

Motif-Based Prompt Learning for Universal Cross-Domain Recommendation

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ABSTRACT

Cross-Domain Recommendation (CDR) stands as a pivotal technology addressing issues of data sparsity and cold start by transferring general knowledge from the source to the target domain. However, existing CDR models suffer limitations in adaptability across various scenarios due to their inherent complexity. To tackle this challenge, recent advancements introduce universal CDR models that leverage *shared embeddings* to capture general knowledge across domains and transfer it through “Multi-task Learning” or “Pre-train, Fine-tune” paradigms. However, these models often overlook the broader structural topology that spans domains and fail to align training objectives, potentially leading to negative transfer. To address these issues, we propose a motif-based prompt learning framework, MOP, which introduces *motif-based shared embeddings* to encapsulate generalized domain knowledge, catering to both intra-domain and inter-domain CDR tasks. Specifically, we devise three typical motifs: butterfly, triangle, and random walk, and encode them through a Motif-based Encoder to obtain motif-based shared embeddings. Moreover, we train MOP under the “Pre-training & Prompt Tuning” paradigm. By unifying pre-training and recommendation tasks as a common motif-based similarity learning task and integrating adaptable prompt parameters to guide the model in downstream recommendation tasks, MOP excels in transferring domain knowledge effectively. Experimental results on four distinct CDR tasks demonstrate the effectiveness of MOP than the state-of-the-art models.

CCS CONCEPTS

• Information systems → Recommender System.

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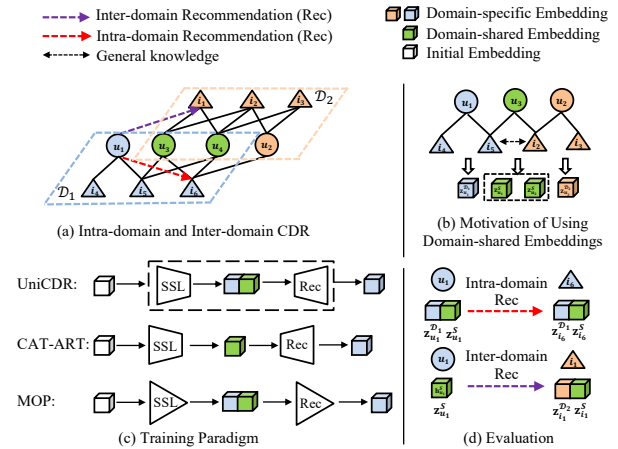


Figure 1: The technical route of universal CDR model.

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1 INTRODUCTION

Recommendation systems (RS) play a crucial role in discovering users’ latent interests and preferences, thereby being embraced by numerous E-commerce platforms and content providers for driving incremental revenue [47, 48]. However, existing RS still suffer from data sparsity and cold-start problems as most users only interact with a fraction of available items, and newly onboard users exhibit no initial interactions. In response to these hurdles, cross-domain recommendation (CDR) is proposed to transfer knowledge from domains with abundant user-item interactions (source) to the domain with few interactions (target). This endeavor seeks to enhance the recommendation performance within the target domain via shared users/items.

In general, CDR tasks can be divided into two distinct categories: intra-domain and inter-domain CDR. Intra-domain CDR operates by harnessing knowledge from other domains to enhance recommendation performance for users who possess limited interactions within the current domain (e.g., recommending item i_6 within the domain to user u_1 , as highlighted by the red dotted line in Fig. 1

(a)). Existing research in this line devises transfer modules such as dual [19] or Bi-directional [28] neural networks upon the overlapped users/items to achieve knowledge transfer. Inter-domain CDR caters to cold-start users in the new scenario (e.g., recommending i_1 for u_1 , as shown by the purple dotted line in Fig. 1 (a)). This task is usually more challenging as cold-start users have no interactions in the new scenario. To address this issue, researchers focus on designing mapping functions [22, 56, 57] upon the overlapped users to build the bridge across domains. However, previous endeavors to address these two types of tasks have often necessitated the design of distinct modules for each scenario, demanding substantial effort and restricting the seamless application of these models to downstream tasks.

Recently, researchers have proposed several universal CDR models to support both intra-domain and inter-domain CDR tasks. These models adhere to a common training paradigm that unfolds as follows: 1) They first integrate users' common interests into *shared embeddings* to capture the general knowledge across domains (as shown in Fig. 1 (b)), with which they can apply their models to both intra-domain and inter-domain CDR tasks. 2) Then, to transfer the general knowledge to the target domain, the "Multi-task Learning" [6] (MTL) or "Pre-train, Fine-tune" [24] (PF) training strategies are often applied. For example, CAT-ART [24] first pre-trains the model using self-supervised learning (SSL) technique such as contrastive learning (CL) and embedding reconstruction (ER) to obtain domain-shared embeddings [50]. These embeddings are then transferred to domain-specific embeddings in the fine-tuning stage. UniCDR [6] adopts MTL, which simultaneously performs CL and recommendation tasks to learn both domain-specific and domain-shared embeddings. Their training paradigms are elucidated in Fig. 1 (c). Nevertheless, both MTL and PF are not the optimal solutions to the challenges of universal CDR due to the divergence in training objectives. As the pre-training and recommendation tasks are not aligned, the obtained domain-shared embeddings hence may encapsulate spurious correlations, which are less effective in enhancing recommendation performance. Moreover, both approaches ignore that the general structural topology across domains is an essential type of transferable knowledge. For example, as shown in Fig. 1 (a), both the local topology $\mathcal{B}_1 = \{u_3, i_5, u_4, i_6\}$ in domain \mathcal{D}_1 and $\mathcal{B}_2 = \{i_2, u_4, i_3, u_2\}$ in domain \mathcal{D}_2 reflect similar user preferences that can be transferred across domains.

To overcome the above challenges, we resort to the "Pre-training & Prompt Tuning" paradigm [31, 42] which enables us to unify pre-training and downstream recommendation tasks into a common template task to address the mismatch issue between the training objectives of pre-training and recommendation, and introduce *motif* [33] to capture the general structural topology across domains. We name our proposed model as MOP, which is short for Motif-based Prompt Learning for Universal CDR. Specifically, we assign each user/item *motif-based domain-specific embeddings* (M-specific) that contain the structural topology within domains and further introduce *motif-based domain-shared embeddings* (M-shared) to capture the general structural topology across domains, because motif [33] involves the structural correlation of nodes. To obtain M-specific and M-shared embeddings, we propose a Motif-based Encoder consisting of a hypergraph-based motif encoding module, a novel Mixture-of-Domain-Experts (MoDE) transformer and

an adaptable READOUT function. Intuitively, the hypergraph can capture complex relationships among nodes within a motif, while the MoDE transformer can handle both M-shared and M-specific embeddings through several MoDE experts. Fig. 2(a) shows how the Motif-based Encoder works. To seamlessly and effectively transfer the general topology knowledge into the target domain, we propose a prompt tuning strategy, where we first transform the SSL and recommendation tasks in our framework into motif-based similarity learning (MSL) tasks, which calculate the cosine similarity between motif-based node embeddings. Then we pre-train MOP using SSL tasks to obtain M-specific and M-shared embeddings. Finally, during the prompt tuning stage, in each target domain, we add extra learnable parameters upon the READOUT function to transfer the M-specific and M-shared embeddings into refined domain-specific embeddings for performing recommendation task (Cf. Fig. 2 (c)).

