The cold-start issue is a fundamental challenge in Recommender Systems. The recent self-supervised learning (SSL) on Graph Neural Networks (GNNs) model, PT-GNN, pre-trains the GNN model to reconstruct the cold-start embeddings and has shown great potential for cold-start recommendation. However, due to the over-smoothing problem, PT-GNN can only capture up to 3-order relation, which cannot provide much useful auxiliary information to depict the target cold-start user or item. Besides, the embedding reconstruction task only considers the intra-correlations within the subgraph of users and items, while ignoring the inter-correlations across different subgraphs. To solve the above challenges, we propose a multi-strategy-based pre-training method for cold-start recommendation (MPT), which extends PT-GNN from the perspective of model architecture and pretext tasks to improve the cold-start recommendation performance. Specifically, in terms of the model architecture, in addition to the short-range dependencies of users and items captured by the GNN encoder, we introduce a Transformer encoder to capture long-range dependencies. In terms of the pretext task, in addition to considering the intra-correlations of users and items by the embedding reconstruction task, we add an embedding contrastive learning task to capture inter-correlations of users and items. We train the GNN and Transformer encoders on these pretext tasks under the meta-learning setting to simulate the real cold-start scenario, making the model able to be easily and rapidly adapted to new cold-start users and items. Experiments on three public recommendation datasets show the superiority of the proposed MPT model against the vanilla GNN models, the pre-training GNN model on user/item embedding inference, and the recommendation task.

CCS Concepts: • Information systems → Social advertising;

Additional Key Words and Phrases: Recommender System, cold-start, pre-training, self-supervised learning

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1 INTRODUCTION

As an intelligent system, the Recommender System (RS) [13, 14, 18] has been built successfully in recent years and aims to alleviate the information overload problem. The most popular algorithm in RS is collaborative filtering, which uses either matrix factorization [18] or neural collaborative filtering [14] to learn the user/item embeddings. However, due to the sparse interactions of the cold-start users/items, it is difficult to learn high-quality embeddings for these cold-start users/items.

To address the cold-start issue, researchers propose to incorporate side information such as knowledge graphs (KGs) [32, 34] or the contents of users/items [3, 41, 44] to enhance the representations of users/items. However, the contents are not always available, and it is not easy to link the items to the entities in KGs due to the incompleteness and ambiguities of the entities. Another research line is to adopt the Graph Neural Networks (GNNs) such as GraphSAGE [10], NGCF [35], and LightGCN [13] to solve the problem. The basic idea is to incorporate the high-order neighbors to enhance the embeddings of the cold-start users/items. However, the GNN models for recommendation cannot thoroughly solve the cold-start problem, as the embeddings of the cold-start users/items aren’t explicitly optimized, and the cold-start neighbors have not been considered in these GNNs.

In our previous work, we proposed PT-GNN [11], which pre-trains the GNN model to reconstruct the user/item embeddings under the meta-learning setting [31]. To further reduce the impact from the cold-start neighbors, PT-GNN incorporates a self-attention-based meta aggregator to enhance the aggregation ability of each graph convolution step, and an adaptive neighbor sampler to select proper high-order neighbors according to the feedback from the GNN model.

However, PT-GNN still suffers from the following challenges: (1) In terms of the model architecture, PT-GNN suffers from lacking the ability to capture long-range dependencies. Existing research such as by Chen and Wong [6] pointed out that GNN can only capture up to 3-hop neighbors due to the overfitting and over-smoothing problems [13]. However, in the cold-start scenario, both low-order neighbors ($L \leq 2$, where $L$ is the convolution layer) and high-order neighbors ($L > 2$) are important to the target cold-start user/item. On one hand, the low-order neighbors are crucial for representing the target cold-start users/items, as the first-order neighbors directly reflect the user’s preference or the item’s target audience, and the second-order neighbors directly reflect the signals of the collaborative users/items. On the other hand, due to the extremely sparse interactions of the cold-start users/items, the first- and second-order neighbors are insufficient to represent a user or an item. Thus, for the target users/items, it is crucial to capture not only the short-range dependencies from their low-order neighbors but also the long-range dependencies from their high-order neighbors. Nevertheless, due to the limitation of the network structure, most of the existing GNN models can only capture the short-range dependencies, which inspires the first research question: how to capture both short- and long-range dependencies of users/items?

(2) In terms of the pretext task, PT-GNN only considers the intra-correlations within the subgraph of the target user or item but ignores the inter-correlations between the subgraphs of different users or items. More concretely, given a target cold-start user or item, PT-GNN samples its high-order neighbors to form a subgraph and leverages the subgraph itself to reconstruct the cold-start embedding. Essentially, the embedding reconstruction task is a generative task, which focuses on exploring intra-correlations between nodes in a subgraph. On the contrary, some recent pre-training GNN models (e.g., GCC [23], GraphCL [46]), depending on the contrastive learning mechanism, can capture the similarities of nodes between different subgraphs, i.e., the inter-correlations. Thus, this inspires the second research question: how to capture the inter-correlations of the target cold-start users/items in addition to the intra-correlations?
We propose a Multi-strategy-based Pre-Training method for cold-start recommendation (MPT), which extends PT-GNN from the perspective of model architecture and pretext tasks to improve the cold-start recommendation performance. The improvements over PT-GNN are shown in Figure 1.

First, in terms of the model architecture, in addition to the original GNN encoder, which captures the short-range dependencies from the user-item edges in the user-item graph, we introduce a Transformer encoder to capture the long-range dependencies from the user-item paths, which can be extracted by performing random walk [22] starting from the target user or item in the user-item graph. The multi-head self-attention mechanism in the Transformer attends nodes in different positions in a path [29], which can explicitly capture the long-range dependencies between users and items. Besides, we change the RL-based neighbor sampling strategy in the original GNN encoder into a simple yet effective dynamic sampling strategy, which can reduce the time complexity of the neighbor sampling process.

Second, in terms of the pretext task, in addition to the original embedding reconstruction task, which considers the intra-correlations within the subgraph of the target user or item, we add the embedding contrastive learning [38] task to capture the inter-correlations across the subgraphs or paths of different users or items. Specifically, we first augment a concerned subgraph or path by deleting or replacing the nodes in it. Then we treat the augmented subgraphs or paths of the concerned user or item as its positive counterparts, and those of other users or items as the negative counterparts. By contrastive learning upon the set of the positive and negative instances, we can pull the similar user or item embeddings together while pulling away dissimilar embeddings.

We train the GNN and Transformer encoders by the reconstruction and contrastive learning pretext tasks under the meta-learning setting [31] to simulate the cold-start scenario. Specifically, following PT-GNN, we first pick the users/items with sufficient interactions as the target users/items and learn their ground-truth embeddings on the observed abundant interactions. Then for each target user/item, in order to simulate the cold-start scenario, we mask other neighbors and only maintain $K$ first-order neighbors, based on which we form the user-item subgraph and use random walk [22] to generate the paths of the target user or item. Next we perform graph convolution in multiple steps upon the user-item subgraph or self-attention mechanism upon the path to obtain the target user/item embeddings. Finally, we optimize the model parameters with the reconstruction and contrastive losses.

