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# **Dual-Channel Multiplex Graph Neural Networks for** Recommendation

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# ABSTRACT

Efficient recommender systems play a crucial role in accurately capturing user and item attributes that mirror individual preferences. Some existing recommendation techniques have started to shift their focus towards modeling various types of interaction relations between users and items in real-world recommendation scenarios, such as clicks, marking favorites, and purchases on online shopping platforms. Nevertheless, these approaches still grapple with two significant shortcomings: (1) Insufficient modeling and exploitation of the impact of various behavior patterns formed by multiplex relations between users and items on representation learning, and (2) ignoring the effect of different relations in the behavior patterns on the target relation in recommender system scenarios. In this study, we introduce a novel recommendation framework, Dual-Channel Multiplex Graph Neural Network (DCMGNN), which addresses the aforementioned challenges. It incorporates an explicit behavior pattern representation learner to capture the behavior patterns composed of multiplex user-item interaction relations, and includes a relation chain representation learning and a relation chain-aware encoder to discover the impact of various auxiliary relations on the target relation, the dependencies between different relations, and mine the appropriate order of relations in a behavior pattern. Extensive experiments on three real-world datasets demonstrate that our DCMGNN surpasses various state-of-the-art recommendation methods. It outperforms the best baselines by 10.06% and

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12.15% on average across all datasets in terms of R@10 and N@10 respectively.

### **CCS CONCEPTS**

• Mathematics of computing → Graph algorithms; • Computing methodologies  $\rightarrow$  Learning latent representations; • Information systems  $\rightarrow$  Recommender systems.

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# **1 INTRODUCTION**

Recommender systems have become a key component of various online platforms, especially in the fields of e-commerce [8, 15, 33], social media [1], and video platforms [7], to provide users with personalized and accurate information recommendations [29]. The complex interactions between users and items have become increasingly varied and complicated [31], and traditional collaborative filtering-based recommender systems [4, 20] often tend to simplify the relations between users and items, and are unable to fully reflect the diversity of user behaviors and deep interaction patterns. With the development of deep learning and graph neural networks (GNNs), constructing diverse GNNs to capture higher-order neighborhood information of users and items has become a mainstream method [39].

Some existing GNN-based recommendation methods, such as HCCF [45], DCCF [30], LightGCN [17], LightGCL [2], have not been limited to historical collaborative filtering information [6, 18, 24], but enhance the representations of user-item interaction information by introducing techniques such as hypergraph structures [45], singular value decomposition [2], generative self-supervised learning [41], knowledge-aware learning [3, 25, 44]. These methods have

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achieved promising results, but they only focus on a single useritem interaction relation (generally called the target relation, e.g., purchase relation in e-commerce networks), and do not fully explore the complex interaction relations between users and items. To address this problem, some researchers have proposed multi-behavior recommender systems [12, 19, 32], which attempt to meticulously consider multiplex relations between users and items by introducing meta-paths [36, 52], contrastive learning [13, 21, 37, 38, 40], graph disentanglement [30], and other means [5, 26, 48, 50, 54]. However, existing approaches often fail to fully capture the complex impact of user-item interactions, as shaped by multiplex relations, on their respective representations. In response, a specific group of researchers has aimed to address this limitation by capturing the behaviors through the development of multiplex graph neural networks [43], such as HybridGNN [14], MHGCN [53] and BPHGNN [9]. While these models explicitly account for behavior patterns within multiplex relations, they often ignore the effect of different relations in the behavior patterns on the target relations in recommender system scenarios.

Therefore, it is important to acknowledge two important limitations of the current recommendation approaches: First, the impact of various behavior patterns formed by multiplex interactions between users and items on representation learning is not adequately modeled and exploited. The complex interactions between users and items in real-world scenarios require a more nuanced approach to representation learning to encompass the diversity of user behaviors and evolving user preferences [10, 47]. Unfortunately, capturing this information is difficult because the composition of these interactions is complex, and general GNNs are not capable of direct node representation learning. Second, most existing approaches ignore the impact of different interaction relations within behavior patterns on the target relation. User behaviors are inherently multiplex, and the relations formed in these interactions each make their impact and contribution to the target relation in the recommender system. Established approaches ignore the different impacts of each interactive relation in the behavior patterns on the target relation, which hinders the models' ability to understand the user preferences and correlations and dependencies between relations, thus limiting the accuracy of recommendations.

Presented Work. Recognizing the above challenges, we focus on exploring different behavior patterns and the effects of different relations within them on the target relation within the framework underlying multiplex graph representation learning. To this end, this paper proposes a novel Dual-Channel Multiplex Graph Neural Network model (DCMGNN) for multi-behavior recommendation tasks. In DCMGNN, we first design an explicit behavior pattern representation learner to learn potential user preferences by explicitly modeling the complex interaction relations between users and items, based on the multiplex bipartite graph. This enables the recommender system we developed to adequately model and exploit the complex behavior patterns formed by multiplex interactive relations between users and items. Second, we utilize the idea of contrastive learning to capture the effects of different auxiliary relations on the target relation, as well as the correlations and dependencies between different relations in the behavior pattern, respectively. The former achieves agreement between relation-specific embeddings through the constructed relation-based contrastive

learning loss, and the latter takes into account that the correlations and dependencies between relations are of a certain sequence in a behavior pattern. Thus our model goes about exploring the appropriate order of relations in the behavior patterns by designing an *implicit relation chain effect learner* and a *relation chain-aware contrastive learning* module. In particular, the ethical personalized knowledge extracted from the user is then used as a complement to the contrastive learning, and fed into the weighting function to guide the contrastive learning to better distinguish the effects of different auxiliary relations on the target relation. Experiments on three real-world datasets show the significant superiority of our proposed model over state-of-the-art (STOA) baselines.

This work makes the following contributions:

- We propose a novel multi-behavior recommendation model, DCMGNN, that emphasizes the importance of constructing and exploiting user behavior patterns and addresses the issue of the impact of different types of interactive relations on the target relation.
- We present an implicit relation chain effect learner to explore the effect of the sequence of different relations on the target relation. We also design a relation chain-aware contrastive learning paradigm to refine the impact, correlations, and dependencies of different relation chains on the target relation.
- We conduct extensive experiments on three real-world datasets to demonstrate the effectiveness of our proposed frame-work. Experiment results show that DCMGNN achieves up to 11.84% and 14.34% performance improvement compared to STOA baselines in *R*@10 and *N*@10.

### 2 RELATED WORK

Multi-behavior recommendation [16, 23] refers to the utilization of multiplex relations in user-item interactions for recommendation [12, 19]. It has attracted increasing attention in recent years due to its effectiveness in mitigating data sparsity and improving recommendation performance [27, 31, 42]. Early multi-behavior recommendation methods are mainly based on traditional recommendation techniques, and a straightforward approach is to take a traditional matrix factorization technique that runs on a single matrix and extend it to multiple matrices [34, 35, 56]. For recommender systems such as HCCF [45] and LightGCL [2] that focus on only a single relation, important interaction information about other relations between users and items is discarded.

In contrast, another research idea is to consider multiplex relations as auxiliary and target relations, and accordingly, new sampling strategies are designed to enrich the training samples. Loni et al. [22] proposed to assign different preference levels to multiple relations and extended the criterion BPR [31] with a new negative sampling strategy for negative item sampling from different relations. Gu et al. [13] designed a self-supervised task to differentiate the importance of different relations to capture the differences between the embeddings of different relations, complemented by a star-contrastive learning paradigm to capture the embedded commonalities between the target and auxiliary relations. Gu et al. [16]

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used item-item similarity to generate samples from multiple auxiliary behaviors. Huang et al. [45] on the other hand strengthened the information from collaborative filtering by using GCN.

With the rapid development of GNNs or graph convolutional networks (GCNs), it has also been naturally introduced into the field of recommender systems, and recent researchers have also tried to develop multi-behavior recommendation models based on them. In GNN-based models, a common approach is to first learn user and item embeddings from each relation by a designed network, and then aggregate the embeddings learned from different relations for target relation prediction [11, 12, 46]. The difference is that different approaches will design different convolutional networks [53] and attention mechanisms [28]. For example, Zhang et al. [55] utilized Multiplex Graph Neural Networks (MGNNs) to address the multi-behavior recommendation problem from a novel perspective, that of link prediction in multiplex networks. By leveraging multiplex network structures and graph representation learning techniques, MGNN learns shared embeddings and behavior-specific embeddings of users and items to model the collective effects of multiplex behaviors; different from methods that aggregate embeddings from different relations to make the target relation predictions, NTMR [12] develops a neural network model combining with multi-task learning framework to capture complex multi-type interactions between users and items, the model takes into account cascading relationships between different types of behaviors (e.g., users have to click before they can buy).

For GCN models, the general paradigm is to construct a unified user-item graph based on all relations, and then perform GCN operations on the graph to learn user embeddings [5, 19, 46, 49, 51]. MBGCN [19] learns relation contributions on a unified user-item graph and models relation semantics on an item-item interaction graph. The final prediction is an aggregation of the prediction scores obtained from relation contributions and relation semantics. MB-CGCN [5] is a multi-behavior recommendation model with a cascading graph convolutional network that exploits the behavior dependency in embedding learning by using embeddings learned from one relation after a feature transformation operation as input features for embedding learning of the next relation. MBGMN [46] is a multi-behavior recommendation framework with graph metanetworks that incorporates multi-behavior pattern modeling into a meta-learning paradigm to enable user-item interaction learning to discover topologically relevant relation representations to automatically extract behavior heterogeneity and interaction diversity for recommendation. Xuan et al. [49] proposed a knowledge-enhanced multi-behavioral comparative learning recommendation (KMCLR) framework, which includes the use of a multi-behavior learning module to extract personalized relation information about a user to enhance user embedding, a knowledge enhancement module to derive a more robust perceptual representation of item knowledge, and an optimization phase to model the coarse-grained similarities and fine-grained differences between users' multiplex relations. Except for NMTR [12] and MB-CGCN [5], Yan et al. [50] proposed a CRGCN model that addresses this limitation by using a cascaded GCN structure for multi-task learning. However, due to the residual design, it can only use a single layer of GCNs for auxiliary behaviors.

### **3 PRELIMINARY**

Given the user set, the item set, and multiple interaction relations between users and items, we first model them into a multiplex bipartite graph as follows.

DEFINITION 1 (MULTIPLEX BIPARTITE GRAPH). A multiplex bipartite graph is defined as  $\mathcal{G} = \{\mathcal{U}, \mathcal{V}, \mathbf{X}, \mathcal{E}\}$ , where  $\mathcal{U}$  and  $\mathcal{V}$  denote the set of all users and the set of all items respectively,  $\mathbf{X} \in \mathbb{R}^{(|\mathcal{U}|+|\mathcal{V}|) \times f}$ denotes node (include uses and items) attribute feature matrix, and  $\mathcal{E} = \bigcup_{i \in \mathcal{R}} \mathcal{E}_i$  is the collection of various interactive edges between users and items, each edge belonging to a particular interaction type. Here  $\mathcal{R}$  denotes the set of all interaction types.

For example, in typical E-commerce networks, the interaction type set  $\mathcal{R}$  usually includes viewing, add-to-favorite, add-to-cart, purchasing, etc. To capture the impact of multiple interaction relations on user and item representation, following [9], we also adopt the concept of the following basic behavior pattern.

DEFINITION 2 (BASIC BEHAVIOR PATTERN, OR BBP). A basic behavior pattern between users  $\mathcal{U}$  and items  $\mathcal{V}$  in multiplex bipartite graphs is defined as  $\mathcal{U} \xrightarrow{[r_1]\&[r_2]\&...\&[r_{|\mathcal{R}|}]} \mathcal{V}$  that represents a unique interaction behavior pattern between users and items, where  $[\cdot]$  denotes optional,  $|\mathcal{R}|$  is the number of relation types, and at least one interaction relation type  $r_i$  exists.