In summary, this paper makes the following contributions: 1) We propose a universal CDR model, MOP, which introduces motifs to capture the general topology knowledge across domains that can be applied to both intra-domain and inter-domain CDR tasks. 2) We train MOP under the "Pre-training & Prompt Tuning" paradigm to seamlessly transfer the general topology knowledge, which can address the mismatch issue between the training objectives of SSL and recommendation tasks. 3) Experimental results show the superiority of MOP against the state-of-the-art methods on both intra-domain and inter-domain CDR tasks.

2 RELATED WORK

Cross-domain Recommendation (CDR). CDR can be categorized into intra-domain and inter-domain CDR. Intra-domain CDR addresses the data sparsity issue by transferring rich information from other domains to improve the intra-domain recommendation performance for users with few interactions. Existing works mainly use clustering [21, 26, 34, 51], label relevance [29], active learning [53], matrix decomposition [37, 46], dual transfer networks [12–14, 19, 27, 55] to achieve knowledge transfer. Inter-domain CDR involves recommending items from a different domain to cold-start users. This task is more challenging than intra-domain CDR, as the cold-start users have no interactions in the new recommendation scenario. To solve this problem, researchers design mapping functions [22, 56, 57] to transfer the information of the cold-start users from the source to the target domain. Recently, several universal CDR models that unify both intra-domain and inter-domain CDR are proposed. These models first capture the general knowledge across domains through domain-shared embeddings, and then transfer this knowledge through MTL or PF. However, they ignore the fact that the general structural topology across domains is also a type of general knowledge.

Prompt Learning for Recommendation. Prompt learning solves the mismatch between the training objectives of the pre-training and downstream tasks by unifying these tasks as a common template, so as to activate the model's memory for related tasks [4, 35]. The design of prompt templates can be categorized as discrete natural language prompts [10, 39], continuous prompts [30], and bias adjustment strategies [20]. Recently, researchers apply prompt learning to solve various types of recommendation tasks, including

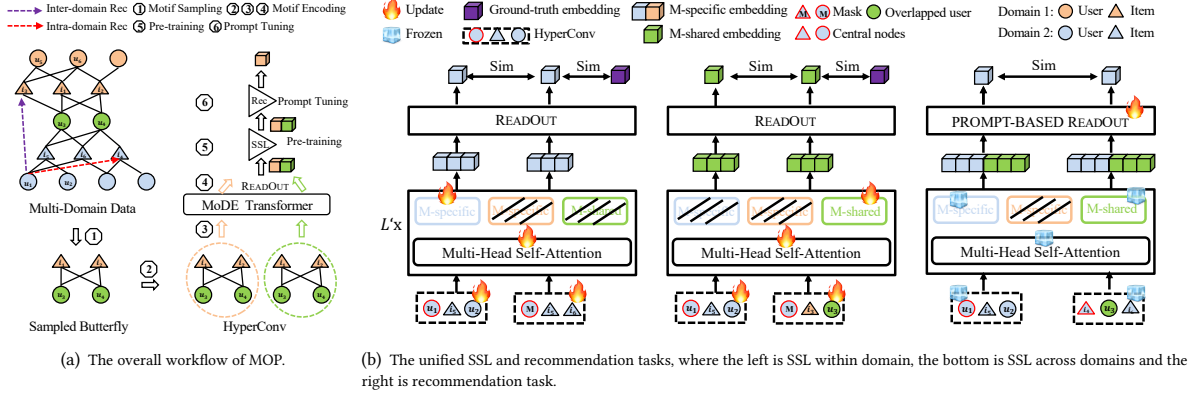


Figure 2: The whole framework of MOP. Figure 2(b) shows an intra-domain CDR example, i.e., recommending i_4 to u_1 within the domain. For inter-domain CDR, i.e., recommending i_3 to u_1 , we only use M-shared embeddings for u_1 , but use both M-shared and M-specific embeddings for i_3 to perform the recommendation task.

news [52], explainable [25], fairness [45] and personalized [11, 31, 40, 42] recommendation. However, prompt learning has not yet been applied to universal CDR. To fill this gap, we propose prompt learning to transfer general knowledge across domains.

3 PROBLEM STATEMENT

Let $\mathcal{D} = \{\mathcal{D}_1, \mathcal{D}_2, \dots\}$ be the multiple domains, where each domain $\mathcal{D}_i = \{V_i, E_i\}$ consists of a node set $V_i = \{U_i, I_i\}$ and an edge set E_i . U_i and I_i denote the user and item set, respectively. CDR aims to improve the recommendation performance in all domains based on \mathcal{D} . Notably, following UniCDR [6], MOP supports both intra-domain and inter-domain CDR tasks that contain Dual-User-Intra, Dual-User-Inter, Multi-Item-Intra and Multi-User-Intra tasks, where Dual/Multi means whether the number of domains is two or more; User/Item means whether the users or items serve as the overlapped role to bridge different domains; Intra/Inter means the corresponding CDR task. For convenience, we take the Dual-User-Intra task that contains two domains $\mathcal{D} = \{\mathcal{D}_1, \mathcal{D}_2\}$ as an example to illustrate the workflow of MOP, and the other three tasks can be explained in a similar way.

4 MOP: MOTIF-BASED PROMPT LEARNING

Fig. 2(a) illustrates the workflow of MOP, which includes motif sampling and encoding, pre-training and prompt tuning processes. In this section, we first introduce motif to capture the general structural topology across domains, as motif [33] involves the structural correlation of nodes. Then we present a *Motif-based Encoder* which consists of a hypergraph-based motif encoding module, a Mixture-of-Domain-Experts (MoDE) Transformer and a READOUT function to obtain M-specific and M-shared embeddings. The hypergraph module models complex correlations of nodes, the MoDE Transformer routes the M-shared or M-specific experts for further embedding refinement, and the READOUT function introduces the central node signals to obtain the final node embeddings containing general structural topology information. Next, we present the reformulated SSL and recommendation tasks into the same template that aims to narrow down the training objective gaps between them.

