Due to the flexibility in modelling data heterogeneity, heterogeneous information network (HIN) has been adopted to characterize complex and heterogeneous auxiliary data in top-$N$ recommender systems, called HIN-based recommendation. HIN characterizes complex, heterogeneous data relations, containing a variety of information that may not be related to the recommendation task. Therefore, it is challenging to effectively leverage useful information from HINs for improving the recommendation performance. To address the above issue, we propose a Curriculum pre-training based HEterogeneous Subgraph Transformer (called CHEST) with new data characterization, representation model and learning algorithm.

Specifically, we consider extracting useful information from HIN to compose the interaction-specific heterogeneous subgraph, containing both sufficient and relevant context information for recommendation. Then we capture the rich semantics (e.g., graph structure and path semantics) within the subgraph via a heterogeneous subgraph Transformer, where we encode the subgraph with multi-slot sequence representations. Besides, we design a curriculum pre-training strategy to provide an elementary-to-advanced learning process, by which we smoothly transfer basic semantics in HIN for modeling user-item interaction relation.

Extensive experiments conducted on three real-world datasets demonstrate the superiority of our proposed method over a number of competitive baselines, especially when only limited training data is available.

CCS Concepts: • Information systems → Recommender systems.

Additional Key Words and Phrases: Curriculum Pre-training, Heterogeneous Information Network, Recommender Systems

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1 INTRODUCTION

Online consumptions (e.g., purchasing goods and watching movies) have become increasingly popular with the rapid development of Internet services. Meanwhile, people repeatedly encounter the choice problem because of Information Overload [21]. To address such problems, recommender systems (RS) have become an important tool in online platforms, which model users’ preferences on items based on their past interactions. Due to the complexity of user behavior, recent works utilize various kinds of auxiliary data to improve recommender systems, such as item attributes and user profiles. These auxiliary data can be considered as important context to understand user-item interaction. It is essential to effectively utilize such context data to improve the recommendation performance [17, 41]. As a promising approach, Heterogeneous Information Network (HIN) [47, 48, 55], consisting of multiple types of nodes and edges, has been widely applied to model rich context information in recommender systems. The recommendation task framed in the HIN setting is usually referred to as HIN-based recommendation [17, 22].

For HIN-based recommendation task, the most essential problem is how to effectively utilize the rich information in HIN for recommendation task. A variety of approaches have been proposed to solve this problem, which roughly fall into path-based methods and graph representation learning methods. Since users and items are connected by paths in HIN, path-based approaches [17, 29] mainly focus on sampling paths from HIN and modeling path-level semantics to characterize the user-item interaction relation. As a widely-used schema, meta-path [48] has been used to extract features for depicting the user-item association [15, 55]. By modeling path-based features via similarity factorization [55], co-attention model [15] and meta-learning [33], it is able to improve the recommendation performance [48, 55]. In the other hand, graph representation learning methods [24, 57] consider aggregating features from neighbor nodes in the HIN [51], and leverage the graph structure information to learn the data representations [18]. These methods focus on learning the structural information (e.g., edges) in the graph without considering the downstream tasks. The learned user and item representations will be utilized for predicting the user-item association.

Although existing methods have shown effective to some extent, there are two major challenges that have not been well addressed in HIN-based recommendation. First, HIN characterizes complex, heterogeneous data relations, hence it is difficult to extract sufficient contextual semantics and meanwhile avoid incorporating task-irrelevant information from HIN. Existing approaches either select limited context information from specially designed strategies (e.g., path-based methods) [17, 29], or consider the global view that may incorporate noisy information from task-irrelevant nodes and edges (e.g., graph representation learning methods) [20]. There is a need to consider both relevance and sufficiency in leveraging HIN information for recommendation. Second, HIN is in essence a general data characterization way, and it is difficult to design suitable learning strategies to derive task-specific data representations for HIN. Existing methods either fully rely on the downstream recommendation task (easy to overfit on training data) [16, 17], or employ task-insensitive pre-training strategy (unaware of the final task goal) [6]. There is a need for a more principled learning algorithm that can more effectively control the learning process with the guidance of the task goal.

To solve the aforementioned issues, we concentrate on user-item interaction to design a systematic approach for HIN-based recommendation. Firstly, we design a more suitable data characterization by introducing interaction-specific heterogeneous subgraph, with both sufficient and relevant context information for recommendation. Then, we further develop a heterogeneous subgraph Transformer that captures rich semantics from interaction-specific subgraphs for the recommendation task. Furthermore, we propose a curriculum pre-training strategy consisting of elementary and
advanced courses (i.e., pre-training tasks) to gradually learn from both local and global contexts in the subgraph tailored to the recommendation task. The above three aspects jointly ensure that our approach can leverage HIN information for recommendation more effectively.

To this end, in this paper, we propose a Curriculum pre-training based HEterogeneous Subgraph Transformer (called CHEST) for HIN-based recommendation. First, we construct the interaction-specific heterogeneous subgraph consisting of high-quality paths (derived from meta-paths) that connect a user-item pair, which are extracted from HIN but specifically for recommendation task. Then, we propose a heterogeneous subgraph Transformer to encode the subgraphs with multi-slot sequence representations. It consists of a composite embedding layer to map useful contextual information of nodes (i.e., node ID, node type, position in sampled paths, and precursors in the subgraph) into dense embedding vectors, and a self-attention layer to aggregate node and subgraph representations. Finally, we devise the curriculum pre-training algorithm with both elementary and advanced courses. The elementary course consists of three pre-training tasks related to node, edge and meta-path, focusing on local context information within the subgraph. The advanced course is a subgraph contrastive learning task, focusing on global context information at subgraph level for user-item interaction.

To demonstrate the effectiveness of our approach, we conduct extensive experiments on three real-world datasets. It shows that our model is able to outperform all baseline models, including path-based methods and graph representation learning methods. In addition, we perform a series of detailed analysis. We find that our model can alleviate the data sparsity problem to some extent, and the learned representations after curriculum learning can aggregate into obvious clusters.

Our main contributions are summarized as follows.

- We construct the interaction-specific heterogeneous subgraph to leverage useful semantics from HIN to capture the correlations between users and items, and propose the heterogeneous subgraph Transformer to learn useful contextual information from the subgraphs for recommendation task.
- We devise the curriculum pre-training strategy to learn local and global context information within the interaction-specific heterogeneous subgraph, which gradually extracts useful evidence for user-item interaction to improve the recommendation task.
- Extensive experiments conducted on three real-world datasets demonstrate the effectiveness of our proposed approach against a number of competitive baselines, especially when only limited training data is available.

We organize the following content as follows: Section 2 discusses the related work of HIN-based recommendation, graph pre-training and curriculum learning. Section 3 and Section 4 introduce the preliminaries and the proposed approach, respectively. We present the experiments in Section 5. Section 6 concludes this manuscript.

2 RELATED WORK

Our work is closely related to the studies on HIN-based recommendation, graph pre-training and curriculum learning.

2.1 HIN-based Recommendation

In the literature of recommender systems, early works mainly adopt collaborative filtering (CF) methods to utilize historical interactions for recommendation [26], where matrix factorization approach [27] and factorization machine [41] has shown effectiveness and efficiency in many applications. Since these methods usually suffer from cold-start problem, many works [60, 61]
attempt to leverage additional information to improve recommendation performance, including social relation [35], item reviewers [30] and knowledge graph [51].

To effectively utilize the additional information, some of works focus on using heterogeneous information network (HIN) [17, 28, 37, 45] in recommender systems. In this way, objects are of different types and links among objects represent different relations, which naturally characterize complex objects and rich relations. A mainstream approach is the path-based methods [17, 55], where the semantic associations between two nodes are reflected by the paths that connect them. Various methods are proposed to characterize path-level semantics for recommendation [17, 33, 55]. Early works [46, 48] propose several path-based similarity measures to evaluate the similarity of objects in heterogeneous information network, which can also apply in recommendation task. Furthermore, the concept of meta-path is introduced into hybrid recommender systems [56]. Yu et al. [55] take advantage of different types of entity relationships in heterogeneous information network and propose a personalized recommendation framework for implicit feedback dataset. Luo et al. [34] propose a collaborative filtering based social recommendation method using heterogeneous relations. Hu et al. [15] leverage the meta-path based contextual information for capturing user-item correlations.