For example,  $\mathcal{U} \xrightarrow{view} \mathcal{V}$  and  $\mathcal{U} \xrightarrow{buy} \mathcal{V}$  are two types of BBPs between users and items, which respectively represent that there is only one interactive behavior of 'view' or 'buy' between users and items.  $\mathcal{U} \xrightarrow{view \& buy} \mathcal{V}$  and  $\mathcal{U} \xrightarrow{view \& cart \& buy} \mathcal{V}$  are also two types of BBPs, and the former means that there are only two interactions of 'view' and 'buy' between users and products at the same time, while the latter means that there are three interactive behaviors of 'view', 'cart' and 'buy' at the same time between users and products. As depicted in Figure 1, the interactive behavior between  $u_1$  and  $i_1$  belongs to pattern  $\mathcal{U} \xrightarrow{view \& buy} \mathcal{V}$ , the interactive behaviors between  $u_2$  and  $i_1$ , between  $u_2$  and  $i_3$  belong to pattern  $\mathcal{U} \xrightarrow{view \& cart \& buy} \mathcal{V}$ , and no interaction belongs to pattern  $\mathcal{U} \xrightarrow{view} \mathcal{V}$ .

To further capture the impact of different relations on the target relation (*e.g.*, buy relation) in the same behavior pattern, we next propose the concept of relation chain as follows.

DEFINITION 3 (RELATION CHAIN). Given a basic behavior pattern that includes at least two interaction relations, a relation chain is defined as a sequence of all relations included in the basic behavior pattern.

Notice that, in general, basic behavior pattern must include the target relation (*e.g.*, 'buy' relation), and the last relation in the relation chain has to be the target relation. The guidelines for defining the sequence of relation chains are implemented in the order of general principles of user behavior. For example, in E-commerce networks, we define the order of interaction relations as:  $view \rightarrow collect \rightarrow cart \rightarrow buy$ . For pattern  $\mathcal{U} \xrightarrow{view \& cart \& buy} \mathcal{V}$ , a corresponding relation chain  $\langle view \rightarrow cart \rightarrow buy \rangle$  is produced.

Finally, we formally defined our studied problem in this work.

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PROBLEM. Given a multiplex bipartite graph  $\mathcal{G} = {\mathcal{U}, \mathcal{V}, \mathbf{X}, \mathcal{E}}$ , the goal of our recommender system is to learn a predictive function which estimates the likelihood of user  $u \in \mathcal{U}$  will interact with item  $v \in \mathcal{V}$  under the target interaction behavior.

### 4 METHODOLOGY

In this section, we present the Dual-Channel Multiplex Graph Neural Network (DCMGNN) for the recommendation, which contains three critical components: *Explicit Behavior Pattern Representation Learner, Implicit Relation Chain Effect Learner*, and *Relation Chainaware Contrastive Learning*. Figure 1 illustrates the overall architecture of the proposed DCMGNN.

# 4.1 Explicit Behavior Pattern Representation Learner

There are multiple interaction relations between users and items in multiplex bipartite graphs, and to better utilize these relations, we use the basic behavior pattern, which contains a series of U-I interactions that represent the complete shopping behavior of a user for an item. Inspired by BPHGNN [9], a model for multiplex graph representation learning, we design an explicit behavior pattern representation learner, which explicitly captures the behavior between users and items into user/item representations. Three key components are included in the explicit behavior pattern representation learner: *basic behavior pattern constructor, local behavior pattern aggregation*, and *global behavior pattern aggregation*.

4.1.1 Basic Behavior Pattern Constructor. Basic behavior pattern constructor extracts all basic behavior pattern matrices directly from the multiplex bipartite graph. First, we decouple the multiplex heterogeneous network structure based on the types of edges (relations). Let  $\{\mathbf{A}_r \in \mathbb{R}^{N \times N} | r = 1, 2, ..., |\mathcal{R}|\}$  denote the adjacency matrix of the generated subgraphs, where  $N = |\mathcal{U}| + |\mathcal{V}|$  is the number of all nodes in the network. Then, each adjacency matrix and the corresponding logic variable (*i.e.*, 1 or 0) is operated with XNOR to generate  $|\mathcal{R}|$  intermediate matrices  $\{\vec{A}_r \in \mathbb{R}^{N \times N} | r = 1, 2, ..., |\mathcal{R}|\}$ . Here, the logic variable is 1 if the relation represented by the adjacency matrix is preserved in the basic behavior pattern, and 0 otherwise. Finally, a per-position AND operation is performed on the intermediate matrix to obtain the basic behavior pattern matrix. By adjusting the logic variables, we can obtain all basic behavior pattern matrices  $\{\bar{A}_i \in \mathbb{R}^{N \times N} | i = 1, 2, ..., 2^{|\mathcal{R}|} - 1\}$ .

4.1.2 Local Behavior Pattern Aggregation. Local behavior patterns are deep aggregations of basic behavior patterns, aiming at capturing the multiplex structure among the nodes from the perspective of local nodes, to mine the interactions among different relations in the behavior patterns. To achieve this goal, local behavior pattern aggregation introduces an attention mechanism that distinguishes the importance of each basic behavior pattern through a set of learnable attention weights  $a_i$ , as shown below:

$$\widetilde{\mathbf{A}}_{loc} = \sum_{i=1}^{\mathbb{N}} a_i \overline{\mathbf{A}}_i,\tag{1}$$

where  $\mathbb{N}$  denotes the number of basic behavior patterns.

Based on previous work, we use a simplified LightGCN [17] to obtain representations, *i.e.*, without linear activation and feature

transformations:

$$\mathbf{H}_{loc}^{(l)} = \widetilde{\mathbf{A}}_{loc} \cdot \mathbf{H}_{loc}^{(l-1)}.$$
 (2)

The depth of the local behavior patterns can be determined by the number of convolutional layers. Eventually, the local node representation  $\mathbf{H}_{loc} \in \mathbb{R}^{N \times d}$  is obtained by fusing the outputs of all the layers to capture all the multiple interaction information in the behavior patterns of different depths as follows:

$$\mathbf{H}_{loc} = \frac{1}{L} \sum_{i=1}^{L} \mathbf{H}_{loc}^{(i)}.$$
 (3)

4.1.3 Global Behavior Pattern Aggregation. Global behavior pattern aggregates features among nodes from a global perspective based on the similarity of basic behavior patterns among nodes. Users with similar behaviors are more likely to exhibit similar purchase preferences. Specifically, we first generate a matrix to represent the users' global behavior patterns based on the obtained basic behavior patterns, adding rows to obtain column vectors for each basic behavior pattern matrix, and each column vector describes the number of basic behavior patterns corresponding to all users relative to all other items. Considering that different behavior patterns contribute differently to the similarity, we use a set of learnable weights  $b_i$  to connect these column vectors to obtain the global behavior pattern matrix  $\mathbf{B} \in \mathbb{R}^{N \times \mathbb{N}}$ :

$$\mathbf{B}_{p(i)} = \sum_{j=1}^{|\mathcal{V}|} \overline{\mathbf{A}}_{p(i,j)},\tag{4}$$

$$\mathbf{B} = \bigoplus_{i=1}^{\mathbb{N}} b_i \cdot \mathbf{B}_i = (\bigoplus_{i=1}^{\mathbb{N}} \mathbf{B}_i) \cdot \mathbf{\Lambda}_b, \tag{5}$$

where  $\mathbf{B}_p \in \mathbb{R}^{N \times 1}$  is the column vector related to the *p*-th basic behavior pattern,  $\oplus$  denotes the concatenation operation and  $\Lambda_b = diag(b_1, b_2, \dots, b_{\mathbb{N}})$  represents the learnable diagonal matrix.

Then we obtain the global behavior pattern similarity matrix  $\widetilde{A}_{qlo}$  by transposition and normalization as follows:

$$\widetilde{\mathbf{A}}_{glo} = norm(\mathbf{B} \cdot \mathbf{B}^T) \in \mathbb{R}^{N \times N}.$$
(6)

We input the global behavior pattern similarity matrix into Light-GCN for information aggregation to obtain node representations:

$$\mathbf{H}_{glo}^{(l)} = \widetilde{\mathbf{A}}_{glo} \cdot \mathbf{H}_{glo}^{(l-1)},\tag{7}$$

and we take the output  $\mathbf{H}_{glo}^{(l)} \in \mathbb{R}^{N \times d}$  as the global node representation  $\mathbf{H}_{alo}$ .

We filter user embedding and item embedding using  $H_{loc}(u)$  and  $H_{loc}(v)$  respectively, and then obtain the Explicit Behavior Pattern (EBP) embeddings of user u or item v ( $H_{u/v} \in \mathbb{R}^d$ ) through the average pooling as:

$$\mathbf{H}_{u/v} = \frac{1}{2} \left( \mathbf{H}_{loc}(u/v) + \mathbf{H}_{glo}(u/v) \right).$$
(8)

### 4.2 Implicit Relation Chain Effect Learner

In this section, we aim to learn the impact of implicit relation chains within behavior patterns on node representation. We first learn multi-relation embeddings of users and items through LightGCN, and then obtain node relation-chain embeddings by capturing the effect of relation chains corresponding to basic behavior patterns.



Figure 1: The overview of the proposed DCMGNN.

4.2.1 Multiplex Relation Embedding Aggregation. In this section, we use LightGCN [17] as an information dissemination mechanism to learn the embeddings of users and items from each relation. For the *r*-th relation in the multiplex bipartite graph, LightGCN utilizes the user-item interactions to propagate the embeddings as follows:

$$e_u^{(r,l)} = \sum_{v \in \mathcal{N}_u^{(r)}} \frac{1}{\sqrt{|\mathcal{N}_u^{(r)}| \cdot |\mathcal{N}_v^{(r)}|}} e_v^{(r,l-1)}, \tag{9}$$

$$e_v^{(r,l)} = \sum_{u \in \mathcal{N}_u^{(r)}} \frac{1}{\sqrt{|\mathcal{N}_v^{(r)}| \cdot |\mathcal{N}_u^{(r)}|}} e_u^{(r,l-1)},$$
(10)

where  $\mathcal{N}_{u}^{r}$  and  $\mathcal{N}_{v}^{r}$  represent the neighbor set of users and items under the *r*-th relation respectively,  $e_{u}^{(r,l)}$  and  $e_{v}^{(r,l)}$  denote the embeddings of user *u* and item *v* under the *r*-th relation throughout the propagation of *l* LightGCN layers. After that, we simply aggregate the embeddings of users  $\{e_{u}^{(r,0)}, e_{u}^{(r,1)}, \dots, e_{u}^{(r,L)}\}$  and those of items  $\{e_{v}^{(r,0)}, e_{v}^{(r,1)}, \dots, e_{v}^{(r,L)}\}$  to get relation-specific embeddings:

$$e_u^{(r)} = \sum_{l=0}^{L} e_u^{(r,l)}, e_v^{(r)} = \sum_{l=0}^{L} e_v^{(r,l)}.$$
 (11)

Finally, we obtain the multi-relation embeddings of users and items as follows:

$$e_u^r = \sum_{r \in \mathcal{R}} e_u^{(r)}, e_v^r = \sum_{r \in \mathcal{R}} e_v^{(r)}.$$
 (12)

4.2.2 Relation Chain Representation Learning. According to Definition 3 (*i.e.*, Relation Chain), a relation chain is generated for each basic behavior pattern containing the target relation (*i.e.*, buy relation) and two or more relations. Let  $\mathbf{W}_{u}^{i,j}$  and  $\mathbf{W}_{v}^{i,j}$  be the learnable transformation matrix parameters of users and items from the *j*-th relation to the (*j* + 1)-th relation in the *i*-th relation chain, and the

transformation is performed as:

$$e_{u}^{i,j+1} = \mathbf{W}_{u}^{i,j} e_{u}^{i,j}, e_{v}^{j+1} = \mathbf{W}_{v}^{i,j} e_{v}^{i,j},$$
(13)

where  $e_u^{i,j}$  and  $e_v^{i,j}$  represent the embeddings of user u and item v of *j*-th relation. When the transformation process is over, we will finally get the relation-chain embeddings  $e_u^c$  and  $e_v^c$  of user u and item v across all relation chains as follows:

$$e_{u}^{c} = \sum_{i=1}^{|C|} \sum_{j=1}^{|C_{i}|} e_{u}^{i,j}, e_{v}^{c} = \sum_{i=1}^{|C|} \sum_{j=1}^{|C_{i}|} e_{v}^{i,j}$$
(14)

where  $C = \{C_1, C_2, ..., C_m\}$  represents the set of relation chains, and *m* denotes the number of relation chains. According to the experiments, it is proved that the feature transformation process among the relation chains is simple and efficient, and the features can be extracted effectively.