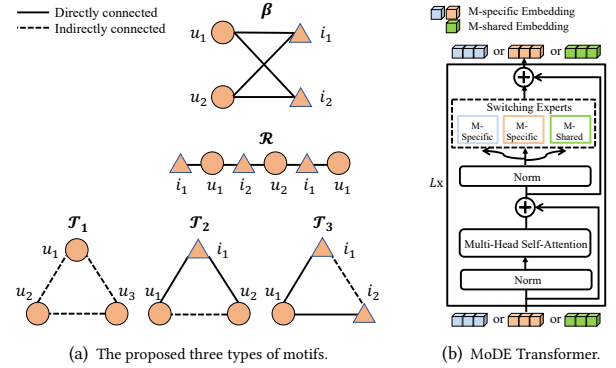


Figure 3: Key components in MOP.

Finally, we illustrate the prompt tuning technique that transfers the general knowledge into each domain to perform the downstream recommendation task.

4.1 Motif Sampling

As motifs have been proven useful in capturing the general structural topology of graphs, we leverage them to model the common correlations of nodes across different domains, where users' interactions within a domain are represented as a user-item graph. By integrating domain knowledge into common motifs and sharing them across or within domains, we can enhance the recommendation performance in both inter-domain and intra-domain CDR tasks. We present three types of motifs (Cf. Fig. 3(a)), i.e., random walk [5], butterfly [38] and triangle [49], to respectively capture the long-term, fully connected short-term, and partially connected short-term dependencies of nodes in both inter-domain and intra-domain CDR tasks. Notably, our model can be seamlessly extended to handle other motifs. We present the sampling process in domain \mathcal{D}_1 as an example, and the sampling process in domain \mathcal{D}_2 can be explained similarly.

4.1.1 Random Walk Sampling. Random walk, which has been extensively studied in the field of social network mining [36], has been successfully utilized to capture the long-term dependencies of nodes. Formally, in domain $\mathcal{D}_i = \{V_i, E_i\}$, a random walk $\mathcal{R} = \{n_1, n_2, \dots, n_{|\mathcal{R}|}\}$ is generated by the random walk algorithm [36] upon the user-item graph, where $|\mathcal{R}|$ is the sequence length. The time complexity of random walk sampling is $O((|V_i| * |\mathcal{R}|))$.

4.1.2 Butterfly Sampling. Butterfly, which is a complete bipartite subgraph consisting of two nodes of one type and two nodes of another type [38], is capable of capturing the fully connected short-term dependencies of nodes with strong connections. Formally, in domain $\mathcal{D}_i = \{U_i, I_i, E_i\}$, a butterfly \mathcal{B} is generated by four nodes u_1, u_2, i_1, i_2 , as shown in Fig. 3(a). Here $\{u_1, u_2\} \in U_i$, $\{i_1, i_2\} \in I_i$, u_1, u_2 are all connected to i_1, i_2 . Inspired by BFC-VP [44], which counts the number of butterflies based on the node priority, we propose a Priority-based Butterfly Sampling method PBS. We first introduce the concept of priority and then provide a detailed explanation of the PBS method.

Definition 1: Priority. In domain $\mathcal{D}_i = \{U_i, I_i, E_i\}$, the priority $p(n)$ of each node $n \in \{U_i, I_i\}$ is an integer where $p(n) \in [1, |U_i| + |I_i|]$. For any two nodes $n_1, n_2 \in \{U_i, I_i\}$, the condition $p(n_1) > p(n_2)$ is satisfied if either 1) $deg(n_1) > deg(n_2)$ or 2) $deg(n_1) = deg(n_2)$ and $n_1.id > n_2.id$. Here, $n_1.id$ and $n_2.id$ represent the indices of n_1 and n_2 , $deg(n_1)$ and $deg(n_2)$ represent the degrees of these nodes. Since domain \mathcal{D}_i is an undirected graph, the priority of each node n can be calculated simply by determining the number of its neighbor sets, i.e., $|\mathcal{N}(n)|$, where $|\mathcal{N}(n)|$ denotes the first-order neighbor set of node n .

Algorithm 1 shows the details of our PBS method. Given $\mathcal{D}_i = \{U_i, I_i, E_i\}$, we first calculate the priority $p(n)$ of each central node n , and then sort them in descending order. After that, for each central node n in the sorted list, we find its second-order set $\{\mathcal{N}(n') | n' \in \mathcal{N}(n)\}$ and calculate the common neighbor set $\mathcal{N}(n) \cap \mathcal{N}(n')$ between the central node n and its second-order neighbor n' . We then select two nodes from this common neighbor set (e.g., $n_1, n_2 \in \mathcal{N}(n) \cap \mathcal{N}(n')$), together with node n, n' , form a butterfly. Notably, following [44], to avoid duplication, we process the nodes that meet $p(n'') < p(n') < p(n)$. Besides, the process of selecting two nodes from the common neighbor set can be viewed as a combination problem [32], where we should enumerate two nodes from the set $\mathcal{N}(n) \cap \mathcal{N}(n')$. The total time complexity of PBS is $O(\sum_{(n,n') \in E_i} (\min\{deg(n), deg(n')\})^2)$, as the process of finding the common neighbor set is $O(\sum_{(n,n') \in E_i} (\min\{deg(n), deg(n')\})^2)$ (Line 1-10), and the time complexity of enumerating the subsets for all central nodes is also $O(\sum_{(n,n') \in E_i} (\min\{deg(n), deg(n')\})^2)$ (Line 11-14).

4.1.3 Triangle Sampling. Triangle is successfully deployed to capture the partially connected short-term dependencies of nodes with weak connections [2, 49]. Formally, in domain $\mathcal{D}_i = \{U_i, I_i, E_i\}$, a triangle is defined as a set of three nodes $\mathcal{T} = \{n_1, n_2, n_3\}$, where some nodes are indirectly connected (e.g., users are friends with each other). As shown in Fig. 3(a), we propose three types of triangles. $\mathcal{T}_1 \subset \mathcal{T}$ depicts three users are friends with each other, where any two users contain at least a_1 common items. $\mathcal{T}_2 \subset \mathcal{T}$ depicts two similar users purchasing one item, where the users contain at

Algorithm 1: PBS: The Sampling Process of Butterfly.

Input: $\mathcal{D}_i = \{U_i, I_i, E_i\}$, The empty butterfly dictionary \mathcal{B}_i .

