve this, we draw inspiration from a domain adaptation technique [4] and label the learned representations X_A and X_B with the value '1', while labelling X with the value '0'. We then train a domain classifier $\mathcal{H}_D(\cdot; \psi_D)$ to predict the label as shown in the following equation:

$$\hat{d} = Sigmoid(\mathcal{H}_D(GRL(\cdot); \psi_D)), \tag{4}$$

where $(\cdot)$ represents the learned causal embedding of the user's domain-shared interest and domain-specific interest. Here, we utilize the gradient reversal layer (GRL) to extract the domain-shared information by confusing the domain classifier during the training process of the encoder $X = F(\cdot; \theta_s)$. The GRL acts as an identity transformation during forward propagation, i.e., $GRL(X) = X$, but during backpropagation, it assigns the gradients as a negative constant, effectively reversing the sign of the gradients, i.e., $\frac{\partial GRL(X)}{\partial \theta_s} = -I$. This reversal masks force the encoder $X = F(\cdot; \theta_s)$ to learn domain-invariant information, making it difficult for the domain classifier to distinguish between the source and target domains. Next, we train the domain classification loss using the following equation:

$$\text{L}_{domain} = \sum_{* \in \{A,B\}} -d_* \log \hat{d}_* - 2(1 - d_s) \log (1 - \hat{d}_s), \tag{5}\text{where}$$ d_* and d_s represent the ground truth labels for the instances from
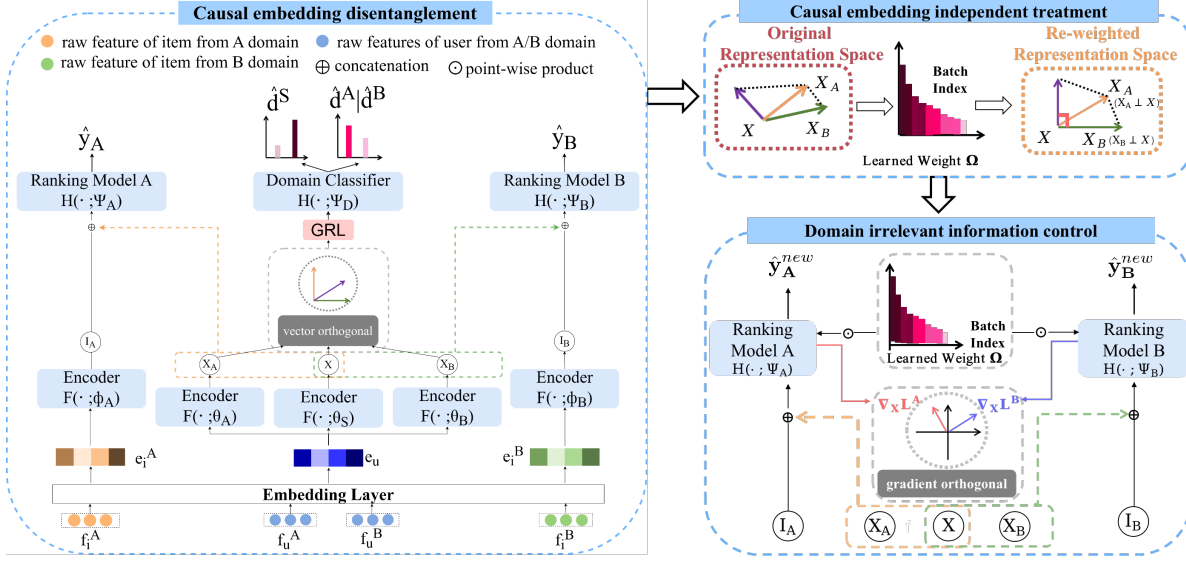
Figure 3: The training procedure of C^2DR. 1. C^2DR trains multiple encoders and employs a domain classifier with a gradient reverse layer (GRL) to extract domain-shared information effectively. 2. C^2DR learns a weight vector that re-weights the representation space to enable the independent treatment of causal variables. 3. C^2DR mitigates negative transfer of domain irrelevant information by enforcing orthogonality between the domain-shared information X and the gradients of the loss function in each domain.

domain-shared information and domain-specific information. Similarly, $\hat{d}_*$ and $\hat{d}_s$ refer to the outputs of the domain classifier when given X_A, X_B, and X as inputs, respectively.