Based on the learned EBP embeddings  $H_{u/v}$ , multi-relation-based embeddings  $e_{u/v}^r$ , and relation-chain embeddings  $e_{u/v}^c$ , we can obtain the final embeddings of user *u* and item *v*, respectively:

$$e_{u}^{final} = Mean\left(\mathbf{H}_{u}, e_{u}^{r}, e_{u}^{c}\right), e_{v}^{final} = Mean\left(\mathbf{H}_{v}, e_{v}^{r}, e_{v}^{c}\right).$$
(15)

### 4.3 Relation Chain-aware Contrastive Learning

In E-commerce networks, different users have different interaction preferences in their behavior patterns toward items. In multiplex bipartite graphs, multiple behavior patterns lead to different item-relational interactions for different users, so it is important to effectively model the dependencies and correlations between the different types of relations in behavior patterns.

Before that, it is also important to consider the multiple useritem interaction relations contained in different behavior patterns, so we first set up a relation-based contrastive learning module for distinguishing between the target 'buy' relation and other different auxiliary relations. Specifically, we set different relations for the same user as positive sample pairs and different users are considered negative ones. For user-item interactions, the intuition is represented by different interaction relations, so setting up such a comparison learning module helps us to capture the relation between the auxiliary relation and the target buy relation.

To achieve this goal, we introduce a relation chain-aware contrastive learning framework for integrating explicit weighting functions for contrastive losses of different relations in multiple basic behavior patterns. The relation chain-aware contrastive learning is divided into two phases: First, we use a relation-aware encoder to represent different relation chains to capture the multi-relational features of user-item interactions, reflecting user shopping preferences under different relation chains; Second, the knowledge extracted from the relation-aware encoder serves as an input to a relation chain-aware network that generates customized contrastive loss weights for the relation chain dependency modeling.

4.3.1 *Relation-based Contrastive Learning.* Following existing methods, we use the InfoNCE loss in the relation-based contrastive learning module to measure the difference between relation-specific embeddings. We calculate the relation-based contrastive loss as follows:

$$\mathcal{L}_{rcl}^{r',r} = \sum_{u \in \mathcal{U}} -\log \frac{\exp(\phi(e_u^{(r)}, e_u^{(r')})/\tau)}{\sum_{u' \in \mathcal{U}} \exp(\phi(e_u^{(r)}, e_{u'}^{(r')})/\tau)},$$
(16)

where  $\phi(\cdot)$  denotes the similarity function between two embeddings,  $\tau$  denotes the temperature hyperparameter for *Softmax* function. Generally, we maximize the contrastive loss to make the different relations more distinguishable from each other than before and use this to measure the variability between different users.

4.3.2 *Relation Chain-aware Encoder.* In the relation chain-aware contrastive learning module, we first extract the relation-aware knowledge to preserve relation dependencies and correlations. Inspired by the feature extraction mechanism in CML [37], we set two kinds of relation-aware encoder within two types of aggregation techniques based on the learned users' relation embeddings, relation-chain embeddings, and final embeddings as follows:

$$\mathbf{F}_{u}^{c,r_{t}} = (dup(\sum_{r \in c} \mathcal{L}_{rcl}^{r,r_{t}}) \cdot \mu) \oplus e_{u}^{c} \oplus e_{u}^{final},$$
(17)

$$\mathcal{F}_{u}^{r,r_{t}} = \mathcal{L}_{rcl}^{r,r_{t}} \cdot (e_{u}^{(r)} \oplus e_{u}^{final}), \tag{18}$$

where  $r_t$  denotes the target relation, and  $\mathbf{F}_u^{c,r_t}$  represents the dependencies that retain user preference information between all relations in the user relation chain and the target relation, and  $dup(\cdot)$  denotes the duplicate function which aims to generate a vector that has the same embedding dimensionality,  $\oplus$  represents the embedding concatenation,  $\mu$  denotes the scale factor for the enlarge value.  $\mathcal{F}_u^{r,r_t}$  cooperatively represents the relation-aware knowledge between relation-specific embedding and user embedding. According to this, relation dependencies and correlations in the relation chain and relation-specific embeddings can be preserved.

Next, we transform the preserved information into relation chainaware contrastive weights. Let  $\varphi(\cdot)$  represent the transformation function, and we can obtain the relation dependencies and correlations  $\varphi(\mathbf{F}_{u}^{c,r_{t}})$  as follows:

$$\varphi(\mathbf{F}_{u}^{c,r_{t}}) = LeakyReLU(\mathbf{F}_{u}^{c,r_{t}} \cdot \mathbf{W}^{\varphi} + b^{\varphi}), \tag{19}$$

Table 1: Statistical information of evaluation datasets.

Datasets	Users	Items	Interactions	Relation Type
Retail	2,174	30,113	$9.7 \times 10^4$	{View, Cart, Buy}
Tmall	15,449	11,953	$1.2 \times 10^6$	{View, Cart, Buy}
Yelp	19,800	22,734	$1.4 \times 10^6$	{Tips, Like, Neutral, Dislike}

where  $\mathbf{W}^{\varphi}$  and  $b^{\varphi}$  represent the projection and bias item in the *LeakyReLU*, and we can obtain  $\varphi(\mathcal{F}_{u}^{c,r_{t}})$  by obeying the same way.

# 4.4 Joint Optimization

In this section, we introduce the objective of DCMGNN model.

We leverage the BPR loss to learn corresponding parameters in the model inference of DCMGNN. Formally, the BPR loss is defined as follows:

$$\mathcal{L}_{BPR}^{c} = \sum_{(u,v^{+},v^{-})\in O_{c}} -\ln(Sigmoid(\hat{y}_{u,v^{+}}^{c} - \hat{y}_{u,v^{-}}^{c})) + \lambda ||\Theta||^{2}$$
(20)

where  $\hat{y}_{u,v^+}^c = e_u^{c^+} e_{v^+}^c$ ,  $O_c$  denotes the training samples of *c*-th relation chain, *i.e.*,  $O_c = \{(u, v^+, v^-) | (u, v^+) \in \mathcal{R}^+, (u, v^-) \in \mathcal{R}^-\}$ .  $\mathcal{R}^+$  and  $\mathcal{R}^-$  denote the observed and unobserved interaction in the corresponding behavior pattern,  $\Theta$  represents the learnable parameter.  $L_2$  regularization is adopted to prevent over-fitting, and  $\lambda$  is a coefficient to control the  $L_2$  regularization.

$$\mathcal{L}_{BPR} = \sum_{c \in C} \varphi(\mathbf{F}_{u}^{c,r_{l}}) \cdot \mathcal{L}_{BPR}^{c},$$
(21)

$$\mathcal{L}_{rcl} = \sum_{r \in \mathcal{R} - \{r_t\}} \varphi(\mathcal{F}_u^{r,r_t}) \cdot \mathcal{L}_{rcl}^{r,r_t},$$
(22)

where *C* denotes the set of all relation chains, and  $r_t$  denotes the target relation.

$$\mathcal{L}_{BPR}^{final} = \sum_{(u,v^+,v^-)\in O} -\ln(Sigmoid(\hat{y}_{u,v^+} - \hat{y}_{u,v^-})) + \lambda ||\Theta||^2$$
(23)

where  $\hat{y}_{u,v^+} = e_u^{final^{\mathsf{T}}} e_{v^+}^{final}$ .

The final loss of the proposed DCMGNN is as follows:

$$\mathcal{L} = \mathcal{L}_{BPR} + \mu_1 \mathcal{L}_{rcl} + \mu_2 \mathcal{L}_{BPR}^{f\,inal} \tag{24}$$

# **5 EXPERIMENTS**

### 5.1 Datasets

In our experiments, three real-world publicly available datasets are utilized, *i.e.*, Retail\_Rocket (Retail for short) [29], Tmall [5], and Yelp [13]. We detail the dataset description in the supplementary material. The statistics of three datasets are summarized in Table 1.

### 5.2 Evaluation Metrics

For all experiments, we evaluate our DCMGNN and baselines in terms of the top-*k* recommended items with the following metrics: the Recall (*R*@5, *R*@10, *R*@20, *R*@40) and the Normalized Discounted Cumulative Gain (NDCG) (*N*@5, *N*@10, *N*@20, *N*@40).

### 5.3 Baselines

We compare our DCMGNN with the following nineteen baselines, which can be divided into two main categories: Single-behavior recommendation methods include **BPR** [31], **LightGCN** [17], **HCCF** [45], **DCCF** [30], **AutoCF** [41], and **LightGCL** [2]; multi-behavior

recommendation methods contain RGCN [32], NMTR [12], MBGCN [19], MB-HGCN [51], MB-CGCN [5], MBGMN [46], CRGCN [50], HMG-CR [52], S-MBRec [13], CML [37], KMCLR [49], and BPHGNN [9]. More information can be found in the supplement.

### 5.4 Experimental Setting

In our experiments, our models are optimized using the Adam optimizer. The embedding dimension d and batch size are set from {8, 16, 32, 64, 128, 256} and 128 for all methods, while the learning rate is varied in the range {1e-2, 1e-3, 1e-4}. In addition, we initialize the model parameters (relation feature transformation matrix) using the *Xavier* initializer. The number of LightGCN layers per relation is varied in the range {1,2,3,4}. Unless otherwise stated, for multiple relations in a relation chain, we use solid three LightGCN layers. For all baselines, we directly use their source code and the parameter settings recommended in their papers to ensure that their method achieves results as close as possible to their claims. Each experiment is performed ten times and the average value is reported.

### 5.5 Overall Performance

We perform a performance comparison between DCMGNN and all baselines, with results shown in Table 2. The best results are highlighted in bold, and the second-best results are underlined. As we can see, our DCMGNN achieves the optimal performance, significantly outperforming all baselines across multiple metrics on the three datasets, with specific emphasis on the improvement relative to the state-of-the-art (SOTA). Our model yields notable enhancements, achieving a 14.34% improvement in terms of N@10on Retail dataset, a 11.84% improvement in terms of R@10 on Tmall dataset, and a 12.12% improvement in terms of N@10 on Yelp dataset. It is worth noting that the top three baselines, namely CML, KMCLR, and MB-CGCN, have already demonstrated substantial improvements on these datasets, providing strong evidence of the effectiveness of our DCMGNN.

For multi-behavior recommendation models, most of them have achieved better results than single-behavior recommendation models. These approaches try to model the complex relationship between users and items from graph structure learning, capture the higher-order interaction information that is difficult to access by collaborative filtering, and also achieve refreshing results. In addition, some works based on MBGCN (e.g., MB-RGCN, MB-CGCN, MBGMN, and CRGCN), intend to capture more U-I interaction information by improving the graph convolution mechanism. CML captures the dependency between different auxiliary behaviors and the target behavior through the improvement of the contrast learning mechanism, and KMCLR supplements the missing node by introducing the knowledge graph attribute features. All in all, the results of these methods further prove the superiority of our method in capturing the impact of explicit multi-relational behavior patterns and the effect of implicit relation chains on target relations simultaneously.

### 5.6 Ablation Study

To evaluate the effectiveness of each component of our DCMGNN, we further conduct ablation studies on different variants. To be specific, we generate variants as follows:



Figure 2: Hyperparameter impact of embedding dimension *d* and graph propagation layer *L* 

- w/oE removes explicit behavior pattern representation learner.
- w/o M removes multiplex relation embedding aggregation.
- w/o R removes relation chain representation learning.
- w/o RCL excludes relation-based contrastive learning.
- *w/o RCE* excludes relation chain-aware encoder and *L*<sub>BPR</sub>.
- *w/o FNL* excludes the  $\mathcal{L}_{BPR}^{final}$

We report the results for the recommendation task on the three datasets in Table 3. Our five variants significantly perform worse than DCMGNN model in terms of R@10 and N@10, which proves that our proposed five variants are effective and necessary. Among them, w/o R performs the worst, which demonstrates the effectiveness of relation chains in extracting useful information from early relations to help learn user and item embeddings in later relations, as the latter relations in a relation chain are usually more revealing of a user's interactive preference for an item. w/o RCL performs only better than w/o R, which demonstrates the importance of contrastive learning in distinguishing between different relation types and enhancing the learning process of characterizing the target relation (e.g., 'buy'). Meanwhile, based on the experimental results of w/o M, it is important to take full advantage of the multiple relations between users and items in our model. w/o RCE, on the other hand, learns the correlations and dependencies between different relations from a new perspective, especially considering the effect of auxiliary relations in relation chains on the target relation, and the experimental results also prove the importance of this component. The results of *w/o E* once again confirm that explicit multi-relational behavioral pattern representation learning is crucial and reasonable for multi-behavior recommendation tasks.