We adopt the pre-training and fine-tuning paradigm [23] to train MPT. During the pre-training stage, in order to capture the correlations of users and items from different views (i.e., the short- and long-range dependencies, the intra- and inter-correlations), we assign each pretext task an independent set of initialized embeddings and train these tasks independently. During the
fine-tuning state, we fuse the pre-trained embeddings from each pretext task and fine-tune the encoders by the downstream recommendation task. The contributions can be summarized as:

- We extend PT-GNN from the perspective of model architecture. In addition to the short-range dependencies of users and items captured by the GNN encoder, we add a Transformer encoder to capture long-range dependencies.
- We extend PT-GNN from the perspective of pretext tasks. In addition to considering the intra-correlations of users and items by the embedding reconstruction task, we add an embedding contrastive learning task to capture inter-correlations of users and items.
- Experiments on both intrinsic embedding evaluation and extrinsic downstream tasks demonstrate the superiority of our proposed MPT model against the state-of-the-art GNN model and the original proposed PT-GNN.

2 PRELIMINARIES

In this section, we first define the problem and then introduce the original proposed PT-GNN.

2.1 Notation and Problem Definition

**Bipartite Graph.** We denote the user-item bipartite graph as $G = (U, I, E)$, where $U = \{u_1, \ldots, u_{|U|}\}$ is the set of users and $I = \{i_1, \ldots, i_{|I|}\}$ is the set of items. $E \subseteq U \times I$ denotes the set of edges that connect the users and items. Notation $N^l(u)$ denotes the $l$-order neighbors of user $u$. When ignoring the superscript, $N(u)$ denotes the first-order neighbors of $u$. $N^l(i)$ and $N(i)$ are defined similarly for items.

**User-item Path.** The user-item path is generated by the random walk strategy from the user-item interaction data and has the same node distribution with the graph $G$ as Perozzi et al. [22] proposed. Formally, there exist two types of paths: $P = UIUI\lor P = IUIU$, where $U$ denotes that the node type is user and $I$ denotes that the node type is item.

**Problem Definition.** Let $f: U \cup I \rightarrow \mathbb{R}^d$ be the encoding function that maps the users or items to $d$-dimension real-valued vectors. We denote a user $u$ and an item $i$ with initial embeddings $h^0_u$ and $h^0_i$, respectively. Given the bipartite graph $G$ or the path $P$, we aim to pre-train the encoding function $f$ that is able to be applied to the downstream recommendation task to improve its performance. Note that for simplicity, in the following sections, we mainly take user embedding as an example to explain the proposed model, as item embedding can be explained in the same way.

2.2 A Brief Review of PT-GNN

The basic idea of PT-GNN is to leverage the vanilla GNN model as the encoder $f$ to reconstruct the target cold-start embeddings to explicitly improve their embedding quality. To further reduce the impact from the cold-start neighbors, PT-GNN incorporates a self-attention-based meta-aggregator to enhance the aggregation ability of each graph convolution step and an adaptive neighbor sampler to select proper high-order neighbors according to the feedback from the GNN model.

2.2.1 Basic Pre-training GNN Model. The basic pre-training GNN model reconstructs the cold-start embeddings under the meta-learning setting [31] to simulate the cold-start scenario. Specifically, for each target user $u$, we mask some neighbors and only maintain at most $K^l$ neighbors ($K$ is empirically selected as a small number, e.g., $K=3$) at the $l$th layer. Based on this we perform graph convolution in multiple steps to predict the target user embedding. Take GraphSAGE [10] as the backbone GNN model as an example: the graph convolution process at the $l$th layer is

$$h^l_u = \sigma(W^l \cdot (h^{l-1}_u \parallel h^l_{N(u)})),$$

(1)
where $h^l_u$ is the refined user embedding at the $l$th convolution step; $h^{l-1}_u$ is the previous user embedding ($h^0_u$ is the initialized embedding); $h^l_{N(u)}$ is the averaged embedding of the neighbors, in which the neighbors are sampled by the random sampling strategy; $\sigma$ is the sigmoid function; $W^l$ is the parameter matrix; and $||$ is the concatenate operation.

We perform graph convolution in $L$-1 steps, aggregate the refined embeddings of the first-order neighbors ($h^{l-1}_1, \ldots, h^{l-1}_K$) to obtain the smoothed embedding $h^l_{N(u)}$, and transform it into the target embedding $h^l_u$, i.e., $h^l_{N(u)} = \text{AGGREGATE}((h^{l-1}_i, \forall i \in N(u)))$, $h^l_u = \sigma(W^l \cdot h^l_{N(u)})$. Then we calculate the cosine similarity between the predicted embedding $h^l_u$ and the ground-truth embedding $h_u$ to optimize the parameters of the GNN model:

$$\Theta^* = \arg \max_{\Theta} \sum_u \cos(h^l_u, h_u),$$

(2)

where the ground-truth embedding $h_u$ is learned by any recommender algorithms (e.g., NCF [14], LightGCN [13]²), and $\Theta$ is the model parameters. Similarly, we can obtain the item embedding $h^l_i$ and optimize model parameters by Equation (2).

2.2.2 Enhanced Pre-training Model: PT-GNN. The basic pre-training strategy has two problems. On one hand, it cannot explicitly deal with the high-order cold-start neighbors during the graph convolution process. On the other hand, the GNN sampling strategies such as random sampling [10] or importance sampling [4] strategies may fail to sample high-order relevant cold-start neighbors due to their sparse interactions.

To solve the first challenge, we incorporate a meta aggregator to enhance the aggregation ability of each graph convolution step. Specifically, the meta aggregator uses the self-attention mechanism [29] to encode the initial embeddings $\{h^0_1, \ldots, h^0_K\}$ of the $K$ first-order neighbors for $u$ as input and outputs the meta embedding $\hat{h}_u$ for $u$. The process is

$$\{h_1, \ldots, h_K\} \leftarrow \text{SELF\_ATTENTION}((h^0_1, \ldots, h^0_K)),$$

$$\hat{h}_u = \text{AVERAGE}((h_1, \ldots, h_K)).$$

(3)

We use the same cosine similarity described in Equation (2) to measure the similarity between the predicted meta embedding $\hat{h}_u$ and the ground-truth embedding $h_u$.

To solve the second challenge, we propose an adaptive neighbor sampler to select proper high-order neighbors according to the feedbacks from the GNN model. The adaptive neighbor sampler is formalized as a hierarchical Markov Sequential Decision Process, which sequentially samples from the low-order neighbors to the high-order neighbors and results in at most $K^l$ neighbors in the $l$th layer for each target user $u$. After sampling the neighbors of the former $L$ layers, the GNN model accepts the sampled neighbors to produce the reward, which denotes whether the sampled neighbors are reasonable or not. Through maximizing the expected reward from the GNN model, the adaptive neighbor sampler can sample proper high-order neighbors. Once the meta aggregator and the adaptive neighbor sampler are trained, the meta embedding $\hat{h}_u$ and the averaged sampled neighbor embedding $\tilde{h}^l_{N(u)}$ at the $l$th layer are added into each graph convolution step in Equation (1):

$$h^l_u = \sigma(W^l \cdot \hat{h}_u || h^{l-1}_u || \tilde{h}^l_{N(u)}).$$

(4)

For the target user $u$, Equation (4) is repeated in $L - 1$ steps to obtain the embeddings $\{h^{l-1}_1, \ldots, h^{l-1}_k\}$ for its $K$ first-order neighbors, and then the predicted embedding $h^l_u$ is obtained.

