SDBC-RO: STRONG-DEPENDENCY BEHAVIOR CHAIN GUIDED MULTI-VIEW BEHAVIOR SEMANTICS-AWARE REPRESENTATION OPTIMIZATION

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ABSTRACT

With the continuous expansion of data scale and increasingly diverse interaction scenarios on e-commerce platforms, accurately capturing users' true preferences and decision intentions from massive heterogeneous behavioral data has become a central challenge in Multi-Behavior Recommendation (MBR). Current mainstream MBR methods have an inherent flaw: their modeling relies heavily on predefined behavioral partial order relations, which largely deviate from users' real behavior patterns. This easily causes over-strengthening of auxiliary behaviors and marginalization of target behaviors, ultimately leading to representation distortion. In addition, existing methods typically fail to fully leverage both users' behavioral habits and category preferences, resulting in incomplete semantic representations. To address the above issues, we propose Strong-Dependency Behavior Chain Guided Multi-View Behavior Semantics-Aware Representation Optimization (SDBC-RO). We first define a strong-dependency behavior chain (SDBC) in the form of "auxiliary behavior set $>$ target behavior". This design avoids the cumulative interference from multi-level auxiliary behaviors while preserving the dominant role of the target behavior. Meanwhile, we jointly leverage large language models and knowledge graphs to model behavior semantics and behavioral partial order relations, so as to generate high-quality behavior representations. On this basis, we develop a two stage multi-view representation optimization framework guided by SDBC. In the former stage, a two-level heterogeneous hypergraph is constructed from user–item–category ternary interactions to learn the basic representations of users, items, and categories. In the latter, behavior semantics-aware knowledge graphs are constructed from user–user, item–item, and category–category relational views to deeply integrate behavior semantics with the three types of representations. Finally, adaptive cross chain fusion and category-aware representation enhancement are employed to improve recommendation performance. Extensive experiments on two real world benchmark datasets, Tmall and Taobao, demonstrate that SDBC-RO substantially outperforms state-of-the-art baselines, achieving relative improvements of 17.78% and 10.09% in HR@10 and NDCG@10 on Tmall, and 23.21% and 3.68% on Taobao, respectively.

1 INTRODUCTION

With the in-depth development of e-commerce online service platforms, the information interaction between users and platforms has shown the characteristics of high frequency and diversification. As a key technology connecting massive resources and individual needs, recommender system has become an important support for alleviating information overload, optimizing user experience and improving platform service efficiency. Traditional recommendation methods typically infer user preferences from a single target behavior, such as Buy, and therefore suffer from sparse supervision and limited preference signals. MBR addresses this limitation by jointly exploiting heterogeneous behaviors, such as Click, Cart, and Buy, to capture users' true preferences and decision intentions more comprehensively. However, most existing MBR methods heavily rely on manually predefined fixed behavioral partial-order relations, which often fail to match users' differentiated real behavior paths. This easily triggers the superposition effect of multi-level auxiliary behaviors during the

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modeling process, weakening the target behavior and ultimately leading to distorted representations. Therefore, effectively exploiting auxiliary behaviors while preserving the dominant role of the target behavior remains a fundamental challenge in MBR.

From the perspective of multi-behavior information fusion, existing MBR methods mainly follow two paradigms: parallel and cascading. The former constructs dedicated subgraphs for Click, Cart, Buy and other behaviors in a unified framework, and mitigates target behavior data sparsity via multi-behavior representation fusion. However, behaviors are largely modeled independently, making latent dependencies between auxiliary behaviors and the target behavior difficult to capture explicitly. Cascading methods instead organize behaviors according to predefined behavioral partial-order relations and progressively propagate information across behavior specific modules. Although the latter can realize explicit cross behavior dependency modeling, predefined multi-level behavior chains may cumulatively reinforce auxiliary behaviors and weaken the target behavior. Moreover, fixed global behavior orders may fail to accommodate diverse and non-standard behavior paths, leading to inaccurate preference representations.

In addition, existing MBR methods also suffer from two key representation learning limitations. First, most methods introduce user preference similarity or item category relevance only on top of basic user-item interaction modeling, neglecting latent dynamic correlations across different real-world behavior chains and thus degrading node representation quality. Second, most methods fail to jointly integrate behavior semantics and item category into the core modeling framework; even the few methods that consider these two factors only adopt simple encoding or concatenation, and cannot deeply fuse users' dual semantic features from behavioral habits and category preferences.