Output: Sampled butterfly dictionary \mathcal{B}_i .

```

1 foreach  $n \in \{U_i, I_i\}$  do
2   Compute  $p(n)$ ;
3   Sorted  $\mathcal{N}(n)$  in descending order according to  $p(n)$ ;
4 foreach  $n \in \{U_i, I_i\}$  do
5    $cur = []$ ;
6   foreach  $n' \in \mathcal{N}(n) : p(n') < p(n)$  do
7     foreach  $n'' \in \mathcal{N}(n') : p(n'') < p(n)$  do
8       if  $\{n, n''\} \notin \mathcal{B}_i.keys()$  then
9          $\mathcal{B}_i[\{n, n''\}] = []$ ;
10         $cur.append([n, n''])$ ;
11   foreach  $\{n, n''\}$  in  $cur$  do
12     Select all possible subsets  $s_i = [n_{i_1}, n_{i_2}]$  in  $\mathcal{N}(n) \cap \mathcal{N}(n'')$ 
13     ;
14     foreach  $s_i = [n_{i_1}, n_{i_2}] \in \mathcal{N}(n) \cap \mathcal{N}(n'')$  do
15        $\mathcal{B}_i[\{n, n''\}].append([n_{i_1}, n_{i_2}])$ ;
16 return  $\mathcal{B}_i$ 

```

least a_2 common items. $\mathcal{T}_3 \subset \mathcal{T}$ depicts a user and his interacted items, where the item similarity should be greater than a_3 .

In practice, we set the values of a_1 and a_2 as the average median number of items that the users in each domain interact with. As a_3 represents the similarity between items, we use EASE^R [41] to calculate the item-item matrix \mathbf{B} , and set a_3 as 0 to represent the lowest similarity score. Following [41], we first obtain the adjacent matrix $\mathbf{A} \in \{0, 1\}^{|U_i| \times |I_i|}$ based on $\mathcal{D}_i = \{U_i, I_i, E_i\}$, then calculate \mathbf{B} through $\mathbf{B} = \mathbf{I} - \mathbf{P} \cdot \text{DIAGMAT}(\mathbf{1} \oslash \text{DIAG}(\mathbf{P}))$, where $\mathbf{P} = (\mathbf{A}^\top \mathbf{A} + \lambda_F \mathbf{I})^{-1}$, λ_F is a hyperparameter of Frobenius norm regularizer, $\text{DIAG}(\cdot)$ means the matrix diagonal elements, DIAGMAT is a diagonal matrix, \mathbf{I} is identity matrix, $\mathbf{1}$ is a vector of ones and \oslash means element-wise division. The time complexity of sampling $\mathcal{T}_1, \mathcal{T}_2$ is both $O(\sum_{n \in U_i} deg(n))$, while the time complexity of sampling \mathcal{T}_3 is $O(|I_i|^2) + O(\sum_{n \in U_i} deg(n))$.

For the sake of convenience, in **Section 4.2- Section 4.4**, we take a triangle as an example to illustrate the encoding process, and other motifs can be explained in a similar way.

4.2 Motif-based Encoder

This section introduces the motif-based encoder, which consists of a hypergraph-based motif encoding module, a MoDE Transformer and a READOUT function.

4.2.1 Hypergraph Convolution. We apply hypergraph convolution upon the sampled motifs to refine node embeddings, as hypergraph [3] brings a natural way to model complex correlations of nodes. Following [49], we define our hypergraph convolution as: $\mathbf{X}^{(l+1)} = \mathbf{D}^{-1} \mathbf{H} \mathbf{W} \mathbf{B}^{-1} \mathbf{H}^\top \mathbf{X}^{(l)}$, where $\mathbf{X}^{(l)}$ represents the embedding matrix of the whole node set at the l -th convolution process, \mathbf{D} and \mathbf{B} are the diagonal matrices, \mathbf{H} is the incidence matrix, where $H_{i\epsilon} = 1$ if the hyperedge ϵ contains a node $v_i \in \{U_i, I_i\}$, and 0 otherwise.

After L convolution operations, we can obtain the refined node embedding matrix $\mathbf{X}^L = \frac{1}{L+1} \sum_{l=0}^L \mathbf{X}^{(l)}$. To capture the general topology of each triangle across domains and the domain-specific topology within domains, we conduct the lookup operation twice in \mathbf{X}^L . This results in the acquisition of the M-shared embedding \mathbf{T}_S^0 and the M-specific embedding $\mathcal{T}_{\mathcal{D}_1}^0$, which are then fed into the MoDE Transformer.

4.2.2 MoDE Transformer. To effectively capture the structural topology within or across domains, we propose the Mixture-of-Domain-Experts (MoDE) Transformer (c.f., Fig. 3(b)), which is inspired by the MoME Transformer [1], due to its ability to separately encode text and image domains, thereby facilitating effective interaction between multi-modalities. The MoDE Transformer encodes the topology information within or across domains by replacing the feed-forward networks in the standard Transformer [43] with M-shared or M-specific experts. Formally, after performing hypergraph convolution, we feed the M-shared and M-specific embeddings $\mathbf{T}_S^0, \mathbf{T}_{\mathcal{D}_1}^0$ into the MoDE Transformer. Take \mathbf{T}_S^0 as an example, the encoding process is: $\mathbf{T}_S^l = \text{MSA}(\text{LN}(\mathbf{T}_S^{l-1})) + \mathbf{T}_S^{l-1}$, and $\mathbf{T}_S^l = \text{MFFN}(\text{LN}(\mathbf{T}_S^l)) + \mathbf{T}_S^l$, where l is the l -th ($1 \leq l \leq L'$) Transformer layer, LN represents layer normalization, MSA denotes multi-head self-attention, and MFFN refers to routing experts. At the final Transformer layer, we obtain the encoded triangle embedding, denoted as $\mathbf{T}_S^{L'}$.

4.2.3 READOUT Function. Since the goal of recommendation is to obtain the central user/item embeddings, to achieve this, we employ a READOUT function to aggregate the triangle embedding, and then incorporate the central node signal. Assuming the central node in $\mathbf{T}_S^{L'}$ is n , the process is defined as follows:

$$\mathbf{z}^S = \text{READOUT}(\{\mathbf{t}_S^{L'} | \mathbf{t}_S^{L'} \in \mathbf{T}_S^{L'}\}), \quad (1)$$

$$\mathbf{z}_n^S = \text{CONCAT}(\mathbf{z}^S, \mathbf{z}'_n), \quad (2)$$

where \mathbf{z}_n^S is the M-shared embeddings for node n , \mathbf{z}^S denotes the shared aggregated motif embedding, $\mathbf{z}'_n \in \mathcal{X}^L$ refers to the central node signal, $\mathbf{t}_S^{L'}$ is the refined node embedding in $\mathbf{T}_S^{L'}$, CONCAT is the concatenate operation, and READOUT is instantiated as the mean operation. Similarly, we can obtain M-specific embeddings $\mathbf{z}_n^{\mathcal{D}_1}$ for node n . Next, we will illustrate how to train MOP with both M-shared and M-specific embeddings under the ‘‘Pre-training & Prompt Tuning’’ paradigm.

4.3 Pre-training Stage

To reduce the training objective gaps between the SSL and recommendation tasks, we unify them as a common template, namely the motif-based similarity learning (MSL) task. We adopt contrastive learning (CL) and embedding reconstruction (ER) as the SSL tasks, but our model can also handle other SSL tasks. Specifically, the CL task is reformulated as maximizing the similarity between motifs centered on the same node while minimizing the similarity between motifs centered on different nodes. The ER task is reformulated as maximizing the similarity between the ground-truth and predicted node embeddings. To enhance interaction among different domains, both the CL and ER tasks are trained within and across different

domains. In the following part, we illustrate the unified common template and present the reformulated CL and ER tasks.

