Knowledge-aware Neural Networks with Personalized Feature Referencing for Cold-start Recommendation

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Abstract—Incorporating knowledge graphs (KGs) as side information in recommendation has recently attracted considerable attention. Despite the success in general recommendation scenarios, prior methods may fall short of performance satisfaction for the cold-start problem in which users are associated with very limited interactive information. Since the conventional methods rely on exploring the interaction topology, they may however fail to capture sufficient information in cold-start scenarios. To mitigate the problem, we propose a novel Knowledge-aware Neural Networks with Personalized Feature Referencing Mechanism, namely KPER. Different from most prior methods which simply enrich the targets’ semantics from KGSs, e.g., product attributes, KPER utilizes the KGs as a “semantic bridge” to extract feature references for cold-start users or items. Specifically, given cold-start targets, KPER first probes semantically relevant but not necessarily structurally close users or items as adaptive seeds for referencing features. Then a Gated Information Aggregation module is introduced to learn the combinatorial latent features for cold-start users and items. Our extensive experiments over four real-world datasets show that, KPER consistently outperforms all competing methods in cold-start scenarios, whilst maintaining superiority in general scenarios without compromising overall performance, e.g., by achieving 0.81%~16.08% and 1.01%~14.49% performance improvement across all datasets in Top-10 recommendation.

Index Terms—Cold-start Problem; Knowledge-aware Recommendation; Knowledge Graph; Personalized Feature Referencing

1 INTRODUCTION

With the explosive growth of web information, recommender systems (RSs), as a useful tool for information filtering [1], [2], nowadays are versatile to various Internet databases and applications. Among recent advances in online recommender models, incorporating Knowledge Graphs (KGS) as side information has lately attracted considerable attention [3]–[6]. Instead of simply leaning on user-item interaction data, with the rich and heterogeneous relational information in KGSs to supplement additional semantics, KG-based RS methods thus have the potential to provide more precise, diverse, and explainable information organization and recommendation.

Despite their progress in general recommendation scenarios, existing KG-based models still fall short of performance satisfaction for the cold-start problem. Generally, cold-start problem describes the scenario where users tend to have extremely limited interactive transactions [7]–[9]. This problem is ubiquitous in applications where user and item databases are frequently updated [7], e.g., E-commerce platforms and social networks. Although KGSs are capable of contributing auxiliary semantic enrichment, e.g., product attributes and profiles, the learning process however can hardly gather sufficient interactive information [10] in the cold-start scenario, restricting the performance of KG-based recommender methods.

Technically, prior models dedicate to designing better knowledge extraction paradigms, which however are constrained by topology sparsity for information propagation. Specifically, early works [11]–[13] follow certain manually defined patterns (i.e., meta-paths), to summarize information from KGSs with specific semantic meanings. Other models [4], [14], [15] design additional regularization loss terms to jointly learn user-item latent features and KG embeddings for both sides of interaction data and KGSs. However, in a cold-start scenario with sparse user-item interactions, these methods may collapse to merely optimize KG embeddings and fail to learn sufficient collaborative signals [5] for modeling the interactive information of target users and items. Recent works [16]–[18] adopt Graph Neural Networks (GNNs) to conduct explicit message passing from KGSs to eventually enrich user-item embeddings. One similar inadequacy is that current GNN-based models heavily rely on topology exploration to propagate distant knowledge. As shown in

Fig. 1. Motivation illustration (best view in color).
Fig. 1(a), if the user-item interactions are sufficient, the interactive information, a.k.a., collaborative signals [5], [19–22], can easily propagate back and forth, e.g., via the path \( u_1 - i_2 - i_3 - u_1 \), while the KG information is “icing on the cake” to further boost the semantics incidentally. But in sparse interaction structures shown in Fig. 1(b), such an information propagation mechanism thus hardly produces prompt and effective information dissemination via the long passing path \( u_1 - i_2 - e_2 - i_3 - e_3 - i_4 - u_3 \).