4.2.3 Causal embedding independent treatment.

We treat the independence of causal embedding from both spatial geometry and statistical distribution perspective, so as to remove the undesired variable correlations, as described in subsection 4.1.

From a spatial geometry standpoint, we introduce a vector orthogonal regularizer to enforce orthogonality between the variables X, X_A, and X_B. This regularizer encourages the embedding vectors to be mutually orthogonal, promoting their independence. We calculate the vector orthogonal regularizer $\mathcal{L}_{vec}$ as follows:

$$\mathcal{L}_{vec} = \sum^{N} \text{cosine}(X, X_A) + \text{cosine}(X, X_B) + \text{cosine}(X_A, X_B), \quad (6)$$

where $\text{cosine}(\cdot, \cdot)$ represents the cosine similarity between two variables.

From a statistical distribution standpoint, since X, X_A, and X_B are continuous random variables, we achieve independence of causal embedding based on their underlying probability distribution. However, accurately estimating the probability distribution of these variables poses a challenge in our task. Therefore, we relax the strict requirement of statistical independence and instead focus on constraining the covariance between variables. For example, to encourage $X \perp X_A$, we enforce the covariance between these variables to be zero: $cov(X, X_A) = \mathbb{E}(X, X_A) - \mathbb{E}(X)\mathbb{E}(X_A) = 0$. To address this, we draw inspiration from the findings of Shen et al. [23] and introduce a learnable weight vector $\Omega \in \mathbb{R}^N$. This weight vector allows us to modify the distribution by reweighting the causal variables. By adjusting the weights, we can ensure that

the covariance between the re-weighted causal variables becomes zero. Consequently, we can calculate the learnable weight Ω based on the following relationship:

$$\begin{aligned}
\mathcal{L}_u(\Omega) = & \left\| \mathbf{X_A}^T \Sigma_\Omega \mathbf{X}/N - \mathbf{X_A}^T \Omega/N \cdot \mathbf{X}^T \Omega/N \right\|_F \\
& + \left\| \mathbf{X_B}^T \Sigma_\Omega \mathbf{X}/N - \mathbf{X_B}^T \Omega/N \cdot \mathbf{X}^T \Omega/N \right\|_F \\
& + \left\| \mathbf{X_B}^T \Sigma_\Omega \mathbf{X_A}/N - \mathbf{X_B}^T \Omega/N \cdot \mathbf{X_A}^T \Omega/N \right\|_F = 0,
\end{aligned} \quad (7)$$

where N denotes the batch size, $\Sigma_\Omega \in \mathbb{R}^{N \times N}$ is a diagonal matrix with the values of the weight vector as its diagonal elements and 0 in other positions, and $|\cdot|_F$ represents the Frobenius norm. To simplify the calculation, we transform Equation (7) and optimize the learnable weight Ω by minimizing the following objective:

$$\begin{aligned}
& \min_\Omega \mathcal{L}_u(\Omega) \\
& \text{s.t} \quad \frac{1}{N} \sum_{i=1}^N \Omega_i^2 < \lambda_1, \\
& \left(\frac{1}{N} \sum_{i=1}^N \Omega_i - 1 \right)^2 < \lambda_2, \Omega \geq \mathbf{0},
\end{aligned} \quad (8)$$

where Ω_i is the value at the i-th position of Ω, and λ_1 and λ_2 are hyperparameters used to regularize the value of the weight vector. By solving this optimization problem, we can update the learnable weight vector Ω. Next, we update the ranking model $\mathcal{H}(\cdot; \psi_*)$ in

the re-weighted representation space with the following objective:

$$\mathcal{L}^*_{new} = \sum_{i=1}^{N} \sum_{*\in\{A,B\}} \Omega_i(-y^* \log \hat{y}^*_{new}) - \Omega_i \left(1-y^*\right) \log \left(1 - \hat{y}^*_{new}\right),$$ (9)

where $\hat{y}^{new}$ represents the ultimate user-item matching score based on the causal embedding of domain-shared information X and domain-specific information X_*:

$$\hat{y}^*_{new} = Sigmoid(\mathcal{H}(X_* \oplus X \oplus I_*; \psi_*)).$$ (10)