To address these limitations, we propose **Strong-Dependency Behavior Chain Guided Multi-View Behavior Semantics-Aware Representation Optimization (SDBC-RO)** framework. By defining and constructing strong-dependency behavior chain (SDBC) in the form of "auxiliary behavior set $>$ target behavior", we can reduce the cumulative influence of multi-level auxiliary behaviors while preserving the dominant role of the target behavior. Based on these chains, we develop a two-stage multi-view representation optimization framework. First, SDBC guided two-level heterogeneous hypergraphs learn representations for users, items, and categories from user–item–category ternary interactions, while LLMs and KGs jointly encode behavior semantics and behavioral partial-order relations. Second, behavior semantics-aware knowledge graphs further optimize these representations from user–user, item–item, and category–category relational views. Finally, adaptive cross chain fusion and category-aware representation enhancement are employed for recommendation. The main contributions are as follows:

- **SDBC guided two-level heterogeneous hypergraph representation learning.** By defining and mining multiple strong-dependency behavior chains(SDBCs), we build two-level heterogeneous hypergraphs guided by these chains from the user-item-category ternary interaction perspective, fundamentally eliminate the superposition effect of multi-level auxiliary behaviors, and effectively boost the representation quality.
- **Multi-view behavior semantics-aware representation optimization.** We jointly model behavior semantics and behavioral partial-order relations using LLMs and KGs, then construct a behavior semantics-aware knowledge graph from the relational views of user-user, item-item, and category-category respectively, to further enhance the node representations.
- **Category-aware cross chain adaptive representation fusion.** With a cross behavior chain adaptive fusion mechanism for effective aggregation of diverse node representations, we concatenate item-level and category-level information to produce category-aware comprehensive representations and further enrich representation semantics.

2 Related Work

Cascading Modeling for MBR. The cascading methods can explicitly characterize the latent dependencies between different behaviors, and enhance representation quality by leveraging the cross-behavior information propagation mechanism.Cheng et al. (2023) propagated information from lower value to higher value behaviors, while Yan et al. (2024a) introduced residual connections to alleviate information attenuation and over-smoothing. Zhu et al. (2024) further extended fixed behavior chains to personalized directed acyclic behavior graphs with attention based aggregation.

However, these methods still largely rely on predefined behavioral partial-order relations, which may deviate from users' actual behavior patterns and limit representation quality.

Hypergraph Based MBR. Benefiting from its superior high-order correlation modeling capability, Hypergraph Neural Network (HGNN) has been widely introduced into MBR scenarios in recent years. Yin et al. (2024) constructed behavior-specific user–user and item–item hypergraphs with intra- and inter-behavior consistency constraints. Choi et al. (2025) combined temporal graph convolution with hypergraph modeling, while Li et al. (2024) modeled cross behavior dependencies and long- and short-term interests through multi-behavior hypergraphs. Yan et al. (2024b) further incorporated positional context and hypergraph contrastive learning. Nevertheless, most hypergraphs are constructed merely based on user preference similarity or item category correlation, overlooking the latent dynamic associations under different behavior chains, thereby constraining node representation capability.

Knowledge Graph Enhanced MBR. As a structured modeling paradigm, Knowledge Graph (KG) natively supports complex relation modeling, missing knowledge completion and implicit semantic reasoning, to effectively uncover deep latent associations in heterogeneous data.Xia et al. (2021a) incorporated item categories, locations, and interaction relations into item-side knowledge graphs, while Xuan et al. (2023) introduced multiple knowledge views with knowledge-aware contrastive learning. Park et al. (2025) modeled multi-level category semantics, Li et al. (2025) incorporated temporal information, and Du & Guan (2026) unified multi-behavior interactions and item-side knowledge through graph attention. However, most existing methods predominantly leverage item-side attributes and semantic relations, while overlooking the guiding role of users' personalized behavioral patterns in recommendation decision-making.

Large Language Models for Recommendation. Large language models (LLMs) have recently been explored for recommendation tasks, leveraging their strong semantic understanding and reasoning capabilities.Zhang et al. (2025) formulated recommendation as an instruction-following task, while Tang et al. (2025) employed LLMs as unified cross-domain recommendation models. Chen et al. (2024) studied LLMs for personalized recommendation, and Elmoghazy et al. (2025) reviewed their applications in semantic understanding and preference modeling. Kim et al. (2025) further demonstrated the zero-shot recommendation capability of LLMs. In summary, LLMs facilitate the generation of richer, more accurate, and generalizable semantic representations.

3 METHODOLOGY

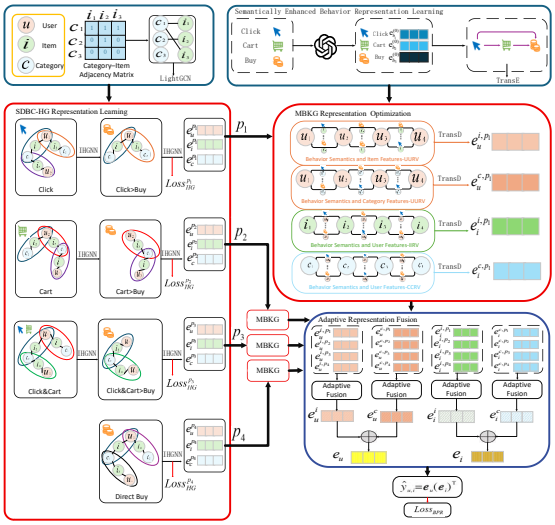


Figure 1: The SDBC-RO framework consists of three main components: SDBC Guided Two-Level Heterogeneous Hypergraph Representation Learning, Multi-View Behavior Semantics-Aware Knowledge Graph Representation Optimization, and Category-Aware Cross Chain Adaptive Representation Fusion.