To address these issues, we propose Knowledge-aware Neural Networks with Personalized Feature Referencing (KPER). KPER specializes to alleviate the cold-start problem without compromising overall recommendation performance. We propose a novel and effective mechanism named Personalized Feature Referencing. As shown in Fig. 1(c), this mechanism utilizes the KG as a “semantic bridge” so as to reference representative latent features to users and items that originally suffer from insufficient learning of interactive information. Orthogonal to the aforementioned methods, our model can get rid of the interaction sparsity constraint, and achieve the embedding enrichment in the latent semantic space. Technically, KPER establishes the sequential pipeline with the following three modules where:

1) **Interactive Information Encoding.** We first employ it to summarize the latent features from the observed interactions to sketch the representations for both users and items.

2) **Attentive Knowledge Encoding.** We further develop multi hops of knowledge extraction from the KG whilst maintaining knowledge diversity across different users and items.

3) **Personalized Feature Referencing.** Integrating both sides of the information learned so far, for a given user (or item), we then employ Adaptive Seed Probing to explicitly detect user (or item) representatives. Intuitively, these representatives possess sufficient interaction information and share semantically similar features with the given user (or item), but may be structurally distant. We provide an effective Continuous Approximation approach to introduce the more stable model training, followed by the Gated Information Aggregation equipped with such augmented feature referencing, the cold-start problem can thus be substantially alleviated.

**Empirical Results.** We conduct the comprehensive experiments and analyses on four real-world datasets:

- In general recommendation scenarios, KPER outperforms the state-of-the-art Collaborative-filtering-based and KG-based recommender models by 0.81%–16.08% and 1.01%–14.49% performance improvement across all datasets, in terms of Recall and Precision metrics of Top-10 recommendation task.

- In cold-start recommendation scenarios, our model KPER consistently presents the performance superiority over all competing models, across various user or item groups with different levels of interaction sparsity.

- Our detailed empirical analysis and ablation study not only demonstrates the effectiveness of our proposed Personalized Feature Referencing Mechanism, but also validates the solidity of each model component in contributing to holistic model performance.

**Discussion.** It is worthwhile mentioning that there are few KG-based methods targeted at alleviating the cold-start problem via Meta-Learning [8], [9] and Graph Semi-Supervised Learning [7]. In this work, we focus on proposing an effective neural network architecture, i.e., KPER. Hence, we believe that KPER is motivationally similar but technically orthogonal to these learning paradigms. We provide their model introduction in § 2 and also include them for performance comparison in experiments.

**Organization.** The rest of this paper is organized as follows. We first review the related work in § 2. Then we present the detailed explanation of our model KPER in § 3 and attach model analysis in § 4. We report the extensive experiments in § 5 with conclusion in § 6.

## 2 Related Work

### 2.1 Cold-start Recommendation

**Asking to Rate.** Early solutions to address the cold-start issue mainly focus on the asking to rate. This is a explicitly-interactive operation that profiles target “cold” users by presenting items to them [23]. They can be generally categorized into (1) adaptive and (2) non-adaptive methods. Concretely, non-adaptive methods present the identical item lists to all users for the explicit ratings, which seeks to improve the model performance globally. To achieve this, various strategies have been deployed, such as Entropy [24], Random, Popularity, and Balanced strategies [25]. As for the adaptive methods, the item list asking for ratings is consistent with each target user’s opinions and preference. Therefore, the rated items with personalized orderings enable the cold-start recommendation accuracy to be more effectively improved; but the interview process will also be more complicated with increased costs. Related methods are referred in [24]–[26].

**Incorporating with Content Information.** Apart from solely relying on the rating information, several models are proposed to combine preference and additional content information [27]–[29]. However, the content part of these methods is typically generative [28]–[30] such that the models are optimized to “explain” the content rather than maximizing the recommendation accuracy [31]. One recent work [31] starts to employ deep neural networks to leverage preference and content information without explicitly relying on both being present. Another recent work [32] proposes a deep attentive neural architecture to model both content and interactive information for generalization ability enhancement. However, one major issue is that the intra-relationships of the additional information are not captured. To tackle this, KGs, as they are capable of modeling various kinds of relational knowledge and side information within the graph structures, enable KG-based recommender models to receive a wide range of attention recently.