*4.2.4 **Domain irrelevant information control**.* Note that the ranking model $\mathcal{H}(\cdot; \psi_*)$ is jointly trained on both domains (Equation (9)), it is important to address the challenge of negative transfer of domain-irrelevant information. This issue becomes particularly evident when the user-item matching scores (Y_A, Y_B) of the two domains exhibit a high degree of uncorrelation. In such cases, a decrease in the loss of one domain can lead to an increase in the loss of the other domain, thereby hindering the convergence of the model. To tackle this issue, we propose the adoption of an orthogonalization constraint on the gradients of the loss function with respect to the domain-shared information (X) in both domains. The orthogonalization constraint is defined as:

$$\mathcal{L}_{grad} = \sum_{i=1}^{N} l_2^{norm} \left(\frac{\nabla_X \mathcal{L}^A_{new}}{\left\| \nabla_X \mathcal{L}^A_{new} \right\|} \cdot \frac{\nabla_X \mathcal{L}^B_{new}}{\left\| \nabla_X \mathcal{L}^B_{new} \right\|} \right),$$ (11)

where $l_2^{norm}(\cdot)$ denotes the L2 norm of vectors. This constraint enforces orthogonality between the domain-specific information X_B and the ranking results Y_A, as well as between X_A and Y_B, i.e., $X_B \perp Y_A$ and $X_A \perp Y_B$. By imposing orthogonality, we ensure that the gradients of the loss function with respect to the domain-shared information are orthogonal to the gradients with respect to the ranking results in both domains. Enforcing orthogonality allows us to control the flow of domain-specific and domain-shared information, enabling the model to prioritize the relevant aspects of each domain while mitigating interference from other domains. As a result, the model can focus on the relevant aspects of each domain, allowing for more robust recommendation .

*4.2.5 **Model training and evaluation**.* The totally loss function of C^2DR contains two stages. In the first stage, we update the domain-shared information encoder $F(\cdot; \theta_S)$, domain-specific information encoder $F(\cdot; \theta_*)$, item representation encoder $F(\cdot; \phi_*)$, and ranking models $\mathcal{H}(\cdot; \psi_*)$ as follows.

$$\mathcal{L}_1 = \mathcal{L}_o + \alpha\mathcal{L}_{domain} + \beta\mathcal{L}_{vec},$$ (12)

where α and β are the hyperparameter. In the second stage, we learn the re-weight vector based on Equation (8), and further update the ranking models $h(\cdot; \psi_*)$ as follows.

$$\mathcal{L}_2 = \mathcal{L}^*_{new} + \gamma\mathcal{L}_{grad},$$ (13)

where γ is the hyperparameter.

5 EXPERIMENTS

In this section, we present the extensive experiments conducted to evaluate the performance of our proposed C^2DR model and address the following research questions:

- RQ1: Does C^2DR achieve significant performance improvements compared to existing CDR methods?
- RQ2: To what extent does each loss component in the C^2DR model contribute to overall performance improvement? Is the inclusion of each component necessary?
- RQ3: To evaluate whether the carefully designed information disentanglement regularization terms work as expected and if the learned representations satisfy the causality depicted in Figure 2.

To answer these questions, we performed the following comprehensive set of experiments and analyses.

5.1 Experimental Setup

5.1.1 Dataset. In this section, we describe the datasets used to evaluate and compare the proposed model with other models. The experiments were conducted on three large real-world datasets, each containing interaction records from two domains with a common user. We refer to the domain with fewer interaction records as the target domain and the other as the source domain. The details of the datasets used in our experiments are shown in table 1.