Unified Task Template. We redefine the CL and ER tasks as the MSL task. Formally, let \mathbf{z}_n^S and $\mathbf{z}_n^{\mathcal{D}_1}$ represent the M-shared and M-specific embeddings of node n , and let $\text{sim}(\cdot)$ denote the cosine similarity function. As shown in Fig. 2(b), the CL and ER tasks can be mapped to the computation of motif-based node similarity, which is defined as follows.

Contrastive Learning. We maximize the similarity between motifs centered on the same node while minimizing the similarity between motifs centered by different nodes. To strengthen knowledge transfer among different domains, we not only sample motifs centered on nodes within each domain, but also sample motifs centered on overlapped nodes across domains. Specifically, the positive pair in the CL task consists of two parts, one for overlapped nodes, i.e., $\{(\mathbf{z}'_{n_s}, \mathbf{z}''_{n_s}) | n_s \in \{V_1 \cap V_2\}\}$, where n_s is an overlapped node in domain \mathcal{D}_1 and \mathcal{D}_2 ; and one for non-overlapped nodes, denoted as $\{(\mathbf{z}'_{n_p}, \mathbf{z}''_{n_p}) | n_p \in V_1\}$, where n_p is sampled within \mathcal{D}_1 . We treat motifs centered on different nodes as negative pairs, denoted as $\{(\mathbf{z}'_{n_p}, \mathbf{z}''_{n_q}) | p \neq q, \{n_p, n_q\} \in V_1\}$. Following SimCLR [9], we use the InfoNCE loss [15] to optimize the model parameters. The loss function in domain \mathcal{D}_1 is:

$$\begin{aligned} \mathcal{L}_{c_1} = & - \sum_{n_s \in \{V_1 \cap V_2\}} \log \frac{\exp(\text{sim}(\mathbf{z}'_{n_s}, \mathbf{z}''_{n_s})/\tau)}{\sum_{n_q \in \{V_1\} \setminus n_s} \exp(\text{sim}(\mathbf{z}'_{n_s}, \mathbf{z}''_{n_q})/\tau)} \\ & - \sum_{n_p \in V_1 \setminus \{V_1 \cap V_2\}} \log \frac{\exp(\text{sim}(\mathbf{z}'_{n_p}, \mathbf{z}''_{n_p})/\tau)}{\sum_{n_q \in \{V_1\} \setminus n_p} \exp(\text{sim}(\mathbf{z}'_{n_p}, \mathbf{z}''_{n_q})/\tau)}, \quad (3) \end{aligned}$$

where τ is the temperature hyperparameter. Similarly, we can define \mathcal{L}_{c_2} in domain \mathcal{D}_2 , and the total CL loss is $\mathcal{L}_c = \mathcal{L}_{c_1} + \mathcal{L}_{c_2}$.

Embedding Reconstruction. The objective of the ER task is to maximize the similarity between positive pairs while minimizing the similarity between negative pairs. Positive pairs consist of the predicted and ground-truth embeddings of the same node, whereas negative pairs consist of the predicted and ground-truth embeddings of different nodes. Formally, we first sample a set of triangles \mathcal{T} centered on n with abundant interactions from $\{V_1 \cup V_2\}$, and use any CDR method (e.g., UniCDR [6]) to obtain its ground-truth embedding \mathbf{z}_n , as Hao et al. [16, 17] have demonstrated the base recommendation model can generate high-quality node embeddings when the nodes have abundant interactions. We then mask some nodes, resulting in a masked triangle set $\hat{\mathcal{T}}$. Next, we randomly select one masked triangle and feed it into the Motif-based Encoder to obtain the reconstructed embedding. If n is an overlapped node, we feed the corresponding M-shared embedding into the Motif-based Encoder, resulting in a reconstructed embedding $\hat{\mathbf{z}}_n^S$. If n is a non-overlapped node, we instead use M-specific embedding, resulting in a reconstructed embedding $\hat{\mathbf{z}}_n^{\mathcal{D}_1}$. Similar to the CL task, we also adopt the InfoNCE loss to optimize the model parameters. The loss function is defined as follows:

$$\begin{aligned} \mathcal{L}_{e_1} = & - \sum_{n_s \in \{V_1 \cap V_2\}} \log \frac{\exp(\text{sim}(z_{n_s}, \hat{z}_{n_s}^S)/\tau)}{\sum_{n_q \in \{V_1\} \setminus n_s} \exp(\text{sim}(z_{n_s}, \hat{z}_{n_q}^S)/\tau)} \\ & - \sum_{n_p \in V_1 \setminus \{V_1 \cap V_2\}} \log \frac{\exp(\text{sim}(z_{n_p}, \hat{z}_{n_p}^{D_1})/\tau)}{\sum_{n_q \in \{V_1\} \setminus n_p} \exp(\text{sim}(z_{n_p}, \hat{z}_{n_q}^{D_1})/\tau)}. \end{aligned} \quad (4)$$

Similarly, we can define \mathcal{L}_{e_2} in domain \mathcal{D}_2 . The total ER loss is $\mathcal{L}_e = \mathcal{L}_{e_1} + \mathcal{L}_{e_2}$. The pre-training loss $\mathcal{L}_{pre} = \lambda_1 \mathcal{L}_c + (1 - \lambda_1) \mathcal{L}_e$, where λ_1 controls the balance of the CL and ER tasks.

4.4 Prompt Tuning Stage

The goal of prompt tuning is twofold: 1) unleash MOP’s inherent capacity to generate high-quality user/item embeddings tailored for recommendation tasks within each domain, and 2) unify the recommendation task into the common MSL task as outlined in Section 4.3, so as to align the training objectives between the SSL and recommendation tasks. In the following part, we present the prompt design and illustrate the prompt tuning process in solving both the intra-domain and inter-domain CDR tasks.

Prompt Design. In contrast to the prompt tuning methods in natural language processing that use handwritten prompt words to stimulate the model’s understanding of different contexts [35], our focus is on capturing the topology in the user-item graph. As the READOUT function plays a key role in refining motif-induced embeddings for recommendation, we add learnable parameters to the READOUT function in Eq. (1) and \mathbf{p} in Eq. (2) in each domain to guide MOP in generating distinctive M-shared and M-specific embeddings for different downstream recommendation tasks. Here we take generating the M-shared embedding z_n^S as an example, and the process of generating M-specific embedding $z_n^{D_1}$ in domain \mathcal{D}_1 can be explained similarly. The proposed READOUT-based prompts are shown as follows:

- Element-wise Multiplication:

$$z^S = \text{READOUT}(\{\mathbf{p}_n \odot \mathbf{t}_S^{L'} \mid \mathbf{t}_S^{L'} \in \mathbf{T}_S^{L'}\}), \quad (5)$$

where z^S refers to the shared aggregated motif embedding, \odot denotes the element-wise multiplication. This operation is a feature weighted summation of the nodes in the motif.