In recent years, graph representation learning [51, 59] has been introduced to model HINs for improving various downstream applications, including the recommendation task. Typical works adopt graph neural network (GNN) to aggregate the heterogeneous information from adjacent nodes [52, 59], and utilize general-purpose objective to learn node or graph representations. Zhang et al. [57] propose heterogeneous graph neural network to aggregate feature information of sampled neighboring nodes, and leverage graph context loss to train the model. Wang et al. [51] utilize graph attention network to aggregate features from meta-path based neighbors in a hierarchical manner, which mainly focuses on semi-supervised classification task. Wang et al. [53] learn disentangled user/item representations from different aspects in a HIN, which use meta relations to decompose high-order connectivity between node pairs.

Compared with these studies, our approach combines the merits of path-based and graph representation learning methods to learn recommendation-specific data representations.

2.2 Graph Pre-training

Inspired by the success of pre-training methods in computer vision (CV) [43] and natural language processing (NLP) [3], pre-training technique has been recently applied to graph datasets for improving GNNs [19]. The purpose of pre-training on graph is to learn parameters of the model for producing general graph representations, which can be further fine-tuned on different downstream tasks. It has been shown that pre-training methods have the potential to address scarce labeled data [14] and out-of-distribution prediction [18].

As an effective unsupervised pre-training strategy, mutual information maximization [25, 50] has been utilized to capture the correlations within the graph (e.g., nodes, edges and subgraphs). Velickovic et al. [50] propose graph information maximization method to learn node representations, which is mindful of the global structural properties of the graph. Ren et al. [40] explore the use of mutual information maximization for heterogeneous graph representation learning, which focuses on learning high-level representations based on meta-path. Hu et al. [18] pre-train an expressive GNN at the level of individual nodes as well as entire graphs so that the GNN can learn useful local and global representations simultaneously.

Besides, contrastive learning and graph generation strategies are also utilized to pre-train GNNs. Qiu et al. [38] utilize contrastive learning to capture the universal network topological properties across multiple networks, which empowers graph neural networks to learn the intrinsic and transferable structural representations. You et al. [62] develop a framework about contrastive learning
with augmentations for GNN, which can produce graph representations of better generalizability, transferrability and robustness. Hu et al. [19] introduces a self-supervised attributed graph generation task to pre-train a GNN so that it can capture the structural and semantic properties of the graph.

Generally, most of these methods aim to learn general node representations based on the whole graph. As a comparison, we propose a curriculum pre-training strategy to learn recommendation-specific representations, which helps extract useful information from HIN to recommendation task.

2.3 Curriculum Learning

Inspired by the human learning process, curriculum learning [1] is proposed as a learning paradigm that starts from simple patterns and gradually increases to more complex patterns. Several studies [10, 31] have shown that this training approach results in better generalization and speeds up the convergence.

Most of the works [10, 31] on curriculum learning focus on feeding training instances to the model from easy to hard. Gong et al. [10] and utilize curriculum learning in image classification task and show the effectiveness. In NLP tasks, Guo et al. [9] and Liu et al. [8] improve the performance on machine translation and question answer tasks. Recently, some works [32, 44] explore the curriculum learning strategies in task level, and show that a group of well-designed curriculums are helpful to learn complex knowledge. Liu et al. [31] train the model with sequentially increased degrees of parallelism to train the model from easy to hard, which achieves significant accuracy improvements over previous non-autoregressive neural machine translation methods. Sarafianos. [7] utilize curriculum learning to transmit the acquired knowledge to the target task [44].

In this paper, we design a curriculum pre-training strategy to gradually learn from both local and global contexts in the subgraph, which helps our model to leverage HIN information for recommendation more effectively.

3 PROBLEM FORMULATION

A heterogeneous information network (HIN) is a special kind of information network, which either contains multiple types of objects or multiple types of links. We consider the recommendation task in the setting of Heterogeneous Information Network.

Definition 1. Heterogeneous Information Network (HIN). A HIN [5, 47, 54] is defined as a graph $G = (V, E)$, in which $V$ and $E$ are the sets of nodes and edges, respectively. Each node $v$ and edge $e$ are associated with their type mapping functions $\phi: V \rightarrow A$ and $\varphi: E \rightarrow R$, respectively, where $A$ and $R$ denote the sets of pre-defined entity and edge types, where $|A| + |R| > 2$.

Recently, HIN has become a mainstream approach to model various complex interaction systems [37, 47]. Specially, it has been adopted in recommender systems for characterizing complex and heterogeneous recommendation settings. Based on the above preliminaries, we define our task as following.

Definition 2. HIN-based Recommendation. In a recommender system, various kinds of information can be modeled by a HIN $G = (V, E)$. On recommendation-oriented HINs, two kinds of entities (i.e., users and items) together with the relations between them (i.e., rating relation) are our focus. Let $U \in E$ and $I \in E$ denote the sets of users and items respectively, for each user $u \in U$, our task is to recommend a ranked list of items that are of interest to $u$ based on her/his historical record $I_u$, where $I_u \subset I$ denotes the set of items that $u$ has interacted with before.

In HIN, two objects can be connected via different semantic patterns, which are defined as meta-paths [48].
### Table 1. Notations and explanations

| Notation | Explanation |
|----------|-------------|
| $\mathcal{G}$ | heterogeneous information network |
| $\mathcal{G}_{u,i}$ | a heterogeneous subgraph connecting user-item pair $(u, i)$ |
| $\mathcal{V}$ | the set of nodes |
| $\mathcal{E}$ | the set of edges |
| $\mathcal{A}$ | the set of pre-defined entity types |
| $\mathcal{R}$ | the set of pre-defined edge types |
| $\mathcal{U}$ | the set of users |
| $\mathcal{I}$ | the set of items |
| $\mathcal{I}_u$ | the set of items that $u$ has interacted with before |
| $\mathcal{S}$ | the set of slots |
| $\mathcal{P}$ | the set of meta-paths |
| $u$ | a user |
| $r$ | a relation |
| $o$ | an object |
| $a$ | an attribute |
| $\rho$ | a meta-path |
| $p$ | a path instance |
| $i$ | an item |
| $i'$ | a random sampled negative item |
| $v$ | a node |
| $C_v$ | the surrounding context for $v$ in a heterogeneous subgraph |
| $Pr(\rho|u,i)$ | the preference score of the user $u$ and item $i$ |
| $\sigma$ | the sigmoid function |
| $M_V, M_A, M_S, M_P$ | the embedding matrices of node ID, node type, slot and precursor |
| $E_V, E_A, E_S, E_P$ | the embedding matrices of node ID, node type, slot and precursor for a heterogeneous subgraph |
| $E$ | the composite embedding matrix of a heterogeneous subgraph |
| $W^O, W_i^O, W_i^K, W_i^V$ | learnable parameter matrices in multi-head self-attention layer |
| $W_1, W_2$ | learnable parameter matrices in point-wise feed-forward network |
| $W_N, W_E$ | learnable parameter matrices for masked node/edge prediction task |
| $b_1, b_2$ | learnable parameter vectors |
| $f^l$ | the input of the $l$-th layer |
| $f^L_{u, i}$ | the representations of user $u$ and item $i$ from the last self-attention layer |
| $e_v$ | the node ID embedding of $v$ |
| $z_G$ | the subgraph representation |
| $\text{head}_i$ | the output of the $i$-th head of self-attention layer |
| $d$ | the embedding dimension |
| $L$ | the number of layers in the Transformer model |
| $n$ | the number of nodes in the subgraph |
| $h$ | the number of head in the multi-head self-attention layer |
| $\tau$ | the hyper-parameter for softmax temperature |
4 APPROACH

In this paper, we propose a novel Curriculum pre-training based Heterogeneous subgraph Transformer (called as CHEST) to effectively utilize HIN information for improving the recommendation performance. Tailored to the recommendation task, we first construct an interaction-specific heterogeneous subgraph to extract useful contextual information from HIN for the user-item pair, and then design a heterogeneous subgraph Transformer to model this subgraph. Finally, we introduce curriculum pre-training strategy to learn recommendation-specific representations. Figure 2 presents the overall illustration of the proposed CHEST approach. Next, we describe each part in detail.