Table 1: Statistics of three public datasets. (avg. - average)

Dataset	Douban	Huawei	Amazon
# Shared Users	23,706,610	65297	87,896
#Items(Source)	54,829,040	98600	673,826
# Items(Target)	13,149,185	12615	100,164
#Instances	445,821,389	10903249	1,290,358
Avg.# clicked(Source)	94	18	39
Avg. # clicked(Target)	60	118	36

- Huawei[2]: We obtained a large-scale dataset from Huawei's 2022 cross-domain Click-Through Rate (CTR) prediction competition. It includes extensive features and comprises a 'news' source domain and an 'advertisement' target domain.
- Amazon[3]: We utilized the publicly available Amazon reviews dataset, focusing on the 'music' and 'movie' categories. Common users were extracted, treating 'movie' as the source domain and 'music' as the target domain.
- Douban[4]: This dataset was collected from Douban, encompassing three popular domains: Douban Book, Douban Movie, and Douban Music. 'Movie' was used as the source domain, and 'Book' was used as the target domain in our experiments. Please note that this dataset is not publicly accessible and has been employed in a prior study [27].

5.1.2 Baseline. For the baseline models, we include DIN [33] and its two variants as representatives of single-domain methods. Additionally, we select the following seven models as representatives of cross-domain methods:

Single-domain methods.

- DIN [33]: This attention-based pooling model predicts click-through rates (CTR) effectively by capturing user interests. It serves as the baseline without knowledge-transfer modules.

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[2]https://www.huawei.com/
[3]http://jmcauley.ucsd.edu/data/amazon/index_2014.html
[4]https://www.douban.com/

- DIN (Mix): This variant of the single-domain DIN model which is trained and tested on a dataset that consists of overlapped user features from two domains.
- DIN (Finetune): This variant of the single-domain DIN model is initially pre-trained on the source domain and subsequently fine-tuned on the target domain.

Cross-domain methods : Embedding and Mapping.

- EMCDR [24]: This approach combines matrix factorization and Bayesian personalized ranking to generate latent factors and incorporates a nonlinear multi-layer perceptron (MLP) for ranking.
- PTUPCDR [36]: This method utilizes a meta mapping network as a personalized bridge function based on EMCDR.

Cross-domain methods : Deep Knowledge Transfer

- CSN [15]: This model achieves bidirectional knowledge transfer by combining feature maps in a high-dimensional space.
- CoNet [7]: This model uses cross-connection units and a shared transfer matrix for fine-grained knowledge transfer.
- MiNet [16]: This model employs a hierarchical attention mechanism to extract and transfer knowledge between domains.
- ACDR [9]: This model incorporates adversarial learning to capture both global user preferences and domain-specific user preferences across different domains.
- MADD [31]: This model utilizes the attention mechanism to construct personalized preferences by disentangling raw user behavior into domain-shared and domain-specific features.

5.1.3 Evaluation Metrics. We evaluate the performance of C^2DR and selected baseline models on different datasets with the following ranking metrics:

- AUC over the test set [35]. It is a widely used metric for CTR prediction. It reflects the probability that a model ranks a randomly chosen positive instance higher than a randomly chosen negative instance.
- RelaImpr (Relative Improvement) [22]. It calculates the percentage improvement achieved by the target model over the baseline models. It allows for a comparative analysis of the performance enhancement.

5.2 Performance Comparisons (RQ1)

We perform 10 random experiments for each model on prediction tasks across three cross-domain datasets. The reported results represent the mean performance averaged over these experiments. To ensure fairness and validity, we adjust the structure of the baseline models to match the complexity of the model C^2DR. Based on the experimental results presented in Table 2, we make the following observations.

The semantic correlation of data in different domains has a significant impact on the performance of CDR models. Traditional methods demonstrate significant improvement in datasets with strong inter-domain correlation. Specifically, EMCDR and PTUPC models outperform the baseline model by 0.07% and 1.18%, respectively. However, in the Amazon dataset characterized by weak domain correlation, traditional methods encounter difficulties in establishing meaningful connections between the two domains, resulting in performance degradation 1.08% for EMCDR and 1.18%

for PTUPCDR. In contrast, The proposed C^2DR shows better performance than traditional baselines in both dataset, which validates the importance of considering domain differences and transferring domain-specific knowledge to achieve robust recommendations.