3.1 Problem Formulation

This paper aims to enhance the modeling quality of user preferences and item features by fully exploiting the multi-dimensional heterogeneous interaction information in MBR, so as to improve the recommendation performance. Let $U = \{u_1, u_2, \ldots, u_{|U|}\}$, $I = \{i_1, i_2, \ldots, i_{|I|}\}$, and $C = \{c_1, c_2, \ldots, c_{|C|}\}$ denote the sets of users, items, and categories, respectively, where $|U|$, $|I|$, and $|C|$ denote their corresponding cardinalities. The historical interaction data is denoted as R, where each interaction is associated with a user, an item, a category, and a behavior type. Let $B = \{b_1, b_2, \ldots, b_{|B|}\}$ denote the set of behavior types. We regard the first $|B| - 1$ behaviors as auxiliary behaviors and the last behavior $b_{|B|}$ as the target behavior. Accordingly, the auxiliary behavior set is defined as $B_{\text{aux}} = \{b_1, b_2, \ldots, b_{|B|-1}\}$. Given the user set U, item set I, category set C, historical multi-behavior interactions R, and behavior set B, the goal of MBR is to learn a prediction function $\hat{y}_{ui} = f(u, i \mid R, B)$, where $\hat{y}_{ui}$ represents the predicted preference score indicating the probability that user u will interact with candidate item i under the target behavior $b_{|B|}$.

3.2 SDBC Guided Two-Level Heterogeneous Hypergraph Representation Learning

This section first defines Strong-Dependency Behavior Chain (SDBC) to capture users' real behavior patterns, then constructs a two-level heterogeneous hypergraph across users, items and categories to enhance representation quality.

3.2.1 Definition of SDBC

To capture direct dependencies between auxiliary behaviors and the target behavior while avoiding the cumulative influence of multi-level auxiliary behaviors, we define the SDBC based on users' actual behavior transitions. First, the historical interaction set R is partitioned according to each individual auxiliary behavior $b_{pri} \in B$ and their combinations $S_{b_{pri}} \subset \{b_1, b_2, \ldots, b_{|B|-1}\}$. Let $R_{b_{pri}}$ denote the interaction set corresponding to the auxiliary behavior b_{pri}, and $R_{S_{b_{pri}}}$ denote the interaction set corresponding to the auxiliary behavior set $S_{b_{pri}}$. These interaction sets satisfy $R_{b_{pri}} \cap R_{b'_{pri}} = \emptyset$, $R_{S_{b_{pri}}} \cap R_{S_{b'_{pri}}} = \emptyset$, and $R_{b_{pri}} \cap R_{S_{b_{pri}}} = \emptyset$. Next, the interaction sets $R_{b_{sub}}$ and $R'_{b_{sub}}$ involving the target behavior b_{sub} are extracted from $R_{b_{pri}}$ and $R_{S_{b_{pri}}}$, respectively, such that $R_{b_{pri}} \cap R_{b_{sub}} = R_{b_{sub}}$, $R_{S_{b_{pri}}} \cap R'_{b_{sub}} = R'_{b_{sub}}$, and $R_{b_{sub}} \cap R'_{b_{sub}} = \emptyset$. Based on these interactions, multiple SDBCs are constructed in the form $B_{pri} > b_{sub}$, where B_{pri} denotes the corresponding auxiliary behavior set and b_{sub} denotes the target behavior. For interactions occurring only under the target behavior, a SDBC with $B_{pri} = \emptyset$ is constructed. All SDBCs constitute $P = \{p_1, p_2, \ldots, p_{|P|}\}$, where p_m denotes the m-th SDBC and $|P|$ denotes the total number of chains. Figure 2 compares the conventional behavior chain with the proposed SDBC.

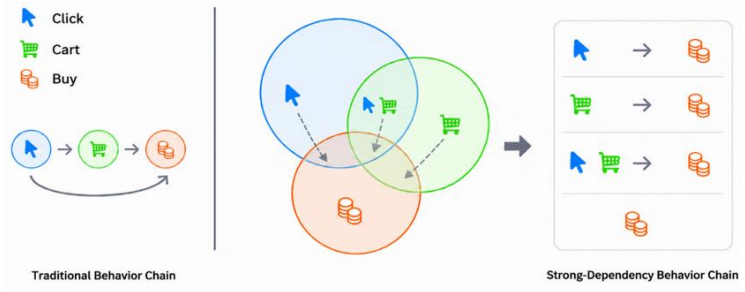


Figure 2: Comparison between the conventional behavior chain and the proposed SDBC.

3.2.2 Two-Level Heterogeneous Hypergraph Representation Learning

We initialize user, item, and category embeddings $e_u^{(0)}, e_i^{(0)}, e_c^{(0)} \in \mathbb{R}^d$ using Xavier initialization. A category–item bipartite graph $G_{ci} = (V_{ci}, E_{ci})$, where $V_{ci} = C \cup I$, is first constructed. LightGCN (He et al., 2020) is applied to obtain enhanced category and item embeddings:

$$\begin{bmatrix} \tilde{e}_c^{(0)} \\ \tilde{e}_i^{(0)} \end{bmatrix} = \mathrm{LightGCN}\left(G_{ci}, \begin{bmatrix} e_c^{(0)} \\ e_i^{(0)} \end{bmatrix} \right). \tag{1}$$