4.1 Constructing Interaction-Specific Heterogeneous Subgraph

In our task, it is essential to leverage useful semantics from HIN to capture the connections between users and items for effective recommendation. Different from prior studies [17, 51], we collect the most relevant paths that connect the two nodes. Then, these paths (including nodes and edges) compose a heterogeneous subgraph specially for the user-item pair \( \langle u, i \rangle \), denoted by \( G_{u,i} \). We expect such a subgraph to contain most of the relevant context information for a specific user-item interaction.

To derive relevant and reliable paths between two nodes, following existing works [15, 48], we pre-define multiple meta-paths to guide the selection of paths. For each meta-path, we follow MCRec [17] to adopt a “priority”-based strategy to generate the path instances. Specifically, we use metapath2vec [4] to learn latent vectors of all the nodes, and then a path is evaluated based on the average cosine similarity between the latent vectors of two consecutive nodes on it. Note that the pre-learned latent vectors are only used for path sampling. For each meta-path, we only
Fig. 2. The overview of our proposed Transformer model and curriculum pre-training strategy. The elementary courses are three pre-training objectives: (1) Masked Node Prediction (MNP), (2) Masked Edge Prediction (MEP) and (3) Meta-path Type Prediction (MTP). And the advanced course is the Subgraph Contrastive Learning (SCL) task.

keep top-$K$ path instances with the highest average similarities. For efficiency consideration, at each step, we walk to nodes in a probabilistic sampling way according to the priority scores of nodes (i.e., its similarity with the incoming node). Such an approximate way can reduce the time complexity for constructing heterogeneous subgraphs in practice.

In Figure 1, we present an example for our interaction-specific heterogeneous subgraph for user $u_1$ and item $i_1$, where we consider two types of meta-paths "$UIUI" or "$UIAI". For each meta-path, we obtain the corresponding path instances from the HIN by the "priority"-based sampling strategy. In detail, we acquire the paths $u_1\rightarrow i_2\rightarrow u_2\rightarrow i_1$, $u_1\rightarrow i_3\rightarrow a_1\rightarrow i_1$ and $u_1\rightarrow i_3\rightarrow a_2\rightarrow i_1$ connecting the user-item pair $\langle u_1, i_1 \rangle$ according to meta-paths "$UIUI" and "$UIAI"; respectively. Finally, we re-connect all the nodes with the edges in these paths, and produce the interaction-specific heterogeneous subgraph as the right part of Figure 1. With heterogeneous subgraphs, we can explicitly keep the semantics of multiple meta-paths and model the correlations among nodes across different paths. It is safer and more efficient to aggregate neighboring node information within a compact, relevant subgraph than the entire graph [17, 58], since many of irrelevant nodes in HIN are excluded through the "priority"-based sampling strategy.

4.2 Heterogeneous Subgraph Transformer

Given the interaction-specific heterogeneous subgraph for a special user-item pair, we design the heterogeneous subgraph Transformer to capture useful semantics within it, which consists of an embedding layer and a self-attention layer.

4.2.1 Embedding Layer. Unlike the embedding mechanism in BERT [3] for sequences, we need to effectively model the nodes in the subgraph. To preserve the rich semantics in subgraphs, a key point is how to model the position information (i.e., location) of a node and its links with other nodes in the subgraph. For this purpose, we first assign a slot index to a node according to the relative position w.r.t. the target user node in a sampled path. In this way, each node is placed according to its slot index and the original subgraph will be converted into a multi-slot sequence. To model the links in subgraphs, we further incorporate a precursor index to trace the precursor in
paths for a node. To facilitate the multi-slot sequence representation, we incorporate four types of node embeddings to preserve the subgraph information:

- **Node ID Embedding**: For each node \( v \) in the heterogeneous subgraph \( G_{u,i} \), we maintain an ID embedding matrix \( M_V \in \mathbb{R}^{|V| \times d} \), which projects the high-dimensional one-hot ID representation of a node into low-dimensional dense representation.

- **Node Type Embedding**: In HIN, each node is associated with a specific node type \( A \). Therefore, we also maintain a node type embedding matrix \( M_A \in \mathbb{R}^{|A| \times d} \) to project the one-hot node type representation into dense representation.

- **Slot Embedding**: The interaction-specific heterogeneous subgraph is composed by multiple paths. For a node, its distance to the starting node (i.e., the target user) is important to consider for the recommendation task. Since we have assigned a slot index for each node according to the relative position in the involved paths, we use a slot embedding matrix \( M_S \in \mathbb{R}^{|S| \times d} \) to project the slot index of nodes into corresponding representations, where \(|S|\) is the number of slots in the subgraph.

- **Precursor Embedding**: Although the slot embedding has modeled the relative distance with the starting user node, it cannot capture the adjacent relations between two consecutive nodes in the subgraph. Hence, we further add a precursor index to record the preceding nodes of each node in the subgraph. We maintain a precursor embedding matrix \( M_P \in \mathbb{R}^{n \times d} \) to project the precursor indices of each node into embeddings, where \( n \) is the number of nodes in the subgraph. Since a node may have multiple precursors, we sum the embeddings of the precursor indices as a single vector.

Based on the above embeddings, we aggregate them together to produce the node representations in a multi-slot sequence form. Formally, the node representations of the subgraph is a node embedding matrix \( E \in \mathbb{R}^{|N| \times d} \), which is composed of four parts:

\[
E = E_V + E_A + E_S + E_P,
\]

where the four matrices \( E_V, E_A, E_S \) and \( E_P \) denote the node ID embedding, node type embedding, slot embedding and precursor embedding, respectively, which are obtained by the look-up operation from \( M_V, M_A, M_S \) and \( M_P \), respectively. It is worth noting that through the above representations, the heterogeneous (e.g., node type), path-level (e.g., position in the path) and graph-structure (e.g., edges in the subgraph) information from subgraph \( G_{u,i} \) have been encoded in the composite embedding matrix \( E \).

**4.2.2 Self-Attention Layer.** Similar to the architecture of Transformer [49], based on the embedding layer, we develop the subgraph encoder by stacking multiple self-attention layers. A self-attention layer generally consists of two sub-layers, i.e., a multi-head self-attention layer and a point-wise feed-forward network. Specifically, the multi-head self-attention is defined as:

\[
MHAttn(F^l) = [head_1, head_2, ..., head_h]W_O,
\]

\[
head_i = \text{Attention}(F^lW_i^Q, F^lW_i^K, F^lW_i^V),
\]

where the \( F^l \) is the input for the \( l \)-th layer, when \( l = 0 \), we set \( F^0 = E \), and the projection matrix \( W_i^Q \in \mathbb{R}^{d \times d/h}, W_i^K \in \mathbb{R}^{d \times d/h}, W_i^V \in \mathbb{R}^{d \times d/h} \) and \( W^O \in \mathbb{R}^{d \times d} \) are the corresponding learnable parameters for each attention head. The attention function is implemented by scaled dot-product operation:

\[
\text{Attention}(Q, K, V) = \text{softmax}(\frac{QK^T}{\sqrt{d/h}})V,
\]
where \( Q = F^l W^Q_j \), \( K = F^l W^K_j \), and \( V = F^l W^V_j \) are the linear transformations of the input embedding matrix, and \( \sqrt{d/h} \) is the scale factor to avoid large values of the inner product. After the multi-head attention layer, we endow the non-linearity of the self-attention layer by applying a point-wise feed-forward network. The computation is defined as:

\[
F^l = [\text{FFN}(F^l_1)^\top; \cdots; \text{FFN}(F^l_n)^\top],
\]

\[
\text{FFN}(x) = (\text{ReLU}(xW_1 + b_1))W_2 + b_2,
\]

where \( W_1, b_1, W_2, b_2 \) are trainable parameters.