### 2.2 Knowledge Graph-based Recommendation

Studying KGs as a kind of side-information has aroused interests in various applications including recommender systems. Existing KG-based recommender models are mainly in three types: (1) path-based [11], [13], [33], [54], (2) embedding-based [14], [15], [55], and (3) hybrid methods [3–6], [20].
Path-based Methods. Path-based methods explore various connecting patterns among items in KGs (i.e., meta-paths or meta-graphs) to provide additional guidance for recommendations. Generally, the generation of such connecting patterns heavily relies on either the path generation algorithm \cite{38} or manual creation \cite{11}. Although path-based methods naturally bring interpretability and explanation into the recommendation process, it can be difficult to design such patterns with limited domain knowledge. Thus for the large-scaled and complicated KGs, it is impractical to perform the exhaustive path retrieval and generation, while the selected paths make a great impact on the final recommendation performance.

Embedding-based Methods. These methods adopt knowledge graph embedding (KGE) algorithms \cite{37} to directly exploit the semantic information in KGs, and then enrich the representations of users and items. For instance, DKN \cite{14} utilizes TransD \cite{38} to jointly process the KGs and learn item embeddings. KV-MN \cite{15} proposes a knowledge-enhanced key-value memory network which adapts TransE \cite{39} to depict user preference in sequential recommendation. KTUP \cite{12} adopts TranH \cite{40} to learn the KG embeddings via hyperplanes to further improve the recommendation performance.

Hybrid Methods. They combine the above two techniques to achieve the state-of-the-art performance, and thus have attracted much attention in recent years. They usually apply iterative information propagation under graph neural network framework to generate the entity representations for information enrichment. For example, CKN \cite{5} employs a heterogeneous propagation strategy along multi-hop links to encode knowledge associations for users and items. CG-KGR \cite{20} customizes KG information with the proposed collaborative guidance mechanism which encapsulates historical interaction information to provide personalized recommendation. However, all of these methods are not designed for cold-start recommendation. Two models MetaHIN and MetaKG \cite{8,9} exploit the power of meta-learning paradigm. Technically, they model the preference learning for each user as a single meta-learning task. However, one major issue is that optimizing every single meta-learner for each user from the interaction record would incur expensive computational costs. Another latest model KGPL \cite{7} adopts graph semi-supervised learning to develop pseudo-labeling via random walk. This essentially is a graph simulation to increase interaction density by assigning pseudo-positive items to users. However, it starts with the structure exploration and thus may be influenced by the initial state of interaction sparsity, while those de facto negative labeling computed from the sparse substructures would thus perturb and destabilize the model training for recommendation. We include them in the experiments for performance comparison.

3 PROBLEM FORMULATION

User-item interactions can be represented by a bipartite graph $G_1 = \{(u, r, i) | u \in \mathcal{U}, i \in \mathcal{I} \}$, where $r$ generalizes all user behaviours, e.g., click, purchase, as one relation type between user $u$ and item $i$. $\mathcal{U}$ and $\mathcal{I}$ are the sets of users and items, respectively. We use $y_{ui} = 1$ to indicate the user $u$ has interacted with the item $i$, otherwise $y_{ui} = 0$. We have the knowledge graph $G_2 = \{(h, r, t) | h, t \in \mathcal{E}, r \in \mathcal{R} \}$ in which $\mathcal{E}$ and $\mathcal{R}$ are the collections of entities and relations. Each knowledge triple $(h, r, t)$ denotes that there is a relation $r$ connecting from head entity $h$ to tail entity $t$. Similar to $\mathcal{E}$ and $\mathcal{R}$, each item can be matched with an entity in the knowledge graph (i.e., $\mathcal{I} \subseteq \mathcal{E}$). For ease of interpretation, we unify the user-item bipartite graph $G_1$ and knowledge graph $G_2$ into the collaborative knowledge graph (CKG) $G = (\mathcal{E}', \mathcal{R}')$, where $\mathcal{E}' = \mathcal{E} \cup \mathcal{U}$ and $\mathcal{R}' = \mathcal{R} \cup \{r_1 \}$.

Notations. We use bold lowercase, bold uppercase, and calligraphy letters for vectors, matrices, and sets, respectively. Non-bold ones are used to denote graph nodes or scalars. We list the key notations in Table 1.