- Matrix Multiplication:

$$z^S = \text{READOUT}(\{\mathbf{p}_n \mathbf{t}_S^{L'} \mid \mathbf{t}_S^{L'} \in \mathbf{T}_S^{L'}\}), \quad (6)$$

This operation is a linear projection upon the nodes in the motif.

- Attention:

$$z^S = \text{READOUT}(\{p_{n_j} \mathbf{t}_{S_j}^{L'} \mid \mathbf{t}_{S_j}^{L'} \in \mathbf{T}_S^{L'}\}), \quad (7)$$

where $p_{n_j} = \frac{\exp(\mathbf{W} \mathbf{t}_{S_j}^{L'})}{\sum_{h=1}^3 \exp(\mathbf{W} \mathbf{t}_h^{L'})}$ is the attention weight for the node embedding $\mathbf{t}_{S_j}^{L'}$ in the motif, \mathbf{W} is a weight matrix. This operation can distinguish the importance of nodes in the motif.

After we obtain z^S , we further add \mathbf{p} in Eq. (2) to obtain the M-shared embedding z_n^S , i.e., $z_n^S = \mathbf{p} \cdot \text{CONCAT}(z^S, z_n')$. Similarly, we can obtain the M-specific embedding $z_n^{D_1}$.

Table 1: Statistics of four CDR scenarios.

Scenarios	Datasets	U	V	Training	Valid	Test	Median
Scenario 1	Sport	9,928	30,796	92,612	-	8,326	6
	Cloth	9,928	39,008	87,829	-	7,540	6
	Elec	3,325	17,709	50,407	-	2,559	21
	Phone	3,325	38,706	115,554	-	2,560	12
Scenario 2	Sport	27,328	12,655	163,291	3,589	3,546	5
	Cloth	41,829	17,943	187,880	3,156	3,085	4
	Game	25,025	12,319	155,036	1,381	1,304	5
	Video	19,457	8,751	156,091	1,435	1,458	6
Scenario 3	M1	7,109	2,198	48,302	3,526	3,558	6
	M2	2,697	1,357	19,615	1,362	1,310	6
	M3	3,328	1,245	23,367	1,629	1,678	6
	M4	5,482	2,917	41,226	2,720	2,727	6
	M5	6,466	9,762	77,173	3,090	3,154	10
Scenario 4	D1	231,444	2,096	491,098	13,435	13,437	1
	D2	507,715	595	1,068,490	36,013	35,985	1
	D3	773,188	1,312	3,785,720	92,659	92,672	3

Prompt Tuning. We froze the parameters of Motif-based Encoder and only update the prompt parameters in the unified recommendation task (As shown in Fig. 2(b)). The loss function in domain \mathcal{D}_1 is defined as follows:

$$\mathcal{L}_{Rec_1} = - \sum_{(u,i) \in E_i} \log \frac{\exp(\text{sim}(\tilde{z}_u, \tilde{z}_i)/\tau)}{\sum_{(u,i') \notin E_i} \exp(\text{sim}(\tilde{z}_u, \tilde{z}_{i'})/\tau)}. \quad (8)$$

where \tilde{z}_u and \tilde{z}_i are refined user/item embeddings, which are capable of performing both intra-domain and inter-domain CDR tasks. For intra-domain CDR, we set \tilde{z}_u as $\text{CONCAT}(z_u^S, z_u^{D_1})$, while for inter-domain CDR, we set \tilde{z}_u as z_u^S . We set \tilde{z}_i as $\text{CONCAT}(z_i^S, z_i^{D_1})$ in both these two tasks. Similarly, we can obtain the recommendation loss \mathcal{L}_{Rec_2} in domain \mathcal{D}_2 , and the total recommendation loss is $\mathcal{L}_{Rec} = \mathcal{L}_{Rec_1} + \mathcal{L}_{Rec_2}$.

5 EXPERIMENTS

We conduct comprehensive experiments on four CDR scenarios to answer the following research questions: **RQ1:** How does our proposed MOP model perform when compared to the state-of-the-art CDR models? **RQ2:** Are SSL tasks (i.e., the CL and ER tasks) beneficial to the downstream recommendation (Rec) task? **RQ3:** What are the impacts of the three proposed motifs on the downstream Rec task? **RQ4:** Are the encoding components (i.e., hypergraph and MoDE Transformer) beneficial to the downstream Rec task? **RQ5:** Does the proposed “Pre-training & Prompt Tuning” (PPT) paradigm, which includes prompt tuning and the prompt-based READOUT function, benefit the downstream Rec task? **RQ6:** How do the hyperparameters of MOP affect the downstream Rec task?

5.1 Datasets

Following UniCDR [6], we conduct four CDR tasks, including Dual-User-Intra (Scenario 1), Dual-User-Inter (Scenario 2), Multi-Item-Intra (Scenario 3) and Multi-User-Intra (Scenario 4). The statistics of the datasets utilized in these tasks are presented in Table 1.

Table 2: Performance comparison (%) on Dual-User-Intra/Dual-User-Inter CDR tasks. *a*: UniCDR [6], *b*: DisenCDR [7], *c*: CDRIB [8]

Models	Metrics	Dual-User-Intra				Dual-User-Inter			
		Sport	Cloth	Elec	Phone	Sport	Cloth	Game	Video
SOTA	HR@10	18.37 ^a	17.85 ^a	24.57 ^b	28.76 ^b	12.04 ^c	12.48 ^a	8.78 ^a	13.17 ^c
	NDCG@10	10.98 ^a	11.20 ^a	14.51 ^b	16.13 ^b	7.04 ^a	7.52 ^a	4.63 ^a	6.49 ^c
MOP	HR@10	19.23	18.18	25.19	28.82	13.09	13.03	7.98	14.13
	NDCG@10	11.37	10.19	15.11	18.02	8.09	9.01	4.09	6.88

Table 3: Performance comparison (%) on Multi-Item-Intra/Multi-User-Intra CDR tasks. *a*: UniCDR [6], *d*: S³-Rec [54]

Models	Metrics	Multi-Item-Intra					Multi-Item-Intra		
		M1	M2	M3	M4	M5	D1	D2	D3
SOTA	HR@10	73.13 ^d	60.86 ^d	66.53 ^d	48.46 ^d	22.66 ^d	32.60 ^a	64.37 ^a	73.89 ^a
	NDCG@10	59.57 ^a	47.52 ^a	53.24 ^a	42.54 ^a	18.63 ^d	13.56 ^a	50.48 ^a	59.15 ^a
MOP	HR@10	74.01	61.29	68.03	49.02	22.79	31.88	65.24	74.29
	NDCG@10	60.10	48.01	52.08	43.82	20.06	12.86	66.23	60.02

5.2 Experimental Setting

5.2.1 Evaluation Protocol. We adopt HR@*K* and NDCG@*K* as the evaluation metrics, with *K* set to 10 by default. Following previous study [6], for the first three scenarios, we conduct the leave-one-out strategy, i.e., for each positive item in the valid/test set, we randomly sample 999 negative items to alleviate the biased Rec phenomena [23]. We adopt the full-ranked strategy in the fourth CDR scenario to evaluate the model performance.