Finally, we can compute the representation for the interaction-specific heterogeneous subgraph \( G_{u,i} \) based on the representations at the final self-attention layer as:

\[
z_{G_{u,i}} = \text{MLP}(F^L_u \oplus F^L_i),
\]

where “\( \oplus \)” denotes the vector concatenation operation, \( F^L_u \) and \( F^L_i \) are the representations of user \( u \) and item \( i \) from the last self-attention layer, which represent the starting user \( u \) and ending item \( i \) in the subgraph, and \( L \) is the number of self-attention blocks.

### 4.3 Curriculum Pre-training

With the above model architecture, we focus on developing an effective representation learning approach that is specially for HIN-based recommendation. Considering that HIN encodes complex and heterogeneous data relations, our idea is to gradually extract and learn useful information from local (e.g., node-level) to global (i.e., subgraph-level) context from interaction-specific heterogeneous subgraphs. Such an idea can be in essence characterized by curriculum learning [1, 32, 44], which starts from simple tasks or instances and gradually transforms to more complex ones. Based on this idea, we develop a novel curriculum pre-training strategy that designs both elementary and advanced courses (i.e., pre-training tasks) with increasing difficulty levels.

#### 4.3.1 Elementary Course

Elementary course aims to leverage local context information from interaction-specific heterogeneous subgraphs. We propose to train the proposed heterogeneous subgraph Transformer model with three new tasks, namely masked node prediction, masked edge prediction and meta-path type prediction. The first two tasks focus on enhancing the node-level representations, while the meta-path type prediction task is designed for capturing path-level semantics for user-item interactions.

- **Masked Node Prediction**: This task is to infer a masked node based on its surrounding context in a heterogeneous subgraph. Following the Cloze task in BERT [3], we randomly mask a proportion of nodes in a heterogeneous subgraph and then predict the masked nodes based on the remaining contexts. Assume that we mask node \( v_t \) in a multi-slot sequence \( \{v_1, \cdots, v_t, \cdots, v_n\} \). We treat the rest sequence \( \{v_1, \cdots, \text{MASK}, \cdots, v_n\} \) as the surrounding context for \( v_t \), denoted by \( C_{v_t} \). Given the surrounding context \( C_{v_t} \) and the masked node \( v_t \), we minimize the Masked Node Prediction (MNP) loss by:

\[
L_{MNP}(C_{v_t}, v_t) = -\log \left( \sigma(F^T_t W_N e_{v_t}) - \sigma(F^T_t W_N e_{\tilde{v}}) \right),
\]

where \( \tilde{v} \) denotes an irrelevant node, \( e_{v_t} \) and \( e_{\tilde{v}} \) denote the node ID embedding for \( v_t \) and \( \tilde{v} \) respectively, \( W_N \in \mathbb{R}^{d \times d} \) is a parameter matrix to learn and \( F_t \) is the learned representation for the \( t \)-th position using our subgraph encoder as in Eq. 5.

- **Masked Edge Prediction**: The masked edge prediction task is to recover the masked edge of two adjacent nodes based on surrounding context. Similar to masked node prediction, we randomly mask a proportion of edges in the input (i.e., removing the precursor index) and then predict the
masked edges based on the surrounding contexts. Formally, the Masked Edge Prediction (MEP) loss for the edge \( \langle v_j, v_k \rangle \) can be given as:

\[
L_{MEP}(v_j, v_k) = -\log (\sigma(F_j^T W_E F_k) - \sigma(F_j^T W_E F'_k)),
\]

(9)

where \( v_k' \) is a sampled node that is not adjacent to \( v_j \), \( W_E \in \mathbb{R}^{d \times d} \) is a parameter matrix to learn, \( F_j, F_k \) and \( F'_k \) are the learned representations for the corresponding positions obtained in the same way as Eq. 5.

- **Meta-path Type Prediction**: Since the user-item interaction subgraph is composed by multiple paths, path-level semantics encode important evidence to explain the underlying reasons why a specific user-item interaction occurs [16, 17]. We would like to directly capture the semantics from meta-paths for improving the path semantic information in representations. Specifically, we consider meta-path type prediction as a classification task, and introduce the Meta-path Type Prediction (MTP) loss as:

\[
L_{MTP}(u, i) = -\sum_{\rho \in \mathcal{P}} y_{u, i, \rho} \cdot \log \Pr(\rho|u, i) + (1 - y_{u, i, \rho}) \cdot \log (1 - \Pr(\rho|u, i)),
\]

(10)

where \( y_{u, i, \rho} \) is a binary label indicating whether there exists a path from the meta-path \( \rho \) between \( u \) and \( i \), \( \mathcal{P} \) is the meta-path set, and \( \Pr(\rho|u, i) \) is the probability that the user and item are connected by the meta-path \( \rho \), which is defined as:

\[
\Pr(\rho|u, i) = \sigma(\text{MLP}(F_u^L \oplus F_i^L)),
\]

(11)

where MLP(·) is a multi-layer perceptron with the sigmoid function as output.

### 4.3.2 Advanced Course

Although the above pre-training tasks have captured local context information (e.g., node, edge and path) from the heterogenous subgraph, the global correlations at subgraph level cannot be effectively learned by elementary course. To characterize the overall effect of global contexts on recommendation, we devise an advanced course to train the heterogeneous subgraph Transformer with a Subgraph Contrastive Learning (SCL) task. Based on the original subgraph, the core idea is to augment a number of interaction-specific subgraphs. Then, we apply contrastive learning [2, 11] to further capture subgraph-level evidence for modeling user-item interaction. Here, we consider three path-based subgraph augmentation strategies:

- **Path Removal**: It augments new subgraphs by randomly removing a small portion of paths from the original user-item interaction subgraph, which is expected to make the learned representations less sensitive to structural perturbation.

- **Path Insertion**: It introduces a small proportion of new paths into the original subgraph. Many user-item interactions are with sparse connected paths, which is easy to result in over-fitting on the observed data. This task is able to improve the robustness of the recommendation model.

- **Path Substitution**: It can be considered as the combination of the path removal and path insertion strategies. By further enlarging the difference between the augmented subgraphs and original subgraph, this task enforces the model to capture the most fundamental semantics for user-item interactions.

Given the target user-item subgraph \( G_{u,i} \) (focusing on user \( u \) and \( i \)), we first augment a set of new subgraphs with the above subgraph augmentation strategies, and consider them as positive subgraphs, denoted by \( \{G_{u,i}^+\} \). While, we consider the subgraphs connecting the same user \( u \) with other items \( i' \) as negative subgraphs, denoted by \( \{G_{u,i}^-\} \). Following a standard contrastive learning approach [2], we maximize the difference of augmented positive subgraphs and negative subgraphs,
w.r.t. the original subgraph:

\[
L_{SCL}(\mathcal{G}, \mathcal{G}^+, \{\mathcal{G}^-\}) = -\log \frac{\exp \left( \frac{\text{sim}(z_{\mathcal{G}}, z_{\mathcal{G}^+})}{\tau} \right)}{\exp \left( \frac{\text{sim}(z_{\mathcal{G}}, z_{\mathcal{G}^+})}{\tau} \right) + \sum_{\mathcal{G}^-} \exp \left( \frac{\text{sim}(z_{\mathcal{G}}, z_{\mathcal{G}^-})}{\tau} \right)},
\]

(12)

where \(z_{\mathcal{G}}, z_{\mathcal{G}^+}\) and \(z_{\mathcal{G}^-}\) are the produced subgraph representations from the heterogeneous subgraph Transformer (Eq. 7) for the original subgraph, augmented positive subgraph and augmented negative subgraph (we omit \(u\) and \(i\) in subscripts for simplicity), respectively, \(\text{sim}(x, y)\) denotes the cosine similarity function, and \(\tau\) is a hyper-parameter for softmax temperature.