Task Formulation. Given the CKG $G$, we aim to train a recommender model $\mathcal{F}(\cdot, \cdot; \Theta, G)$, with the capability of estimating probability $\hat{y}_{ui}$ that user $u$ will engage with item $i$, i.e., $\hat{y}_{ui} = \mathcal{F}(u, i; \Theta, G)$, where $\Theta$ is the parameter set in $\mathcal{F}$.

4 KPER METHODOLOGY

4.1 Model Overview

We detail the proposed KPER model framework, with the architecture illustration in Fig. 2. KPER consists of three main components in which: (1) Interactive Information Encoding adaptively embeds the interactive information from observed historical interactions (§4.2); (2) Attentive Knowledge Encoding employs an attentive neural module to generate knowledge-aware embeddings for both users and items (§4.3); (3) Personalized Feature Referencing then combines the information from modules (1) and (2) to firstly probe representative user-item candidates, and then use the corresponding embeddings for feature referencing to alleviate the cold-start recommendation.
4.2 Interactive Information Encoding

In cold-start scenarios, it is essential to learn interactive information from the observed neighbors, as this can directly reflect the users’ preference towards items and items’ targeting costumers in users. Following this intuition, we firstly introduce our Interactive Information Encoding. Let \( o \) denote a node placeholder for users (or items), concretely, the neighboring interactive information of \( o \) is defined as:

\[
v_o = \sum_{o' \in N(o)} \alpha(v_{o_p}, v_{o'}) v_{o'},
\]

where \( v_o, v_{o_p}, v_{o'} \in \mathbb{R}^d \) denote the embeddings of \( o, o' \)’s target node \( o_p \), and the historical interacted counterpart \( o' \) from \( o \)’s neighbor set \( N(o) \), e.g., node \( u_2 \), node \( i_2 \) and node set \( \{i_1, i_3, i_4\} \) in Fig. 2(b), respectively. Coefficient \( \alpha(v_{o_p}, v_{o'}) \) is calculated as:

\[
\alpha(v_{o_p}, v_{o'}) = \frac{\exp(v_{o_p}^T v_{o'})}{\sum_{o' \in N(o)} \exp(v_{o_p}^T v_{o'})}.
\]

Intuitively, the encoding process of node \( o \)’s embedding dynamically adjusts the information compositions from historical interactions, i.e., \( N(o) \), whilst considering their matching relevance with the specific node \( o' \), i.e., \( \alpha(v_o, v_{o'}) \).

4.3 Attentive Knowledge Encoding

In addition to learning interaction information, we also explore the KG structure and explicitly propagate the knowledge therein to enrich the embedding semantics for both users and items. Specifically, we propose Attentive Knowledge Encoding, which employs the (1) K-hop Knowledge Sampling and (2) Knowledge Encoding accordingly.

4.3.1 K-hop Knowledge Sampling

We first sample node \( o \)’s distant entity-neighbors, via recursively exploring the knowledge triplets, e.g., \( (h, r, t) \in \mathcal{G} \), in \( K \) hops of KG substructures:

\[
\mathcal{E}_o^k = \{(h, r, t) \in \mathcal{G} \text{ and } h \in \mathcal{E}_{o'}^{k-1} \}, \quad k = 1, 2, \ldots, K,
\]

where \( k \) indicates the distance from the initial neighbor set of users and items, e.g., \( \mathcal{E}_u^0 \) and \( \mathcal{E}_i^0 \), that are defined as follows:

\[
\mathcal{E}_u^0 = \{e|[(i, e) \in \mathcal{G}, (u, i) \in \mathcal{G}], \mathcal{E}_i^0 = \{e|(u, e) \in \mathcal{G}, (u, i) \in \mathcal{G} \}.
\]

For example, as shown in Fig. 2(a), let \( o = u_1 \), the initial entity-neighbor set and 1-hop entity-neighbor set of \( u_1 \) is \( \mathcal{E}_{u_1}^0 = \{i_1, i_2\} \) and \( \mathcal{E}_{u_1}^1 = \{e_1, e_2, e_3\} \), respectively. Then based on these KG substructures, we define the fixed-size knowledge triple sampling set from \( \mathcal{E}_o^k \) as follows:

\[
\mathcal{T}_o^k = \{(h, r, t)|h \in \mathcal{E}_o^{k-1}\}, \quad k = 1, 2, \ldots, K.
\]