For each SDBC p_m, we construct a two-level heterogeneous hypergraph over users, items, and categories. The first-level hypergraph $G_{B_{pri}}^{p_m} = (V_{B_{pri}}^{p_m}, E_{B_{pri}}^{p_m}, H_{B_{pri}}^{p_m})$ is built from auxiliary behavior interactions $R_{B_{pri}}^{p_m}$, while the second-level hypergraph $G_{b_{sub}}^{p_m} = (V_{b_{sub}}^{p_m}, E_{b_{sub}}^{p_m}, H_{b_{sub}}^{p_m})$ is built from target behavior interactions $R_{b_{sub}}^{p_m}$. For both levels, $V \subset U \cup I \cup C$, each hyperedge represents a user–item–category interaction (u, i, c), and the corresponding incidence matrix $H \in \mathbb{R}^{|V| \times |E|}$ indicates node–hyperedge membership.

We then employ IHGNN (Cheng et al., 2022) to sequentially propagate information through the two levels:

$$\begin{bmatrix} e_u^{pri,p_m} \\ e_i^{pri,p_m} \\ e_c^{pri,p_m} \end{bmatrix} = \mathrm{IHGNN}\left(G_{B_{pri}}^{p_m}, \begin{bmatrix} e_u^{(0)} \\ \tilde{e}_i^{(0)} \\ \tilde{e}_c^{(0)} \end{bmatrix} \right). \tag{2}$$

$$\begin{bmatrix} e_u^{p_m} \\ e_i^{p_m} \\ e_c^{p_m} \end{bmatrix} = \mathrm{IHGNN}\left(G_{b_{sub}}^{p_m}, \begin{bmatrix} e_u^{pri,p_m} \\ e_i^{pri,p_m} \\ e_c^{pri,p_m} \end{bmatrix} \right). \tag{3}$$

3.2.3 Loss Function for Representation Learning

For the first-level hypergraph, $D_{B_{pri}}^{p_m} = \{(u, i^+, i^-)\}$ denotes the training triplet set, where i^+ is an item interacted with by user u under the auxiliary behavior set B_{pri} and i^- is an unobserved item. Its loss is $\mathrm{Loss}_{B_{pri}}^{p_m} = -\sum_{(u,i^+,i^-) \in D_{B_{pri}}^{p_m}} \ln \sigma \left((e_u^{pri,p_m})^T e_{i^+}^{pri,p_m} - (e_u^{pri,p_m})^T e_{i^-}^{pri,p_m} \right)$. For the second-level hypergraph, $D_{b_{sub}}^{p_m} = \{(u, i^+, i^-)\}$ denotes the training triplet set, where i^+ is an item interacted with by user u under the target behavior b_{sub}, while i^- is preferentially sampled from items interacted with under B_{pri} but not under b_{sub}; otherwise, an unobserved item is sampled. Its loss is $\mathrm{Loss}_{b_{sub}}^{p_m} = -\sum_{(u,i^+,i^-) \in D_{b_{sub}}^{p_m}} \ln \sigma \left((e_u^{sub,p_m})^T e_{i^+}^{sub,p_m} - (e_u^{sub,p_m})^T e_{i^-}^{sub,p_m} \right)$. The representation learning loss for SDBC p_m is $\mathrm{Loss}_{HG}^{p_m} = \mathrm{Loss}_{B_{pri}}^{p_m} + \mathrm{Loss}_{b_{sub}}^{p_m}$.

3.3 Multi-view Behavior Semantics-aware Representation Optimization

To capture users' behavior habits and category preferences, while alleviating the data sparsity issue caused by SDBC partitioning, we constructs behavior semantics-aware knowledge graphs from multiple relational views driven by users, items and categories, to further enrich the semantic information of representations.

3.3.1 Semantics-Enhanced Behavior Representation Learning

For each behavior $b_j \in B = \{b_1, \ldots, b_{|B|}\}$, we assign a natural-language description t_{b_j} and obtain its semantic embedding using an LLM encoder:

$$e_{b_j}^{(0)} = \mathrm{LLM}(t_{b_j}). \tag{4}$$

Then we construct a behavior partial-order knowledge graph $G_B = \{(b_i, r, b_j) \mid b_i, b_j \in B,\ b_i \neq b_j\}$, where r denotes the behavioral partial-order relation. Since G_B contains only one relation type, TransE (Bordes et al., 2013) is adopted:

$$f_B(e_{b_i}, e_r, e_{b_j}) = \left\| e_{b_i}^{(0)} + e_r - e_{b_j}^{(0)} \right\|_2^2. \tag{5}$$

The corresponding objective is $\text{Loss}_{TransE} = \sum_{(b_i,r,b_j)\in G_B} \sum_{(b_i',r,b_j')\notin G_B} [\gamma + f_B(e_{b_i}, e_r, e_{b_j}) - f_B(e_{b_i'}, e_r, e_{b_j'})]_+$, where negative triplets are generated by replacing the head or tail entity, γ is the margin parameter, and $[x]_+ = \max(x, 0)$.

