

Disentangled Contrastive Collaborative Filtering

Xubin Ren
University of Hong Kong
Hong Kong, China
xubinrengs@gmail.com

Lianghao Xia
University of Hong Kong
Hong Kong, China
aka_xia@foxmail.com

Jiashu Zhao
Wilfrid Laurier University
Waterloo, Canada
jzhao@wlu.ca

Dawei Yin
Baidu Inc
Beijing, China
yindawei@acm.org

Chao Huang*
University of Hong Kong
Hong Kong, China
chao Huang75@gmail.com

ABSTRACT

Recent studies show that graph neural networks (GNNs) are prevalent to model high-order relationships for collaborative filtering (CF). Towards this research line, graph contrastive learning (GCL) has exhibited powerful performance in addressing the supervision label shortage issue by learning augmented user and item representations. While many of them show their effectiveness, two key questions still remain unexplored: i) Most existing GCL-based CF models are still limited by ignoring the fact that user-item interaction behaviors are often driven by diverse latent intent factors (e.g., shopping for family party, preferred color or brand of products); ii) Their introduced non-adaptive augmentation techniques are vulnerable to noisy information, which raises concerns about the model's robustness and the risk of incorporating misleading self-supervised signals. In light of these limitations, we propose a Disentangled Contrastive Collaborative Filtering framework (DCCF) to realize intent disentanglement with self-supervised augmentation in an adaptive fashion. With the learned disentangled representations with global context, our DCCF is able to not only distill finer-grained latent factors from the entangled self-supervision signals but also alleviate the augmentation-induced noise. Finally, the cross-view contrastive learning task is introduced to enable adaptive augmentation with our parameterized interaction mask generator. Experiments on various public datasets demonstrate the superiority of our method compared to existing solutions. Our model implementation is released at the link <https://github.com/HKUDS/DCCF>.

CCS CONCEPTS

• Information systems → Recommender systems.

KEYWORDS

Collaborative Filtering, Contrastive Learning, Disentangled Representation, Graph Neural Networks, Recommendation

*Chao Huang is the corresponding author.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than the author(s) must be honored. Abstracting with credit is permitted. To copy otherwise, to republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

SIGIR'23, July 23–27, 2023, Taipei, Taiwan

© 2023 Copyright held by the owner/author(s). Publication rights licensed to ACM.
ACM ISBN 978-1-4503-9408-6/23/07...\$15.00
<https://doi.org/10.1145/3539618.3591665>

ACM Reference Format:

Xubin Ren, Lianghao Xia, Jiashu Zhao, Dawei Yin, and Chao Huang. 2023. Disentangled Contrastive Collaborative Filtering. In *Proceedings of the 46th International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR'23)*, July 23–27, 2023, Taipei, Taiwan. ACM, Taipei, Taiwan, 10 pages. <https://doi.org/10.1145/3539618.3591665>

1 INTRODUCTION

Recommender systems have become fundamental services for suggesting personalized items to users by learning their preference from historical interactions [3, 40]. Graph neural networks have recently achieved remarkable success in collaborative filtering (CF) modeling user-item interaction with high-order connectivity, such as NGCF [32], MCCF [35], LightGCN [13], and GCCF [7]. Those GNN-based CF models encode user-item bipartite graph structures into representations via iterative message passing for collaborative information aggregation [37]. By capturing the high-order user (item) similarity in latent embedding space, graph neural CF methods have provided state-of-the-art recommendation performance.

However, user-item interactions, which serve as important labels for supervised recommendation models, are often highly sparse in real-world recommender systems [41, 49, 50]. To address the issue of supervision shortage in recommendations, recent works [39, 42] attempt to marry the power of contrastive learning with GNNs to explore the unlabeled information and offer self-supervision signals. These graph contrastive learning (GCL) methods propose to learn invariant user (item) representations by maximizing agreement between established contrastive augmentation views. In general, by following the mutual information maximization principle [22, 28], the agreements of pre-defined positive pairs are achieved, and embeddings of negative pairs are pushed apart. Two key research lines of augmentation schemes have recently emerged in GCL-based collaborative filtering. To be specific, SGL [39] generates contrastive views with stochastic augmentors, e.g., random node/edge dropout. To supplement the direct graph connections, HCCF [42] and MHCN [46] propose to pursue the consistency between node-level representations and graph-level semantic embeddings.

Although promising results have been achieved, we argue that two key limitations exist in current GCL recommender systems.

First, most previous studies have ignored the fact that the latent factors behind user-item interactions are highly entangled due to preference diversity, resulting in suboptimal augmentation-induced user representations. In real-life applications, the formation of user-item interactions is driven by many intent factors [34, 36], such as

purchasing products for a family party or being attracted to certain clothing characteristics. However, the learned user preferences with the encoded invariant representations in current GCL-based recommendation approaches are entangled, making it difficult to capture the finer-grained interaction patterns between users and items. This hinders the recommender’s ability to capture genuine user preferences and provide accurate intent-aware self-supervision. Therefore, there is an urgent need for a new method that can generate disentangled contrastive signals for informative augmentation.

Second, many existing GCL-based methods still struggle to provide accurate self-supervised learning (SSL) signals against data noise, which makes it difficult to adapt contrastive learning to user-item interaction graphs with diverse structures. Specifically, the introduced stochastic augmentation strategy [39] may not preserve the original semantic relationships well, as they use random dropout operators. For example, dropping hub nodes can damage important inter-community connection structures, resulting in an augmented user-item relation graph that may not be positively related to the original interaction structures. Additionally, although some methods incorporate graph-level semantics into auxiliary self-supervised signals [42, 46] via self-discrimination over all nodes, their model performance is vulnerable to user interaction data noise, such as misclicks or popularity bias. Under a contrastive augmentation framework, if the importance of node- or edge-wise SSL signals is not differentiated, methods can be easily biased by supplementing the main recommendation task with self-supervised signals derived from noisy nodes, *e.g.*, users with many misclick behaviors or high conformity to popularity bias [30].

In this paper, we propose a new disentangled contrastive learning-based collaborative filtering model, called DCCF, to address the limitations of existing methods. Specifically, Our model encodes multi-intent representations by considering the global dependencies between users and items. We achieve this by designing intent-aware information passing and aggregation between patch-level nodes and global-level intent prototypes. We aim to identify important graph structural information that captures accurate and helpful environment-invariant patterns with intent disentanglement. In this way, we can prevent the distillation of self-supervised information with severe noisy signals. To achieve our goal, we create parameterized edge mask generators that capture implicit relationships among users and items, and we inject intent-aware global dependencies. As a result, the graph structure masker can naturally capture the importance of each interaction for contrastive augmentation, which is adaptive to the user-item relations.

To sum up, the main contributions of this work are as follows:

- In this work, we study the **generalization problem of GCL-based recommender systems** in a more challenging yet practical scenario: adapting graph contrastive learning to intent disentanglement with self-supervision noise for collaborative filtering.
- We develop a new recommendation model called DCCF, with parameterized mask generators that are adaptive to build over the global context-enhanced disentangled GNN architecture. This enhances **recommender robustness and generalization ability**.
- Extensive experimental results demonstrate that our new method achieves superior recommendation performance compared to more than 10 existing solutions. Furthermore, the effectiveness

of our disentangled adaptive augmentation is justified by studies of model ablation, robustness, and interpretability.

2 RELATED WORK

GNNs-based Recommender Systems. Graph neural networks (GNNs) have demonstrated strong performance in representation learning of user preference for recommendation. These GNN-based recommenders perform recursive message passing over graph structures to model high-order collaborative relations [8, 40, 44]. Towards this line, Many efforts have been made to build recommender systems based on various graph neural techniques. For instance, graph convolutional networks have been widely adopted as encoders to model the user-item interaction graph, such as LightGCN, LR-GCCF [7], and HGCF [25]. Additionally, graph-enhanced attention mechanisms explicitly distinguish influence for embedding propagation among neighboring nodes, and serve as important components in various recommenders, including social relation learning DGR [24], multi-behavior recommendation [43], knowledge graph-based recommenders KGAT [31], JNSKR [4].

Recommendation with Disentangled Representations. Learning disentangled representations of user latent intents from implicit feedback has been a popular topic in recent years. Various approaches have been proposed, such as using variational auto-encoders to encode high-level user intentions for improving recommendation [20]. DGCF [34] builds upon this idea of intent disentanglement, and performs disentangled representation learning over graph neural network with embedding splitting. To incorporate side information from user or item domain into recommendation, DisenHAN [36] attempts to learn disentangled user/item representations with heterogeneous graph attention network. KGIN [33] is a method that aims to encode latent user intents using item knowledge graph to improve recommendation performance. DCF [10] decomposes users and items into factor-level representations and using a factor-level attention mechanism to capture the underlying intents. In CDR [6], a dynamic routing mechanism is designed to characterize correlations among user intentions for embedding denoising. However, most existing disentangled recommender systems are built in a fully supervised manner, which can be limited by the sparsity of user-item interactions in real-world scenarios. To address this challenge, we propose a new model that leverages self-supervised learning for intent-aware augmentation.