4.3.2 Knowledge Encoding

Based on sampled knowledge associations, e.g., \( (h, r, t) \in \mathcal{T}_o^k \), we learn the knowledge-aware embeddings for \( o \):

\[
v_o^k = \sum_{(h, r, t) \in \mathcal{T}_o^k} \pi(v_h, v_r) v_t, \quad k = 1, 2, \ldots, K,
\]

where coefficient \( \pi(v_h, v_r) \) is attentively calculated as:

\[
\pi(v_h, v_r) = \frac{\exp(\text{mlp}(v_h|v_r))}{\sum_{(h', r', t') \in \mathcal{T}_o^k} \exp(\text{mlp}(v_{h'}|v_{r'}))}.
\]

Notation \( || \) denotes the concatenation operation. \( v_h, v_t \in \mathbb{R}^d \) are the embeddings of head entity \( h \) and tail entity \( t \). \( v_r \in \mathbb{R}^d \) is the embeddings of relation \( r \). \text{mlp}(\cdot) is implemented by a two-layer MLP with the nonlinear activation RELU \([41]\).

Notice that the attention mechanism in encoding our knowledge-aware embeddings (Equations (6)–(7)) provides the relevance calibration functionality to tail entity \( t \) by considering the semantics of head entity \( h \) and relation \( r \). For example, knowledge triplets (SpaceX, Founded by, Elon Musk) and (Iron Man 2, Guest Performed by, Elon Musk) exhibit two different roles of tail entity “Elon Musk”, which thus calibrates its knowledge relevance in embedding encoding. Furthermore, by increasing \( k \) from 1 to \( K \), we can achieve the high-order knowledge encoding in deeper KG structures, which substantially enriches the embedding semantics to improve the cold-start recommendation performance.
After learning the embeddings from interactive (§ 4.2) and KG sides (§ 4.3), we then condense them into a 2d-dimensional embeddings as follows:

\[ v_o^* = v_o \| \text{mean}(\{v_k\}_{k=1}^K). \] (8)

Intuitively, embedding \( v_o^* \in \mathbb{R}^{2d} \) collects information from both data sides, making the preparation for next-stage Personalized Feature Referencing, which specializes the customized feature enrichment to nodes with sparse interactions.

### 4.4 Personalized Feature Referencing

**Motivation.** The conventional methodology to alleviate the cold-start issue usually focuses on the simulation on interaction graph structures to increase interaction density, e.g., via random walk [7]. However, it relies on the local topology exploration, and may thus fail to find those structurally distant but semantically similar node candidates. On the contrary, thanks to the rich semantic supplementation from both interactive and KG sides, we seek to achieve such a candidate probing process mainly in the embedding space, where both structural and semantic information are well encoded.

**Challenges.** A straightforward implementation would be performing certain clustering algorithms, e.g., K-means [42], to locate node candidates that are near the cluster centroids, as these centroids are usually more representative to present unique semantics than other ordinary nodes. Despite the straightforwardness, we argue that this trivial implementation may contain several inadequacies, which may lead to sub-optimal recommendation performance: (1) These clustering methods usually proceed independently of the personalized recommendation. Since users have diverse item-preferences (like users possess various attracting-groups to users), a unified candidate selection approach may however be too coarser-grained especially for personalized recommendation. (2) Moreover, aside from the difference in users’ preferences and items’ attractiveness, the number of the desired candidates should also vary for different users and items. However, the existing clustering methods may hardly provide such customization, e.g., by detecting whether a user has a wide or narrow interest coverage; otherwise, the manual pruning may be extremely resource-expensive.

To address these issues, we propose an adaptive candidate probing method, which enables the effective searching for semantic focused and coverage pruned seeds (a.k.a. users or items that are used for information referencing). To furnish a tractable model training, we then introduce an advanced continuous approximation approach for it and finally we explain the information aggregation procedure to enrich the user-item representations for cold-start recommendation.