5.2.2 Baselines. We compare MOP with universal CDR models including UniCDR [6], CAT-ART [24], GRAPHPROMPT [31] and GPPT [42]. We also select other baseline models presented in UniCDR [6]. For ease of comparison, we report the best performance of the baseline models and use the symbol "SOTA" to denote it.

5.2.3 Implementation Details. For fair comparison, we follow the original settings for the baseline models. We set the latent embedding dimension as 128, the learning rate as 0.001, the batch size as 1024, the negative number as 4, the random walk length as {3, 6, 9}, the temperature τ as 0.5, the balance factor λ_1 as 0.5, the MoDE Transformer layer L' as 2, the hypergraph layer L as 4, a_3 as 0 in all CDR scenarios. Table 1 shows the settings of a_1 , a_2 in all CDR scenarios. We use the butterfly as the motif and element-wise multiplication as the READOUT function by default.

5.3 Performance Comparisons

5.3.1 Overall Performance (RQ1). We report the overall Rec performance on four CDR scenarios in Table 2 and Table 3. The results show that: 1) our proposed MOP has the best or most competitive performance than the "SOTA" methods. 2) MOP supports both inter-domain and inter-domain CDR tasks, which allows for more efficient use of time and resources in the model design process.

Table 4: Performance comparison (%) of pre-training tasks.

Scenarios	Metrics	Variant Models		
		CL-/CL*/CL	ER-/ER*/ER	A-/A*/A
Sport	HR@10	10.37/12.23/18.45	8.84/11.28/13.25	11.03/18.89/19.23
	NDCG@10	6.37/8.23/10.49	5.73/7.74/9.45	9.37/11.19/11.37
Cloth	HR@10	15.88/16.74/17.99	6.72/8.48/10.42	14.37/17.98/18.18
	NDCG@10	8.68/8.91/9.92	5.64/6.52/8.19	8.87/10.02/10.19
Elec	HR@10	21.88/24.25/25.07	17.37/19.22/20.18	22.37/24.82/25.19
	NDCG@10	11.37/14.22/15.18	8.80/9.28/10.82	12.37/14.86/15.11
Phone	HR@10	27.37/27.22/27.99	18.35/19.22/19.98	12.37/27.21/28.82
	NDCG@10	16.07/16.92/17.19	11.79/12.12/14.99	12.96/17.21/18.02

5.3.2 Effectiveness of the Pre-training Tasks (RQ2). To explore whether the CL and ER tasks can benefit the Rec task, we propose three variant models, i.e., one performs only CL, one performs only ER, and one jointly performs both of them (denoted as A). Besides, we examine the potential benefits of pre-training MOP across domains by proposing three additional variant models, i.e., CL-, ER- and A-. We train these models using their respective loss functions only within domains. Furthermore, we perform the original CL and ER task to explore whether unifying them as the MSL task could benefit the Rec task. The corresponding variant models are CL*, ER* and A*. Table 4 shows the results¹. We find that: 1) Jointly performing the CL and ER tasks leads to the best performance, suggesting that these two tasks can benefit the Rec task. 2) When performing each pre-training task separately, CL is better than ER, as it focuses more on motif correlations. 3) Performing the pre-training tasks within each domain results in lower Rec performance, verifying that transferring knowledge across domains can benefit the Rec task. 4) Compared with the original CL and ER tasks, unifying the CL and ER tasks as the MSL task leads to better performance, indicating that MSL can narrow the training gap between the pre-training and downstream tasks.

5.3.3 Effectiveness of the Motif Types (RQ3). We report the Rec performance using different types of motifs in Table 5, where notations \mathcal{B} , \mathcal{R}_3 , \mathcal{R}_6 , \mathcal{R}_9 ; \mathcal{T}_1 , \mathcal{T}_2 , \mathcal{T}_3 denote the use of butterfly and random walks (with length of 3, 6, 9), and three different triangles as motifs. We further integrate $\{\mathcal{B}, \mathcal{R}_6, \mathcal{T} = \{\mathcal{T}_1, \mathcal{T}_2, \mathcal{T}_3\}\}$ as the motif, and denote this model variant as \mathcal{A} . Following [49], we treat each type of motif as a channel, and use an attention mechanism [49] to obtain fused node embeddings. The results show that: 1) Butterfly consistently yields the best performance in most cases, which implies capturing short-term dependencies of nodes with strong connections can benefit the knowledge transfer. 2) The performance first increases and then decreases as the random walk length becomes larger because shorter sequences lack useful information while longer sequences contain more noise. 3) Compared to \mathcal{T}_1 , \mathcal{T}_2 , \mathcal{T}_3 , combining all types of triangles leads to the performance gain, verifying that each triangle type is important. 4) In most cases, \mathcal{A} does not perform best, as some motifs bring extra noise.

¹In RQ2-RQ6, due to the space constraints, we only report the performance of the Dual-User-Intra CDR task. The remaining three tasks exhibit the same trend.

Table 5: Performance comparison (%) of motif types.