Contrastive Learning in Recommendation. Recently, contrastive learning (CL) has gained considerable attention in various recommendation scenarios, such as sequential recommendation [9], knowledge graph-enhanced recommendation [51], multi-interest recommendation [47] and multi-behavior recommendation [38]. The most relevant research line in recommendation systems is to enhance graph neural network (GNN)-based collaborative filtering with contrastive learning. To this end, several recently proposed models, such as SGL [39], NCL [17], and HCCF [42], have achieved state-of-the-art performance by leveraging contrastive augmentation. For example, SGL [39] uses random dropout operators to corrupt interaction graph structures for augmentation. In NCL [17], representation alignment is performed between individual users and semantic-centric nodes. While these models have been effective in improving recommendation accuracy, they may fall short in encoding latent factors behind user-item interactions, which

can result in suboptimal representations with coarse-grained user preference modeling for recommendation.

3 METHODOLOGY

3.1 Disentangled Intent Representation

3.1.1 Modeling Latent Intent Factors. In our recommendation scenario, we represent the interaction matrix between the user set $\mathcal{U} = u_1, \dots, u_i, \dots, u_I$ (with size I) and item set $\mathcal{I} = v_1, \dots, v_j, \dots, v_J$ (with size J) as $\mathcal{A} \in \mathbb{R}^{I \times J}$. The entry $\mathcal{A}_{i,j} \in \mathcal{A}$ is set to 1 if user u_i has adopted item v_j before, and $\mathcal{A}_{i,j} = 0$ otherwise. **Our model aims to predict the likelihood that a candidate user will adopt an item given their observed interactions.** From a probabilistic perspective, our predictive model aims to estimate the conditional probability $P(y|u_i, v_j)$ for the interaction between user u_i and item v_j , where y is the learned preference score.

When interacting with items, users often have **diverse intents**, such as preferences for specific brands or interests in the genres and actors of movies [21, 48]. To capture these diverse intents, we assume K different intents c_u and c_v from the user and item sides, respectively. The intent on the item side can also be understood as the context of the item, for example, a user who intends to shop for Valentine's Day may have a preference for items that have a "romantic" context. Our predictive objective of user-item preference can be presented as follows:

$$\int_{c_u} \int_{c_v} P(y, c_u, c_v | u, v) dc_v dc_u = \sum_k P(y, c_u^k, c_v^k | u, v) \quad (1)$$

The user-item interaction probability y is determined by the latent intents c_u and c_v and can be derived using the formulas:

$$\sum_k P(y, c_u^k, c_v^k | u, v) = \sum_k P(y | c_u^k, c_v^k) P(c_u^k | u) P(c_v^k | v) \quad (2)$$

$$= \mathbb{E}_{P(c_u|u)P(c_v|v)} [P(y | c_u, c_v)]. \quad (3)$$

Here, we use $f(\cdot)$ to denote the forecasting function over the encoded intents. Following the statistical theory in [29, 30], we make the following approximation to derive our prediction objective:

$$\mathbb{E}_{P(c_u|u)P(c_v|v)} [f(c_u, c_v)] \approx f(\mathbb{E}_{P(c_u|u)} [c_u], \mathbb{E}_{P(c_v|v)} [c_v]). \quad (4)$$

With the above inference, **the approximation error, known as Jensen gap** [1], can be well bounded in our forecasting function $f(\cdot)$ [12].

3.1.2 Multi-Intent Representation with Global Context. While intent diversity has been encoded in existing recommender systems through disentangled representations, global-level intent-aware collaborative relations have been largely overlooked. Global-level user (item) dependency modeling can enhance the robustness of GNN-based message passing models against sparsity and over-smoothing issue, via propagating information without the limitation of direct local connections [42]. Towards this end, we propose to disentangle collaborative relations among users and items with both local- and global-level embedding for information propagation.

Graph-based Message Passing. Owing to the strength of graph neural networks, GNNs has become the prevalent learning paradigm to capture collaborative filtering signals in state-of-the-art recommender systems. Examples include LightGCN [13], LR-GCCF [7], and HGCF [25]. The insights offered by these studies have inspired

us to build our DCCF model using a graph-based message passing framework for user representations. In general, our message propagation layer is formally presented with the user/item embedding matrix $\mathbf{E}^{(u)} \in \mathbb{R}^{I \times d}$ and $\mathbf{E}^{(v)} \in \mathbb{R}^{J \times d}$ as follows:

$$\mathbf{Z}^{(u)} = \bar{\mathcal{A}} \cdot \mathbf{E}^{(v)}, \quad \mathbf{Z}^{(v)} = \bar{\mathcal{A}}^T \cdot \mathbf{E}^{(u)}, \quad (5)$$

The aggregated representations from neighboring nodes to the target ones are denoted by $\mathbf{Z}^{(u)} \in \mathbb{R}^{I \times d}$ and $\mathbf{Z}^{(v)} \in \mathbb{R}^{J \times d}$. Here, $\bar{\mathcal{A}} \in \mathbb{R}^{I \times J}$ denotes the normalized adjacent matrix which is derived from the user-item interaction matrix \mathcal{A} as $\bar{\mathcal{A}} = \mathbf{D}_{(u)}^{-1/2} \cdot \mathcal{A} \cdot \mathbf{D}_{(v)}^{-1/2}$, where $\mathbf{D}_{(u)} \in \mathbb{R}^{I \times I}$ and $\mathbf{D}_{(v)} \in \mathbb{R}^{J \times J}$ are **diagonal degree matrices**.

To exploit high-order collaborative filtering signals, we perform GNN-based embedding propagation across different graph layers, such as from the $(l-1)$ -th to the (l) -th layer, as follows:

$$\mathbf{E}_l^{(u)} = \mathbf{E}_{l-1}^{(u)} + \mathbf{Z}_{l-1}^{(u)}, \quad \mathbf{E}_l^{(v)} = \mathbf{E}_{l-1}^{(v)} + \mathbf{Z}_{l-1}^{(v)}, \quad (6)$$

To suppress the over-smoothing effect, residual connections are applied to the aggregation phase [7, 42].

Intent-aware Information Aggregation. We will describe how to incorporate intent-aware global user (item) dependencies into our GNN-based collaborative filtering framework. In our **multi-intent encoder**, disentangled user-item preferences are preserved in $\mathbb{E}_{P(c_u|u)} [c_u]$ and $\mathbb{E}_{P(c_v|v)} [c_v]$. In our DCCF, we define K global intent prototypes $\{\mathbf{c}_u^k \in \mathbb{R}^d\}_{k=1}^K$ and $\{\mathbf{c}_v^k \in \mathbb{R}^d\}_{k=1}^K$ for user and item, respectively. With these learnable intent embeddings, we generate user and item representations by aggregating information across different K intent prototypes with the global context at the l -th graph embedding layer, using the following design:

$$\mathbf{r}_{i,l}^{(u)} = \mathbb{E}_{P(c_u|\mathbf{e}_{i,l}^{(u)})} [\mathbf{c}_u] = \sum_k \mathbf{c}_u^k P(\mathbf{c}_u^k | \mathbf{e}_{i,l}^{(u)}), \quad (7)$$

$$\mathbf{r}_{j,l}^{(v)} = \mathbb{E}_{P(c_v|\mathbf{e}_{j,l}^{(v)})} [\mathbf{c}_v] = \sum_k \mathbf{c}_v^k P(\mathbf{c}_v^k | \mathbf{e}_{j,l}^{(v)}), \quad (8)$$

The l -th layer-specific user and item embeddings are denoted by $\mathbf{e}_{i,l}^{(u)} \in \mathbf{E}_l^{(u)}$ and $\mathbf{e}_{j,l}^{(v)} \in \mathbf{E}_l^{(v)}$, respectively. The relevance score between user u_i and each intent prototype \mathbf{c}_u is defined as $P(\mathbf{c}_u^k | \mathbf{e}_{i,l}^{(u)})$, which can be derived as follows:

$$P(\mathbf{c}_u^k | \mathbf{e}_{i,l}^{(u)}) = \frac{\eta(\mathbf{e}_{i,l-1}^{(u)\top} \mathbf{c}_u^k)}{\sum_{k'} \eta(\mathbf{e}_{i,l-1}^{(u)\top} \mathbf{c}_u^{k'})}, \quad P(\mathbf{c}_v^k | \mathbf{e}_{j,l}^{(v)}) = \frac{\eta(\mathbf{e}_{j,l-1}^{(v)\top} \mathbf{c}_v^k)}{\sum_{k'} \eta(\mathbf{e}_{j,l-1}^{(v)\top} \mathbf{c}_v^{k'})}$$