This constative learning loss enforces the model to learn subgraph-level semantics for user-item interaction. By combining with the elementary course, both local and global context information can be captured in final learned representations. In particular, we schedule the pre-training tasks from two courses in an "easy-to-difficult" order, which is necessary to model complex data relations in HIN.

4.4 Learning and Discussion

In this part, we present the learning and related discussions of our approach for HIN-based recommendation.

4.4.1 Learning. The entire procedure of our approach consists of two major stages, namely curriculum pre-training and fine-tuning stages. At the curriculum pre-training stage, we first pre-train our model on the elementary course, consisting of three pre-training objectives to learn local context information in the subgraph, then pre-train on the advanced course to learn global context information from HIN. At the fine-tuning stage, we utilize the pre-trained parameters to initialize the parameters, and then adopt the recommendation task to train our model. Given user \(u\) and item \(i\), the preference score is calculated by:

\[
\Pr(u, i) = \sigma(z_{\mathcal{G}_{u,i}}),
\]

(13)

where \(\sigma(.)\) is the sigmoid function and \(z_{\mathcal{G}_{u,i}}\) is the representation for \(\mathcal{G}_{u,i}\) defined in Eq. 7. We adopt the binary cross-entropy loss as the final objective:

\[
L_{\text{rec}}(u, i) = -\log \Pr(u, i) - \log(1 - \Pr(u, i')),
\]

(14)

where we pair each ground-truth item \(i\) with one (or several) negative item \(i'\) that is randomly sampled. The detailed learning process is shown in Algorithm 1.

4.4.2 Time complexity. In recommender systems, online service time is more important to consider than offline training time. Once our model has been learned (after pre-training and fine-tuning), online service time mainly includes the cost of evaluating all the candidate items according to Eq. 13 and the cost of selecting top items, which is similar to previous neural collaborative filtering methods [13]. A major preprocessing cost lies in the construction of heterogeneous subgraphs for possible user-item pairs. As discussed before, we can pre-compute the priority scores of neighbors for all the nodes. Based on priority scores, we can sample a high-quality path instance in a time roughly as \(O(\bar{L})\) using pre-built efficient data structures such as alias table [28] (taking time \(O(1)\) to sample from categorical distributions), where \(\bar{L}\) is the average path length. In practice, the number of meta-paths and the number of paths in a subgraph are usually set to small values, so that the number of nodes in a subgraph can be bounded below a reasonable value (e.g., 50). In this way, our pre-training and fine-tuning costs are similar to train/pre-train Transformer architecture [3, 49] over sequence data, which can be efficient if we use very few self-attention layers or parallelize the computation.
Algorithm 1: The overall training process for the CHEST model.

\textbf{Input:} The heterogeneous information network $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, pre-defined meta-paths $\mathcal{P}$, the user set $\mathcal{U}$, the item set $\mathcal{I}$, the user-item historical records $\mathcal{D} = \langle u, i \rangle$.

\textbf{Output:} The learned node embedding matrix $E$, the learned parameters of the self-attention layer $\Theta$.

1. Use metapath2vec to learn latent vectors of all the nodes in $\mathcal{G}$.
2. for $j = 1 \rightarrow |\mathcal{U}|$ do
3.     for $k = 1 \rightarrow |\mathcal{I}|$ do
4.         for $l = 1 \rightarrow |\mathcal{P}|$ do
5.             Collect the top-$K$ path instances with the highest average similarities corresponding to the meta-path $\rho_l$ that connect the user node $u_j$ and item nodes $i_k$.
6.         end
7.     end
8. end
9. Randomly initialize $E$ and $\Theta$.
10. for $j = 1 \rightarrow |\mathcal{U}|$ do
11.     for $k = 1 \rightarrow |\mathcal{I}|$ do
12.         Transform the subgraph $\mathcal{G}_{u_j, i_k}$ for the user-item pair into multi-slot sequence.
13.         Acquire ID embeddings $E_V$, node type embeddings $E_A$, slot embeddings $E_S$ and precursor embeddings $E_P$ for the nodes in the subgraph $\mathcal{G}_{u_j, i_k}$.
14.         Acquire the composite embedding matrix $E$ using Eq. 1.
15.         Acquire the subgraph representations $F^L$ by multiple self-attention layers using Eq. 2, Eq. 3, Eq. 5, Eq. 6 and Eq. 7.
16.         Pre-train the parameters $E$ and $\Theta$ using Eq. 8, Eq. 9 and Eq. 10.
17. end
18. end
19. for $t = 1 \rightarrow |\mathcal{D}|$ do
20.     encode the subgraph $\mathcal{G}_{u_j, i_k}$ using the operations from line 13 to line 16.
21.     Compute $Pr(u, i)$ using Eq. 13.
22.     Fine-tune the parameters $E$ and $\Theta$ using Eq. 14.
23. end
24. return $E$ and $\Theta$.

4.4.3 Discussion. Compared with existing work for HIN-based recommendation, our approach has two major differences. In our approach, data characterization, representation model and learning algorithm are specially designed for user-item interaction based on HIN. As for data characterization, we introduce interaction-specific heterogeneous subgraph to reduce the incorporation of irrelevant information. Based on such a subgraph structure, we further propose a novel heterogeneous subgraph Transformer as the representation model, which can effectively model the subgraph semantics. Furthermore, we propose a novel learning algorithm by designing a curriculum pre-training approach, in which elementary and advanced courses are organized to gradually extract local and global context information from HIN to recommendation task. The three aspects jointly ensure that our approach can better extract and leverage relevant contextual information from HIN for modeling user-item interaction.

Our work is related to two categories of models, namely path-based methods [17, 56], graph representation learning methods [38, 51, 59]. The former category separately models the sampled paths, so that graph-structure or cross-path node correlation cannot be explicitly captured. Besides,
these path-based methods rely on the recommendation task to learn the representations, which may suffer from data sparsity problem and cause overfitting. As a comparison, our approach construct an interaction-specific heterogeneous subgraph based on high-quality paths, which is able to capture richer semantics from the subgraph structure. In addition, we propose an elementary-to-advanced curriculum pre-training strategy to gradually learn from both local and global contexts in the subgraph, which is able to learn more effective representations. Graph representation learning methods aggregate information from neighbouring nodes in the entire HIN and then learn the representations via task-insensitive objectives. In this way, noisy information from recommendation-irrelevant nodes can be incorporated into the learned representations, and the learning process may be unnecessary for downstream tasks. In our approach, the interaction-specific heterogeneous subgraph is utilized to incorporate high-quality context information, and meanwhile reduce the the influence of irrelevant nodes and edges. Then, we design a curriculum pre-training strategy based on the subgraph to learn the user-item association, which is more suitable to the recommendation task.

5 EXPERIMENT

In this section, we first set up the experiments, and then present the results and analysis.

5.1 Experimental Setup

5.1.1 Datasets. We conduct experiments on three widely-used datasets from different domains, namely Movielens\(^1\), Amazon\(^2\) and Yelp\(^3\), where movies, products and businesses are considered as items for recommendation, respectively. We treat a rating as an interaction record, indicating whether a user has rated an item or not. For reproducible comparison, we reuse the preprocessed results and the selected meta-paths released in \([16]\)^4. The detailed statistics of these datasets after preprocessing are summarized in Table 2, where we report the statistics by different edge relations. The first row of each dataset corresponds to the number of users, items and interactions, while the other rows correspond to the statistics of other relations. The selected meta-paths for each dataset are in the last column.

5.1.2 Evaluation Metrics. We use two commonly used metrics to evaluate the performance of our proposed model.

- Hit Rate: Hit rate (HR) measures the percentage that recommended items contain at least one correct item interacted by the user, which does not consider the actual rank of the items and has been widely used in previous works \([33, 41]\).

\[
HR@k = \frac{1}{|U|} \sum_{u \in U} I(|\hat{I}_{u,k} \cap I_u| > 0),
\]

where \(\hat{I}_{u,k}\) denotes the set of top-\(k\) recommended items for user \(u\) and \(I_u\) is the set of testing items for user \(u\), and \(I(\cdot)\) is an indicator function.