3.3.2 Multi-View Behavior Semantics-Aware Knowledge Graph Modeling

For each SDBC p_m = "$B_{pri}^{p_m} > b_{sub}^{p_m}$", we construct four behavior semantics-aware knowledge graphs from different relational views. The item-driven user–user graph $KG_{uu,i}^{p_m} = \{(u, r_{uu,i}^{(p_m,b_k)}, u') \mid u, u' \in U,\ u \neq u'\}$ establishes a directed relation $r_{uu,i}^{(p_m,b_k)}$ from u to u' when users u and u' sequentially interact with the same item i under behavior b_k. Similarly, the category-driven user–user graph $KG_{uu,c}^{p_m} = \{(u, r_{uu,c}^{(p_m,b_k)}, u') \mid u, u' \in U,\ u \neq u'\}$ establishes $r_{uu,c}^{(p_m,b_k)}$ from u to u' when they sequentially interact with the same category c under behavior b_k. Conversely, the user-driven item–item graph $KG_{ii,u}^{p_m} = \{(i, r_{ii,u}^{(p_m,b_k)}, i') \mid i, i' \in I,\ i \neq i'\}$ establishes $r_{ii,u}^{(p_m,b_k)}$ from i to i' when user u sequentially interacts with items i and i' under behavior b_k, while the user-driven category–category graph $KG_{cc,u}^{p_m} = \{(c, r_{cc,u}^{(p_m,b_k)}, c') \mid c, c' \in C,\ c \neq c'\}$ establishes $r_{cc,u}^{(p_m,b_k)}$ from c to c' when user u sequentially interacts with categories c and c' under behavior b_k. Here, $b_k \in \{B_{pri}^{p_m}, b_{sub}^{p_m}\}$.

3.3.3 Representation Optimization Based on Behavior Semantics-Aware Knowledge Graphs

Given the multi-dimensional semantics and one-to-many/many-to-many entity relations in the above four knowledge graphs, we adopt TransD (Ji et al., 2015), a strong complex relation model, as the embedding module. Taking $KG_{uu,i}^{p_m}$ as an example, its relation embedding is $e_{r_{uu,i}^{(p_m,b_k)}} = W_{uu,i}[e_i^{p_m} + e_{b_k}] + b_{uu,i}$, where $W_{uu,i} \in \mathbb{R}^{d\times d}$ and $b_{uu,i} \in \mathbb{R}^d$. The behavior representation is $e_{b_k} = e_{b_{pri}^{p_m}}$ when $|B_{pri}^{p_m}| = 1$; $e_{b_k} = e_{b_{pri}^{p_m}} + \cdots + e_{b_{pri'}^{p_m}}$ when $|B_{pri}^{p_m}| > 1$; and $e_{b_k} = e_{b_{sub}^{p_m}}$ otherwise. TransD then yields the behavior semantic-aware item-level user preference:

$$e_u^{i,p_m} = \text{TransD}\left(KG_{uu,i}^{p_m}, e_u^{p_m}, e_{r_{uu,i}^{(p_m,b_k)}}\right). \tag{6}$$

The other three views are optimized analogously, yielding the category-level user preference representation $e_u^{c,p_m} \in \mathbb{R}^d$, the behavior semantics-aware item representation $e_i^{u,p_m} \in \mathbb{R}^d$, and the behavior semantics-aware category representation $e_c^{u,p_m} \in \mathbb{R}^d$. All four graphs share the same TransD objective. For example, $\text{Loss}_{KG_{uu,i}^{p_m}} = \sum_{(h,r,t)\in KG_{uu,i}^{p_m}} \sum_{(h',r,t')\notin KG_{uu,i}^{p_m}} [\gamma + \|e_h + r - e_t\|_2^2 - \|e_{h'} + r - e_{t'}\|_2^2]_+$, where negative triplets are generated by replacing the head or tail entity. The chain level optimization loss is $\text{Loss}_{KG}^{p_m} = \text{Loss}_{KG_{uu,i}^{p_m}} + \text{Loss}_{KG_{uu,c}^{p_m}} + \text{Loss}_{KG_{ii,u}^{p_m}} + \text{Loss}_{KG_{cc,u}^{p_m}}$.

3.4 Category-aware Cross Chain Adaptive Representation Fusion

In this section, we adaptively fuse node representations across different SDBCs and obtain the final category-aware user and item representations. For e_u^{i,p_m}, the attention score is $a_u^{i,p_m} = (q_u^i)^T \tanh(W_u^i e_u^{i,p_m} + b_u^i)$, where $W_u^i \in \mathbb{R}^{d\times d}$ and $b_u^i, q_u^i \in \mathbb{R}^d$ are learnable parameters. The normalized weight is $\beta_u^{i,p_m} = \exp(a_u^{i,p_m}) / \sum_{n=1}^{|P|} \exp(a_u^{i,p_n})$, and the fused representation is $e_u^i = \sum_{p_m\in P} \beta_u^{i,p_m} e_u^{i,p_m}$. The same cross-chain fusion is independently applied to e_u^{c,p_m} and e_i^{u,p_m} to obtain e_u^c and e_i^u, respectively, while the category representations e_c^{u,p_m} associated with item i are fused to obtain e_i^c. Finally, through concatenation, we obtain the comprehensive user representation $e_u = e_u^i \parallel e_u^c$ and the comprehensive item representation $e_i = e_i^u \parallel e_i^c$, where $e_u, e_i \in \mathbb{R}^{2d}$.