### 5.7 Performance on Mitigating Data Sparsity

In this section, we explain that DCMGNN helps to mitigate the data sparsity problem. Experimental results with different interaction sparsity on Tmall dataset are shown in Figure 3. In the experiments, we select several of the best-performing baselines, *i.e.*, MB-CGCN,

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Table 2: Performance comparison of all models on three datasets. *Improvement* denotes the improvement of our results compared with the second-best results. Marker \* indicates the results is statistically significant (t-test with p-value < 0.01).

	Retail					Tmall				Yelp			
Method	R@10	R@20	N@10	N@20	R@10	R@20	N@10	N@20	R@10	R@20	N@10	N@20	
BPR	0.0230	0.0316	0.0124	0.0144	0.0236	0.0311	0.0128	0.0152	0.0175	0.0287	0.0103	0.0129	
LightGCN	0.0383	0.0438	0.0209	0.0233	0.0411	0.0546	0.0240	0.0266	0.0191	0.0302	0.0119	0.0144	
HCCF	0.0396	0.0471	0.0214	0.0238	0.0424	0.0558	0.0242	0.0271	0.0189	0.0381	0.0133	0.0156	
DCCF	0.0395	0.0476	0.0218	0.0239	0.0423	0.0561	0.0241	0.0279	0.0207	0.0405	0.0134	0.0161	
AutoCF	0.0402	0.0477	0.0222	0.0238	0.0415	0.0525	0.0239	0.0277	0.0208	0.0399	0.0135	0.0174	
LightGCL	0.0409	0.0489	0.0229	0.0242	0.0441	0.0597	0.0255	0.0289	0.0249	0.0451	0.0149	0.0189	
RGCN	0.0363	0.0446	0.0188	0.0204	0.0315	0.0426	0.0234	0.0275	0.0305	0.0537	0.0204	0.0237	
NMTR	0.0372	0.0448	0.0198	0.0210	0.0682	0.0842	0.0273	0.0303	0.0397	0.0579	0.0215	0.0266	
MBGCN	0.0379	0.0457	0.0209	0.0227	0.0809	0.0991	0.0294	0.0350	0.0416	0.0634	0.0229	0.0258	
MB-HGCN	0.0412	0.0472	0.0232	0.0258	0.1098	0.1783	0.0635	0.0852	0.0528	0.0698	0.0256	0.0274	
MB-CGCN	0.0418	0.0492	0.0249	0.0253	0.1233	0.2007	0.0657	0.0876	0.0573	0.0725	0.0285	0.0302	
CRGCN	0.0411	0.0471	0.0232	0.0252	0.0855	0.1369	0.0539	0.0776	0.0561	0.0682	0.0237	0.0269	
MBCMN	0.0405	0.0478	0.0217	0.0241	0.0857	0.1578	0.0607	0.0763	0.0537	0.0698	0.0273	0.0287	
HMG-CR	0.0363	0.0446	0.0213	0.0234	0.0854	0.1546	0.0663	0.0714	0.0555	0.0707	0.0263	0.0275	
S-MBRec	0.0386	0.0461	0.0234	0.0248	0.0877	0.1691	0.0642	0.0795	0.0559	0.0723	0.0287	0.0311	
CML	0.0428	0.0492	0.0251	0.0263	0.1203	0.2092	0.0661	0.0852	0.0577	0.0745	0.0294	0.0321	
KMCLR	0.0428	0.0501	0.0247	0.0264	0.1185	0.2107	0.0659	0.0882	0.0578	0.0752	0.0297	0.0319	
BPHGNN	0.0376	0.0449	0.0217	0.0245	0.0991	0.1806	0.0641	0.0836	0.0537	0.0705	0.0275	0.0289	
DCMGNN	0.0471*	0.0544*	0.0287*	0.0293*	0.1379*	0.2304*	0.0727*	0.0943*	0.0626*	0.0835*	0.0333*	0.0351*	
Improvement	10.05%	8.58%	14.34%	10.98%	11.84%	9.35%	9.98%	6.92%	8.30%	10.91%	12.12%	9.35%	

Table 3: The comparison of DCMGNN and its variants.

Dataset	Re	tail	Tn	nall	Yelp		
Metrics	R@10	N@10	R@10	N@10	R@10	N@10	
w/o E	0.0371	0.0246	0.0982	0.0554	0.0475	0.0261	
w/o M	0.0345	0.0211	0.0927	0.0494	0.0461	0.0232	
w/o R	0.0311	0.0173	0.0868	0.0466	0.0391	0.0219	
w/o RCL	0.0334	0.0199	0.0928	0.0489	0.0443	0.0247	
w/o RCE	0.0412	0.0238	0.1182	0.0628	0.0527	0.0275	
w/o FNL	0.0325	0.0185	0.0912	0.0458	0.0405	0.0229	
DCMGNN	0.0471	0.0287	0.1379	0.0727	0.0626	0.0333	



Figure 3: Performance comparison *w.r.t* different sparsity degrees on Tmall dataset.

S-MBRec, CML, KMCLR, and BPHGNN. Specifically, we categorized users into six groups ("[0,4)", "[4,5)", "[5,6)", "[6,7)", "[7,10)", and "[10,60)") based on the number of interactions they had. The model performance measured by R@10 and N@10 (shown on the right axis in Figure 3) is the average of all users in each group. The total number of users in each group is shown on the left axis in Figure 3. Based on the experimental results, we observe that: i) An increase in the number of user interactions improves the recommendation accuracy of all the methods. This is because high-quality relational embeddings are more likely to be learned through sufficient user-item interactions. ii) Considering that CML and KMCLR have better results in mitigating the data sparsity problem alone, our model consistently outperforms them, which confirms the fact that DCMGNN is indeed better at mitigating the data sparsity problem.

### 5.8 Parameter Sensitivity

5.8.1 The Effect of Hidden Embedding Dimensionality. As shown in Figure 2(a-b), our model achieves the best when d = 64 on Retail and Tmall datasets, which indicates that our DCMGNN can improve the performance with smaller hidden embedding dimensions.

5.8.2 The Effect of Graph Propagation Layers. It can be concluded from Figure 2(c-d) that the more graph propagation layers the better the performance of the model when  $L \leq 3$ . However continuing to superimpose more layers may bring such things as noise effects, over-smoothing problems, etc. to the user and item representations.

5.8.3 The Effect of Relation Order. We consider six containment order relation chains on two datasets:  $C1 : \langle buy \rightarrow view \rightarrow cart \rangle$ ,  $C2 : \langle buy \rightarrow cart \rightarrow view \rangle$ ,  $C3 : \langle view \rightarrow buy \rightarrow cart \rangle$ , C4 : $<math>\langle cart \rightarrow buy \rightarrow view \rangle$ ,  $C5 : \langle cart \rightarrow view \rightarrow buy \rangle$ , and C6 : $<math>\langle view \rightarrow cart \rightarrow buy \rangle$ . The performance of the relation chains with different orders on the two datasets is shown in Figure 4. It can be found that the relation chains in which the target buy relation is the last relation show the best performance, *i.e.*, *C5* and *C6* are consistently better than other relation chains with different orders.



### Figure 4: Effects of orders in relation chains

Since the relation chains are with order, the embedding learned from the previous relations will directly influence the embedding learned from the next relation. Therefore, pre-setting a reasonable relation order is necessary to enhance the recommendation effect. The order of relation chains designed and adopted in this work has achieved significant advantages, which also shows that the impact of the order of different relations in the relation chains on the target relation is also different and crucial for item recommendations.

### 6 CONCLUSION

In this work, we propose a model called DCMGNN for multibehavior recommendation task, the purpose of each component in it is to learn feature embeddings of users and items from different perspectives, especially in relation chain-aware encoder we reinforce the correlations and dependencies between different auxiliary and target relation, which is one of the most important innovations of our model. Experiments on three real-world datasets show that DCMGNN outperforms state-of-the-art multi-behavior recommendation models with decent performance gains. Further ablation studies validate the effectiveness of each feature embedding learning part of our model. KDD'24, August 25-29, 2024, Barcelona, Spain

### REFERENCES

- Anitha Anandhan, Liyana Shuib, Maizatul Akmar Ismail, and Ghulam Mujtaba. 2018. Social media recommender systems: review and open research issues. *IEEE Access* 6 (2018), 15608–15628.
- [2] Xuheng Cai, Chao Huang, Lianghao Xia, and Xubin Ren. 2023. LightGCL: Simple Yet Effective Graph Contrastive Learning for Recommendation. arXiv preprint arXiv:2302.08191 (2023).
- [3] Yao Chang, Wei Zhou, Haini Cai, Wei Fan, Linfeng Hu, and Junhao Wen. 2023. Meta-relation assisted knowledge-aware coupled graph neural network for recommendation. *Information Processing & Management* 60, 3 (2023), 103353.
- [4] Zhiyong Cheng, Ying Ding, Lei Zhu, and Mohan Kankanhalli. 2018. Aspect-aware latent factor model: Rating prediction with ratings and reviews. In Proceedings of the 2018 world wide web conference. 639–648.
- [5] Zhiyong Cheng, Sai Han, Fan Liu, Lei Zhu, Zan Gao, and Yuxin Peng. 2023. Multi-Behavior Recommendation with Cascading Graph Convolution Networks. In Proceedings of the ACM Web Conference 2023. 1181–1189.
- [6] Zhiyong Cheng, Fan Liu, Shenghan Mei, Yangyang Guo, Lei Zhu, and Liqiang Nie. 2022. Feature-level attentive ICF for recommendation. ACM Transactions on Information Systems (TOIS) 40, 4 (2022), 1–24.
- [7] Germán Cheuque, José Guzmán, and Denis Parra. 2019. Recommender systems for Online video game platforms: The case of STEAM. In Companion Proceedings of The 2019 World Wide Web Conference. 763-771.
- [8] Yashar Deldjoo, Markus Schedl, Paolo Cremonesi, and Gabriella Pasi. 2020. Recommender systems leveraging multimedia content. ACM Computing Surveys (CSUR) 53, 5 (2020), 1–38.
- [9] Chaofan Fu, Guanjie Zheng, Chao Huang, Yanwei Yu, and Junyu Dong. 2023. Multiplex Heterogeneous Graph Neural Network with Behavior Pattern Modeling. In Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining. 482–494.
- [10] Mingxin Gan, Gangxin Xu, and Yingxue Ma. 2023. A multi-behavior recommendation method exploring the preference differences among various behaviors. *Expert Systems with Applications* 228 (2023), 120316.
- [11] Chen Gao, Xiangnan He, Dahua Gan, Xiangning Chen, Fuli Feng, Yong Li, Tat-Seng Chua, and Depeng Jin. 2019. Neural multi-task recommendation from multi-behavior data. In 2019 IEEE 35th international conference on data engineering (ICDE). IEEE, 1554–1557.
- [12] Chen Gao, Xiangnan He, Dahua Gan, Xiangning Chen, Fuli Feng, Yong Li, Tat-Seng Chua, Lina Yao, Yang Song, and Depeng Jin. 2019. Learning to recommend with multiple cascading behaviors. *IEEE transactions on knowledge and data engineering* 33, 6 (2019), 2588–2601.
- [13] Shuyun Gu, Xiao Wang, Chuan Shi, and Ding Xiao. 2022. Self-supervised graph neural networks for multi-behavior recommendation. In International Joint Conference on Artificial Intelligence (IJCAI).
- [14] Tiankai Gu, Chaokun Wang, Cheng Wu, Yunkai Lou, Jingcao Xu, Changping Wang, Kai Xu, Can Ye, and Yang Song. 2022. HybridGNN: Learning hybrid representation for recommendation in multiplex heterogeneous networks. In 2022 IEEE 38th International Conference on Data Engineering (ICDE). IEEE, 1355–1367.
- [15] Long Guo, Lifeng Hua, Rongfei Jia, Binqiang Zhao, Xiaobo Wang, and Bin Cui. 2019. Buying or browsing?: Predicting real-time purchasing intent using attention-based deep network with multiple behavior. In Proceedings of the 25th ACM SIGKDD international conference on knowledge discovery & data mining. 1984–1992.
- [16] Wei Guo, Chang Meng, Enming Yuan, Zhicheng He, Huifeng Guo, Yingxue Zhang, Bo Chen, Yaochen Hu, Ruiming Tang, Xiu Li, et al. 2023. Compressed Interaction Graph based Framework for Multi-behavior Recommendation. arXiv preprint arXiv:2303.02418 (2023).
- [17] Xiangnan He, Kuan Deng, Xiang Wang, Yan Li, Yongdong Zhang, and Meng Wang. 2020. Lightgcn: Simplifying and powering graph convolution network for recommendation. In Proceedings of the 43rd International ACM SIGIR conference on research and development in Information Retrieval. 639–648.
- [18] Xiangnan He, Lizi Liao, Hanwang Zhang, Liqiang Nie, Xia Hu, and Tat-Seng Chua. 2017. Neural collaborative filtering. In Proceedings of the 26th international conference on world wide web. 173–182.
- [19] Bowen Jin, Chen Gao, Xiangnan He, Depeng Jin, and Yong Li. 2020. Multibehavior recommendation with graph convolutional networks. In Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval. 659–668.
- [20] Yehuda Koren, Robert Bell, and Chris Volinsky. 2009. Matrix factorization techniques for recommender systems. Computer 42, 8 (2009), 30–37.
- [21] Qingfeng Li, Huifang Ma, Ruoyi Zhang, Wangyu Jin, and Zhixin Li. 2023. Intraand Inter-behavior Contrastive Learning for Multi-behavior Recommendation. In International Conference on Database Systems for Advanced Applications. Springer, 147–162.
- [22] Babak Loni, Roberto Pagano, Martha Larson, and Alan Hanjalic. 2016. Bayesian personalized ranking with multi-channel user feedback. In Proceedings of the 10th ACM conference on recommender systems. 361–364.