- Normalized Discounted Cumulative Gain: Normalized Discounted Cumulative Gain (NDCG) takes the positions of correct recommended items into consideration, which is important in settings

\(^1\)https://grouplens.org/datasets/movielens/100k/
\(^2\)http://jmcauley.ucsd.edu/data/amazon/links.html
\(^3\)https://www.yelp.com/dataset
\(^4\)Accessible via the link: https://github.com/librahu/HIN-Datasets-for-Recommendation-and-Network-Embedding
Table 2. Basic statistics of the three datasets.

| Datasets  | Relations       | #Type A | #Type B | #A-B Metapath |
|-----------|-----------------|---------|---------|---------------|
| Movielens | User-Movie      | 943     | 1,682   | 100,000       |
|           | Movie-Movie     | 1,682   | 1,682   | 82,798        |
|           | User-Occupation | 943     | 21      | 943           |
|           | Movie-Genre     | 1,682   | 18      | 2,861         |
|           | User-Product    | 3,584   | 2,753   | 50,903        |
|           | Product-View    | 2,753   | 3,857   | 5,694         |
|           | Product-Brand   | 2,753   | 334     | 2,753         |
|           | Product-Category| 2,753   | 22      | 5,508         |
|           | User-Business   | 16,239  | 14,284  | 198,397       |
|           | User-User       | 16,239  | 16,239  | 158,590       |
|           | Business-City   | 14,284  | 47      | 14,267        |
|           | Business-Category| 14,284 | 511     | 40,009        |

where the order of recommendations matters.

\[
\text{NDCG}@k = \frac{\text{DCG}@k}{\text{iDCG}},
\]

\[
\text{DCG}@k = \frac{1}{|U|} \sum_{u \in U} \sum_{j=1}^{k} \frac{\mathbb{1}(\hat{I}_{u,j} \in I_u)}{\log_2 (j+1)}
\]

where \(\hat{I}_{u,j}\) denotes the \(j\)-th recommended item for the user \(u\), \(u\), and \(\text{iDCG}\) denotes the ideal discounted cumulative gain, which is a normalization constant and is the maximum possible value of \(\text{DCG}@k\).

We report results on HR@\{10, 20\} and NDCG@\{10, 20\}. Following [39], we apply the leave-one-out strategy for evaluation. Concretely, for each user, we randomly hold out an interaction record as the test set, another interaction record as the validation set and the remaining data is used for training. Since it is time-consuming to rank all items for every user during evaluation, we pair the ground-truth item with 1000 randomly sampled negative items that the user has not interacted with. We calculate all metrics according to the ranking of the items and report the average score over all test users.

5.1.3 Baselines. We consider the following baselines:

- BPR [42] is a classic personalized ranking algorithm that optimizes the pairwise ranking loss function of latent factor model with implicit feedback via stochastic gradient descent.
- FM [41] utilizes a generic factorization machine to model the pairwise interactions between different features and further to characterize second order feature interactions.
- NCF [13] integrates both generalized matrix factorization and multi-layer perceptron (MLP) to capture user-item interactions, where the MLP is utilized to explore non-linear interactions between the user and item.
- NGCF [51] adopts GNN layers on the user-item interaction graph, which exploits the user-item graph structure by propagating embeddings on it to refine user and item representations.
• LightGCN [12] is the state-of-the-art graph neural network based collaborative filtering model which simplifies the design of GCN to make it more concise and appropriate for recommendation.
• HGT [20] introduces node- and edge-type dependent attention mechanism to model heterogeneous graph, which assigns different weights on neighbors during aggregation to capture the interactions among different types of nodes.
• HAN [51] treats meta-paths as virtual edges to connect nodes and utilizes a hierarchical attention mechanism to capture both node-level and semantic-level information.
• HERec [45] adopts a meta-path based random walk to generate meaningful object sequences for network embedding. And then the embeddings are fused in matrix factorization method for recommendation.
• LGRec [16] employs a co-attention mechanism to model most informative local neighbor information, and learns effective global relation representations between users and items in HIN for recommendation.
• MCRec [17] utilizes convolutional neural network to construct meta-path embeddings and further leverages co-attention mechanism to model interactions among users, items and meta-paths.
• PF-HIN [6] designs a ranking-based breadth-first search strategy to generate node sequence and utilizes masked node prediction to pre-train the nodes representations.
• GCC [38] is a recently proposed pre-training method for homogeneous graph via contrastive learning. We fine-tune the pre-trained model released by the authors on our datasets.
• Graph-BERT [58] is a pre-trained graph neural network solely based on attention mechanism without any graph convolution or aggregation operators.
• MTRec [29] introduces a multi-task learning framework for HIN-based recommender systems. It utilize link prediction as an auxiliary task to improve the recommendation performance.

Our baselines can be roughly categorized into four groups: (1) BPR, FM, NCF, NGCF and LightGCN are classic or neural collaborative filtering methods; (2) HGT and HAN are specially designed graph neural networks for modeling HIN; (3) HERec, LGRec and MCRec extract meta-path based context from HIN, and then model the paths using neural networks; (4) PF-HIN, GCC, Graph-BERT and MTRec are pre-training methods that utilize auxiliary supervised signal to pre-train or regularize the model parameters.

5.1.4 Implementation Details. To compare the performance of these methods, we either adopt the suggested parameter settings from original papers, or optimize the model performance on the validation set. In Table 4, models with “♦” are implemented by provided source code while those with “♥” are implemented by ourselves. For all methods that use meta-paths, we use the same meta-paths as shown in the last column of Table 2 and sample five path instances for each meta-path. For MCRec, we also pre-learned the latent vectors for nodes to initialize parameters as the authors suggested.

In our model, we use two self-attention blocks each with two attention heads, and set the embedding size as 64. In the pre-training stage, the mask proportions of nodes and edges are set as 0.4 and 0.2, and the weights for the three pre-training losses in the elementary course (i.e., MNP, MEP and MTP) are set as 0.4, 0.2, and 0.4, and the softmax temperature in the advanced course is set to 1. We use the Adam optimizer [23] with learning rates of 0.001 for pre-training and fine-tuning stages. For the baselines, all the models have some parameters to tune. We either follow the reported optimal parameter settings or optimize each model separately using the validation set. We report the parameter setting used throughout the experiments in Table 3.

The code and dataset will be available after the review period.
Table 3. Parameter settings of all models.

| Models     | Settings                                                                 |
|------------|---------------------------------------------------------------------------|
| BPR        | embedding-size=64, learning-rate=0.01, batch-size=256, RMSprop optimizer |
| FM         | embedding-size=32, learning-rate=0.001, batch-size=256, Adam optimizer    |
| NCF        | factor-num=8, layer-size=3, learning-rate=0.001, dropout-rate=0.5, sample-neg-num=4 batch-size=256, Adam optimizer |
| HGT        | embedding-size=64, hidden-size=64 learning-rate=0.001 batch-size=256, Adam optimizer |
| HAN        | embedding-size=16, attention-heads=8, dropout-rate=0.5 learning-rate=0.005, batch-size=256, Adam optimizer |
| HERec      | factor-num=16, batch-size=256                                            |
| LGRec      | neighbor-size=100, embedding-size=128, hidden-size=128, learning-rate=0.001, batch-size=256, dropout-rate=0.2, Adam optimizer |
| MRec       | embedding-size=64, learning-rate=0.001, batch-size=256, Adam optimizer    |
| PF-HIN     | layer-size=2, attention-heads=2, hidden-size=64 learning-rate=0.001, pre-train-epochs=50, dropout-rate=0.5, Adam optimizer |
| GCC        | hidden-size=128, batch-size=256, learning-rate=0.001, Adam optimizer      |
| Graph-BERT | layer-size=2, attention-heads=2, hidden-size=32, k=7, learning-rate=0.001, dropout-rate=0.3, Adam optimizer |
| MTRec      | hidden-size=64 learning-rate=0.001, dropout-rate=0.5, Adam optimizer      |
| CHEST (Our)| layer-size=2, attention-heads=2, hidden-size=128, batch-size=256, mask-node-prob=0.4, mask-edge-prob=0.2, learning-rate-for-pretrain=0.001, mnp-loss-weight=0.4, mep-loss-weight=0.2, mtp-loss-weight=0.4, learning-rate-for-finetune=0.0001, Adam optimizer |

5.2 Performance Comparison

Table 4 presents the performance comparison of different methods on the recommendation task.