²They are good enough to learn high-quality user/item embeddings from the abundant interactions, and we will discuss this in Section 5.3.1.
by averaging the first-order embeddings. Finally, Equation (2) is used to optimize the parameters of the pre-training GNN model. The pre-training parameter set \( \Theta = \{ \Theta_{gnn}, \Theta_f, \Theta_s \} \), where \( \Theta_{gnn} \) is the parameters of the vanilla GNN, \( \Theta_f \) is the parameters of the meta aggregator, and \( \Theta_s \) is the parameters of the neighbor sampler. The item embedding \( h_i^L \) can be obtained in a similar way.

### 2.2.3 Downstream Recommendation Task

We fine-tune PT-GNN in the downstream recommendation task. Specifically, for each target user \( u \) and his or her neighbors \( \{ N^1(u), \ldots, N^L(u) \} \) of different order, we first use the pre-trained adaptive neighbor sampler to sample proper high-order neighbors \( \{ \hat{N}^1(u), \hat{N}^2(u), \ldots, \hat{N}^L(u) \} \), and then use the pre-trained meta aggregator to produce the user embedding \( h_u^L \). The item embedding \( h_i^L \) can be obtained in the same way. Then we transform the embeddings to calculate the relevance score between a user and an item, i.e.,

\[
y(u, i) = \sigma(W \cdot h_u^L)^\top \sigma(W \cdot h_i^L)
\]

with parameters \( \Theta_r = \{W\} \). Finally, we adopt the BPR loss [13] to optimize \( \Theta_r \) and fine-tune \( \Theta \):

\[
\mathcal{L}_{BPR} = \sum_{(u, i) \in E, (u, j) \notin E} -\ln \sigma(y(u, i) - y(u, j)).
\]

However, as shown in Figure 1, due to the limitation of the GNN model, PT-GNN can only capture the short-range dependencies of users and items; besides, the embedding reconstruction task only focuses on exploring the intra-correlations within the subgraph of the target user or item. Therefore, it is necessary to fully capture both short- and long-range dependencies of users and items, and both intra- and inter-correlations of users or items.

### 3 THE PROPOSED MODEL MPT

We propose a novel Multi-strategy-based Pre-Training method (MPT), which extends PT-GNN from the perspective of model architecture and pretext tasks. Specifically, in terms of the model architecture, in addition to using the GNN encoder to capture the short-range dependencies of users and items, we introduce a Transformer encoder to capture long-range dependencies. In terms of the pretext task, in addition to considering the intra-correlations of users and items by the embedding reconstruction task, we add an embedding contrastive learning task to capture inter-correlations of users and items. Hence, by combining each architecture and each pretext task, there are four different implementations of pretext tasks, as shown in Figure 2. We detail each pretext task implementation in Section 3.1 to Section 3.4 and then present the overall model training process in Section 3.5. Finally, we analyze the time complexity of the pretext task implementation in Section 3.6.

#### 3.1 Reconstruction with GNN Encoder

In this pretext task, we primarily follow the original PT-GNN model to reconstruct the user embedding, as proposed in Section 2.2. We modify PT-GNN in terms of its neighbor sampling strategy to reduce the time complexity.

The adaptive neighbor sampling strategy in PT-GNN suffers from the slow convergence issue, as it is essentially a Monte-Carlo-based policy gradient strategy (REINFORCE) [27, 36] and has the complex action-state trajectories for the entire neighbor sampling process. To solve this problem, inspired by the dynamic sampling theory that uses the current model itself to sample instances [1, 52], we propose the dynamic sampling strategy, which samples from the low-order neighbors to the high-order neighbors according to the enhanced embeddings of the target user and each neighbor. The enhanced embedding for the target user (or each neighbor) is obtained by concatenating the meta embedding produced by the meta aggregator in PT-GNN (Section 2.2.2) and the current trained embedding. The meta embedding enables considering the cold-start
characteristics of the neighbors, and the current trained embedding enables dynamically selecting proper neighbors. Formally, at the $l$th layer, the sampling process is

$$a^u_j = \cos(\tilde{h}_u || \tilde{h}_j || h_j^l), \quad \{h_1^l, \ldots, h_{K_l}^l\} \leftarrow \text{S.TOP}(a^u_1, \ldots, a^u_j, \ldots, a^u_{N_l(u)}),$$

where $||$ is the concatenate operation, $a^u_j$ is the cosine similarity between the enhanced target user embedding $\tilde{h}_u || h_j^l$ and the enhanced $j$th neighbor embedding $\tilde{h}_j || h_j^l$. $\tilde{h}_u$ and $\tilde{h}_j$ are the meta embeddings produced by the meta aggregator, $h_u^l$ and $h_j^l$ are the current trained user embedding, and $\{h_1^l, \ldots, h_{K_l}^l\}$ are the top $K_l$ relevant neighbors. S.TOP is the operation that selects the top neighbor embeddings with top cosine similarity. Compared with the adaptive sampling strategy in PT-GNN, the proposed dynamic sampling strategy not only speeds up the model convergence but also has competitive performance as it does not need multiple sampling processes and considers the cold-start characteristics of the neighbors during the sampling process. Notably, the training process of the dynamic sampling strategy is not a fully end-to-end fashion. In each training epoch, we first select $K_l$ relevant neighbors as the sampled neighbors for each target node according to Equation (6), and then we can obtain the adjacency matrix of the user-item graph. Next, we perform the graph convolution operation to reconstruct the target node embedding to optimize the model parameters. Finally, the updated current node embedding, together with the fixed meta node embedding produced by the meta aggregator, is used in the next training epoch, which enables dynamically sampling proper neighbors.

Once the neighbors are sampled, at the $l$th layer, we use the meta embedding $\tilde{h}_u$, the previous user embedding $h_u^{l-1}$, and the averaged dynamically sampled neighbor embedding $h_{N_l(u)}^l$ to perform graph convolution, as shown in Equation (4). Then we perform graph convolution $L$ steps to obtain the predicted user embedding $h_u^{R_l}$, and use Equation (2) to optimize the model parameters. Figure 2(a) shows this task, and the objective function is as follows:

$$L_1 := \arg \max_{\Theta_1} \sum_u \cos(h_u^{R_l}, h_u).$$
3.2 Contrastive Learning with GNN Encoder

In this pretext task, we propose to contrast the user embedding produced by the GNN encoder across subgraphs, as shown in Figure 2(b). Similar to PT-GNN, we also train this task under the meta-learning setting to simulate the cold-start scenario. Specifically, we also select users with abundant interactions and randomly select at most $K'(1 \leq l \leq L)$ neighbors at layer $l$ to form the subgraph $G_u$. Then we perform contrastive learning (CL) upon $G_u$ to learn the representations of users. In the following part, we first present the four components in the CL framework and then detail the key component, i.e., the data augmentation operation.