- [23] Tie-min Ma, Xue Wang, Fu-cai Zhou, and Shuang Wang. 2023. Research on diversity and accuracy of the recommendation system based on multi-objective optimization. *Neural Computing and Applications* 35, 7 (2023), 5155–5163.
- [24] Kelong Mao, Jieming Zhu, Xi Xiao, Biao Lu, Zhaowei Wang, and Xiuqiang He. 2021. UltraGCN: ultra simplification of graph convolutional networks for recommendation. In Proceedings of the 30th ACM International Conference on Information & Knowledge Management. 1253–1262.
- [25] Chang Meng, Chenhao Zhai, Yu Yang, Hengyu Zhang, and Xiu Li. 2023. Parallel knowledge enhancement based framework for multi-behavior recommendation. In Proceedings of the 32nd ACM International Conference on Information and Knowledge Management. 1797–1806.
- [26] Chang Meng, Hengyu Zhang, Wei Guo, Huifeng Guo, Haotian Liu, Yingxue Zhang, Hongkun Zheng, Ruiming Tang, Xiu Li, and Rui Zhang. 2023. Hierarchical projection enhanced multi-behavior recommendation. In Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining. 4649–4660.
- [27] Chang Meng, Ziqi Zhao, Wei Guo, Yingxue Zhang, Haolun Wu, Chen Gao, Dong Li, Xiu Li, and Ruiming Tang. 2023. Coarse-to-fine knowledge-enhanced multi-interest learning framework for multi-behavior recommendation. ACM Transactions on Information Systems 42, 1 (2023), 1–27.
- [28] Xingchen Peng, Jing Sun, Mingshi Yan, Fuming Sun, and Fasheng Wang. 2023. Attention-guided graph convolutional network for multi-behavior recommendation. *Knowledge-Based Systems* 280 (2023), 111040.
- [29] Xubin Ren, Lianghao Xia, Yuhao Yang, Wei Wei, Tianle Wang, Xuheng Cai, and Chao Huang. 2023. SSLRec: A Self-Supervised Learning Library for Recommendation. arXiv preprint arXiv:2308.05697 (2023).
- [30] Xubin Ren, Lianghao Xia, Jiashu Zhao, Dawei Yin, and Chao Huang. 2023. Disentangled Contrastive Collaborative Filtering. arXiv preprint arXiv:2305.02759 (2023).
- [31] Steffen Rendle, Christoph Freudenthaler, Zeno Gantner, and Lars Schmidt-Thieme. 2012. BPR: Bayesian personalized ranking from implicit feedback. arXiv preprint arXiv:1205.2618 (2012).
- [32] Michael Schlichtkrull, Thomas N Kipf, Peter Bloem, Rianne Van Den Berg, Ivan Titov, and Max Welling. 2018. Modeling relational data with graph convolutional networks. In *The Semantic Web: 15th International Conference, ESWC 2018, Heraklion, Crete, Greece, June 3–7, 2018, Proceedings 15.* Springer, 593–607.
- [33] Yanyan Shen, Baoyuan Ou, and Ranzhen Li. 2022. MBN: Towards multi-behavior sequence modeling for next basket recommendation. ACM Transactions on Knowledge Discovery from Data (TKDD) 16, 5 (2022), 1–23.
- [34] Ajit P Singh and Geoffrey J Gordon. 2008. Relational learning via collective matrix factorization. In Proceedings of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining. 650–658.
- [35] Liang Tang, Bo Long, Bee-Chung Chen, and Deepak Agarwal. 2016. An empirical study on recommendation with multiple types of feedback. In Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining. 283–292.
- [36] Weiwei Wang, Liting Wei, Yun Li, Yi Zhu, Bin Li, and Lejun Zhang. 2022. Attentional Meta-path Contrastive Graph Convolutional Networks for Knowledge Concept Recommendation. In 2022 Tenth International Conference on Advanced Cloud and Big Data (CBD). IEEE, 200–205.
- [37] Wei Wei, Chao Huang, Lianghao Xia, Yong Xu, Jiashu Zhao, and Dawei Yin. 2022. Contrastive meta learning with behavior multiplicity for recommendation. In Proceedings of the fifteenth ACM international conference on web search and data mining. 1120–1128.
- [38] Wei Wei, Lianghao Xia, and Chao Huang. 2023. Multi-relational contrastive learning for recommendation. In Proceedings of the 17th ACM Conference on Recommender Systems. 338–349.
- [39] Le Wu, Xiangnan He, Xiang Wang, Kun Zhang, and Meng Wang. 2022. A survey on accuracy-oriented neural recommendation: From collaborative filtering to information-rich recommendation. *IEEE Transactions on Knowledge and Data Engineering* 35, 5 (2022), 4425–4445.
- [40] Yiqing Wu, Ruobing Xie, Yongchun Zhu, Xiang Ao, Xin Chen, Xu Zhang, Fuzhen Zhuang, Leyu Lin, and Qing He. 2022. Multi-view multi-behavior contrastive learning in recommendation. In *International Conference on Database Systems for Advanced Applications*. Springer, 166–182.
- [41] Lianghao Xia, Chao Huang, Chunzhen Huang, Kangyi Lin, Tao Yu, and Ben Kao. 2023. Automated Self-Supervised Learning for Recommendation. In Proceedings of the ACM Web Conference 2023. 992–1002.
- [42] Lianghao Xia, Chao Huang, Yong Xu, Peng Dai, Mengyin Lu, and Liefeng Bo. 2021. Multi-behavior enhanced recommendation with cross-interaction collaborative relation modeling. In 2021 IEEE 37th International Conference on Data Engineering (ICDE). IEEE, 1931–1936.
- [43] Lianghao Xia, Chao Huang, Yong Xu, Peng Dai, Bo Zhang, and Liefeng Bo. 2020. Multiplex behavioral relation learning for recommendation via memory augmented transformer network. In Proceedings of the 43rd international ACM SIGIR conference on research and development in information retrieval. 2397–2406.
- [44] Lianghao Xia, Chao Huang, Yong Xu, Peng Dai, Xiyue Zhang, Hongsheng Yang, Jian Pei, and Liefeng Bo. 2021. Knowledge-enhanced hierarchical graph transformer network for multi-behavior recommendation. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 35. 4486–4493.

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- [45] Lianghao Xia, Chao Huang, Yong Xu, Jiashu Zhao, Dawei Yin, and Jimmy Huang. 2022. Hypergraph contrastive collaborative filtering. In Proceedings of the 45th International ACM SIGIR conference on research and development in information retrieval. 70–79.
- [46] Lianghao Xia, Yong Xu, Chao Huang, Peng Dai, and Liefeng Bo. 2021. Graph meta network for multi-behavior recommendation. In Proceedings of the 44th international ACM SIGIR conference on research and development in information retrieval. 757–766.
- [47] Xin Xin, Xiangyuan Liu, Hanbing Wang, Pengjie Ren, Zhumin Chen, Jiahuan Lei, Xinlei Shi, Hengliang Luo, Joemon M Jose, Maarten de Rijke, et al. 2023. Improving implicit feedback-based recommendation through multi-behavior alignment. In Proceedings of the 46th international ACM SIGIR conference on research and development in information retrieval. 932–941.
- [48] Hongrui Xuan and Bohan Li. 2023. Temporal-Aware Multi-behavior Contrastive Recommendation. In International Conference on Database Systems for Advanced Applications. Springer, 269–285.
- [49] Hongrui Xuan, Yi Liu, Bohan Li, and Hongzhi Yin. 2023. Knowledge Enhancement for Contrastive Multi-Behavior Recommendation. In Proceedings of the Sixteenth ACM International Conference on Web Search and Data Mining. 195–203.
- [50] Mingshi Yan, Zhiyong Cheng, Chen Gao, Jing Sun, Fan Liu, Fuming Sun, and Haojie Li. 2023. Cascading residual graph convolutional network for multibehavior recommendation. ACM Transactions on Information Systems (2023).

- [51] Mingshi Yan, Zhiyong Cheng, Jing Sun, Fuming Sun, and Yuxin Peng. 2023. MB-HGCN: A Hierarchical Graph Convolutional Network for Multi-behavior Recommendation. arXiv preprint arXiv:2306.10679 (2023).
- [52] Haoran Yang, Hongxu Chen, Lin Li, S Yu Philip, and Guandong Xu. 2021. Hyper meta-path contrastive learning for multi-behavior recommendation. In 2021 IEEE International Conference on Data Mining (ICDM). IEEE, 787–796.
- [53] Pengyang Yu, Chaofan Fu, Yanwei Yu, Chao Huang, Zhongying Zhao, and Junyu Dong. 2022. Multiplex heterogeneous graph convolutional network. In Proceedings of the 28th ACM SIGKDD Conference on Knowledge Discovery and Data Mining. 2377–2387.
- [54] Chi Zhang, Rui Chen, Xiangyu Zhao, Qilong Han, and Li Li. 2023. Denoising and Prompt-Tuning for Multi-Behavior Recommendation. In Proceedings of the ACM Web Conference 2023. 1355–1363.
- [55] Weifeng Zhang, Jingwen Mao, Yi Cao, and Congfu Xu. 2020. Multiplex graph neural networks for multi-behavior recommendation. In Proceedings of the 29th ACM international conference on information & knowledge management. 2313– 2316.
- [56] Zhe Zhao, Zhiyuan Cheng, Lichan Hong, and Ed H Chi. 2015. Improving user topic interest profiles by behavior factorization. In *Proceedings of the 24th International Conference on World Wide Web*. 1406–1416.