3.5 Model Training

We adopt Bayesian Personalized Ranking (BPR) for target behavior prediction, where i^+ denotes an item interacted with by user u under the target behavior, i^- denotes an item not interacted with by u under the target behavior. The BPR loss is $\text{Loss}_{BPR} = -\sum_{(u,i^+,i^-)\in D} \ln \sigma(\hat{y}_{ui^+} - \hat{y}_{ui^-}) + \lambda\|\theta\|_2^2$,

where $\hat{y}_{ui} = e_u^T e_i$, θ denotes the learnable parameters, and λ is the regularization coefficient. The overall objective is $\text{Loss}_{final} = \text{Loss}_{TransE} + \sum_{m=1}^{|P|}(\text{Loss}_{HG}^{p_m} + \text{Loss}_{KG}^{p_m}) + \text{Loss}_{BPR}$.

4 EXPERIMENTS

4.1 EXPERIMENTAL DATASETS AND EVALUATION METRICS

In Table 1, We evaluate SDBC-RO on two large scale e-commerce datasets, Tmall and Taobao, both containing three behaviors: Click, Cart, and Buy.

Table 1: Statistics of the datasets.

Dataset	Users	Items	Categories	Interactions	Click	Cart	Buy
Tmall	15,449	11,953	1,273	1,173,759	873,954	195,476	104,329
Taobao	48,749	39,493	1,632	1,952,931	1,548,162	193,747	211,022

In Table 2, $Q_1^{p_m}$ denotes the interaction proportion of chain p_m, and $Q_2^{p_m}$ denotes its Buy conversion rate. Specifically, for $m \in \{1, 2, 3\}$, $Q_1^{p_m} = N_{B_{pri}}^{p_m} / (\sum_{m=1}^{3} N_{B_{pri}}^{p_m} + N_{b_{sub}}^{p_4})$, whereas $Q_1^{p_4} = N_{b_{sub}}^{p_4} / (\sum_{m=1}^{3} N_{B_{pri}}^{p_m} + N_{b_{sub}}^{p_4})$, $Q_2^{p_m} = N_{b_{sub}}^{p_m} / N_{B_{pri}}^{p_m}$.

Table 2: Statistics of SDBCs.

Dataset	Strong-Dependency Behavior Chain	$N_{B_{pri}}^{p_m}$	$N_{b_{sub}}^{p_m}$	$Q_1^{p_m}$	$Q_2^{p_m}$
Tmall	p_1: Click>Buy	839,233	62,137	80.3%	7.4%
	p_2: Cart>Buy	160,755	25,398	15.4%	15.8%
	p_3: Click&Cart>Buy	34,721	6,249	3.3%	18.0%
	p_4: Direct Buy	$\emptyset$	10,545	1.0%	–
Taobao	p_1: Click>Buy	1,510,933	137,185	87.7%	9.1%
	p_2: Cart>Buy	156,518	48,662	9.0%	31.1%
	p_3: Click&Cart>Buy	37,229	7,934	2.2%	21.3%
	p_4: Direct Buy	$\emptyset$	17,241	1.1%	–

As shown in Table 2, Click covers most interactions but has a relatively low Buy conversion rate, whereas Cart and Click & Cart are less frequent but exhibit stronger conversion signals. This heterogeneity motivates adaptive weighting of representations from different SDBCs. We evaluate recommendation performance using Hit Ratio (HR) and Normalized Discounted Cumulative Gain (NDCG), where higher values indicate better performance.

4.2 PARAMETER SETTINGS

SDBC-RO is optimized with Adam using a batch size of 1024, learning rate 0.001, 1000 epochs, and margin $\gamma = 1$. The embedding dimension and number of hypergraph convolution layers are selected from $d \in \{64, 128, 256, 512\}$ and $L \in \{1, 2, 3, 4\}$, respectively. Xavier initialization with random seed 2025 is used, and the recommendation list length is set to $K \in \{10, 20\}$. For behavior semantic encoding, we map the Click, Cart, and Buy behaviors to three dedicated semantic descriptions — "initial interest and click", "strong interest and add-to-cart", and "explicit purchase intention and transaction completion" — and encode them via the BAAI/bge-m3 model.

4.3 COMPARATIVE EXPERIMENTAL RESULTS AND ANALYSIS

We compare SDBC-RO with representative single-behavior and multi-behavior recommendation methods. For single-behavior recommendation, **LightGCN** (He et al., 2020) simplifies graph convolution for collaborative filtering; **SGL** (Wu et al., 2021) introduces self-supervised contrastive learning through graph augmentation; and **HCCF** (Xia et al., 2022) combines hypergraph convolution with contrastive learning to capture high-order collaborative signals. For MBR, **NMTR** (Gao et al., 2019) models behavior dependencies through multi-task learning; **EHCF** (Chen et al., 2020) transfers information across behaviors without negative sampling; **MATN** (Xia et al., 2020) employs Transformer-based multi-behavior relation modeling with memory-augmented attention; and **MBGMN** (Xia et al., 2021b) models heterogeneous behavior contributions through graph meta-learning. **GHCF** (Chen et al., 2021) performs relation-aware propagation over heterogeneous interaction graphs, while **S-MBRec** (Gu et al., 2022) combines supervised and self-supervised learning

to capture cross-behavior commonality and heterogeneity. **CRGCN** (Yan et al., 2024a) and **MB-CGCN** (Cheng et al., 2023) model behavioral partial-order relations through cascading graph propagation. **PKEF** (Meng et al., 2023) disentangles shared and behavior-specific preferences through parallel knowledge enhancement. **DA-GCN** (Zhu et al., 2024) replaces fixed behavior chains with personalized directed acyclic behavior graphs, while **HEC-GCN** (Yin et al., 2024) constructs behavior specific user–user and item–item hypergraphs to capture high-order dependencies.