- An augmentation module $AUG(\cdot)$ augments the user subgraph $G_u$ by deleting or replacing the users or items in it, which results in two random augmentations $\hat{G}_{u_1} = AUG(G_u, seed_1)$ and $\hat{G}_{u_2} = AUG(G_u, seed_2)$, where $seed_1$ and $seed_2$ are two random seeds. In this article, we evaluate the individual data augmentation operation, i.e., performing either deletion or substitution operation. We leave the compositional data augmentation operation as future work.
- A GNN encoder performs the graph convolution $L$ steps using Equation (4) to generate the representation of the target user for each augmented subgraph, i.e., $h_{u_1}^{C_b} = GNN(\hat{G}_{u_1})$ and $h_{u_2}^{C_b} = GNN(\hat{G}_{u_2})$.
- A neural network encoder $g$ maps the encoded augmentations $h_{u_1}^{C_b}$ and $h_{u_2}^{C_b}$ into two vectors $z_1 = g(h_{u_1}^{C_b})$, $z_2 = g(h_{u_2}^{C_b})$. This operation is the same as SimCLR [5] in its observation that adding a nonlinear projection head can significantly improve the representation quality.
- A contrastive learning loss module maximizes the agreement between positive augmentation pair $(\hat{s}_1, \hat{s}_2)$ in the set $\{\hat{s}\}$. We construct the set $\{\hat{s}\}$ by randomly augmenting twice for all users in a mini-batch $s$ (assuming $s$ is with size $N$), which gets a set $\hat{s}$ with size $2N$. The two variants from the same original user form the positive pair, while all the other instances from the same mini-batch are regarded as negative samples for them. Then the contrastive loss for a positive pair is defined as

$$l_c(m, n) = -\log\frac{\exp(\cos(z_m, z_n)/\tau)}{\sum_{k=1}^{2N} 1_{k \neq m} \exp(\cos(z_m, z_n)/\tau)},$$

where $1_{k \neq m}$ is the indicator function to judge whether $k \neq m$, $\tau$ is a temperature parameter, and $\cos(z_m, z_n) = z_m^T z_n/(||z_m||_2||z_n||_2)$ denotes the cosine similarity of two vector $z_m$ and $z_n$. The overall contrastive loss $L_2$ defined in a mini-batch is

$$L_2 := \min_{\Theta_2} \sum_{m=1}^{2N} \sum_{n=1}^{2N} 1_{m=n} l_c(m, n),$$

where $1_{m=n}$ is an indicator function that returns 1 when $m$ and $n$ are a positive pair and returns 0 otherwise, and $\Theta_2$ is the parameters of the CL framework.

The key method in CL is the data augmentation strategy. In a recommender system, since each neighbor may play an essential role in expressing the user profile, it remains unknown whether data augmentation would benefit the representation learning and what kind of data augmentation could be useful. To answer these questions, we explore and test two basic augmentations, deletion and substitution. We believe there exist more potential augmentations, which we will leave for future exploration.

- **Deletion.** At each layer $l$, we randomly select $a\%$ users or items and delete them. If a parent user or item is deleted, its child users or items are all deleted.
• **Substitution.** At each layer \( l \), we randomly select \( b\% \) users or items. For each user \( u \) or item \( i \) in the selected list, we randomly replace \( u \) or \( i \) with one of its parent’s interacted first-order neighbors. Note that in order to illustrate the two data augmentation strategies, we present the deletion and substitution operations in Figure 2(b), but in practice we perform an individual data augmentation strategy, i.e., performing either a deletion or substitution operation, and analyze whether the substitution or deletion ratio used for the target user (or target item) can affect the recommendation performance in Section 5.3.3.

Once the CL framework is trained, we leave out other parts and only maintain the parameters of the trained GNN encoder. When a new cold-start user \( u \) comes in, same as in Section 3.1, the GNN encoder performs graph convolution in \( L \) steps to obtain the enhanced embedding \( \mathbf{h}_u^{C_\Theta} \).

### 3.3 Reconstruction with Transformer Encoder

In this pretext task, we propose using the Transformer encoder to reconstruct the embeddings of target users in the user-item path, as shown in Figure 2(c). This pretext task is also trained under the meta-learning setting. Specifically, similar to PT-GNN, we first choose abundant users and use any recommender algorithms to learn their ground-truth embeddings. Then for each user, we sample \( K^l (1 \leq l \leq L) \) neighbors, based on which we use random walk [22] to obtain the user-item path \( \mathcal{P} = UIUI \) (or \( \mathcal{P} = UIUI \)) with path length \( T \). Finally, we mask the target user in the input path with special tokens “[mask]” and use the Transformer encoder to predict the target user embedding.

Formally, given an original path \( \mathcal{P} = [x_1, \ldots, x_T] \), where each node \( x_i \) in \( \mathcal{P} \) represents the initial user embedding \( \mathbf{h}_u^0 \) or the initial item embedding \( \mathbf{h}_i^0 \), we first construct a corrupted path \( \hat{\mathcal{P}} \) by replacing the target user token in \( \mathcal{P} \) to a special symbol “[mask]” (suppose the target user is at the \( t \)th position in \( \hat{\mathcal{P}} \)). Then we use the Transformer encoder to map the input path \( \hat{\mathcal{P}} \) into a sequence of hidden vectors \( \text{Tr}(\hat{\mathcal{P}}) = [\text{Tr}(\hat{\mathcal{P}})_1, \ldots, \text{Tr}(\hat{\mathcal{P}})_T] \). Finally, we fetch the \( t \)th embedding in \( \text{Tr}(\hat{\mathcal{P}}) \) to predict the ground-truth embedding and use cosine similarity to optimize the parameters \( \Theta_3 \) of the Transformer encoder. For simplicity, we use notation \( \mathbf{h}_u^{R_p} \) to represent the \( t \)th predicted embedding, i.e., \( \text{Tr}(\hat{\mathcal{P}})_t = \mathbf{h}_u^{R_p} \). The objective function is

\[
\mathcal{L}_3 := \arg \max_{\Theta_3} \sum_u \cos(\mathbf{h}_u^{R_p}, \mathbf{h}_u) .
\]

Once the Transformer encoder is trained, we can use it to predict the cold-start embedding. When a new cold-start user \( u \) with his or her interacted neighbors comes in, we first use random walk to generate the path set \( \{\mathcal{P}_1, \ldots, \mathcal{P}_t, \ldots, \mathcal{P}_T\} \), where in the \( t \)th path \( \mathcal{P}_t \), \( u \) is in the \( t \)th position. Then we replace \( u \) with the “[mask]” signal to generate the corrupted path \( \hat{\mathcal{P}}_t \). Next we feed all the corrupted paths \( \{\hat{\mathcal{P}}_1, \ldots, \hat{\mathcal{P}}_T\} \) into the Transformer encoder and obtain the predicted user embeddings \( \{\mathbf{h}_{u_1}^{R_p}, \ldots, \mathbf{h}_{u_T}^{R_p}\} \). Finally, we average these predicted embeddings to obtain the final user embedding \( \mathbf{h}_u^{R_p} \).