# A SUPPLEMENT

# A.1 Notations

### Table 4: Summary of key notations.

NotationDefinition $\mathcal{G}$ the input multiplex bipartite graph $\mathcal{U}, \mathcal{V}$ the set of users/items $\mathbf{X}$ the node attribute feature matrix $\mathcal{E}$ the collection of various interactive edges in $\mathcal{G}$ $\mathcal{R}$ the set of all interaction types in $\mathcal{G}$ $u, v$ a user/item $\mathbf{A}_r$ the adjacency matrix for $r$ -th relation of $\mathcal{G}$ $\bar{\mathbf{A}}_p$ the adjacency matrix of BBP type $p$ $a_{loc}$ the learnable weights for BBP type $p$ $\bar{\mathbf{A}}_{loc}$ the local aggregated adjacency matrix $\mathbf{B}$ the global behavior pattern matrix $\bar{\mathbf{A}}_{glo}$ the global behavior pattern similarity matrix $\mathbf{H}_{loc}, \mathbf{H}_{glo}$ the number of nodes/BBPs $\mathcal{N}_u^u, \mathcal{N}_v^v$ user/item relation-specific embedding for $r$ -th relation $e_u^{(r,l)}, e_v^{(r,l)}$ user/item relation-specific embedding for $r$ -th relation chain $e_v^{i,j}, \mathbf{W}_v^i$ the item emb. at $j$ -th relation in $i$ -th relation chain $\mathbf{W}_u^u, \mathbf{W}_v^v$ trans matrix of user/item in relation chains $\mathbf{W}_u^{i,j}, \mathbf{W}_v^{i,j}$ the set of relation chains, the $i$ -th relation chain		
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Notation	Definition
$ \begin{array}{c c} \mathcal{U}, \mathcal{V} & \text{the set of users/items} \\ \mathbf{X} & \text{the node attribute feature matrix} \\ \mathcal{E} & \text{the collection of various interactive edges in } \mathcal{G} \\ \mathcal{R} & \text{the set of all interaction types in } \mathcal{G} \\ \mathcal{R} & \text{the set of all interaction types in } \mathcal{G} \\ \mathcal{R} & \text{the adjacency matrix for } r\text{-th relation of } \mathcal{G} \\ \bar{\mathbf{A}}_{p} & \text{the adjacency matrix of BBP type } p \\ \mathbf{a}_{p}, \mathbf{b}_{p} & \text{the adjacency matrix of BBP type } p \\ \bar{\mathbf{A}}_{loc} & \text{the local aggregated adjacency matrix} \\ \mathbf{B} & \text{the global behavior pattern matrix} \\ \mathbf{A}_{glo} & \text{the global behavior pattern matrix} \\ \mathbf{H}_{loc}, \mathbf{H}_{glo} & \text{the number of nodes/BBPs} \\ \mathcal{N}_{u}^{r}, \mathcal{N}_{v}^{r} & \text{the neighbor set of user/item for } r\text{-th relation} \\ \mathbf{e}_{u}^{(r,l), \mathbf{e}_{v}^{(r,l)}} & \text{user/item embedding at } l\text{-th layer for } r\text{-th relation the user remb. at } j\text{-th relation in } i\text{-th relation chain} \\ \mathbf{e}_{v}^{i,j}, \mathbf{W}_{v}^{i,j} & \text{the set of user/item in relation chains} \\ \mathbf{W}_{u}^{i,j}, \mathbf{W}_{v}^{i,j} & \text{the set of relation chains, the } i\text{-th relation chain} \\ \mathbf{F}_{u}^{r,r,r} & \text{relation chains, the } i\text{-th relation chain} \\ \mathbf{F}_{u}^{r,r,r} & \text{relation chains, the } i\text{-th relation chains} \\ \mathbf{F}_{u}^{r,r,r} & \text{relation chains, the i-th relation chain} \\ \mathbf{F}_{u}^{r,r,r} & \text{relation chains, the } i\text{-th relation chain} \\ \mathbf{F}_{u}^{r,r,r} & \text{relation chains, the i-th relation chain} \\ \mathbf{F}_{u}^{r,r,r} & \text{relation chains, the i-th relation chain} \\ \mathbf{F}_{u}^{r,r,r} & \text{relation chains, the i-th relation chain} \\ \mathbf{F}_{u}^{r,r,r} & \text{relation chains, the i-th relation chain} \\ \mathbf{F}_{u}^{r,r,r} & \text{relation chains, the i-th relation chain} \\ \mathbf{F}_{u}^{r,r,r} & \text{relation chains, the i-th relation chain} \\ \mathbf{F}_{u}^{r,r,r} & \text{relation chain-aware knowledge} \\ \mathbf{F}_{u}^{r,r,r} & \text{relation chain-aware knowledge} \\ \mathbf{F}_{u}^{r,r,r} & \text{relation chain} \\ \mathbf{F}_{u}^{r,r,r} & \text{relation chain} \\ \mathbf{F}_{u}^{r,r,r} & \text{relation chain} \\ \mathbf{F}_{u}^{r,r,r} & \mathbf{F}_{u}^{r,r,r} & \text{relation chain} \\ \mathbf{F}_{u}^{$	G	the input multiplex bipartite graph
$ \begin{array}{c cccc} \mathbf{X} & \text{the node attribute feature matrix} \\ & & & & & & & & & & & & & & & & & & $	$\mathcal{U},\mathcal{V}$	the set of users/items
$ \begin{array}{lll} \mathcal{E} & \mbox{the collection of various interactive edges in } \mathcal{G} \\ \mathcal{R} & \mbox{the set of all interaction types in } \mathcal{G} \\ \mathcal{R} & \mbox{the set of all interaction types in } \mathcal{G} \\ \mathcal{R} & \mbox{the set of all interaction types in } \mathcal{G} \\ \mathcal{R} & \mbox{the set of all interaction types in } \mathcal{G} \\ \mathcal{R} & \mbox{the adjacency matrix for } r\text{-th relation of } \mathcal{G} \\ \bar{A}_p & \mbox{the adjacency matrix of BBP type } p \\ \mathcal{A}_{loc} & \mbox{the learnable weights for BBP type } p \\ \bar{A}_{loc} & \mbox{the local aggregated adjacency matrix} \\ \bar{B} & \mbox{the global behavior pattern matrix} \\ \bar{A}_{glo} & \mbox{the global behavior pattern similarity matrix} \\ \mathbf{H}_{loc}, \mathbf{H}_{glo} & \mbox{the selobal behavior pattern similarity matrix} \\ \mathbf{H}_{loc}, \mathbf{H}_{glo} & \mbox{the number of nodes/BBPs} \\ \mathcal{N}_u^r, \mathcal{N}_v^r & \mbox{the neighbor set of user/item for } r\text{-th relation} \\ e_u^{(r,l),e_v^{(r,l)}} & \mbox{user/item relation-specific embedding for } r\text{-th relation} \\ e_u^{i,j} & \mbox{the user emb. at } j\text{-th relation in } i\text{-th relation chain} \\ e_u^{i,j} & \mbox{the user/item embedding of relation chains} \\ \mathbf{W}_u^{i,j}, \mathbf{W}_v^{i,j} & \mbox{trans matrix of user/item in relation chains} \\ \mathbf{W}_u^{i,j}, \mathbf{W}_v^{i,j} & \mbox{trans matrix of user/item in relation chains} \\ \mathbf{F}_u^{r,r_r} & \mbox{relation chain-aware knowledge} \\ \mathcal{F}_u^{r,r_r} & \mbox{relation-aware knowledge between embeddings} \\ \end{array} \right$	Х	the node attribute feature matrix
$ \begin{array}{llllllllllllllllllllllllllllllllllll$	3	the collection of various interactive edges in ${\cal G}$
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	${\mathcal R}$	the set of all interaction types in ${\cal G}$
$\begin{array}{lll} \mathbf{A}_{r} & \text{the adjacency matrix for } r\text{-th relation of } \mathcal{G} \\ \bar{\mathbf{A}}_{p} & \text{the adjacency matrix of BBP type } p \\ a_{p}, b_{p} & \text{the learnable weights for BBP type } p \\ \mathbf{A}_{loc} & \text{the local aggregated adjacency matrix} \\ \mathbf{B} & \text{the global behavior pattern matrix} \\ \widetilde{\mathbf{A}}_{glo} & \text{the global behavior pattern similarity matrix} \\ \mathbf{H}_{loc}, \mathbf{H}_{glo} & \text{the global behavior pattern similarity matrix} \\ \mathbf{M}_{u}, \mathbf{N}_{v}^{n} & \text{the number of nodes/BBPs} \\ \mathcal{N}_{u}^{r}, \mathcal{N}_{v}^{r} & \text{the neighbor set of user/item for } r\text{-th relation} \\ e_{u}^{(r,l),e_{v}^{(r,l)}} & \text{user/item relation-specific embedding for } r\text{-th relation} \\ e_{u}^{i,j} & \text{the item emb. at } j\text{-th relation in } i\text{-th relation chain} \\ e_{v}^{i,v}, \mathbf{W}_{v}^{i,j} & \text{the set of relation chains} \\ \mathbf{W}_{u}^{i,j}, \mathbf{W}_{v}^{i,j} & \text{the set of relation chains, the } i\text{-th relation chains} \\ \mathbf{F}_{u}^{r,r,r} & \text{relation-aware knowledge} \\ \mathcal{F}_{u}^{r,r,r} & \text{relation-aware knowledge between embeddings} \\ \end{array}$	и, v	a user/item
$ \begin{array}{c c} \bar{\mathbf{A}}_p & \text{the adjacency matrix of BBP type $p$} \\ a_p, b_p & \text{the learnable weights for BBP type $p$} \\ \bar{\mathbf{A}}_{loc} & \text{the local aggregated adjacency matrix} \\ \bar{\mathbf{B}} & \text{the global behavior pattern matrix} \\ \overline{\mathbf{A}}_{glo} & \text{the global behavior pattern similarity matrix} \\ \mathbf{H}_{loc}, \mathbf{H}_{glo} & \text{the global behavior pattern similarity matrix} \\ \mathbf{H}_{loc}, \mathbf{H}_{glo} & \text{the global behavior pattern similarity matrix} \\ \mathbf{H}_{loc}, \mathbf{H}_{glo} & \text{the mumber of nodes} \\ d & \text{the dimension of embeddings} \\ \mathbf{N}, \mathbb{N} & \text{the number of nodes/BBPs} \\ \mathbf{N}_{u}^{r}, \mathbf{N}_{v}^{r} & \text{the neighbor set of user/item for $r$-th relation} \\ \mathbf{e}_{u}^{(r,l), \mathbf{e}_{v}^{(r,l)}} & \text{user/item relation-specific embedding for $r$-th relation} \\ \mathbf{e}_{u}^{i,j} & \text{the user emb. at $j$-th relation in $i$-th relation chain} \\ \mathbf{e}_{v}^{i, v} \mathbf{e}_{v}^{c} & \text{the user/item embedding of relation chains} \\ \mathbf{W}_{u}^{i, j}, \mathbf{W}_{v}^{i, j} & \text{trans matrix of user/item in relation chains} \\ \mathbf{F}_{u}^{c, r, r_{t}} & \text{relation-chains, the $i$-th relation chain} \\ \mathbf{F}_{u}^{r, r_{t}} & \text{relation chains, the $i$-th relation chains} \\ \mathbf{F}_{u}^{r, r_{t}} & \text{relation-aware knowledge between embeddings} \\ \end{array} $	$A_r$	the adjacency matrix for $r$ -th relation of ${\mathcal G}$
$\begin{array}{lll} \begin{array}{c} a_{p}, b_{p} \\ \overline{A}_{loc} \\ \overline{A}_{loc} \\ \overline{B} \\ \end{array} \begin{array}{l} \mbox{the local aggregated adjacency matrix} \\ \overline{B} \\ \overline{A}_{glo} \\ \overline{A}_{glo} \\ \hline B \\ \end{array} \begin{array}{l} \mbox{the global behavior pattern matrix} \\ \overline{A}_{glo} \\ \hline A_{loc}, H_{glo} \\ \hline A_{loc}, H_{glo} \\ \hline A_{glo} \\ \hline A_{glo}$	$\bar{A}_p$	the adjacency matrix of BBP type $p$