As we can see, for five classic recommendation baselines, FM performs better than BPR, NCF and NGCF on the more sparse datasets (i.e., Amazon and Yelp), because FM can incorporate context features and characterize second-order feature interaction. For the three neural collaborative filtering methods, the performance order is consistent across all datasets, i.e., LightGCN > NGCF > NCF. A possible reason is that LightGCN and NGCF utilize graph neural network to learn high-order interaction in a more effective way.

Second, HAN performs much better than HGT in most cases. A major reason is that HGT requires to set meta-relations, which is slightly different from our setting. However, the two methods are general GNN embedding methods, which may be not aware of the recommendation task and cannot perform better than classic recommender systems.

Third, for meta-path based baselines, the performance order is consistent, i.e., MRec > LGRec > HERec. Because MRec samples path instances through “priority” based strategy and utilizes pre-learned embeddings to initialize the representations in HIN.

Furthermore, the baselines with auxiliary supervision signals perform better than those from other categories on average. Specially, MTRec performs the best among all the baselines, which has designed a special auxiliary task for improving the recommendation performance. It relies on self-attention mechanism to learn the semantics of meta-paths in HIN and jointly optimizes the tasks of both recommendation and link prediction. While, GCC and Graph-BERT perform slightly worse than MTRec, which verifies that homogeneous graph pre-training methods cannot be directly utilized in HIN-based recommendation.
Table 4. Performance comparison of different methods on HIN-based recommendation. The best and second best results are in bold and underlined fonts respectively. "†" indicates the statistical significance for $p < 0.01$ compared to the best baseline.

| Datasets | Models       | Hit Ratio@10 | NDCG@10 | Hit Ratio@20 | NDCG@20 |
|----------|--------------|--------------|---------|--------------|---------|
| Movielens| BPR          | 0.3383       | 0.1937  | 0.4624       | 0.2249  |
|          | FM           | 0.3722       | 0.2144  | 0.5069       | 0.2482  |
|          | NCF          | 0.3807       | 0.2205  | 0.5122       | 0.2541  |
|          | NGCF         | 0.3945       | 0.2264  | 0.5260       | 0.2593  |
|          | LightGCN     | 0.3977       | 0.2367  | 0.5514       | 0.2753  |
|          | HGT          | 0.2630       | 0.1499  | 0.3828       | 0.1801  |
|          | HAN          | 0.3065       | 0.1613  | 0.4358       | 0.1915  |
|          | HERec        | 0.1729       | 0.1007  | 0.2641       | 0.1232  |
|          | LGRec        | 0.3754       | 0.2154  | 0.5111       | 0.2495  |
|          | MRec         | 0.3828       | 0.2218  | 0.5345       | 0.2601  |
|          | PF-HIN       | 0.3054       | 0.1822  | 0.4422       | 0.2175  |
|          | GCC          | 0.3860       | 0.2219  | 0.5408       | 0.2612  |
|          | Graph-BERT   | 0.3712       | 0.2200  | 0.5270       | 0.2591  |
|          | MTRec        | 0.3955       | 0.2231  | 0.5440       | 0.2608  |
|          | CHEST        | **0.4401†**  | **0.2495†** | **0.5981†** | **0.2892†** |
| Amazon   | BPR          | 0.0791       | 0.0390  | 0.1300       | 0.0518  |
|          | FM           | 0.0916       | 0.0459  | 0.1515       | 0.0610  |
|          | NCF          | 0.0825       | 0.0363  | 0.1434       | 0.0514  |
|          | NGCF         | 0.0887       | 0.0417  | 0.1485       | 0.0567  |
|          | LightGCN     | 0.1028       | 0.0519  | 0.1605       | 0.0664  |
|          | HGT          | 0.0496       | 0.0286  | 0.0684       | 0.0334  |
|          | HAN          | 0.0679       | 0.0346  | 0.1182       | 0.0472  |
|          | HERec        | 0.0355       | 0.0154  | 0.0867       | 0.0282  |
|          | LGRec        | 0.0616       | 0.0304  | 0.0969       | 0.0393  |
|          | MRec         | 0.0951       | 0.0552  | 0.1277       | 0.0634  |
|          | PF-HIN       | 0.0243       | 0.0129  | 0.0506       | 0.0195  |
|          | GCC          | 0.0715       | 0.0326  | 0.1206       | 0.0449  |
|          | Graph-BERT   | 0.0893       | 0.0422  | 0.1511       | 0.0577  |
|          | MTRec        | 0.1062       | 0.0618  | 0.1412       | 0.0706  |
|          | CHEST        | **0.1204†**  | **0.0703†** | **0.1765†** | **0.0844†** |
| Yelp     | BPR          | 0.1362       | 0.0717  | 0.2069       | 0.0899  |
|          | FM           | 0.1777       | 0.1031  | 0.2605       | 0.1239  |
|          | NCF          | 0.1451       | 0.0772  | 0.2212       | 0.0963  |
|          | NGCF         | 0.1586       | 0.0851  | 0.2399       | 0.1055  |
|          | LightGCN     | 0.1658       | 0.0895  | 0.2530       | 0.1115  |
|          | HGT          | 0.1689       | 0.0956  | 0.2420       | 0.1139  |
|          | HAN          | 0.1759       | 0.1025  | 0.2532       | 0.1219  |
|          | HERec        | 0.1768       | 0.0956  | 0.2518       | 0.1146  |
|          | LGRec        | 0.1908       | 0.1076  | 0.2762       | 0.1292  |
|          | MRec         | 0.2193       | 0.1310  | 0.3064       | 0.1528  |
|          | PF-HIN       | 0.1889       | 0.1071  | 0.2804       | 0.1301  |
|          | GCC          | 0.1956       | 0.1086  | 0.3006       | 0.1349  |
|          | Graph-BERT   | 0.1894       | 0.1043  | 0.2865       | 0.1286  |
|          | MTRec        | 0.2245       | 0.1332  | 0.3142       | 0.1556  |
|          | CHEST        | **0.2441†**  | **0.1441†** | **0.3630†** | **0.1711†** |
Finally, our model CHEST performs consistently better than all the baselines by a large margin on three datasets. Different from these baselines, our heterogeneous subgraphs are specially sampled for user-item interaction, which is tailored to the recommendation task. Besides, our proposed heterogeneous subgraph Transformer is able to preserve graph-structure and path-level semantics within the subgraph via special composite node embeddings. We further propose the curriculum pre-training strategy to learn effective representations for utilizing useful information in HIN for recommendation task. Comparing our approach with all the baseline models, it can be observed that the above strategies are very useful to improve the recommendation performance.

### 5.3 Detailed Analysis

In this section, we perform a series of detailed analysis on the performance of our model.

#### 5.3.1 Ablation Study

In our proposed CHEST, we have incorporated four types of node embeddings and design curriculum pre-training strategy for HIN-based recommendation. In this part, we examine the effectiveness of these proposed techniques or components on the model performance. We conduct the ablation study on Movielens and Amazon datasets, and adopt HR@20 and NDCG@20 as evaluation metrics.