### 3.4 Contrastive Learning with Transformer Encoder

In this task, we propose to contrast the user embedding produced by the Transformer encoder across different paths, as shown in Figure 2(d). We train this task under the meta-learning setting. Same as in Section 3.3, we choose abundant users, sample \( K^l (1 \leq l \leq L) \) order neighbors, and use random walk to obtain the path \( \mathcal{P}_u \). Then we perform the CL framework to learn the cold-start user embedding:

- An augmentation module AUG(.) augments the path \( \mathcal{P}_u = [x_1, \ldots, x_T] \) by randomly deleting or replacing the users or items in it, i.e., \( \hat{\mathcal{P}}_{u_1} = \text{AUG}(\mathcal{P}_u, \text{seed}_1) \) and \( \hat{\mathcal{P}}_{u_2} = \text{AUG}(T_u, \text{seed}_2) \). Similar to Section 3.2, we evaluate the individual data augmentation operation.
A Transformer encoder accepts $\tilde{P}_{u_1}, \tilde{P}_{u_2}$ as input and encodes the target user from two augmented paths into latent vectors, i.e., $h^{C_p}_{u_1} = \text{Tr}(\tilde{P}_{u_1})$ and $h^{C_p}_{u_2} = \text{Tr}(\tilde{P}_{u_2})$.

A neural network encoder $g'$ maps the encoded augmentations $h^{C_p}_{u_1}$ and $h^{C_p}_{u_2}$ into two vectors $z'_1 = g'(h^{C_p}_{u_1})$, $z'_2 = g'(h^{C_p}_{u_2})$.

A contrastive learning loss module maximizes the agreement between positive augmentation pair $(\tilde{s}_1, \tilde{s}_2)$ in the set $\{\tilde{s}\}$. Same as in Section 3.2, we also construct the set $\{\tilde{s}\}$ by randomly augmenting twice for all users in a mini-batch $s$ to get a set $\tilde{s}$ with size $2N$, use the two variants from the same original user as a positive pair, use all the other instances from the same mini-batch as negative samples, and use Equation (8) as the contrastive loss $l_c(m, n)$ for a positive pair. Similar to Equation (9), the overall contrastive loss $L_4$ defined in a mini-batch is

$$L_4 := \min_{\Theta_4} \sum_{m=1}^{2N} \sum_{n=1}^{2N} \mathbb{1}_{m=n} l_c(m, n),$$

(11)

where $\Theta_4$ is the parameters of the CL framework.

The data augmentation strategies are as follows:

- **Deletion.** For each path $P_{u}$, we randomly select $a\%$ users and items and delete them.
- **Substitution.** For each path $P_{u}$, we randomly select $b\%$ users and items. For each user $u$ or item $i$ in the selected list, we randomly replace $u$ or $i$ with one of its parent’s interacted first-order neighbors. Note that in order to illustrate the two data augmentation strategies, we present the deletion and substitution operations in Figure 2(d), but in practice we perform an individual data augmentation strategy, i.e., performing either a deletion or substitution operation, and analyze whether the substitution or deletion ratio used for the target user (or target item) can affect the recommendation performance in Section 5.3.3. Note that we perform an individual data augmentation strategy, i.e., performing either deletion or substitution operation, and analyze whether the substitution or deletion ratio used for the target user (or target item) can affect the recommendation performance in Section 5.3.3.

Once the CL framework is trained, we leave out other parts and only maintain the parameters of the Transformer encoder. When a new cold-start user $u$ with his or her interacted neighbors comes in, same as in Section 3.3, we generate the path set $\{P_1, \ldots, P_T\}$, use the Transformer encoder to obtain the encoded embeddings $\{h^{C_p}_{u_1}, \ldots, h^{C_p}_{u_T}\}$, and average these embeddings to obtain the final embedding $h^{C_p}_{u}$.

### 3.5 Model Pre-training and Fine-tuning Process

We adopt the pre-training and fine-tuning paradigm [23] to train the GNN and Transformer encoders.

During the pre-training stage, we independently train each pretext task using the objective functions in Equations (7), (9), (10), and (11) to optimize the parameters $\{\Theta_1, \Theta_2, \Theta_3, \Theta_4\}$. We assign each pretext task an independent set of initialized user and item embeddings and do not share embeddings for these pretext tasks. Therefore, we can train these pretext tasks in a fully parallel way.

During the fine-tuning process, we initialize the GNN and Transformer encoders with the trained parameters and fine-tune them via the downstream recommendation task. Specifically, for each target cold-start user and his or her interacted neighbors $\{N^{1}(u), \ldots, N^{L}(u)\}$ of each order, we first use the trained GNN and Transformer encoders corresponding to each pretext task to
generate the user embedding $\mathbf{h}_u^g$, $\mathbf{h}_u^c$, $\mathbf{h}_u^p$, and $\mathbf{h}_u^c$. Then we concatenate the generated embeddings and transform them into the final user embedding:

$$\mathbf{h}_u^* = W \cdot (\mathbf{h}_u^g || \mathbf{h}_u^c || \mathbf{h}_u^p)$$

where $\Theta_r = \{W\}$ is the parameter matrix. We generate the final item embedding $\mathbf{h}_i^*$ in a similar next. We calculate the relevance score as the inner product of user and item final embeddings, i.e., $y(u, i) = \mathbf{h}_u^T \mathbf{h}_i^*$. Finally, we use BPR loss defined in Equation (5) to optimize $\Theta_r$ and fine-tune $\{\Theta_1, \Theta_2, \Theta_3, \Theta_4\}$.

3.6 Discussions

As we can see, the GNN and Transformer encoders are the main components of the pretext tasks. For the GNN encoder, the time complexity is $O(T_{GNN} + T_S)$, where $O(T_{GNN})$ represents the time complexity of the layer-wise propagation of the GNN model, and $O(T_S)$ represents the time complexity of the sampling strategy. Since different GNN models have different time complexity $O(T_{GNN})$, we select classic GNN models and show their $O(T_{GNN})$. LightGCN [13]: $O(|R^+| + T_S)$, NGCF [35]: $O(|R^+| \cdot d^2 + T_S)$, GCN [28]: $O(|R^+| \cdot d^2 + T_S)$, GraphSAGE [10]: $O(|N^+| + T_S)$, where $|R^+|$ denotes the number of nonzero entries in the Laplacian matrix, $|N^+|$ is the number of totally sampled instances, and $d$ is the embedding size. We present the time complexity of dynamic sampling strategy $O(T_S) = O(\frac{E^*d^*|N^+|}{M})$ and the adaptive sampling strategy $O(T_S) = O(\frac{E^*d^*|N^+|}{E^*M^*d^*})$, where $E$ is the number of convergent epochs, and $M$ is the sampling times. Compared with the adaptive sampling strategy, the dynamic strategy does not need multiple sampling time $M$ and has fewer convergent epochs $E$, and thus has smaller time complexity. For the Transformer encoder, the time complexity is $O(T^2 \cdot d)$, where $T$ is the length of the user-item path.

4 EXPERIMENTS

Following PT-GNN [11], we conduct an intrinsic evaluation task to evaluate the quality of user/item embeddings, and an extrinsic task to evaluate the cold-start recommendation performance. We answer the following research questions:

- RQ1: How does MPT perform embedding inference and cold-start recommendation compared with the state-of-the-art GNN and pre-training GNN models?
- RQ2: What are the benefits of performing pretext tasks in both intrinsic and extrinsic evaluation?
- RQ3: How do different settings influence the effectiveness of the proposed MPT model?

4.1 Experimental Settings

4.1.1 Datasets. We select three public datasets, MovieLens-1M (ML-1M) [12], MOOCs [51], and Gowalla [17]. Table 1 illustrates the statistics of these datasets.