$ \begin{array}{c c} \widetilde{\mathbf{A}}_{loc} & \text{the local aggregated adjacency matrix} \\ \mathbf{B} & \text{the global behavior pattern matrix} \\ \widetilde{\mathbf{A}}_{glo} & \text{the global behavior pattern matrix} \\ \mathbf{H}_{loc}, \mathbf{H}_{glo} & \text{the global behavior pattern similarity matrix} \\ \mathbf{H}_{loc}, \mathbf{H}_{glo} & \text{the global behavior pattern similarity matrix} \\ \mathbf{H}_{loc}, \mathbf{H}_{glo} & \text{the number of nodes} \\ d & \text{the dimension of embeddings} \\ \mathbf{N}, \mathbb{N} & \text{the number of nodes/BBPs} \\ \mathbf{N}_{u}^{r}, \mathbf{N}_{v}^{r} & \text{the neighbor set of user/item for } r\text{-th relation} \\ \mathbf{e}_{u}^{(r,l), \mathbf{e}_{v}^{(r,l)}} & \text{user/item embedding at } l\text{-th layer for } r\text{-th relation} \\ \mathbf{e}_{u}^{(r)}, \mathbf{e}_{v}^{(r)} & \text{user/item relation-specific embedding for } r\text{-th relation thain} \\ \mathbf{e}_{v}^{i,j} & \text{the item emb. at } j\text{-th relation in } i\text{-th relation chain} \\ \mathbf{e}_{v}^{i,j}, \mathbf{W}_{v}^{i,j} & \text{trans matrix of user/item in relation chains} \\ \mathbf{W}_{u}^{i,j}, \mathbf{W}_{v}^{i,j} & \text{trans matrix of user/item in relation chains} \\ \mathbf{F}_{u}^{c,r,r_{t}} & \text{relation-aware knowledge} \\ \mathcal{F}_{u}^{r,r,r_{t}} & \text{relation-aware knowledge between embeddings} \\ \end{array} $	$a_p, b_p$	the learnable weights for BBP type $p$
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	$\widetilde{A}_{loc}$	the local aggregated adjacency matrix
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $	В	the global behavior pattern matrix
$\begin{array}{c c} \mathbf{H}_{loc}, \mathbf{H}_{glo} \\ d \\ \mathbf{M}_{loc}, \mathbf{H}_{glo} \\ d \\ \mathbf{M}_{loc}, \mathbf{M}_{glo} \\ \mathbf{M}_{loc}, \mathbf{M}_{loc}, \mathbf{M}_{loc} \\ \mathbf{M}_{u}, \mathbf{M}_{v}^{r} \\ \mathbf{M}_{u}^{r}, \mathbf{M}_{v}^{r} \\ \mathbf{M}_{v}^{r} \\ \mathbf{M}_{v}^{r}, \mathbf{M}_{v}^{r} \\ \mathbf{M}_{v}^{r$	$\widetilde{A}_{alo}$	the global behavior pattern similarity matrix
$ \begin{array}{c c} d & \text{the dimension of embeddings} \\ N, \mathbb{N} & \text{the number of nodes/BBPs} \\ N_u^r, N_v^r & \text{the neighbor set of user/item for } r\text{-th relation} \\ e_u^{(r)}, e_v^{(r)} & \text{user/item embedding at } l\text{-th layer for } r\text{-th relation} \\ e_u^{(r)}, e_v^{(r)} & \text{user/item relation-specific embedding for } r\text{-th relation} \\ e_u^{(r)}, e_v^{(r)} & \text{user/item relation-specific embedding for } r\text{-th relation} \\ e_u^{(r)}, e_v^{(r)} & \text{the user emb. at } j\text{-th relation in } i\text{-th relation chain} \\ e_u^{(r)}, e_v^{(r)} & \text{the item emb. at } j\text{-th relation in } i\text{-th relation chain} \\ e_u^{(r)}, e_v^{(r)} & \text{the user/item embedding of relation chains} \\ W_u^{(i,j)}, W_v^{(i,j)} & \text{trans matrix of user/item in relation chains} \\ W_u^{(i,j)}, W_v^{(i,j)} & \text{trans matrix of user/item in relation chains} \\ F_u^{(r,r_t)} & \text{relation chain-aware knowledge} \\ \mathcal{F}_u^{(r,r_t)} & \text{relation-aware knowledge between embeddings} \\ \end{array} $	H <sub>loc</sub> , H <sub>alo</sub>	the hidden representation for nodes
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $	d	the dimension of embeddings
$ \begin{array}{c c} \mathcal{N}_{u}^{r}, \mathcal{N}_{v}^{r} & \text{the neighbor set of user/item for } r\text{-th relation} \\ e_{u}^{(r,l),e_{v}^{(r,l)}} & \text{user/item embedding at } l\text{-th layer for } r\text{-th relation} \\ e_{u}^{(r,l),e_{v}^{(r)}} & \text{user/item relation-specific embedding for } r\text{-th relation} \\ e_{u}^{i,j} & \text{user/item relation-specific embedding for } r\text{-th relation} \\ e_{v}^{i,j} & \text{the user emb. at } j\text{-th relation in } i\text{-th relation chain} \\ e_{v}^{i,j} & \text{the user emb. at } j\text{-th relation in } i\text{-th relation chain} \\ e_{v}^{i,j}, \mathbf{W}_{v}^{i,j} & \text{the user/item embedding of relation chains} \\ \mathbf{W}_{u}^{i,j}, \mathbf{W}_{v}^{i,j} & \text{trans matrix of user/item in relation chains} \\ \mathbf{K}_{u}^{c,r,r_{i}} & \text{relation chains, the } i\text{-th relation chain} \\ \mathbf{F}_{u}^{c,r,r_{i}} & \text{relation chain-aware knowledge} \\ \mathcal{F}_{u}^{r,r_{r}} & \text{relation-aware knowledge between embeddings} \end{array} $	$N,\mathbb{N}$	the number of nodes/BBPs
$ \begin{array}{ll} e_{u}^{(r,l),e_{v}^{(r,l)}} & \text{user/item embedding at }l\text{-th layer for }r\text{-th relation} \\ e_{u}^{(r)},e_{v}^{(r)} & \text{user/item relation-specific embedding for }r\text{-th relation} \\ e_{u}^{i,j} & \text{user/item relation-specific embedding for }r\text{-th relation} \\ e_{u}^{i,j} & \text{the user emb. at }j\text{-th relation in }i\text{-th relation chain} \\ e_{v}^{i,j} & \text{the user emb. at }j\text{-th relation in }i\text{-th relation chain} \\ e_{u}^{i,j}, \mathbf{W}_{v}^{i,j} & \text{the user/item embedding of relation chains} \\ \mathbf{W}_{u}^{i,j}, \mathbf{W}_{v}^{i,j} & \text{trans matrix of user/item in relation chains} \\ \mathbf{K}_{u}^{i,j}, \mathbf{W}_{v}^{i,j} & \text{the set of relation chains, the }i\text{-th relation chain} \\ \mathbf{F}_{u}^{e,r,r_{t}} & \text{relation chain-aware knowledge} \\ \mathcal{F}_{u}^{r,r,r_{t}} & \text{relation-aware knowledge between embeddings} \end{array} $	$\mathcal{N}_{u}^{r}, \mathcal{N}_{v}^{r}$	the neighbor set of user/item for $r$ -th relation
$ \begin{array}{c c} e_{u}^{(r)}, e_{v}^{(r)} & \text{user/item relation-specific embedding for } r\text{-th relation} \\ e_{u}^{i,j} & \text{the user emb. at } j\text{-th relation in } i\text{-th relation chain} \\ e_{v}^{i,j}, e_{v}^{c} & \text{the item emb. at } j\text{-th relation in } i\text{-th relation chain} \\ e_{u}^{i,j}, e_{v}^{c} & \text{the item emb. at } j\text{-th relation in } i\text{-th relation chain} \\ e_{u}^{i,j}, \mathbf{W}_{v}^{i,j} & \text{the user/item embedding of relation chains} \\ \mathbf{W}_{u}^{i,j}, \mathbf{W}_{v}^{i,j} & \text{trans matrix of user/item in relation chains} \\ C, C_{i} & \text{the set of relation chains, the } i\text{-th relation chain} \\ \mathbf{F}_{u}^{c,r_{t}} & \text{relation chain-aware knowledge} \\ \mathcal{F}_{u}^{r,r_{t}} & \text{relation-aware knowledge between embeddings} \end{array} $	$e_u^{(r,l),e_v^{(r,l)}}$	user/item embedding at <i>l</i> -th layer for <i>r</i> -th relation
$ \begin{array}{c c} e_{u}^{i,j} & \text{the user emb. at } j\text{-th relation in } i\text{-th relation chain} \\ e_{v}^{l,j} & \text{the item emb. at } j\text{-th relation in } i\text{-th relation chain} \\ e_{v}^{c}, e_{v}^{c} & \text{the item emb. at } j\text{-th relation in } i\text{-th relation chain} \\ W_{u}^{i,j}, W_{v}^{i,j} & \text{trans matrix of user/item in relation chains} \\ W_{u}^{i,j}, W_{v}^{i,j} & \text{trans matrix of user/item in relation chains} \\ C, C_{i} & \text{the set of relation chains, the } i\text{-th relation chain} \\ F_{u}^{c,r_{t}} & \text{relation chain-aware knowledge} \\ \mathcal{F}_{u}^{r,r_{t}} & \text{relation-aware knowledge between embeddings} \end{array} $	$e_u^{(r)}, e_v^{(r)}$	user/item relation-specific embedding for <i>r</i> -th relation
$ \begin{array}{c c} e_v^{i,j} & \text{the item emb. at } j\text{-th relation in } i\text{-th relation chain} \\ e_v^{c}, e_v^{c} & \text{the user/item embedding of relation chains} \\ \mathbf{W}_u^{i,j}, \mathbf{W}_v^{i,j} & \text{trans matrix of user/item in relation chains} \\ C, C_i & \text{the set of relation chains, the } i\text{-th relation chain} \\ \mathbf{F}_u^{c,r_i} & \text{relation chain-aware knowledge} \\ \mathcal{F}_u^{r,r_r} & \text{relation-aware knowledge between embeddings} \end{array} $	$e_u^{i,j}$	the user emb. at $j$ -th relation in $i$ -th relation chain
$ \begin{array}{c} e^c_u, e^c_v \\ W^{i,j}_u, W^{i,j}_v \end{array} \qquad \mbox{the user/item embedding of relation chains} \\ W^{i,j}_u, W^{i,j}_v \qquad \mbox{trans matrix of user/item in relation chains} \\ C, C_i \\ F^{C,r_i}_u \\ \mathcal{F}^{r,r_r}_u \end{aligned} \qquad \mbox{the set of relation chains, the $i$-th relation chain} \\ relation chain-aware knowledge \\ \mathcal{F}^{r,r_r}_u \end{aligned} \qquad \mbox{relation-aware knowledge between embeddings} $	$e_v^{i,j}$	the item emb. at <i>j</i> -th relation in <i>i</i> -th relation chain
$ \begin{array}{ll} \mathbf{W}_{u}^{i,j}, \mathbf{W}_{v}^{i,j} & \text{trans matrix of user/item in relation chains} \\ C, C_{i} & \text{the set of relation chains, the } i\text{-th relation chain} \\ \mathbf{F}_{u}^{c,r_{t}} & \text{relation chain-aware knowledge} \\ \mathcal{F}_{u}^{r,r_{t}} & \text{relation-aware knowledge between embeddings} \end{array} $	$e_u^c, e_v^c$	the user/item embedding of relation chains
$C, C_i$ the set of relation chains, the <i>i</i> -th relation chain $\mathbf{F}_u^{c,r_t}$ relation chain-aware knowledge $\mathcal{F}_u^{r,r_t}$ relation-aware knowledge between embeddings	$\mathbf{W}_{u}^{i,j}, \mathbf{W}_{v}^{i,j}$	trans matrix of user/item in relation chains
$ \begin{array}{c c} \mathbf{F}_{u}^{c,r_{t}} & \text{relation chain-aware knowledge} \\ \mathcal{F}_{u}^{r,r_{t}} & \text{relation-aware knowledge between embeddings} \end{array} $	$C, C_i$	the set of relation chains, the <i>i</i> -th relation chain
$\mathcal{F}_{u}^{r,r_{t}}$ relation-aware knowledge between embeddings	$\mathbf{F}_{u}^{c,r_{t}}$	relation chain-aware knowledge
	$\mathcal{F}_{u}^{r,r_{t}}$	relation-aware knowledge between embeddings