Table 3: Results on the Tmall and Taobao datasets.

Tmall

Model	HR@10	HR@20	N@10	N@20
LightGCN	0.0379	0.0504	0.0221	0.0252
SGL	0.0390	0.0526	0.0219	0.0253
HCCF	0.0387	0.0528	0.0229	0.0264
NMTR	0.0195	0.0361	0.0086	0.0127
EHCF	0.0399	0.0567	0.0269	0.0322
MATN	0.0325	0.0471	0.0245	0.0286
MBGMN	0.0481	0.0677	0.0317	0.0364
GHCF	0.0688	0.0926	0.0397	0.0458
S-MBRec	0.0494	0.0777	0.0237	0.0308
CRGCN	0.0945	0.1386	0.0514	0.0625
MB-CGCN	0.1279	0.1654	0.0703	0.0846
PKEF	0.1277	0.1864	0.0721	0.0912
DA-GCN	0.1458	0.1971	0.0841	0.0969
HEC-GCN	<u>0.1715</u>	<u>0.2081</u>	<u>0.0922</u>	<u>0.1021</u>
SDBC-RO	**0.2020**	**0.2199**	**0.1015**	**0.1087**

Taobao

Model	HR@10	HR@20	N@10	N@20
LightGCN	0.0379	0.0498	0.0219	0.0249
SGL	0.0396	0.0530	0.0232	0.0266
HCCF	0.0365	0.0502	0.0209	0.0243
NMTR	0.0128	0.0275	0.0053	0.0089
EHCF	0.0370	0.0502	0.0258	0.0300
MATN	0.0346	0.0482	0.0235	0.0270
MBGMN	0.0438	0.0621	0.0326	0.0365
GHCF	0.0424	0.0546	0.0272	0.0302
S-MBRec	0.0629	0.0903	0.0307	0.0376
CRGCN	0.0985	0.1361	0.0570	0.0665
MB-CGCN	0.1342	0.1624	0.0752	0.0829
PKEF	0.1385	0.1798	0.0785	0.1054
DA-GCN	0.1597	0.1985	0.1029	0.1126
HEC-GCN	<u>0.1960</u>	<u>0.2211</u>	<u>0.1061</u>	<u>0.1207</u>
SDBC-RO	**0.2415**	**0.2463**	**0.1100**	**0.1298**

As shown in Table 3, SDBC-RO achieves the best performance across all four metrics. Multi-behavior methods generally outperform single-behavior baselines, confirming the value of auxiliary behaviors for target behavior prediction. Cascading methods such as CRGCN and MB-CGCN further benefit from modeling behavioral partial-order relations, while DA-GCN enables more flexible behavior-path modeling and HEC-GCN captures higher-order relations through behavior-specific hypergraphs. SDBC-RO further improves performance by modeling multiple strong-dependency behavior chains in the form of "auxiliary behavior set $>$ target behavior", thereby reducing the cumulative influence of multi-level auxiliary behaviors while preserving the dominant role of the target behavior. Moreover, its multi-view behavior semantics-aware knowledge graphs capture user–user, item–item, and category–category relations across behavior chains, alleviating data sparsity and enriching representation semantics.

4.4 Ablation Study

We construct seven variants to evaluate each component: **w/o HHG** replaces user–item–category ternary hypergraphs with pairwise LightGCN; **w/o Cascade-HG** replaces sequential two-level propagation with parallel modeling; **w/o Adaptive-Chain** uses a single "Click $>$ Cart $>$ Buy" chain; **w/o Semantic** replaces natural-language behavior descriptions with numerical identifiers; **w/o TransE** removes the behavior partial-order knowledge graph; **w/o MBKG** removes multi-view behavior semantics-aware knowledge graph optimization; and **w/o Hier-Fusion** retains only item-level representations.

Table 4: Ablation results on Tmall and Taobao.