Here, $\eta(\cdot) = \exp(\cdot)$. After generating the propagated message, we refine it by integrating the local collaborative filtering signals with the global disentangled collaborative relations, as follows:

$$\mathbf{E}_l^{(u)} = \mathbf{E}_{l-1}^{(u)} + \mathbf{Z}_{l-1}^{(u)} + \mathbf{R}_{l-1}^{(u)}, \quad \mathbf{E}_l^{(v)} = \mathbf{E}_{l-1}^{(v)} + \mathbf{Z}_{l-1}^{(v)} + \mathbf{R}_{l-1}^{(v)}. \quad (9)$$

In this equation, $\mathbf{R}_{l-1}^{(u)} \in \mathbb{R}^{I \times d}$ and $\mathbf{R}_{l-1}^{(v)} \in \mathbb{R}^{J \times d}$ represent the stacked intent-aware user embeddings ($\mathbf{r}_{i,l-1}^{(u)}$) and item embeddings ($\mathbf{r}_{j,l-1}^{(v)}$), respectively. Incorporating intent disentanglement into the graph neural architecture enables our learned representations to

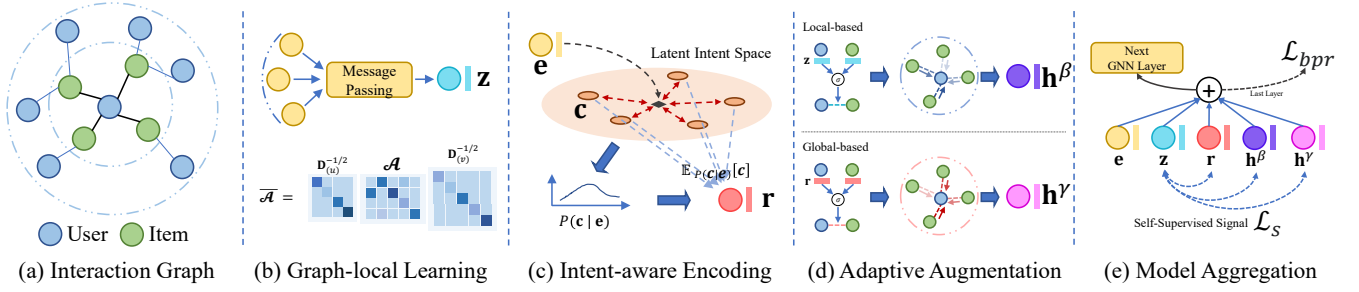


Figure 1: The overall framework of our proposed DCCF model involves adaptive augmentation through the integration of global intent disentanglement and interaction pattern encoding, resulting in disentangled environment-invariant representations.

effectively disentangle the latent factors driving complex user-item interaction behaviors.

3.2 Disentangled Contrastive Learning

Taking inspiration from recent developments in contrastive learning, we explore the potential of contrastive augmentation with intent disentanglement to address the data sparsity issue in recommender systems. Although self-supervision signals can be generated by maximizing the consistency between positive pairs among contrastive views, we argue that such augmentation is susceptible to data noise, such as misclicks. Noisy contrastive regularization may mislead the self-supervised learning process. For instance, reinforcing the model to achieve embedding agreement via node self-discrimination on noisy interaction edges may involve noisy self-supervised signals and lead to suboptimal representations.

To address this challenge, we design learnable augmenters that consider both local collaborative relations and global disentangled user (item) dependencies. By doing so, the learnable contrastive augmenters can adaptively learn disentangled SSL signals.

3.2.1 Disentangled Data Augmentation. To enable the augmentation to be adaptive to each connection hop, we introduce a learnable relation matrix $\mathcal{G}^l \in \mathbb{R}^{I \times J}$ for each (l)-th GNN layer to encode the implicit relationships between users and items. Inspired by previous work on graph denoising [18, 26], we aim to generate a graph mask $\mathcal{M}^l \in \mathbb{R}^{I \times J}$, which can be used to obtain the relation matrix through element-wise multiplication: $\mathcal{G}^l = \mathcal{M}^l \odot \mathcal{A}$.

Learning Graph Mask. Each entry $\mathcal{M}_{i,j}^l \in [0, 1]$ in the graph mask \mathcal{M}^l reflects the degree to which the interaction between user i and item j is masked. The closer the value is to 0, the less important the interaction is, and vice versa. In our DCCF model, we derive $\mathcal{M}_{i,j}^l$ based on the disentangled embeddings of user ($\mathbf{r}_{i,l}^{(u)}$) and item ($\mathbf{r}_{j,l}^{(v)}$) to preserve the intent-aware interaction patterns. Specifically, we use cosine similarity [11, 26] between node embeddings to measure the importance of interactions:

$$s(\mathbf{r}_{i,l}^{(u)}, \mathbf{r}_{j,l}^{(v)}) = \frac{\mathbf{r}_{i,l}^{(u)T} \mathbf{r}_{j,l}^{(v)}}{\|\mathbf{r}_{i,l}^{(u)}\|_2 \|\mathbf{r}_{j,l}^{(v)}\|_2}. \quad (10)$$

The mask value is obtained by linearly transforming the range of the similarity to $[0, 1]$, using the formula: $\mathcal{M}_{i,j}^l = (s(\mathbf{r}_{i,l}^{(u)}, \mathbf{r}_{j,l}^{(v)}) + 1)/2$.

Learnable Augmentation. $\mathcal{A}_{i,j}$ is 0 when there is no interaction between user i and item j . \mathcal{G}^l is obtained by element-wise multiplication of \mathcal{M}^l and \mathcal{A} . Only the mask values of observed interactions are calculated for computational simplicity. With the learned relation matrix, we then normalize it with the degree of the node as follows (layer index is omitted for simplicity):

$$\tilde{\mathcal{G}}_{i,j} = \mathcal{G}_{i,j} / \sum_{j'} \mathcal{G}_{i,j'}, \quad \tilde{\mathcal{G}}_{j,i}^T = \mathcal{G}_{j,i}^T / \sum_{i'} \mathcal{G}_{j,i'}^T. \quad (11)$$

To integrate our adaptive augmentation with the message passing scheme, we apply our normalized learned relation matrix $\tilde{\mathcal{G}}^l$ over the messages of nodes for learnable propagation. With this design, we perturb the graph structure to generate contrastive learning views with adaptive augmentation. The augmentation with adaptive masking can be formally presented as follows:

$$\mathbf{H}_l^{(u)} = \tilde{\mathcal{G}} \cdot \mathbf{E}_l^{(v)}, \quad \mathbf{H}_l^{(v)} = \tilde{\mathcal{G}}^T \cdot \mathbf{E}_l^{(u)}, \quad (12)$$

To generate multiple contrastive views, we consider both local collaborative signals and global disentangled relationships. In particular, we perform augmentation using two learnable mask matrices over encoded local embeddings ($\mathbf{Z}_l^{(u)}$ and $\mathbf{Z}_l^{(v)}$ in Eq. 5), and global embeddings with intent disentanglement ($\mathbf{R}_l^{(u)}$ and $\mathbf{R}_l^{(v)}$ in Eq. 7). We derive two mask values $\mathcal{M}_{i,j}^l$ separately using the following formulas: $\mathcal{M}_{i,j}^l = (s(\mathbf{r}_{i,l}^{(u)}, \mathbf{r}_{j,l}^{(v)}) + 1)/2$ and $\mathcal{M}_{i,j}'^l = (s(\mathbf{z}_{i,l}^{(u)}, \mathbf{z}_{j,l}^{(v)}) + 1)/2$. After that, our augmentation-aware message passing paradigm can be described with the following embedding refinement details:

$$\mathbf{E}_l^{(u)} = \mathbf{E}_{l-1}^{(u)} + \mathbf{Z}_{l-1}^{(u)} + \mathbf{R}_{l-1}^{(u)} + \mathbf{H}_{l-1}^{\beta,(u)} + \mathbf{H}_{l-1}^{\gamma,(u)} \quad (13)$$

Here, $\mathbf{H}_{l-1}^{\beta,(u)}$ and $\mathbf{H}_{l-1}^{\gamma,(u)}$ represent the local- and global-level augmented representations, respectively. Similarly, item embeddings are fused in an analogous manner.