4.1.2 Comparison Methods. We select three types of baselines, the neural collaborative filtering model, the GNN models, and the self-supervised graph learning models.

- NCF [14]: is a neural collaborative filtering model that uses multi-layer perceptron and factorization to learn the representations of users/items.
- PinSage [45]: employs the GraphSAGE [10] model, which samples neighbors randomly and aggregates them by the AVERAGE function.

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3https://grouplens.org/datasets/movielens/.

4http://moocdata.cn/data/course-recommendation.

5https://snap.stanford.edu/data/loc-gowalla.html. 

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### Table 1. Statistics of the Datasets

| Dataset        | #Users | #Items | #Interactions | #Sparse Ratio |
|----------------|--------|--------|---------------|---------------|
| MovieLens-1M   | 6,040  | 3,706  | 1,000,209     | 4.47%         |
| MOOCs          | 82,535 | 1,302  | 458,453       | 0.42%         |
| Gowalla        | 29,858 | 40,981 | 1,027,370     | 0.08%         |

- **GCMC [28]**: employs the standard GCN [16] model to learn the embeddings of users and items.
- **NGCF [35]**: primarily follows the neural passing-based GNN model [9], but additionally adds second-order interactions during the message passing process.
- **LightGCN [13]**: discards the feature transformation and nonlinear activation functions in NGCF.
- **SGL [37]**: contrasts the node representation within the graphs from multiple views, where node dropout, edge dropout, and random walk are adopted to generate these views. We find edge dropout has the best performance.
- **PT-GNN [11]**: takes the embedding reconstruction as the pretext task to explicitly improve the embedding quality.

For each vanilla GNN model (e.g., GCMC, NGCF), notation GNN means we apply GNN in PT-GNN, and notation GNN* means we apply GNN in MPT. Since SGL adopts a multi-task learning paradigm for recommendation, for fair comparison, we compare it in the extrinsic recommendation task and use notation GNN-SGL to denote it.

#### 4.1.3 Intrinsic and Extrinsic Settings

Following PT-GNN [11], we divide each dataset into the meta-training set $D_T$ and the meta-test set $D_N$. We train and evaluate the proposed MPT model in the intrinsic user/item embedding inference task on $D_T$. Once the proposed model MPT is trained, we fine-tune it in the extrinsic task and evaluate its performance on $D_N$. We select the users/items from each dataset with sufficient interactions as the target users/items in $D_T$, as the intrinsic evaluation needs the ground-truth embeddings of users/items inferred from the sufficient interactions. In the cold-start user scenario, we divide the users with the number of the direct interacted items (first-order neighbors) more than $n_i$ into $D_T$ and leave the rest of the users in $D_N$. We set $n_i$ as 25, 10, and 25 for the datasets ML-1M, MOOCs, and Gowalla, respectively. Similarly, in the cold-start item scenario, we divide the items with the number of the direct interacted users (first-order neighbors) more than $n_u$ into $D_T$ and leave the rest of the items in $D_N$, where we set $n_u$ as 15, 10, and 15 for ML-1M, MOOCs, and Gowalla, respectively. We set $K$ as 3 and 8 in the intrinsic task, and 8 in the extrinsic task. By default, we set $d$ as 32, the learning rate as 0.003, $L$ as 4, $T$ as 6, $a$ as 0.2, $b$ as 0.2, and $\tau$ as 0.2.

#### 4.1.4 Intrinsic Evaluations: Embedding Inference

We conduct the intrinsic evaluation task, which aims to infer the embeddings of cold-start users and items by the proposed MPT model. Both the evaluations on user embedding inference and item embedding inference are performed.

**Training and Test Settings.** Following PT-GNN [11], we perform intrinsic evaluation on $D_T$. Specifically, same as PT-GNN, we train NCF [14] to get the ground-truth embeddings for the target users/items in $D_T$. We also explore whether MPT is sensitive to the ground-truth embedding generated by other models such as LightGCN [13]. We randomly split $D_T$ into the training set $Train_T$ and the test set $Test_T$ with a ratio of 7:3. To mimic the cold-start users/items on $Test_T$, we...
randomly keep $K$ neighbors for each user/item, which results in at most $K^l$ neighbors ($1 \leq l \leq L$) for each target user/item. Thus, $T_{test}$ is changed into $T_{test}'$.

We train NCF transductively on the merged dataset $Train_T$ and $Test_T'$. We train the vanilla GNN models by BPR loss [13] on $Train_T$. We train PT-GNN on $Train_T$, where we first perform Equation (4) in $L-1$ steps to obtain the refined first-order neighbors, and then average them to reconstruct the target embedding; finally, we use Equation (2) to measure the quality of the predicted embedding. We train MPT on $Train_T$, where we first perform four pretext tasks by Equations (7), (9), (10), and (11), and then use Equation (12) to fuse the generated embeddings; finally, we use Equation (2) to measure the quality of the fused embedding. Note that the embeddings in all the models are randomly initialized. We use cosine similarity to measure the agreement between the ground-truth and predicted embeddings, due to its popularity as an indicator for the semantic similarity between embeddings.

4.1.5 Extrinsic Evaluation: Recommendation. We apply the pre-training GNN model to the downstream recommendation task and evaluate its performance.

**Training and Testing Settings.** We consider the scenario of the cold-start users and use the meta-test set $DN$ to perform recommendation. For each user in $DN$, we select the top $c\%$ ($c\% = 0.2$ by default) of his or her interacted items in chronological order into the training set $Train_N$ and leave the rest of the items in the test set $Test_N$. We pre-train our model on $DT$ and fine-tune it on $Train_N$ according to Section 3.5.

The vanilla GNN and the NCF models are trained by the BPR loss on $DT$ and $Train_N$. For each user in $Test_N$, we calculate his or her relevance score to each of the rest $1-c\%$ items. We adopt $Recall@K$ and $NDCG@K$ as the metrics to evaluate the items ranked by the relevance scores. By default, we set $K$ as 20 for ML-1M, MOOCs, and Gowalla.

5 EXPERIMENTAL RESULTS

5.1 Performance Comparison (RQ1)

5.1.1 Overall Performance Comparison. We report the overall performance of intrinsic embedding inference and extrinsic recommendation tasks in Tables 2 and 3. We find that:

- MPT (denoted as GNN$^*$) is better than NCF and the vanilla GNN model, which indicates the effectiveness of the pre-training strategy. Compared with the pre-training model PT-GNN...
Table 3. Overall Recommendation Performance with Sparse Rate c% = 20%, L = 4

| Methods   | ML-1M     | MOOCs     | Gowalla    |
|-----------|-----------|-----------|------------|
|           | Recall    | NDCG      | Recall     | NDCG      | Recall     | NDCG      |
| NCF       | 0.004     | 0.009     | 0.132      | 0.087     | 0.039      | 0.013     |
| PinSage   | 0.006     | 0.012     | 0.085      | 0.066     | 0.003      | 0.011     |
| PinSage-SGL | 0.040   | 0.033     | 0.172      | 0.086     | 0.011      | 0.021     |
| PinSage⁺   | 0.047     | 0.038     | 0.150      | 0.089     | 0.008      | 0.019     |
| PinSage⁺   | 0.054     | 0.036     | 0.182      | 0.099     | 0.045      | 0.021     |
| GCMC      | 0.008     | 0.006     | 0.232      | 0.172     | 0.006      | 0.033     |
| GCMC-SGL  | 0.038     | 0.037     | 0.239      | 0.177     | 0.033      | 0.055     |
| GCMC⁺     | 0.044     | 0.041     | 0.248      | 0.187     | 0.016      | 0.032     |
| GCMC⁺     | 0.071     | 0.076     | 0.272      | 0.212     | 0.065      | 0.043     |
| NGCF      | 0.052     | 0.058     | 0.208      | 0.171     | 0.009      | 0.013     |
| NGCF-SGL  | 0.062     | 0.079     | 0.216      | 0.177     | 0.028      | 0.014     |
| NGCF⁺     | 0.064     | 0.071     | 0.217      | 0.181     | 0.037      | 0.014     |
| NGCF⁺     | 0.083     | 0.077     | 0.241      | 0.208     | 0.047      | 0.016     |
| LightGCN  | 0.058     | 0.064     | 0.217      | 0.169     | 0.011      | 0.023     |
| LightGCN-SGL | 0.066   | 0.077     | 0.275      | 0.178     | 0.034      | 0.028     |
| LightGCN⁺  | 0.074     | 0.071     | 0.308      | 0.184     | 0.049      | 0.031     |
| LightGCN⁺  | 0.094     | 0.101     | 0.346      | 0.223     | 0.051      | 0.036     |

(denoted as GNN⁺) and SGL (denoted as GNN-SGL), MPT also performs better than them. This indicates the superiority of simultaneously considering the intra- and inter-correlations of nodes as well as the short- and long-range dependencies of nodes.

- In Table 2, when K decreases from 8 to 3, the performance of all the baseline methods drops by a large scale, while MPT drops a little. This indicates MPT is able to learn high-quality embeddings for users or items that have extremely sparse interactions.

- In the intrinsic task (Cf. Table 2), we notice that most models perform generally better on the item embedding inference task than the user embedding inference task. The reason is that the users in DT have more interacted neighbors than the items in DT, and thus the learned ground-truth user embedding shows much more diversity than the learned ground-truth item embedding, and only using K² (K is small) neighbors to learn the user embedding is more difficult than learning the item embedding. To validate our point of view, we calculate the average number of interacted neighbors of users and items in DT among these three datasets. In ML-1M, MOOCs, and Gowalla, when the layer size L = 1, the users interact with an average of 178.26, 134.90, and 178.27 items, while the items interact with an average of 32.14, 15.75, and 32.14 users, respectively. When the layer size L gets larger, the interacted neighbors’ number of users and items show the same trend. The results indicate that the abundant users have much more interacted neighbors than the abundant items, which verifies the above analysis.

- Aligning Tables 2 and 3, we notice that using GCMC, LightGCN as the backbone GNN model can always obtain better performance than using PinSage and NGCF. The possible reason is that compared with PinSage and NGCF, GCMC and LightGCN have discarded the complex feature transformation operation, which will contribute to learning high-quality embeddings and better recommendation performance. This phenomena is consistent with LightGCN’s [13] findings.

5.1.2 Interacted Number and Sparse Rate Analysis. It is still unclear how the MPT handles the cold-start users with different interacted items n_i and sparse rate c%. To this end, we change the interaction number n_i in the range of {5, 10, 15} and the sparse rate c% in the range of {20%, 40%, 60%}, select LightGCN as the backbone GNN model, and report the cold-start recommendation
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Fig. 3. Cold-start recommendation under different $n_i$ and $c\%$.

performance on the MOOCs dataset in Figure 3. The smaller $n_i$ and $c\%$ are, the fewer interactions cold-start users in $D_N$ have. We find that:

- MPT (denoted as LightGCN∗) is consistently superior to all the other baselines, which justifies the superiority of MPT in handling cold-start recommendation with different $n_i$ and $c\%$.
- When $n_i$ decreases from 15 to 5, MPT has a larger improvement compared with other baselines, which verifies its capability to solve the cold-start users with extremely sparse interactions.
- When $c\%$ decreases from 60% to 20%, MPT has a larger improvement compared with other baselines, which again verifies the superiority of MPT in handling cold-start users with different sparse rate.

5.2 Ablation Study (RQ2)

5.2.1 Impact of Pretext Tasks. It is still not clear which part of the pretext tasks is responsible for the good performance in MPT. To answer this question, we apply LightGCN in MPT, perform individual or compositional pretext tasks, and report the performance of intrinsic and extrinsic tasks in Figure 4, where notations $R_g$, $C_g$, $R_p$, and $C_p$ denote the pretext task of reconstruction with GNN (only use the objective function, Equation (7)), contrastive learning with GNN (only use the objective function, Equation (9)), reconstruction with Transformer (only use the objective function, Equation (10)), and contrastive learning with Transformer (only use the objective function, Equation (11)), respectively; notation LightGCN∗-$R_g$ means we only discard the reconstruction task with the GNN encoder and use the other three pretext tasks (use the objective functions, Equations (9), (10), and (11)) as the variant model. Other variant models are named in a similar way. Aligning Table 2 with Figure 4, we find that:

- Combining all the pretext tasks can benefit both embedding quality and recommendation performance. This indicates that simultaneously considering intra- and inter-correlations of users and items can benefit cold-start representation learning and recommendation.
- Compared with other variant models, performing the contrastive learning task with the GNN or Transformer encoder independently or performing the contrastive learning task with both...
The GNN and Transformer encoder leads to poor performance in the intrinsic task but has satisfactory performance in the recommendation task. The reason is that contrastive learning does not focus on predicting the target embedding but can capture the inter-correlations of users or items, and thus can benefit the recommendation task.

5.2.2 Impact of the Sampling Strategy. We study the effect of the proposed dynamic sampling strategy. In this article, we compare four variants of the LightGCN model: LightGCN\textsuperscript{+} that adaptively samples neighbors \cite{11}, LightGCN\textsuperscript{i} that samples neighbors according to the importance sampling strategy \cite{4}, LightGCN\textsuperscript{r} that randomly samples neighbors \cite{10}, and LightGCN\textsuperscript{*} that dynamically samples neighbors. Notably, for fair comparison, for each target node, at the \textit{l}th layer, the number of the sampled neighbors is at most \textit{K}^\textit{l}. We report the average sampling time and the average training time per epoch (the average training time includes the training time of all four pretext tasks but does not include the neighbor sampling time) for these sampling strategies on MOOCs and Ml-1M in Table 4 and report the recommendation performance on MOOCs and Ml-1M in Figure 5. We find that:

- The sampling time of the proposed dynamic sampling strategy is in the same magnitude with the importance sampling strategy and the random sampling strategy, which is totally acceptable. While the adaptive sampling strategy takes too much sampling time, it adopts a Monte-Carlo-based policy gradient strategy and has the complex action-state trajectories for the entire neighbor sampling process. Besides, we report the average training time in each epoch and find that the training time of all the variant models is almost the same, since
Table 4. Analysis of the Average Sampling/Training Time in Each Epoch for Different Sampling Strategies

| Dataset  | MI-1M               | MOOCs              |
|----------|---------------------|--------------------|
| Method   | Avg. Sampling Time  | Avg. Training Time | Avg. Sampling Time  | Avg. Training Time |
| LightGCN | 0.56s               | 201.02s            | 2.78s               | 237.63s            |
| LightGCN | 6.56s               | 204.64s            | 2.86s               | 240.12s            |
| LightGCN | 134.64s             | 205.13s            | 160.37s             | 241.75s            |
| LightGCN | 8.93s               | 205.76s            | 3.20s               | 240.67s            |

We run each variant model 10 times and calculate the average sampling and training time per epoch.