The key notations used in this work are summarized in Table 4 in the supplement.

# A.2 Detailed Dataset Description

Three datasets are adopted for evaluation:

- Retail\_Rocket (Retail for short) [29]: This is a benchmark dataset collected from the Retail\_rocket recommendation system. In this dataset, user interactions include page views (View), add-to-cart (Cart), and transactions (Buy). According to previous research on multi-behavior recommendations [19, 43], the 'Buy' relation is set as the target relation, and the other types of relations are considered as auxiliary relations.
- **Tmall[5]:** This dataset is collected from Tmall, one of the largest e-commerce platforms in China. It contains three interaction relations, i.e., page view (View), add to cart (Cart), and purchase (Buy), where the 'Buy' relation serves as the target relation and the other relations serve as auxiliary relations.
- Yelp[13]: This dataset is collected from Yelp, which contains four interaction relations, *i.e.*, tip (Tips), dislike (Dislike), neutral (Neutral) and like (Like), where the 'Like' relation

serves as the target relation and the other relations serve as auxiliary relations.

# A.3 Baselines

We compare our DCMGNN with the following 18 baselines, which can be deeply divided into three categories: **Single-Behavior Recommendation Methods**:

- **BPR [31]:** It is a widely adopted matrix factorization model with the optimization criterion of Bayesian personalized ranking. https://github.com/bbc/theano-bpr
- LightGCN [17]: it simplifies the GCN-based recommendation architecture by removing the feature transformation and nonlinear activation operations. https://github.com/gusye1234/LightGCN-PyTorch
- HCCF [45]: It is a new self-supervised recommendation framework that can jointly capture local and global collaborative relations with a hypergraph-enhanced cross-view contrastive learning architecture. https://github.com/akaxlh/HCCF
- DCCF [30]: It realizes intent disentanglement with self-supervised augmentation in an adaptive fashion, and with the learned disentangled representations with global context, it is able to not only distill finer-grained latent factors from the entangled selfsupervision signals but also alleviate the augmentation-induced noise. https://github.com/HKUDS/DCCF
- AutoCF [41]: It automatically perform data augmentation for recommendation and focuses on the generative self-supervised learning framework with a learnable augmentation paradigm that benefits the automated distillation of important self-supervised signals. https://github.com/HKUDS/AutoCF
- LightGCL [2]: It is a simple yet effective graph contrastive learning paradigm that mitigates these issues impairing the generality and robustness of CL-based recommenders, and it exclusively utilizes singular value decomposition for contrastive augmentation, which enables the unconstrained structural refinement with global collaborative relation modeling. https://github.com/ HKUDS/LightGCL

### **Multi-Behavior Recommendation Methods:**

- **RGCN [32]:** It differentiates the relations between nodes via edge types in the graph and designs different propagation layers for different relations. This model can adapt to multi-behavior recommendation. https://github.com/SS-00-SS/MBCGCN
- NMTR [12]: It combines the multi-task learning framework and neural collaborative filtering to investigate multi-typed user interaction behaviors based on the predefined cascading relationships. https://github.com/weiwei1206/CML.git
- MBGCN [19]: It is a GCN-based model by capturing the multibehavioral patterns over the constructed user-item interaction graph, and the high-order connectivity is considered during the information propagation. https://github.com/weiwei1206/CML. git
- MB-HGCN [51]: It is a a novel multi-behavior recommendation model that uses a hierarchical graph convolutional network to learn user and item embeddings from coarse-grained on the global level to fine-grained on the behavior-specific level.
- MB-CGCN [5]: It is a novel multi-behavior recommendation model with cascading graph convolution networks, in which

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Table 5: Performance comparison of all models on three real-world datasets. *Improvement* denotes the improvement of the best results compared with second-best results. The best results are shown in bold and the best among baselines is <u>underlined</u>. Marker \* indicates the mean of the results is statistically significant (t-test with p-value < 0.01).

Mathad	Retail				Tmall				Yelp			
Method	R@5	R@40	N@5	N@40	R@5	R@40	N@5	N@40	R@5	R@40	N@5	N@40
BPR	0.0212	0.0434	0.0102	0.0166	0.0216	0.0494	0.0112	0.0193	0.0134	0.0475	0.0095	0.0161
LightGCN	0.0357	0.0513	0.0201	0.0255	0.0341	0.0874	0.0214	0.0338	0.0154	0.0676	0.0101	0.0187
HCCF	0.0359	0.0537	0.0198	0.0258	0.0347	0.0899	0.0215	0.0346	0.0157	0.0687	0.0112	0.0196
DCCF	0.0358	0.0538	0.0212	0.0253	0.0344	0.0901	0.0215	0.0357	0.0151	0.0692	0.0120	0.0198
AutoCF	0.0361	0.0546	0.0212	0.0256	0.0370	0.0866	0.0209	0.0338	0.0155	0.0686	0.0119	0.0205
LightGCL	0.0366	0.0555	0.0223	0.0256	0.0401	0.0935	0.0227	0.0381	0.0178	0.0721	0.0137	0.0221
RGCN	0.0305	0.0503	0.0134	0.0241	0.0134	0.0411	0.0111	0.0260	0.0169	0.0843	0.0185	0.0295
NMTR	0.0347	0.0515	0.0155	0.0249	0.0237	0.1034	0.0107	0.0383	0.0165	0.0824	0.0185	0.0305
MBGCN	0.0359	0.0508	0.0195	0.0253	0.0389	0.1117	0.0231	0.0455	0.0183	0.0858	0.0201	0.0294
MB-HGCN	0.0372	0.0553	0.0207	0.0251	0.0415	0.1234	0.0565	0.0834	0.0187	0.0876	0.0209	0.0312
MB-CGCN	0.0381	0.0564	0.0223	0.0262	<u>0.0986</u>	0.3322	0.0564	0.1134	0.0225	0.1071	0.0241	0.0322
CRGCN	0.0375	0.0550	0.0218	0.0260	0.0744	0.2325	0.0403	0.0866	0.0197	0.0940	0.0217	0.0315
MBCMN	0.0367	0.0529	0.0211	0.0255	0.0791	0.2529	0.0563	0.0855	0.0201	0.0879	0.0220	0.0318
HMG-CR	0.0341	0.0554	0.0197	0.0252	0.0606	0.2584	0.0551	0.0817	0.0213	0.0884	0.0223	0.0299
S-MBRec	0.0372	0.0593	0.0220	0.0269	0.0711	0.2593	0.0547	0.0880	0.0227	0.1135	0.0241	0.0337
CML	0.0408	0.0579	0.0224	0.0272	0.0915	0.3055	0.0573	0.1272	0.0249	0.1157	0.0258	0.0342
KMCLR	0.0407	0.0577	0.0228	0.0273	0.0920	0.3235	0.0574	0.1269	0.0243	0.1157	0.0259	0.0349
BPHGNN	0.0361	0.0537	0.0205	0.0261	0.0895	0.2703	0.0554	0.1089	0.0227	0.0976	0.0240	0.0332
DCMGNN	0.0446*	0.0624*	0.0248*	0.0298*	0.1099*	0.3466*	0.0618*	0.1368*	0.0275*	0.1237*	0.0282*	0.0382*
Improvement	9.31%	5.23%	8.77%	9.16%	11.46%	4.33%	7.67%	7.55%	10.44%	6.91%	8.88%	9.46%

the embeddings learned from one behavior are used as the input features for the next behavior's embedding learning after a feature transformation operation. https://github.com/SS-00-SS/MBCGCN

- **CRGCN [50]:** It adopts a cascading GCN structure to model multi-behavior data. The behavioral features learned from a behavior is delivered to the next behavior with a residual design. This method also adopts the multi-task learning in optimization. https://github.com/SS-00-SS/MBCGCN
- MBGMN [46]: It empowers the user-item interaction learning with the capability of uncovering type-dependent behavior representations, which automatically distills the behavior heterogeneity and interaction diversity for recommendations. https://github.com/akaxlh/MB-GMN
- HMG-CR [52]: It proposes the concept of hyper meta-path to construct hyper meta-paths or hyper meta-graphs to explicitly illustrate the dependencies among different behaviors of a user.
- S-MBRec [13]: It executes the GCNs to learn the user and item embeddings and designs a supervised task, distinguishing the importance of different behaviors, to capture the differences between embeddings. https://github.com/HKUDS/SSLRec
- CML [37]: It is a multi-behavior contrastive learning framework to distill transferable knowledge across different types of behaviors via the constructed contrastive loss. https://github.com/ weiwei1206/CML.git
- **KMCLR [49]:** It designs the multi-behavior learning module to extract users' personalized behavior information for userembedding enhancement, and utilize knowledge graph in the knowledge enhancement module to derive more robust knowledgeaware representations for items.

• **BPHGNN [9]:** It is a multiplex graph neural network representation learning method which can be set to obtain the embeddings of users and items in the multi-behavior recommendation task. https://github.com/FuChF/BPHGNN

# A.4 Detailed Experimental Setting

For the recommendation task, we treat the connected user-item pairs as positive node pairs, and consider other unlinked node pairs as negative pairs. We divide the positive node pairs into the training set and test set according to the proportion of 75% and 25%. At the same time we randomly select the same number of negative node pairs to add to the training set and test set.

For our DCMGNN, we set the number of aggregation layers in LightGCN to 2, and  $\tau$  to 0.1, then we set  $\mu_1$  to 0.1 and  $\mu_2$  to 0.5. For NTMR, we xxxxxx. For MBGCN, we xxxxxx. For MB-HGCN and MB-CGCN, we xxxxxx. For CRGCN, we xxxxxx. For MBCMN, we xxxxxx. For HMG-CR, we xxxxxx. For S-MBRec, we xxxxxx. For CML, we xxxxxx. For KMCLR, we xxxxxx. For BPHGNN, we xxxxxx.

*A.4.1 Time and Space Complexity Analysis.* The DCMGNN consists of three critical components: explicit behavior pattern representation learner, implicit relation chain effect learner and relation chain-aware contrastive learning.

For explicit behavior pattern representation learner, the time complexity of aggregating all basic behavior pattern is  $O(\mathbb{N}N^2)$ , and with the graph convolution, the time complexity of local behavior pattern aggregation is  $O(\mathbb{N}N^2) + O(N^2dl + Nd + Nd^2(l-1)) = O(n^2(\mathbb{N}+dl) + Nd + Nd^2(l-1))$ . Similarly, the time complexity of local behavior pattern aggregation is also  $O(n^2(\mathbb{N}+dl) + Nd + Nd^2(l-1))$ 

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Figure 5: Performance comparison *w.r.t* different relation sparsity degrees on Retail dataset.



Figure 6: Performance comparison *w.r.t* different relation sparsity degrees on Yelp dataset.

1)). So the total time complexity of explicit behavior pattern representation learner is  $O(n^2(\mathbb{N} + dl) + Nd + Nd^2(l - 1))$ . For implicit

relation chain effect learner, the time complexity of multiplex relation embedding aggregation is  $O(N^2 dl + Nd + Nd^2(l-1))$ , the time complex of relation chain representation learning is  $O(N^2 dl + Nd)$ , so the total time complexity of implicit relation chain effect learner is  $O(N^2 dl + Nd + Nd^2(l-1))$ . For relation chain-aware contrastive learning, the time complexity is  $O(N^2 d + Nd)$ . Therefore, the total time complexity of our DCMGNN is  $O((\mathbb{N}+dl)N^2 + (d+d^2(l-1))N)$ .

### A.5 Additional Experiments

A.5.1 Performance on Mitigating Data Sparsity. In this section, we explain that DCMGNN helps to mitigate the data sparsity problem. Figure 5 shows the comparison of experimental results with different interaction sparsity on Retail dataset in Figure 5 and Yelp dataset in Figure 6. In our experiments we select several of the best-performing baselines, MB-CGCN, S-MBRec, CML, KMCLR and BPHGNN. Specifically, we categorized users into six groups ("[0,4)", "[4,5)", "[5,6)", "[6,7)", "[7,10)", and "[10,60)") based on the number of interactions they had. The model performance measured by R@10 and N@10 (shown on the right side of the y-axis in Figure 5) and Fig 6 is the average of all users in each group. The total number of users belonging to each group is shown on the left side of Figure 5 and Figure 6.

*A.5.2* Overall Performance w.r.t. R@5, R@40, N@5 and N@40. Table 5 shows the rest experimental results of the performance comparison of all models.