3.2.2 Contrastive Learning. Using the above augmented representation views, we conduct contrastive learning across different view-specific embeddings of users and items. Following the approach of supervised contrastive signals in [39, 42], we generate each positive pair using the embeddings of the same user (item) from the original CF view and each of the augmented views. The encoded representations of different nodes are treated as negative pairs. Specifically, we generate three augmented views using

our augmenters: i) the local collaborative view with adaptive augmentation ($\mathbf{H}^{\beta,(u)}$); ii) the disentangled global collaborative view ($\mathbf{R}^{(u)}$); and iii) the adaptive augmented view ($\mathbf{H}^{\gamma,(u)}$). We generate contrastive self-supervision signals using InfoNCE loss as follows:

$$\mathcal{I}(\mathbf{m}, \mathbf{n}) = \frac{1}{I} \sum_{i=0}^I \sum_{l=0}^L -\log \frac{\exp(s(\mathbf{m}_{i,l}^{(u)}, \mathbf{n}_{i,l}^{(u)})/\tau)}{\sum_{i'=0}^I \exp(s(\mathbf{m}_{i,l}^{(u)}, \mathbf{n}_{i',l}^{(u)})/\tau)}, \quad (14)$$

Here, \mathbf{m} denotes the original view with vanilla embeddings ($\mathbf{z} \in \mathbf{Z}^{(u)}$) encoded from GNN. \mathbf{n} is sampled from one of three augmented embeddings $\mathbf{h}^\beta \in \mathbf{H}^{\beta,(u)}$, $\mathbf{R}^{(u)}$, and $\mathbf{h}^\gamma \in \mathbf{H}^{\gamma,(u)}$. The cosine similarity function is denoted by $s(\cdot)$. The contrastive learning loss from the user side can be formalized as follows:

$$\mathcal{L}_{cl}^{(u)} = \mathcal{I}(\mathbf{z}, \mathbf{r}) + \mathcal{I}(\mathbf{z}, \mathbf{h}^\beta) + \mathcal{I}(\mathbf{z}, \mathbf{h}^\gamma) \quad (15)$$

By stacking L graph neural layers, the layer-specific embeddings are aggregated across different layers as follows: $\mathbf{E}^{(u)} = \sum_{l=0}^L \mathbf{E}_l^{(u)}$ and $\mathbf{E}^{(v)} = \sum_{l=0}^L \mathbf{E}_l^{(v)}$. The user-item preference score is derived as:

$$\mathbf{Y} = \mathbf{E}^{(u)} (\mathbf{E}^{(v)})^T, \quad \mathbf{Y}_{i,j} = (\mathbf{e}_i^{(u)})^T \mathbf{e}_j^{(v)}. \quad (16)$$

To optimize the classical supervised recommendation task using the estimated preference score, we use the following Bayesian Personalized Ranking (BPR) loss:

$$\mathcal{L}_{bpr} = -\frac{1}{|\mathcal{R}|} \sum_{(i,p_s,n_s) \in \mathcal{R}} \ln \sigma(\mathbf{Y}_{i,p_s} - \mathbf{Y}_{i,n_s}), \quad (17)$$

where \mathcal{R} is the set of sampled interactions in each mini-batch [13]. For each user u_i , we sample S positive items (indexed by p_s) and S negative items (indexed by n_s) from the training data.

Finally, we integrate the self-supervised loss with our classical recommendation loss into a multi-task learning objective as follows:

$$\mathcal{L} = \mathcal{L}_{bpr} + \lambda_1 \cdot (\mathcal{L}_{cl}^{(u)} + \mathcal{L}_{cl}^{(v)}) + \lambda_2 \cdot \|\Theta_1\|_F^2 + \lambda_3 \cdot \|\Theta_2\|_F^2 \quad (18)$$

where λ_1 , λ_2 and λ_3 are tunable weights. $\Theta_1 = \{\mathbf{E}_0^{(u)}, \mathbf{E}_0^{(v)}\}$ and $\Theta_2 = \{\{\mathbf{c}_u^k\}_{k=1}^K, \{\mathbf{c}_v^k\}_{k=1}^K\}$ are trainable parameters in our model.

3.3 Discussions on DCCF Model

In this section, we present theoretical analyses of the benefits of our disentangled contrastive learning paradigm. Initially, for a specific user u_i , the corresponding contrastive self-supervised learning signals are incorporated with $\mathcal{I}(\mathbf{r}_i^{(u)}, \mathbf{z}_i^{(u)})$, where $\mathbf{r}_i^{(u)}$ is the encoded embedding of u_i from the augmentation with intent-aware user global dependency. The gradients of $\mathcal{I}(\mathbf{r}_i^{(u)}, \mathbf{z}_i^{(u)})$ with respect to the disentangled representation $\mathbf{r}_i^{(u)}$ contributed by negative samples can be derived as follows:

$$c(i') = \left(\frac{\mathbf{r}_i^{(u)}}{\|\mathbf{r}_i^{(u)}\|_2} - s(\mathbf{r}_i^{(u)}, \mathbf{z}_{i'}^{(u)}) \frac{\mathbf{z}_{i'}^{(u)}}{\|\mathbf{z}_{i'}^{(u)}\|_2} \right) \times \frac{\exp(s(\mathbf{r}_i^{(u)}, \mathbf{z}_{i'}^{(u)})/\tau)}{\sum_{i'} \exp(s(\mathbf{r}_i^{(u)}, \mathbf{z}_{i'}^{(u)})/\tau)} \quad (19)$$

Without loss of generality, we omit the index of graph layers. Here, i' denotes the negative sample $u_{i'}$ for u_i ($i' \neq i$ & $1 \leq i \leq I$). The L2 norm of $c(i')$ is proportional to a special function as follows:

$$\|c(i')\|_2 \propto \sqrt{1 - s(\mathbf{r}_i^{(u)}, \mathbf{z}_{i'}^{(u)})^2} \cdot \exp\left(\frac{s(\mathbf{r}_i^{(u)}, \mathbf{z}_{i'}^{(u)})}{\tau}\right) \quad (20)$$

In the above equation, $s(\mathbf{r}_i^{(u)}, \mathbf{z}_{i'}^{(u)}) \in [-1, 1]$. For hard negative samples, the corresponding embedding similarity score is close to 1, and the L2 norm of $c(i')$ increases significantly [39, 42]. Similar observations can be made for the contrastive augmentations $\mathcal{I}(\mathbf{z}, \mathbf{h}^\beta)$ and $\mathcal{I}(\mathbf{z}, \mathbf{h}^\gamma)$ using the learnable augmenters. Thus, our disentangled contrastive learning paradigm is capable of seeking hard negative samples to enhance model optimization.

In addition, we further justify the effectiveness of our model design for capturing the implicit cross-intent dependency via the gradient propagation. Here, we discuss how the encoding process of disentangled representation $\mathbf{r}_i^{(u)}$ can propagate gradients to latent intent prototypes $\{\mathbf{c}_u^k\}_{k=1}^K$. Referring to Equation (7) and (9), we have the following partial derivative:

$$\frac{\partial \mathbf{r}_i^{(u)}}{\partial \mathbf{c}_u^k} = \begin{bmatrix} \frac{\partial (\mathbf{r}_i^{(u)})_1}{\partial (\mathbf{c}_u^k)_1} & \cdots & \frac{\partial (\mathbf{r}_i^{(u)})_1}{\partial (\mathbf{c}_u^k)_d} \\ \vdots & \ddots & \vdots \\ \frac{\partial (\mathbf{r}_i^{(u)})_d}{\partial (\mathbf{c}_u^k)_1} & \cdots & \frac{\partial (\mathbf{r}_i^{(u)})_d}{\partial (\mathbf{c}_u^k)_d} \end{bmatrix}, \quad (21)$$

$$\frac{\partial (\mathbf{r}_i^{(u)})_m}{\partial (\mathbf{c}_u^k)_n} = P_t \sum_{k=1}^K P_k [(\mathbf{e}_i^{(u)})_n ((\mathbf{c}_u^k)_m - (\mathbf{c}_u^k)_m) + \mathbb{I}(m=n)]. \quad (22)$$

P_t is short for $P(\mathbf{c}_u^k | \mathbf{e}_i^{(u)})$. As can be seen from the partial derivatives, the intent-aware representations $\mathbf{r}_i^{(u)}$ propagate gradients to the latent intent prototype via the estimation of conditional probability $\sum_k P_k(y, \mathbf{c}_u^k, \mathbf{c}_v^k | u, v)$. During the backward propagation process, the cross-intent embedding aggregation can propagate gradients to all latent intents with the learned relevance weights. Therefore, the gradient learning enhanced by our auxiliary contrastive learning tasks is appropriately distributed to all latent intents, which facilitates the cross-intent dependency modeling and helps to capture accurate user preferences for recommendation.

Time Complexity Analysis. We analyze the time complexity of different components in our DCCF from the following aspects: i) The graph-based message passing procedure takes $\mathcal{O}(L \times |\mathcal{A}| \times d)$ time, where L denotes the number of graph neural layers for message passing. $|\mathcal{A}|$ represents the number of edges in the graph and d is the dimensionality of user/item representations. ii) The intent-aware information aggregation component takes $\mathcal{O}(L \times (I + J) \times K \times d)$ time complexity, where K denotes the number of latent intents. iii) Due to local- and global-based adaptive augmentation, it takes $\mathcal{O}(2 \times L \times |\mathcal{A}| \times d)$ time complexity to generate two augmented views for self-supervision. iv) To calculate the contrastive learning objective, the cost is $\mathcal{O}(L \times B \times (I + J) \times d)$, where B is the number of users/items included in a single mini-batch.