Tmall

Method	HR@10	N@10	HR@20	N@20
w/o HHG	0.1671	0.0653	0.1819	0.0699
w/o Cascade-HG	0.1716	0.0711	0.1868	0.0762
w/o Adaptive-Chain	0.1801	0.0740	0.1960	0.0792
w/o Semantic	<u>0.1984</u>	<u>0.1001</u>	<u>0.2160</u>	<u>0.1072</u>
w/o TransE	0.1919	0.0934	0.2089	0.1000
w/o MBKG	0.1344	0.0535	0.1463	0.0573
w/o Hier-Fusion	0.1833	0.0765	0.1995	0.0819
SDBC-RO	**0.2020**	**0.1015**	**0.2199**	**0.1087**

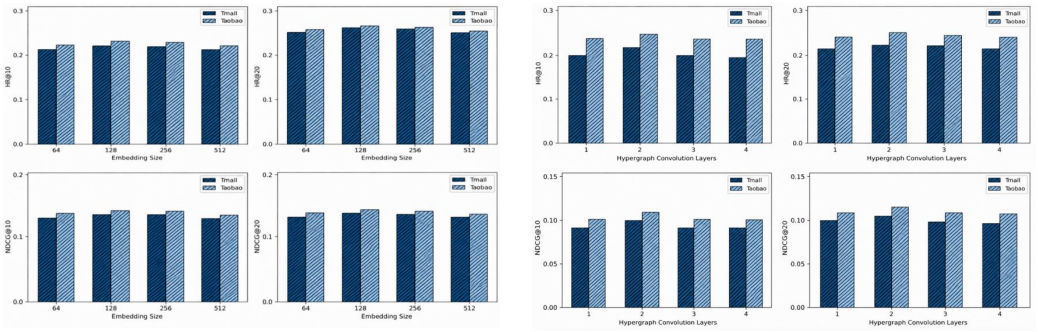
Taobao

Method	HR@10	N@10	HR@20	N@20
w/o HHG	0.2068	0.0758	0.2109	0.0895
w/o Cascade-HG	0.2166	0.0807	0.2209	0.0953
w/o Adaptive-Chain	0.2190	0.0890	0.2234	0.1050
w/o Semantic	<u>0.2348</u>	<u>0.0935</u>	<u>0.2394</u>	<u>0.1103</u>
w/o TransE	0.2288	0.0891	0.2333	0.1051
w/o MBKG	0.1643	0.0571	0.1676	0.0674
w/o Hier-Fusion	0.2208	0.0816	0.2252	0.0963
SDBC-RO	**0.2415**	**0.1100**	**0.2463**	**0.1298**

As shown in Table 4, removing any component degrades performance on both datasets. The largest drop occurs with **w/o MBKG**, highlighting the importance of multi-view behavior semantics-aware knowledge graph optimization for alleviating chain-induced sparsity and integrating behavioral and category-level information. The declines of **w/o HHG**, **w/o Cascade-HG**, and **w/o Adaptive-Chain** validate user–item–category higher-order modeling, sequential two-level propagation, and multiple strong-dependency behavior chains, respectively. The drops of **w/o Semantic** and **w/o TransE** confirm the complementary roles of behavior semantics and behavioral partial-order relations, while **w/o Hier-Fusion** shows the benefit of incorporating category-level preferences and representations.

4.5 Parameter Analysis

We analyze the effects of the embedding dimension d and the number of hypergraph convolution layers L. We vary $d \in \{64, 128, 256, 512\}$ and $L \in \{1, 2, 3, 4\}$ on both Tmall and Taobao, with the results shown in Figure 3.



(a) Embedding dimension d (b) Hypergraph layers L

Figure 3: Effects of the embedding dimension d and the number of hypergraph convolution layers L.

5 Conclusion

In this paper, we propose SDBC-RO, a strong-dependency behavior chain guided multi-view behavior semantics-aware representation optimization framework. The framework constructs diverse SDBCs via real conversion relations between auxiliary behaviors and target behavior. Guided by these distinct SDBCs, it models the high-order "user-item-category" interactions through two-level heterogeneous hypergraphs, effectively mitigating the issues of target behavior weakening and node representation distortion. To further enrich the semantic information of representations, we additionally devise a multi-view behavior semantics-aware knowledge graph representation optimization module, which realizes the deep fusion of behavior semantics with item-level and category-level user preferences, as well as item and category features. The final category-enhanced user and item embeddings are generated via a category-aware cross-behavior-chain adaptive fusion module. Extensive experiments on Tmall and TaoBao datasets show that SDBC-RO outperforms state-of-the-art baselines on HR@10 and NDCG@10, verifying its superiority and effectiveness for MBR scenarios. Despite the promising performance of SDBC-RO, there remains space for improvement. The current work focuses on conversion relations between auxiliary behaviors and target behaviors while ignoring sequential interaction information within each chain. Future work will integrate strong-dependency behavior chains with multi-behavior sequence modeling to capture the temporal dynamics of user interests. Furthermore, causal inference will be introduced to estimate the causal contribution of each behavior to user preferences, suppressing noise from accidental interactions like misclicks and boosting recommendation accuracy and robustness.

AI Use Statement

In this work, generative AI tools were used to assist with English-language polishing, manuscript organization, and LaTeX formatting. The tools were not used to generate or alter experimental data

or reported numerical results. All AI-assisted text and formatting were reviewed and revised by the authors to ensure technical accuracy and consistency with the original research. The authors take full responsibility for the final content.

Reproducibility Statement

We provide detailed descriptions of SDBC-RO and its major components in Section 3. Dataset statistics and behavior-chain construction are reported in Section 4.1, while training settings are provided in Section 4.2. We also report the evaluation metrics, baseline methods, ablation settings, and parameter analyses to facilitate reproducibility.

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