#### 4.4.1 Adaptive Seed Probing

To avoid the exhaustive search over the whole node corpus, we firstly collect a small range of nodes as the initial seed pool \( S \), where \( |S| \ll |G| \). Since cold-start interaction graphs usually follow the long-tailed distribution w.r.t. node degrees [43], similar to work [44], we obtain \( S \) by excluding tailored-nodes and pick those with high popularity (implementation details are reported in § 6.5 of experiments). Then for all seeds in \( S \), we build an additional embedding table as follows:

\[ \{t_1, t_2, \cdots, t_{|S|}\}. \] (9)

These embeddings demonstrate the representative features of highly-interacted users and items, providing the functionality of information aggregation for “cold” nodes with very limited interactions. Similar to [45], [46], we separate these feature referencing embeddings out of those learned in previous encoding sections, e.g., knowledge encoding in Equation (5), mainly to prevent issues such as over-training.

Then for any node \( o \), we expect our model to train an indicator \( z_o \in \{0, 1\}^{|S|} \), in which each 1-valued entry indicates that the seed in this position is selected. Furthermore, to prevent seed redundancy or even noise, these seeds are not only representative but also expected to be concise and precise. To achieve this, we can minimize the objective in Equation (10) to sparsify \( z_o \) (i.e., as few 1-valued entries as possible), by penalizing the number of non-zero entries in \( z_o \):

\[ ||z_o||_0 = \sum_{x=1}^{|S|} I([z_o]_x \neq 0). \] (10)

Here \( I \) counts the number of 1-valued entries in \( z_o \). Then in the holistic training objective, we can further maximize the recommendation accuracy, which eventually makes a trade-off between recommendation performance and seed-searching pruning. However, directly optimizing the objective in Equation (10) is computationally intractable, mainly because its non-differentiability. Thus to address this issue and provide more stable model training, we introduce an advanced solution with the continuous approximation in the following section.

#### 4.4.2 Continuous Approximation

To provide the accordant continuous approximation, we first learn a sequence of continuous scores \( \beta_o \), measuring the selection confidence of seeds in \( S \):

\[ \beta_o = \exp(\langle Wv_o^* + b, \rangle), \] (11)

Where \( W \in \mathbb{R}^{|S| \times 2d} \) and \( b \in \mathbb{R}^{|S|} \) are the learnable parameters. \( v_o^* \) is learned from previous stage in Equation (8), bridging the information learnt from historic interactions (§ 4.2) and knowledge associations (§ 4.3). Then, based on the learned \( \beta_o \), one of trustworthy approaches for relaxing discrete parameters [47], [48] is to explicitly smooth each binary entry in \( z_o \) correlated by certain random variables, e.g., \( \gamma_o \in \mathbb{R}^{|S|} \). Specifically, \( \gamma_o \) is a concrete random variable drawn from:

\[ \gamma_o = \sigma((\log \xi - \log (1 - \xi) + \log \beta_o) / \tau), \xi \sim \text{Uniform}(0, 1), \] (12)

where \( \sigma(\cdot) \) is the sigmoid function and \( \tau \) is the temperature. Since the entries of \( \gamma_o \) ranges in \((0, 1)\), to force those entries of undesired seeds to be exactly 0, we further rescale their ranges to \((\eta, 1)\), with the parameter \( \eta < 0 \):

\[ \bar{\gamma}_o = (1 - \eta)\gamma_o + \eta, \] (13)

Please notice that in practice we implement \( \bar{\gamma}_o \) into two disjoint sets for users and items, respectively. Without loss of generality, their corresponding seed probing processes can be interpreted via the placeholder \( o \) as follows.
which enables the negative entries to be rounded to 0. Then we
obtain our approximated indicator \( z_o \) as follows:
\[
z_o = \max(\gamma_o, 0).
\]
(14)

By developing such continuous relaxation for computa-
tional stable model training, we can effectively learn a
combinatorial seed allocation for personalized information
referencing, whilst achieving the target of search space
pruning in \( S \).