Table 1: Statistics of the experimental datasets.

Dataset	#Users	#Items	#Interactions	Density
Gowalla	50,821	57,440	1,172,425	$4.0e^{-4}$
Amazon-book	78,578	77,801	2,240,156	$3.7e^{-4}$
Tmall	47,939	41,390	2,357,450	$1.2e^{-3}$

4 EVALUATION

In this section, we perform experiments to evaluate our DCCF on different datasets by answering the following research questions:

- **RQ1:** Does our proposed DCCF outperform various recommendation solutions under different experimental settings?
- **RQ2:** Do the designed key components benefit the representation learning of our DCCF in achieving performance improvement?
- **RQ3:** Is our proposed model effective in alleviating the data sparsity issues with our disentangled self-supervised signals?
- **RQ4:** What is the impact of the number of latent intents?
- **RQ5:** How does our DCCF perform *w.r.t* training efficiency?

4.1 Experimental Settings

4.1.1 Datasets. We evaluate our model performance on public datasets: **Gowalla:** This dataset is collected from the Gowalla platform to record check-in relations between users and different locations based on mobility traces. **Amazon-book:** This dataset includes rating behaviors of users over products with book category on Amazon. **Tmall:** It contains customer purchase behaviors from the online retailer Tmall. Table 1 summarizes the dataset statistics.

4.1.2 Evaluation Protocols and Metrics. To alleviate the bias of negative item instance sampling, we follow the all-rank protocol [13, 36, 39] over all items to measure the accuracy of our recommendation results. We use two widely adopted ranking-based metrics to evaluate the performance of all methods, namely *Recall@N* and *NDCG (Normalized Discounted Cumulative Gain)@N*.

4.1.3 Baseline Methods. We include five groups of baseline methods for comprehensive comparison, as detailed below.

(i) Factorization-based Method.

- **NCF** [14]. This method replaces the inner product in MF with a multi-layer perceptron to estimate user-item interactions. For comparison, we include the NeuMF version.

(ii) Autoencoder-based Method.

- **AutoR** [23]. It reconstructs user-item interactions based on the autoencoder to obtain user preference for non-interacted items.

(iii) Recommendation with Graph Neural Network.

- **NGCF** [32]. This method designs the propagation rule to inject collaborative signals into the embedding process of recommendation, which is beneficial for capturing higher-order connectivity.
- **LightGCN** [13]. This method simplifies the message passing rule of GCN by linearly propagate user/item embeddings on the interaction graph for collaborative filtering.

(iv) Disentangled Multi-Intent Recommender Systems.

- **DisenGCN** [19]. This method proposes a neighborhood routing mechanism to learn disentangled node representation. The dot-product is used to predict the interaction likelihood.

- **DisenHAN** [36]. It disentangles user/item representations into different aspects (*i.e.*, latent intents) and then aggregates information from various aspects with attention for recommendation.
- **CDR** [6]. This method utilizes a user’s noisy multi-feedback to mine user intentions and improves the training process through curriculum learning. We implement it with implicit feedback.
- **DGCF** [34]. This method generates the intent-aware graph by modeling a distribution over intents for each interaction and thus learns disentangled representations.
- **DGCL** [16]. This method proposes a factor-wise discrimination objective to learn disentangled representations. We implement it to learn disentangled representations of nodes and make user-item interaction prediction using inner products.

(v) Self-Supervised Learning for Recommendation.

- **SLRec** [45]. This method proposes a multi-task self-supervised learning framework to address the label sparsity problem in large-scale item recommender system.
- **SGL-ED/ND** [39]. This method reinforces user/item representation learning with GNNs by applying an auxiliary self-supervised contrastive learning task through data augmentation, namely edge drop (ED) or node drop (ND).
- **HCCF** [42]. It jointly captures local and global collaborative relations under a hypergraph neural network, and designs cross-view contrastive learning for augmentation.
- **LightGCL** [2]. It is a lightweight graph contrastive learning framework by leveraging singular value decomposition to generate augmented view for embedding contrasting.

4.1.4 Hyperparameter Settings. We implement our DCCF using PyTorch and use Adam [15] as optimizer with learning rate $1e^{-3}$. The number of latent intent prototypes K is selected from the range of $\{32, 64, 128, 256\}$ with $K = 128$ by default. λ_1 , λ_2 and λ_3 are tuned from the range of $[0.001, 0.025, 0.1, 0.2]$, $[2.5e^{-5}, 5e^{-4}, 5e^{-3}]$, $[2.5e^{-5}, 5e^{-4}, 5e^{-3}]$, respectively. To evaluate baseline performance with fair settings, latent embedding dimensionality d and batchsize is set as 32 and 10240 for all compared methods. For graph-based models, the number of propagation layers is chosen from $\{1, 2, 3\}$. Detailed model implementation of our DCCF can be found in our released source code in the Abstract Section.

4.2 Performance Comparison (RQ1)

Table 2 shows the performance comparison of different methods on all datasets. To validate the significant performance improvement achieved by our DCCF model, the p-value is provided. From evaluation results, we summarize the following observations:

- DCCF consistently outperforms all baselines on all three datasets. Through disentangled contrastive learning, DCCF improves the generalization and robustness of recommenders by offering more informative representations. We attribute the significant performance gain of DCCF to two key aspects: (i) DCCF effectively alleviates the data sparsity issue by distilling disentangled self-supervised signals as supplementary training tasks. (ii) Our proposed parameterized graph mask generator is beneficial for achieving adaptive self-supervision against data noise redundancy, which further improves the representation robustness.

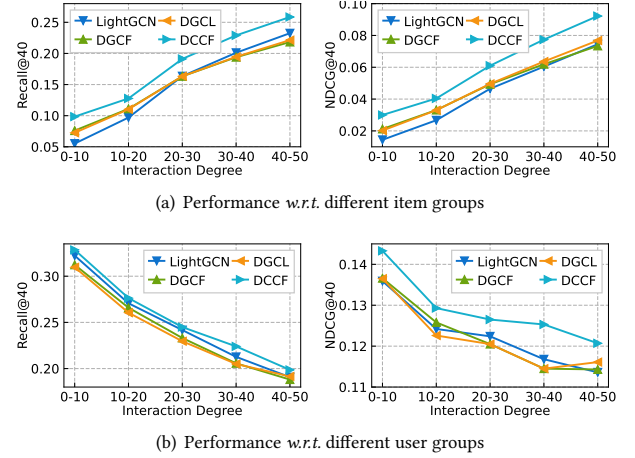
Table 2: Recommendation performance of all compared methods on different datasets in terms of Recall and NDCG.

Data	Gowalla				Amazon-book				Tmall			
Metrics	Recall@20	Recall@40	NDCG@20	NDCG@40	Recall@20	Recall@40	NDCG@20	NDCG@40	Recall@20	Recall@40	NDCG@20	NDCG@40
NCF	0.1247	0.1910	0.0659	0.0832	0.0468	0.0771	0.0336	0.0438	0.0383	0.0647	0.0252	0.0344
AutoR	0.1409	0.2142	0.0716	0.0905	0.0546	0.0914	0.0354	0.0482	0.0336	0.0611	0.0203	0.0295
NGCF	0.1413	0.2072	0.0813	0.0987	0.0532	0.0866	0.0388	0.0501	0.0420	0.0751	0.0250	0.0365
LightGCN	0.1799	0.2577	0.1053	0.1255	0.0732	0.1148	0.0544	0.0681	0.0555	0.0895	0.0381	0.0499
DisenGCN	0.1379	0.2003	0.0798	0.0961	0.0481	0.0776	0.0353	0.0451	0.0422	0.0688	0.0285	0.0377
DisenHAN	0.1437	0.2079	0.0829	0.0997	0.0542	0.0865	0.0407	0.0513	0.0416	0.0682	0.0283	0.0376
CDR	0.1364	0.1943	0.0812	0.0963	0.0564	0.0887	0.0419	0.0526	0.0520	0.0833	0.0356	0.0465
DGCF	0.1784	0.2515	0.1069	0.1259	0.0688	0.1073	0.0513	0.0640	0.0544	0.0867	0.0372	0.0484
DGCL	0.1793	0.2483	0.1067	0.1247	0.0677	0.1057	0.0506	0.0631	0.0526	0.0845	0.0359	0.0469
SLRec	0.1529	0.2200	0.0926	0.1102	0.0544	0.0879	0.0374	0.0490	0.0549	0.0888	0.0375	0.0492
SGL-ED	0.1809	0.2559	0.1067	0.1262	0.0774	0.1204	0.0578	0.0719	0.0574	0.0919	0.0393	0.0513
SGL-ND	0.1814	0.2589	0.1065	0.1267	0.0722	0.1121	0.0542	0.0674	0.0553	0.0885	0.0379	0.0494
HCCF	0.1818	0.2601	0.1061	0.1265	0.0824	0.1282	0.0625	0.0776	0.0623	0.0986	0.0425	0.0552
LightGCL	0.1825	0.2601	0.1077	0.1280	0.0836	0.1280	0.0643	0.0790	0.0632	0.0971	0.0444	0.0562
DCCF	0.1876	0.2644	0.1123	0.1323	0.0889	0.1343	0.0680	0.0829	0.0668	0.1042	0.0469	0.0598
p-val.	$8.9e^{-6}$	$1.3e^{-3}$	$2.6e^{-6}$	$8.1e^{-6}$	$8.6e^{-7}$	$2.2e^{-6}$	$8.6e^{-6}$	$2.2e^{-6}$	$2.6e^{-7}$	$1.4e^{-7}$	$8.6e^{-7}$	$1.8e^{-7}$