The improvement of model performance in the source domain is not as significant as in the target domain. For example, the RelImp of CoNet on Huawei_Ad is +0.21%, but it remains slightly decreases -0.52% on Huawei_News. This observation can be attributed to the fact that the source domain contains more interaction records about the domain-shared representation of user interest. The model pre-trained on the source domain provides a better initial value for training the target domain. MADD and C^2DR achieve relatively consistent performance improvements in both the source and target domains in the three data sets. This is due to the design of a representation decoupling module that facilitates the extraction of complete domain-shared representations of user interest from both domains.

5.3 Discussion of Model Variants (RQ2)

To evaluate the efficacy of each loss component in C^2DR model, we perform ablation experiments on the Huawei and Amazon datasets. The DIN (single-domain) model serves as the baseline for comparison. We compared the five special cases: C^2DR (1) without $\mathcal{L}_u$ that ensures the independence of domain shared and domain-specific information; (2) without $\mathcal{L}_{vec}$ that enforces orthogonality between domain-shared and domain-specific information in vector spaces; (3) without $\mathcal{L}_{domain}$ which involves the constraint of the domain-shared/specific information classifier; and (4) without $\mathcal{L}_{grad}$ that blocks the transfer of domain irrelevant information.

In Figure 4, we observe that all loss components contribute to the recommendation performance. Notably, removing $\mathcal{L}u$ and $\mathcal{L}vec$ has a more detrimental effect on the model's performance compared to removing $\mathcal{L}domain$ and $\mathcal{L}grad$. Similarly, removing $\mathcal{L}domain$ has a more significant negative impact than removing $\mathcal{L}grad$. These findings confirm the benefits of explicit representation disentanglement in improving CDR performance. Additionally, removing $\mathcal{L}u$ results in significantly poorer performance compared to removing $\mathcal{L}vec$. This result further confirms the importance of effectively constraining the dependence between domain-shared and domain-specific information.

5.4 Effectiveness of Disentanglement (RQ3)

In this subsection, we evaluate the performance of cross-domain recommendation in each domain using the extracted representations X_A and X_B, which represent the user's domain-specific interests in the target and source domains, respectively. The analysis is performed on the Huawei and Douban dataset. The results presented in Table 3 and 4 reveal the interesting findings. One can see that the domain-specific representations learned by CoNet exhibit similar recommendation capacity in both domains (i.e., using X_A in the target domain and X_B in the source domain). However, they failed to achieve better results in their respective domains. In contrast, the domain-specific representations X_A and X_B learned by C^2DR demonstrate strong performance within their respective domains and exhibit weak performance when applied to the opposite domains (i.e., using X_A in the source domain and

Table 2: Performance comparison of different methods for CDR scenarios on three datasets. The best-performing method is highlighted in bold font. An asterisk (∗) indicates a p-value < 0.05 for a one-tailed t-test, indicating statistically significant differences. The underlining denotes sub-optimal performance. The reported results are averaged over 10 independent repetitions across all datasets.