Fig. 5. Comparison among different sampling strategies.

5.3 Study of MPT (RQ3)

5.3.1 Effect of Ground-truth Embedding. As mentioned in Section 2, when performing embedding reconstruction with GNN and Transformer encoders, we choose NCF to learn the ground-truth embeddings. However, one may consider whether MPT’s performance is sensitive to the ground-truth embedding. To this end, we use the baseline GNN models to learn the
Fig. 6. Sensitive analysis of ground-truth embeddings.

ground-truth embeddings and only perform the embedding reconstruction task with LightGCN or Transformer. For NCF, we concatenate embeddings produced by both the MLP and GMF modules as ground-truth embeddings. For PinSage, GCMC, NGCF, and LightGCN, we combine the embeddings obtained at each layer to form the ground-truth matrix, i.e., \( E = E^{(0)} + \cdots + E^{(L)} \), where \( E^l \in \mathbb{R}^{(|U|+|I|) \times d} \) is the concatenated user-item embedding matrix at the \( l \)th convolution step.

Figures 6(a) and 6(b) show the recommendation performance using LightGCN and the Transformer encoder, respectively. Suffixes +NCF, +L, +G, +P, and +N denote that the ground-truth embeddings are obtained by NCF, LightGCN, GCMC, PinSage, and NGCF, respectively. We find that:

- All the models equipped with different ground-truth embeddings achieve almost the same performance. This indicates that our model is not sensitive to the ground-truth embeddings, as the NCF and vanilla GNN models are good enough to learn high-quality user or item embeddings from the abundant interactions.
- Besides, when LightGCN is used to obtain the ground-truth embeddings (denoted as LightGCN' +L and Trans' +L), we can obtain a marginal performance gain compared with other variant models.

5.3.2 Effect of Data Augmentation. To understand the effects of individual or compositional data augmentations in the CL task using GNNs or the Transformer encoder, we investigate the performance of CL pretext tasks in MPT when applying augmentations individually or in pairs. We report the performance in Figure 7. Notations LightGCN’D, LightGCN’S, and LightGCN’S/SD mean we apply LightGCN to the CL task and use deletion, substitution, and their combinations, respectively; notations Trans’D, Trans’S, and Trans’SD denote we use the Transformer encoder in the CL task and use deletion, substitution, and their combinations, respectively. We find that:

- Composing augmentations can lead to better recommendation performance than performing individual data augmentation.
Aligning Figure 7 and Table 3, we find that combining substitution and deletion using GNNs has more competitive performance than SGL. The reason is that, same as SGL, our proposed contrastive data augmentation can also change the graph structure, and thus inter-correlations of nodes can be captured.

5.3.3 Effect of Hyperparameters. We move on to study different designs of the layer depth $L$, the deletion ratio $a\%$, the substitution ratio $b\%$, and the user-item path length $T$ in MPT. Due to the space limitation, we omit the results on MOOCs and Gowalla, which have a similar trend to MI-1M.

- We only perform embedding reconstruction with GNNs in MPT and report the results in Figure 8. We find that the performance first increases and then drops when increasing $L$ from 1 to 4. The peak point is 3 at most cases. This indicates GNN can only capture short-range dependencies, which is consistent with LightGCN’s [13] finding.
- We only perform embedding reconstruction with the Transformer encoder in MPT and report the results in Figure 9. We find that the performance first improves when the path length $T$ increases from 3 to 8, and then drops from 8 to 10. This indicates that the Transformer encoder is good at capturing long-range rather than short-range dependencies of nodes.
- We perform contrastive learning with LightGCN and contrastive learning with the Transformer encoder under different deletion ratios $a\%$ and substitutions $b\%$ independently and report the recommendation results in Figure 10. Based on the results, we find that the recommendation performance is not sensitive to the substitution ratio $b\%$ but is a little bit sensitive to the deletion ratio $a\%$. In terms of the deletion ratio $a\%$, the recommendation performance first increases and then drops. The peak point is around 0.2 to 0.3 for most cases. The reason is that when we perform the substitution operation, we randomly replace $u$ or $i$ with one of its parent’s interacted first-order neighbors, and thus the replaced nodes can still reflect its parent’s characteristic to some extent. However, once the deletion ratio gets larger (e.g., 0.9), it will result in a highly skewed graph structure, which cannot bring many useful collaborative signals to the target node.
6 RELATED WORK

Self-supervised Learning with GNNs. The recent advance in self-supervised learning for recommendation has received much attention [24, 39, 40, 47, 49], where self-supervised learning with GNNs aims to find the correlation of nodes in the graph itself, so as to alleviate the data sparsity issue in graphs [2, 15, 23, 26, 30, 46, 48, 50]. More recently, some researchers have explored pre-training GNNs on user-item graphs for recommendation. For example, PT-GNN [11]
reconstructs embeddings under the meta-learning setting. SGL [37] contrasts node representation by node dropout, edge dropout, and random walk data augmentation operations. PMGT [19] reconstructs graph structure and node feature using side information. GCN-P/COM-P [20] learns the representations of entities constructed from the side information. However, these methods suffer from the ineffective long-range dependency problem, as the GNN model can only capture low-order correlations of nodes. Besides, the pretext tasks of these methods consider either intra-correlations [11, 19, 20] or inter-correlations [37] of nodes, rather than both. Further, the side information is not always available, making it difficult to construct the pretext tasks. To solve the above problems, we propose MPT, which considers both short- and long-range dependencies of nodes and both intra- and inter-correlations of nodes.

**Cold-start Recommendation.** Cold-start recommendation is an intractable problem in the Recommender System. Some researchers try to incorporate the side information such as KGs [32, 34] or the contents of users/items [3, 8, 33, 41–44] to enhance the representations of users/items. However, the contents are not always available and it is difficult to align the users/items with the entities in KGs. Another research line is to explicitly improve the quality of cold-start users/items, which uses either meta-learning [7, 21, 25, 31] or the GNNs [13, 35, 43, 45] for recommendation. However, the meta learning technique does not explicitly address the high-order neighbors of the cold-start users/items. The GNNs do not explicitly address the high-order cold-start users/items, which cannot thoroughly improve the embedding quality of the cold-start users/items.
7 CONCLUSION
We propose a multi-strategy-based pre-training method, MPT, which extends PT-GNN from the perspective of model architecture and pretext tasks to improve the cold-start recommendation performance. Specifically, in addition to the short-range dependencies of nodes captured by the GNN encoder, we add a transformer encoder to capture long-range dependencies. In addition to considering the intra-correlations of nodes by the embedding reconstruction task, we add the embedding contrastive learning task to capture inter-correlations of nodes. Experiments on three datasets demonstrate the effectiveness of our proposed MPT model against the vanilla GNN and pre-training GNN models.

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