Table 3: Ablation study on key components of DCCF (measured by Recall@20 and NDCG@20) on different datasets.

Category	Data	Gowalla		Amazon-book		Tmall	
	Variants	Recall	NDCG	Recall	NDCG	Recall	NDCG
DME	-Disen	0.1637	0.0975	0.0772	0.0580	0.0629	0.0437
PAM	-LocalR	0.1719	0.1015	0.0786	0.0593	0.0638	0.0446
	-DisenR	0.1718	0.1016	0.0793	0.0597	0.0640	0.0447
SSL	-DisenG	0.1763	0.1053	0.0829	0.0635	0.0644	0.0449
	-AllAda	0.1845	0.1096	0.0833	0.0632	0.0651	0.0452
DCCF		0.1876	0.1123	0.0889	0.0680	0.0668	0.0469

- Although data augmentation techniques are also proposed in current SSL-based methods (e.g., SGL, HCCF), our DCCF still outperforms them by a large margin. This is because simply learning augmented representations at coarse-grained level cannot disentangle latent intention factors behind user-item interactions. In addition, we notice that most SSL-based methods perform better than conventional GNN-based approaches (e.g., LightGCN, NGCF), which suggests the positive effects of SSL brings to GNN-based CF models. With our disentangled adaptive augmentation, DCCF still pushes that boundary forward, achieving state-of-the-art performance across all datasets.
- The performance improvement of DCCF over other disentangled recommender systems (e.g., DGCF, DisenGCN, CDR) verifies that our approach is not limited to the label shortage issue. The integration of disentangled multi-intent encoding and contrastive learning results in better performance. Existing disentangled learning solutions struggle to generate informative embeddings in the face of insufficient training labels due to the overfitting effect. Although DGCL attempts to use contrastive learning to encode latent factors into augmented representations, its non-adaptive contrastive view generation makes it easily influenced by noise perturbation.

**Figure 2: Performance comparison w.r.t. data sparsity over different user/item groups on Gowalla data.**

4.3 Ablation Study (RQ2)

In this section, to verify the effectiveness of each component, we conduct an ablation study to examine the component-specific benefits of our DCCF framework from three perspectives: (i) Disentangled Multi-intent Encoding (DME); (ii) Parameterized Adaptive Masking (PAM); (iii) Self-supervised Learning (SSL). The performance results are reported in Table 3, and the variant details and impact study are presented as follows:

- **Disentangled Multi-intent Encoding (DME).** We generate the ablation model (-Disen) by removing the disentangled multi-intent encoding module. The performance gap between DCCF and -Disen indicates the contribution of multi-intent representation encoding to the overall performance.
- **Parameterized Adaptive Masking (PAM).** To investigate the effect of our parameterized adaptive masking, we create two variants: (i) -LocalR which removes implicit user-item relation learning based on local relation embeddings; and (ii) -DisenR,

Table 4: The embedding smoothness on Amazon-book and Tmall data measured by MAD metric (the smaller the MAD indicates more obvious the over-smoothing phenomenon).

Embedding Type	DCCF	DCCF-CL	DGCL	DisenGCN	LightGCN
Amazon-book					
User	0.999	0.902	0.980	0.961	0.984
Item	0.990	0.961	0.989	0.986	0.944
Tmall					
User	0.999	0.800	0.897	0.876	0.910
Item	0.998	0.873	0.920	0.992	0.927

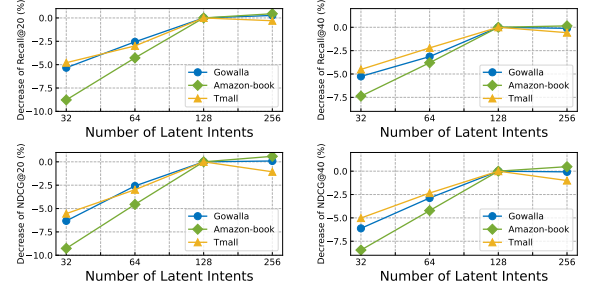
which removes the intent-based graph structure learning process. The results show that both variants lead to a performance degradation, indicating the necessity of adaptive self-supervised signal distillation for contrastive augmentation.

- **Self-Supervised Learning (SSL).** We also examine the influence of our disentangled contrastive learning on performance by adjusting the incorporated self-supervised optimization objectives. Specifically, we create two variants by removing agreements between the original graph representations with auxiliary augmented views: (i) disentangled global collaborative view (-DisenG) and (ii) all augmented views with adaptive masking (-AllAda). Our results show that DCCF achieves the best performance compared to these variants, further emphasizing the benefits of integrating auxiliary self-supervised learning signals from the global view of intent-aware collaborative relationships for adaptive data augmentation.

4.4 In-Depth Analysis of DCCF (RQ3 & RQ4)

4.4.1 Performance w.r.t Data Sparsity. We further verify if DCCF is robust to data sparsity issue. To do this, we divide users and items into different groups based on the number of their interactions, and separately measured recommendation accuracy for each group. From the results in Figure 2, we make two main observations: (i) DCCF consistently outperforms several representative baselines (*i.e.*, LightGCN, DGCL, DGCF) by providing better recommendation results for both inactive and active users. This indicates the benefits of our generated self-supervised signals in alleviating sparse data issues. While DGCL conducts factor-wise alignment with contrastive learning, the interaction noise and bias can still impair the disentangled representation learning for latent factors. (ii) We notice that the performance gap between DCCF and the compared methods is still apparent on low-degree items. This is because the baseline DGCF only focuses on splitting the user representation into multiple intent-aware embeddings, which can easily lead to recommending high-degree items and neglect the long-tail items. In contrast, our DCCF enhances the interaction modeling on long-tail items through effective self-supervised information.

4.4.2 Impact of the Number of Intent Prototypes. To investigate the impact of the number of latent intents on model performance, we select this parameter from the range {32, 64, 128, 256} and re-train the model. The results are shown in Figure 3. It is clear that as the number of intents increases, the performance of the model also improves. However, when the number of intents

**Figure 3: Performance w.r.t the number of latent intents.**

increases from 128 to 256, the performance improvement is limited, and even degrades on the Tmall dataset. To further understand this phenomenon, we transform the intent prototypes into 2D space for visualization using t-SNE [27] and then clustered them. As shown in Figure 4, when the number of intents is 128, some latent intents have begun to cluster together. Further increasing the number of intents causes intent redundancy with too fine-grained latent factor granularity and introduces noise into learning representations.

4.4.3 Robustness of DCCF in Alleviating Over-Smoothing.

To validate the effectiveness of DCCF in alleviating over-smoothing, we calculate the Mean Average Distance (MAD) [5, 42] over encoded user/item embeddings of DCCF and the variant DCCF-CL, which disables the cross-view contrastive learning module. We also calculate the MAD of several representative baseline methods (*i.e.*, DGCL, DisenGCN, LightGCN) for comparison. Note that all the embeddings were normalized before calculating MAD for fair comparison. The results are shown in Table 4. We notice that by removing the SSL objective, the over-smoothing phenomenon becomes more pronounced, which suggests the effectiveness of our contrastive learning component in addressing the over-smoothing problem. Moreover, all the baselines have lower MAD than our DCCF, indicating that DCCF is capable of alleviating the over-smoothing issue in the widely-adopted GNN architecture. Our disentangled contrastive learning approach achieves better representation uniformity in recommendation compared to the baselines.

Table 5: Computational cost evaluation in terms of per-epoch training time (seconds) on Gowalla, Amazon, and Tmall data.