We first analyze the contribution of the composite embeddings. Besides node ID embeddings, we introduce node type embedding, slot embedding and precursor embedding to preserve the semantics of interaction-specific heterogeneous subgraphs in multi-slot sequence representations. The results after embedding ablation (ID embedding is reserved in all cases) are shown in Table 5. As we can see, all the embeddings are useful to improve the model performance. Specially, the precursor embedding seems more important than the other two types of embeddings, since it can preserve the graph-structure semantics within the subgraph.

| Methods       | Movielens | Amazon | Movielens | Amazon |
|---------------|-----------|--------|-----------|--------|
|               | HR@20     | NDCG@20| HR@20     | NDCG@20|
| CHEST         | 0.5981    | 0.2892 | 0.1765    | 0.0844 |
| w/o Node Type | 0.5928    | 0.2835 | 0.1666    | 0.0817 |
| w/o Slot      | 0.5811    | 0.2887 | 0.1601    | 0.0765 |
| w/o Precursor | 0.5811    | 0.2855 | 0.1485    | 0.0696 |

Table 5. Ablation Study of our approach on composite node embeddings.

We further conduct the ablation study on pre-training tasks (P) and other curriculum settings (C). The results are shown in Table 6.

| Methods       | Movielens | Amazon | Movielens | Amazon |
|---------------|-----------|--------|-----------|--------|
|               | HR@20     | NDCG@20| HR@20     | NDCG@20|
| CHEST         | 0.5981    | 0.2892 | 0.1765    | 0.0844 |
| w/o MTP       | 0.5938    | 0.2830 | 0.1703    | 0.0790 |
| w/o MEP       | 0.5875    | 0.2849 | 0.1703    | 0.0803 |
| w/o MNP       | 0.5239    | 0.2437 | 0.1587    | 0.0724 |
| w/o SCL       | 0.5896    | 0.2859 | 0.1715    | 0.0807 |
| Multi-task    | 0.5589    | 0.2715 | 0.1640    | 0.0819 |
| Reverse Courses | 0.5758  | 0.2823 | 0.1700    | 0.0829 |

Table 6. Ablation study of our approach on pre-training tasks (P) and other curriculum settings (C).
Next, we continue to conduct the ablation study to analyze the contribution of each pre-training task and other curriculum settings. As can be seen in Table 6, the performance drops when we remove one of the pre-training tasks, which shows that the above tasks are all beneficial to our model. Among them, the MNP (Masked Node Prediction) is more important than other pre-training tasks. One possible reason is that the correlations between the node and its surrounding context are important for recommendation task. Under the “Multi-task” setting, we pre-train the model on four pre-training tasks via multi-task learning, and the performance drops compared to the curriculum learning paradigm. The “Reverse Courses” setting means reversing the learning order of the elementary course and the advanced course, which decreases the recommendation performance. These findings verify the rationality of our elementary-to-advanced curriculum learning setting.

5.3.2 Subgraph Construction. To construct the interaction-specific heterogeneous subgraph, we keep top-\(K\) path instances with the highest average similarities for each meta-path. We study the effectiveness of different \(K\) on the model performance. As we can see in the Figure 3(a), CHEST achieves good results using only one path instance for each meta-path, which indicates that “priority”-based strategy is able to sample high-quality path instances. But when the \(K\) is too large, the results drop a bit. One possible reason is that we may introduce some noisy path instances into the subgraph.

We also investigate the influence of different meta-paths on the recommendation performance by gradually incorporating meta-paths into the subgraph. As shown in Figure 3(b), the performance of CHEST consistently improves with the incorporation of more meta-paths. The reason is that different meta-paths can introduce different aspects of information for modeling user-item interaction.

5.3.3 Parameter Tuning. Our models include a few parameters to tune. Here, we report the tuning results (HR@20) of two parameters on Movielens datasets, i.e., the node masked proportion and the number of Transformer layers. The cases on other datasets or metrics are similar and omitted.

As shown in Figure 4(a), we can see that CHEST achieves the best performance when the mask proportion is set to 0.4 for Movielens dataset. It indicates that the mask proportion cannot be set too small or too large. Besides, Figure 4(b) shows that CHEST achieves the best performance when the layer number is set to 2 for Movielens dataset. With two self-attention layers, our approach can efficiently learn effective information from HIN for recommendation. It is seen that CHEST is consistently better than CHEST\(_{\text{Base}}\), which verifies the effectiveness of our curriculum pre-training strategy.

![Fig. 3. Performance (HR@20) comparison w.r.t. different #path \(K\) and meta-paths types on Movielens dataset.](image)
Curriculum Pre-Training Heterogeneous Subgraph Transformer for Top-
Recommendation

Woodstock ‘18, June 03–05, 2018, Woodstock, NY

(a) Varying the mask proportion.  
(b) Varying the Trans. layer.

Fig. 4. Performance (HR@20) tuning w.r.t. different mask proportion and Transformer layers on Movielens dataset.

Fig. 5. Performance comparison w.r.t. different sparsity levels on Movielens dataset.

5.3.4 Data Sparsity. Recommender systems usually require a considerable amount of training data, thus they are likely to suffer from data sparsity in practice. This issue can be alleviated by our method because the proposed curriculum pre-training strategy can leverage intrinsic data correlations from input as auxiliary supervision signals. We simulate the data sparsity scenarios by using different proportions of the full training dataset, i.e., 20%, 40%, 60%, 80%, and 100%.

Figure 5 shows the results of data sparsity analysis on Movielens dataset. As we can see, the performance substantially drops when less training data is used. While, CHEST, GCC and MTRec are consistently better than other methods in data sparsity scenarios, especially in an extreme sparsity level (20%). It is because these methods utilize auxiliary supervised signals to enhance the data representations or initialize the model parameters. Among them, CHEST achieves the best performance since it utilizes an elementary-to-advanced training process to learn effective representations tailored to user-item interactions.

5.4 Qualitative Analysis

The above results have shown the effectiveness of curriculum pre-training strategy for the recommendation task. In this section, we present some qualitative analysis to understand why our approach works. Specially, we present two examples to qualitatively illustrate how the elementary-to-advanced training process improves the learning of data representations. We visualize the
two-dimensional projections of learned user embeddings and subgraph representations on MovieLens dataset using t-SNE algorithm [36].

As shown in Figure 6, various colors represent different occupations of users in MovieLens dataset. Before pre-training, the representations of users with the same occupations are distributed randomly. However, after pre-training on the elementary course, our approach derives more coherent clusters corresponding to different occupations. After the advanced course, we can see that the produced clusters of user representations are still separated clearly.

In the meantime, Figure 7 presents the distribution of positive samples (i.e., augmented subgraphs) and negative samples of the original interaction-specific subgraph. As we can see, after trained on elementary course, the subgraph representations have not been aggregated into coherent clusters. One possible reason is that the elementary course only focuses on the local context information (e.g., node, edge and path) by which our model is still unaware of global information of the whole subgraph. While these subgraph representations are clearly separated into two clusters (i.e positive samples and negative samples) after the advanced course. This phenomenon verifies that the advanced course captures global context information of the subgraph.

The above findings indicate that our curriculum pre-training strategy is able to learn local and global semantics underlying HIN, which can enhance the modeling for user-item interaction.

6 CONCLUSION

In this paper, we proposed a curriculum pre-training based heterogeneous subgraph Transformer (CHEST) for HIN-based recommendation task. First, we proposed to use the interaction-specific heterogeneous subgraph to extract sufficient and relevant context information from HIN for each user-item pair. Then we designed the heterogeneous subgraph Transformer to model the subgraph,
in which we incorporated a special composite embedding layer to capture graph-structure and path-level semantics and a self-attentive layer to aggregate the representation for the user-item interaction subgraph. Furthermore, we designed a curriculum pre-training strategy to gradually learn from both local and global contexts in the subgraph tailored to the recommendation task, in which we devised an elementary-to-advanced learning process to learn effective representations with increasing difficulty levels. Extensive experiments conducted on three real-world datasets demonstrated the effectiveness of our proposed approach against a number of competitive baselines, especially when only limited training data is available.

Currently, we have shown that it is promising to utilize curriculum pre-training technique for HIN-based recommendation. As future work, we plan to design a more general and effective pre-training strategy for improving neural recommendation algorithms, especially more complex recommendation task. Besides, we will also consider extending our approach to more complex recommendation task, such as multimedia recommendation and conversational recommendation.

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