Datasets		Metircs	Single-domain Methods			Cross-domain Methods							Ours
			DIN	DIN (Mix)	DIN (Finetune)	EMCDR	PTUPCDR	CSN	CoNet	MiNet	ACDR	MADD	C^2DR
Huawei	Advertisement	AUC	0.7793	0.7847	0.7823	0.7695	0.7795	0.7826	0.7797	0.7799	0.7881	0.7871	**0.7892**∗
		RelImp		1.93%	1.07%	0.07%	1.18%	0.14%	0.21%	2.01%	3.11%	2.79%	**3.54%**
	News	AUC	0.7859	0.7836	0.7857			0.7862	0.7844	0.7905	0.7934	0.7939	**0.7942**∗
		RelImp		-0.80%	-0.07%			0.10%	-0.52%	1.61%	2.62%	2.80%	**2.90%**
Amazon	Music	AUC	0.6852	0.6823	0.6865	0.6832	0.6835	0.6828	0.6826	0.6875	0.6889	0.6885	**0.6898**∗
		RelImp		-1.57%	0.70%	-1.08%	-0.92%	-1.30%	-1.40%	1.24%	2.00%	1.78%	**2.48%**
	Movie	AUC	0.7214	0.7196	0.7219			0.7210	0.7208	0.7238	0.7249	0.7254	**0.7258**
		RelImp		-0.81%	0.23%			-0.18%	-0.27%	1.08%	1.58%	1.81%	**1.99%**
Douban	Book	AUC	0.7562	0.7578	0.7582	0.7576	0.7588	0.7554	0.7542	0.7585	0.759	0.7582	**0.7611**∗
		RelImp		0.62%	0.78%	0.55%	1.01%	-0.31%	-0.78%	0.90%	1.09%	0.78%	**1.91%**
	Movie	AUC	0.7802	0.7732	0.7856			0.7866	0.7906	0.7894	0.7894	0.7915	**0.792**
		RelImp		-2.50%	1.93%			2.28%	3.71%	3.28%	3.28%	4.03%	**4.21%**
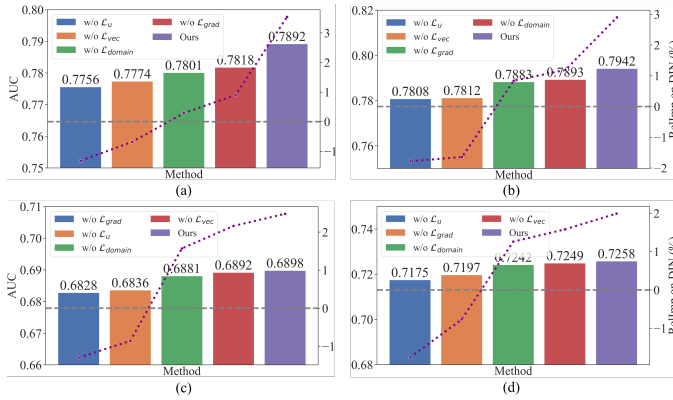
Figure 4: The impact of each loss component of C^2DR on the final performance. (a): Results on the Huawei_News (target domain). (b): Results on the Huawei_Ad (source domain) . (c): Results on the Amazon_Movie (target domain). (d): Results on the Amazon_Music (source domain). w/o '∗' represents the results on the test set for the variant with the '∗' loss component removed from C^2DR. The purple dotted dash line represents the Relative Improvement (RelImpr) of the model performance compared to DIN (depicted by the gray horizontal dashed line).

X_B in the target domain). These findings highlight the capability of C^2DR's causal-based domain information disentanglement

approach in learning domain-specific representations, enabling precise and domain-aware recommendations.

6 CONCLUSION

In this paper, we have proposed a novel causal-based framework, C^2DR, to address the challenges of Cross-Domain Recommendation (CDR) by disentangling domain information from a causal perspective. Our approach leverages causal relationships to identify and transfer the most relevant factors, specifically the domain-shared information, for improving recommendations in different domains. The proposed C^2DR model constructs a causal graph to capture important causal connections and utilizes multiple encoders to learn causal representations for domain-specific interests and domain-shared information. By employing a domain classifier and sample re-weighting techniques, C^2DR disentangles domain-specific and domain-shared information, enabling selective transfer and enhancing recommendation performance. Our research contributes a novel perspective to the field of cross-domain recommendation and opens avenues for further exploration of causal graph formulation and disentangled representations for multi-domain recommendation systems.

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Table 3: AUC performance of CDR based on domain-specific information on Huawei dataset.

Input	C^2DR		CoNet	
	Target domain	Source domain	Target domain	Source domain
X_A	**0.7892**	0.71	0.7799	0.72
X_B	0.71	**0.7942**	0.73	0.7874

Table 4: AUC performance of CDR based on domain-specific information on the Douban dataset.

Input	C^2DR		CoNet	
	Target domain	Source domain	Target domain	Source domain
X_A	**0.761**	0.72	0.754	0.73
X_B	0.73	**0.792**	0.74	0.791

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