Model	DisenGCN	DGCF	DisenHAN	DGCL	Ours
Gowalla	19.1s	25.1s	16.8s	9.3s	12.4s
Amazon-book	42.2s	49.6s	30.6s	12.4s	18.9s
Tmall	43.5s	51.6s	29.8s	12.0s	18.8s

4.5 Model Training Efficiency Study (RQ5)

In this section, we investigate the model efficiency of our DCCF in terms of training computational cost on all datasets. The experiments were conducted on a server with system configurations of an Intel Xeon Gold 6330 CPU, NVIDIA RTX 3090. As shown in Table 5, we compare our DCCF with disentangled recommender systems (*e.g.*, DGCF and DisenHAN) and found that our DCCF achieves comparable training efficiency in all cases. Specifically, while DGCF

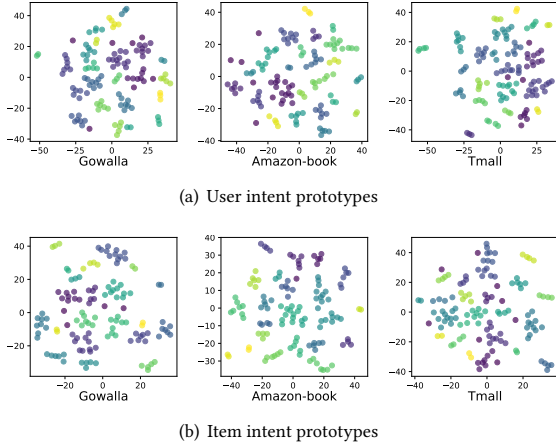


Figure 4: Distribution of latent intent prototypes.

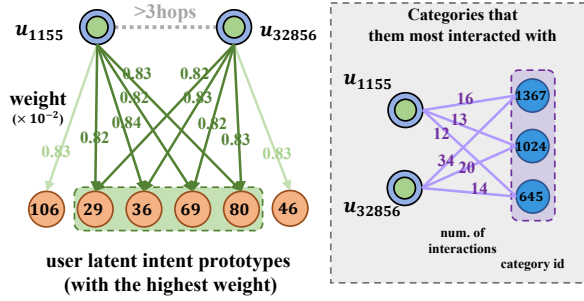


Figure 5: Case study of intent-aware global user relations. Non-locally connected users (u_{1155} and u_{32856}) can be identified with similar user preference (large item category overlap) via our learned disentangled representations.

splits the user embedding into intent-aware vectors to reduce embedding size, the heavy cost of DGCF stems from the recursively routing mechanism for information propagation. It requires extra time to process multiple iterations to obtain intent-relevant weights. In DisenHAN, the time-consuming graph attention network brings high cost due to the need for computing the attention weights.

4.6 Case Study

Global Intent-aware Semantic Dependency. In this section, we examine the potential ability of our DCCF in capturing the global intent-aware semantic dependencies among users. To achieve this goal, we show some concrete examples in Figure 5 to visualize the intent-aware user preferences learned by our DCCF. We observe that u_{1155} and u_{32856} share very similar intent-aware preferences, as shown with intent prototype-specific user weights, despite not being locally connected on the interaction graph. After investigating their interaction patterns, we observe a significant overlap between the categories (categories 29, 36, and 69) of the items they interacted with, indicating the high semantic relatedness of their interaction behaviors. Therefore, in addition to local collaborative relations, the global intent-aware user dependencies can be preserved with

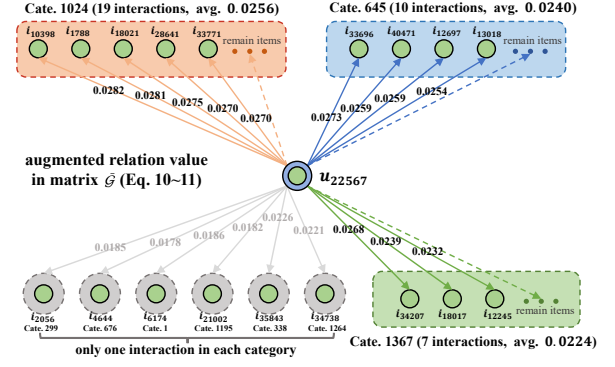


Figure 6: Case study of intent-aware adaptive augmentation over the user-item relation matrix. User interacted items are grouped in terms of their categories. The value of the learned user-item connectivity weight is consistent with the user preference degree, *i.e.*, the higher user-item weight encoded by DCCF indicates stronger user preference.

our encoded disentangled user representations.

Intent-aware Adaptive Augmentation We further analyze the rationality of our intent-aware adaptive augmentation over user-item relations. As shown in Figure 6, we grouped the interacted items of user u_{22567} based on categories (*e.g.*, category 1024, 645). After performing adaptive augmentation over the user-item relation matrix, the implicit dependency weight between each user-item pair was learned through our contrastive intent disentanglement. The value of the learned user-item connectivity weight determines the user’s preference degree over this item. We notice that a higher user-item relation weight (*e.g.*, 0.0282 or 0.0273) indicates a stronger interaction preference over category-specific items, which is consistent with the observation of the category-specific interaction frequency of u_{22567} . For example, the highest item correlation weight (*i.e.*, 0.0282) is generated from the categorical items that u_{22567} interacted with the most. This observation further demonstrates the effectiveness of our disentangled contrastive augmentation, which is easily adaptable to different user-item interaction environments.

5 CONCLUSION

This paper proposes a disentangled contrastive learning method for recommendation that explores latent factors underlying implicit intents for interactions. We introduce a graph structure learning layer that enables adaptive interaction augmentation based on learned disentangled user (item) intent-aware dependencies. Along the augmented intent-aware graph structures, we propose an intent-aware contrastive learning scheme that brings the benefits of disentangled self-supervision signals. Our extensive experiments validate the effectiveness of our proposed model on different recommendation datasets. For future work, one potential extension is to integrate disentangled representation learning with causal analysis to address the bias issues of noisy interaction data. Additionally, by considering the diverse nature of user characteristics, personalized augmentation may further enhance the power of contrastive learning for customized graph perturbing operations in recommenders. By tailoring the augmentation operations to the specific user characteristics, we may better capture the individual preferences.