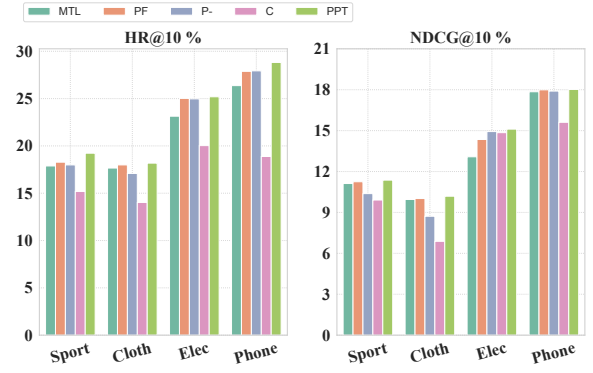
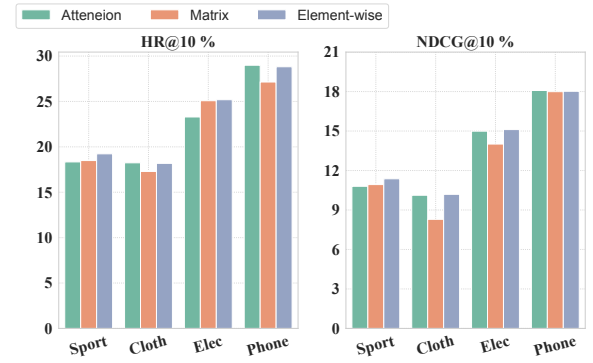
Scenarios	Metrics	Variant Models								
		$\mathcal{B}(\text{MOP})$	\mathcal{R}_3	\mathcal{R}_6	\mathcal{R}_9	\mathcal{T}_1	\mathcal{T}_2	\mathcal{T}_3	\mathcal{T}	\mathcal{A}
Sport	HR@10	19.23	11.03	16.91	16.66	10.23	9.11	12.18	15.66	19.66
	NDCG@10	11.37	6.37	8.12	7.88	5.11	5.37	6.12	9.19	11.13
Cloth	HR@10	18.18	11.92	16.92	17.24	10.23	12.35	11.24	17.23	17.89
	NDCG@10	10.09	8.34	8.93	8.45	4.56	4.67	6.32	8.88	8.40
Elec	HR@10	25.19	20.12	25.24	24.36	20.35	21.35	20.56	24.89	25.02
	NDCG@10	15.11	9.31	14.54	14.31	10.35	10.21	12.31	13.25	14.88
Phone	HR@10	28.82	19.35	28.77	26.24	20.23	21.23	20.56	24.24	29.15
	NDCG@10	18.02	12.35	17.35	16.31	10.42	10.26	12.42	17.21	17.98

Table 6: Performance comparison (%) of variant encoders.

Scenarios	Metrics	Variant Models							
		G	H	VT	MT	G + VT	G + MT	H + VT	MOP
Sport	HR@10	18.77	18.88	18.81	18.94	18.91	18.99	19.03	19.23
	NDCG@10	11.12	11.13	11.08	11.11	11.24	11.30	11.31	11.37
Cloth	HR@10	17.91	17.93	17.88	18.02	17.93	18.01	18.03	18.18
	NDCG@10	9.91	9.92	9.99	9.93	10.01	10.07	10.02	10.19
Elec	HR@10	24.99	24.94	24.98	25.13	25.01	25.09	25.04	25.19
	NDCG@10	14.79	14.81	14.88	14.93	14.98	15.08	15.19	15.11
Phone	HR@10	28.44	28.48	28.52	28.53	28.71	28.68	28.77	28.82
	NDCG@10	17.69	17.75	17.71	17.73	17.91	17.83	17.93	18.02

5.3.4 Effectiveness of the Encoder Components (RQ4). We investigate the effect of the hypergraph and MoDE Transformer by comparing MOP with 7 variant models. Notations G, H, VT, MT denote the use of LightGCN [18], hypergraph, vanilla Transformer [43] and MoDE Transformer as the base encoder, respectively; Notations G + VT, G + MT, H + VT denote the use of combining LightGCN and vanilla Transformer, LightGCN and MoDE Transformer, hypergraph and vanilla Transformer as the base encoder, respectively. Aligning Table 6 and Table 2, we find that: 1) All variant models exhibit competitive performance compared to the ‘‘SOTA’’ method. This suggests the choice of the encoder does not play a decisive role in the Rec task. 2) Combining both the (hyper)graph and the (MoDE)Transformer as the base encoder leads to a performance gain, which indicates both these types of encoders help generate high-quality node embeddings. 3) Compared to the original Transformer, using a MoDE Transformer leads to a slight performance gain, which verifies MoDE architecture can model complex domain interactions. 4) Compared to LightGCN, performing hypergraph convolution leads to a slight performance gain, which verifies hypergraph can model complex nodes correlations.

5.3.5 Effectiveness of Prompt Tuning and Prompt-based READOUT Function (RQ5). We explore the benefits of prompt tuning by comparing MOP with two training paradigms: MTL and PF. In PF, all parameters are updated when we perform the Rec task; In MTL, we discard the prompt tuning operation. Besides, we explore whether the prompt-based READOUT function is useful to summarize the

**Figure 4: Comparison of training paradigms.****Figure 5: Prompt-based READOUT operations comparison.**

motif by comparing MOP with a variant model (denoted as C). We discard the READOUT function in this model and add the CLS token upon each motif to obtain fused node embeddings. We report the results in Fig. 4. We also compare the proposed three prompt tuning templates and report the results in Fig. 5. The results show that: 1) Compared to ‘‘SOTA’’ methods, PPT performs the best, verifying the superiority of the prompt tuning technique. 2) All these training paradigms exhibit competitive performance compared to ‘‘SOTA’’ methods, which implies the training paradigm is not a decisive factor, but the motif is a good choice to achieve general knowledge transfer. 3) MTL performs worse than PF, as PF can reduce the training objective gap during the fine-tuning process. 4) All of the READOUT functions exhibit competitive performance, as they can inspire the model’s capability to handle the Rec task. 5) C performs worse than PPT, which indicates only adding the CLS token is not sufficient for effectively summarizing motifs.

5.3.6 Effectiveness of the Hyperparameters (RQ6). We examine the impact of the balance factor λ_1 and report the results in Fig. 6. We find that: 1) the Rec performance first increases, reaches a peak value of 7 in most cases, and then declines. This suggests CL is more useful than ER, potentially due to its greater focus on motif correlations. 2) Performing only the CL ($\lambda_1 = 1$) or ER ($\lambda_1 = 0$) task results in poorer performance than performing them jointly, indicating that both tasks are necessary for the Rec task.

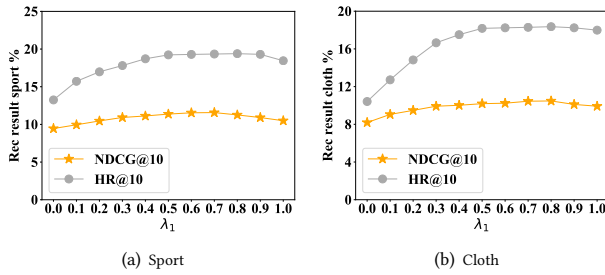


Figure 6: Impact of λ_1 on the Sport-Cloth dataset.

6 CONCLUSION

We propose MOP, which introduces motifs to capture the general topology knowledge across domains in both intra-domain and inter-domain CDR tasks. Specifically, we devise three typical motifs: butterfly, triangle and random walk, and encode them through a Motif-based Encoder to obtain motif-based shared embeddings. Additionally, we train MOP under the “Pre-training & Prompt Tuning” paradigm to effectively transfer the general knowledge by unifying the pre-training and recommendation tasks as a common motif-based similarity learning task, and introduce learnable prompt parameters to assist the model in solving the downstream recommendation task. Experimental results show the superiority of MOP against the state-of-the-art methods on both intra-domain and inter-domain CDR tasks.

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