REFERENCES

- [1] Shoshana Abramovich and Lars-Erik Persson. 2016. Some new estimates of the 'Jensen gap'. *Journal of Inequalities and Applications* 2016, 1 (2016), 1–9.
- [2] Xuheng Cai, Chao Huang, Lianghao Xia, and Xubin Ren. 2023. LightGCL: Simple Yet Effective Graph Contrastive Learning for Recommendation. In *ICLR*.
- [3] Jianxin Chang, Chen Gao, Yu Zheng, Yiqun Hui, Yanan Niu, Yang Song, Depeng Jin, and Yong Li. 2021. Sequential recommendation with graph neural networks. In *SIGIR*. 378–387.
- [4] Chong Chen, Min Zhang, Weizhi Ma, Yiqun Liu, and Shaoping Ma. 2020. Jointly non-sampling learning for knowledge graph enhanced recommendation. In *SIGIR*. 189–198.
- [5] Deli Chen, Yankai Lin, Wei Li, Peng Li, Jie Zhou, and Xu Sun. 2020. Measuring and relieving the over-smoothing problem for graph neural networks from the topological view. In *AAAI*, Vol. 34. 3438–3445.
- [6] Hong Chen, Yudong Chen, Xin Wang, Ruobing Xie, Rui Wang, Feng Xia, and Wenwu Zhu. 2021. Curriculum Disentangled Recommendation with Noisy Multi-feedback. *NeurIPS* 34, 26924–26936.
- [7] Lei Chen, Le Wu, Richang Hong, Kun Zhang, and Meng Wang. 2020. Revisiting Graph Based Collaborative Filtering: A Linear Residual Graph Convolutional Network Approach. In *AAAI*, Vol. 34. 27–34.
- [8] Mengru Chen, Chao Huang, Lianghao Xia, Wei Wei, Yong Xu, and Ronghua Luo. 2023. Heterogeneous Graph Contrastive Learning for Recommendation. In *WSDM*. 544–552.
- [9] Yongjun Chen, Zhiwei Liu, Jia Li, Julian McAuley, and Caiming Xiong. 2022. Intent contrastive learning for sequential recommendation. In *WWW*. 2172–2182.
- [10] Yudong Chen, Xin Wang, Miao Fan, Jizhou Huang, Shengwen Yang, et al. 2021. Curriculum meta-learning for next POI recommendation. In *KDD*. 2692–2702.
- [11] Yu Chen, Lingfei Wu, and Mohammed Zaki. 2020. Iterative deep graph learning for graph neural networks: Better and robust node embeddings. *NeurIPS* (2020), 19314–19326.
- [12] Xiang Gao, Meera Sitharam, and Adrian E Roitberg. 2019. Bounds on the Jensen gap, and implications for mean-concentrated distributions. *AJMAA* 16, 14 (2019), 1–16.
- [13] Xiangnan He, Kuan Deng, Xiang Wang, et al. 2020. Lightgcn: Simplifying and powering graph convolution network for recommendation. In *SIGIR*. 639–648.
- [14] Xiangnan He, Lizi Liao, Hanwang Zhang, Liqiang Nie, Xia Hu, and Tat-Seng Chua. 2017. Neural collaborative filtering. In *WWW*. 173–182.
- [15] Diederik P. Kingma and Jimmy Ba. 2015. Adam: A Method for Stochastic Optimization. In *ICLR*.
- [16] Haoyang Li, Xin Wang, Ziwei Zhang, Zehuan Yuan, Hang Li, and Wenwu Zhu. 2021. Disentangled contrastive learning on graphs. *NeurIPS* 34 (2021), 21872–21884.
- [17] Zihan Lin, Changxin Tian, Yupeng Hou, and Wayne Xin Zhao. 2022. Improving Graph Collaborative Filtering with Neighborhood-enriched Contrastive Learning. In *WWW*. 2320–2329.
- [18] Dongsheng Luo, Wei Cheng, Wenchao Yu, Bo Zong, Jingchao Ni, Haifeng Chen, and Xiang Zhang. 2021. Learning to drop: Robust graph neural network via topological denoising. In *WSDM*. 779–787.
- [19] Jianxin Ma, Peng Cui, Kun Kuang, Xin Wang, and Wenwu Zhu. 2019. Disentangled graph convolutional networks. In *ICML*. PMLR, 4212–4221.
- [20] Jianxin Ma, Chang Zhou, Peng Cui, Hongxia Yang, and Wenwu Zhu. 2019. Learning disentangled representations for recommendation. In *NeurIPS*. 5711–5722.
- [21] Shanlei Mu, Yaliang Li, Wayne Xin Zhao, Siqing Li, and Ji-Rong Wen. 2021. Knowledge-Guided Disentangled Representation Learning for Recommender Systems. *Transactions on Information Systems (TOIS)* 40, 1 (2021), 1–26.
- [22] Zhen Peng, Wenbing Huang, Minnan Luo, et al. 2020. Graph representation learning via graphical mutual information maximization. In *WWW*. 259–270.
- [23] Suvash Sedhain, Aditya Krishna Menon, Scott Sanner, and Lexing Xie. 2015. Autotrec: Autoencoders meet collaborative filtering. In *WWW*. 111–112.
- [24] Weiping Song, Zhiping Xiao, Yifan Wang, Laurent Charlin, Ming Zhang, and Jian Tang. 2019. Session-based social recommendation via dynamic graph attention networks. In *WSDM*. 555–563.
- [25] Jianing Sun, Zhaoyue Cheng, Saba Zuberi, Felipe Pérez, and Maksims Volkovs. 2021. HGCF: Hyperbolic Graph Convolution Networks for Collaborative Filtering. In *WWW*. 593–601.
- [26] Changxin Tian, Yuxiang Xie, Yaliang Li, Nan Yang, and Wayne Xin Zhao. 2022. Learning to Denoise Unreliable Interactions for Graph Collaborative Filtering. In *SIGIR*. 122–132.
- [27] Laurens Van der Maaten and Geoffrey Hinton. 2008. Visualizing data using t-SNE. *Journal of machine learning research* 9, 11 (2008).
- [28] Petar Velickovic, William Fedus, William L Hamilton, Pietro Liò, Yoshua Bengio, and R Devon Hjelm. 2019. Deep Graph Infomax. In *ICLR*.
- [29] Tan Wang, Jianqiang Huang, Hanwang Zhang, and Qianru Sun. 2020. Visual commonsense r-cnn. In *CVPR*. 10760–10770.
- [30] Wenjie Wang, Fuli Feng, Xiangnan He, Xiang Wang, and Tat-Seng Chua. 2021. Deconfounded recommendation for alleviating bias amplification. In *KDD*. 1717–1725.
- [31] Xiang Wang, Xiangnan He, Yixin Cao, Meng Liu, and Tat-Seng Chua. 2019. Kgat: Knowledge graph attention network for recommendation. In *KDD*. 950–958.
- [32] Xiang Wang, Xiangnan He, Meng Wang, Fuli Feng, and Tat-Seng Chua. 2019. Neural Graph Collaborative Filtering. In *SIGIR*.
- [33] Xiang Wang, Tinglin Huang, Dingxian Wang, Yancheng Yuan, Zhengguang Liu, Xiangnan He, and Tat-Seng Chua. 2021. Learning intents behind interactions with knowledge graph for recommendation. In *WWW*. 878–887.
- [34] Xiang Wang, Hongye Jin, An Zhang, Xiangnan He, Tong Xu, and Tat-Seng Chua. 2020. Disentangled graph collaborative filtering. In *SIGIR*. 1001–1010.
- [35] Xiao Wang, Ruijia Wang, Chuan Shi, Guojie Song, et al. 2020. Multi-component graph convolutional collaborative filtering. In *AAAI*, Vol. 34. 6267–6274.
- [36] Yifan Wang, Suyao Tang, et al. 2020. Disenhan: Disentangled heterogeneous graph attention network for recommendation. In *CIKM*. 1605–1614.
- [37] Zhenyi Wang, Huan Zhao, and Chuan Shi. 2022. Profiling the Design Space for Graph Neural Networks based Collaborative Filtering. In *WSDM*. 1109–1119.
- [38] Wei Wei, Chao Huang, Lianghao Xia, Yong Xu, Jiashu Zhao, and Dawei Yin. 2022. Contrastive meta learning with behavior multiplicity for recommendation. In *WSDM*. 1120–1128.
- [39] Jiancan Wu, Xiang Wang, Fuli Feng, Xiangnan He, Liang Chen, Jianxun Lian, et al. 2021. Self-supervised graph learning for recommendation. In *SIGIR*. 726–735.
- [40] Shiwen Wu, Fei Sun, Wentao Zhang, Xu Xie, et al. 2020. Graph neural networks in recommender systems: a survey. *ACM Computing Surveys (CSUR)* (2020).
- [41] Lianghao Xia, Chao Huang, Chunzhen Huang, Kangyi Lin, Tao Yu, and Ben Kao. 2023. Automated Self-Supervised Learning for Recommendation. In *WWW*. 992–1002.
- [42] Lianghao Xia, Chao Huang, Yong Xu, Jiashu Zhao, Dawei Yin, and Jimmy Huang. 2022. Hypergraph contrastive collaborative filtering. In *SIGIR*. 70–79.
- [43] Yuhao Yang, Chao Huang, Lianghao Xia, Yuxuan Liang, Yanwei Yu, and Chenliang Li. 2022. Multi-behavior hypergraph-enhanced transformer for sequential recommendation. In *KDD*. 2263–2274.
- [44] Yonghui Yang, Le Wu, Richang Hong, Kun Zhang, and Meng Wang. 2021. Enhanced graph learning for collaborative filtering via mutual information maximization. In *SIGIR*. 71–80.
- [45] Tiansheng Yao, Xinyang Yi, Derek Zhiyuan Cheng, et al. 2021. Self-supervised Learning for Large-scale Item Recommendations. In *CIKM*. 4321–4330.
- [46] Junliang Yu, Hongzhi Yin, Jundong Li, Qinyong Wang, Nguyen Quoc Viet Hung, and Xiangliang Zhang. 2021. Self-Supervised Multi-Channel Hypergraph Convolutional Network for Social Recommendation. In *WWW*. 413–424.
- [47] Shengyu Zhang, Lingxiao Yang, Dong Yao, Yujie Lu, Fuli Feng, Zhou Zhao, Tat-seng Chua, and Fei Wu. 2022. Re4: Learning to Re-contrast, Re-attend, Re-construct for Multi-interest Recommendation. In *WWW*. 2216–2226.
- [48] Sen Zhao, Wei Wei, Ding Zou, and Xianling Mao. 2022. Multi-view intent disentangle graph networks for bundle recommendation. *AAAI* (2022).
- [49] Kun Zhou, Hui Wang, Wayne Xin Zhao, Yutao Zhu, Sirui Wang, Fuzheng Zhang, Zhongyuan Wang, et al. 2020. S3-rec: Self-supervised learning for sequential recommendation with mutual information maximization. In *CIKM*. 1893–1902.
- [50] Yaochen Zhu and Zhenzhong Chen. 2022. Mutually-regularized dual collaborative variational auto-encoder for recommendation systems. In *WWW*. 2379–2387.
- [51] Ding Zou, Wei Wei, Ziyang Wang, Xian-Ling Mao, Feida Zhu, Rui Fang, and Danyang Chen. 2022. Improving knowledge-aware recommendation with multi-level interactive contrastive learning. In *CIKM*. 2817–2826.