4.4.3 Gated Information Aggregation

Based on the learned seed indicator \( z_o \), we now proceed
to the combinatorial information aggregation for feature
referencing as follows:
\[
t_o^* = \begin{cases} t_o, & \text{if } o \in S \text{ with id a}, \\ \sum_{x=1}^{\vert S \vert} \text{softmax}_x((z_o)_x) t_x, & \text{otherwise}. \end{cases}
\]
(15)

In order to automatically aggregate information for the
“cold” nodes with sparse interactions, inspired by the Gated
Recurrent Unit (GRU) [49], we design the neural Gated
Information Aggregation module:
\[
v_o^+ = \frac{\exp(c_1)}{\exp(c_1) + \exp(c_2)} v_o^* + \frac{\exp(c_2)}{\exp(c_1) + \exp(c_2)} t_o^*.
\]
(16)

where gate signals \( c_1 \) and \( c_2 \) balances the information
contribution, and they can be calculated as follows:
\[
c_1 = q^\top \sigma(W_e v_o^* + b_e), \quad c_2 = q^\top \sigma(W_e t_o^* + b_e).
\]
(17)

\( W_e \in \mathbb{R}^{d \times 2d}, b, q \in \mathbb{R}^d \), are the learnable parameters. As
we can observe from Equation (15), our proposed fusion
gate mechanism can adaptively control the information
integration from two parts, i.e., \( v_o^* \) and \( t_o^* \). And it can prevent
information overload issue especially for those nodes which
are with neutral or even far-from-urgent cold-start recommen-
dation demands. As we will show later in Experiment § 6.4,
our model can thus perform consistently well across all user-
item groups with different interaction density.

4.5 Model Prediction and Optimization

Model Prediction. We package the multiple embedding seg-
ments from Interactive Information Encoding (§ 4.2), Knowledge
Encoding (§ 4.3), and Personalized Feature Referencing (§ 4.4)
into a unified representation:
\[
h_o = v_o || \{ v^{k}^k \}_{k=1}^K || v_o^+.
\]
(18)

Then to estimate the matching probability between a user \( u \)
and item \( i \), we naturally adopt the inner-product as follows:
\[
y_{u,i} = h_u^\top h_i.
\]
(19)

Model Optimization. Our objective function for model
optimization mainly consists of two loss terms:

- \( \mathcal{L}_{CE} \): the cross-entropy loss reconstructs the observed
  interactive topology;
- \( \mathcal{L}_{SP} \): a penalty term sparsifies the personalized seed probing.

Concretely, we implement \( \mathcal{L}_{CE} \):
\[
\mathcal{L}_{CE} = \sum_{u \in U} \left( \sum_{i \in \{ Y_o^+, Y_o^- \}} J(y_{u,i}, \hat{y}_{u,i}) \right).
\]
(20)

\( \mathcal{L}_{SP} \) denotes the positive (ground-truth) interacted items of
user \( u \) and \( \mathcal{L}_{SP}^- \) the negative item set, where \( |Y_o^+| = |Y_o^-| \).
As for \( \mathcal{L}_{SP} \), we first introduce its formulation in Equation
(21) and report the detailed derivation process in later section § 5.

\[
\mathcal{L}_{SP} = \sum_{o \in \{U \cup I\}} \sum_{s=1}^{\vert S \vert} \sigma \left( \log \left( \left| \beta_o \right| S \right) - \tau \log(-\eta) \right).
\]
(21)

Based on these two loss terms, we build up our final
objective function as follows:
\[
\mathcal{L} = \mathcal{L}_{CE} + \lambda_1 \mathcal{L}_{SP} + \lambda_2 \| \Theta \|_2^2.
\]
(22)

where \( \Theta \) is the set of all trainable parameters, and \( \| \Theta \|_2^2 \) is
the \( L_2 \)-regularizer parameterized by \( \lambda \) to avoid over-fitting.
So far, we have introduced all the technical parts of our
model KPER. We attach the pseudo-codes in Algorithm 1
and formally report the model analysis in the following section.

5 ANALYSIS OF OPTIMIZING SEED PROBING

The initial objective function for optimizing binary indicators
can be formulated as follows:
\[
\mathcal{L}_{SP} = \sum_{o \in \{U \cup I\}} \sum_{s=1}^{\vert S \vert} I[\{z_o\}_s \neq 0],
\]
(23)

which however, as we have mentioned before, it could be
computationally intractable to directly optimize. To tackle
this issue, we introduce the continuous relaxation. Then the
corresponding objective function can be re-formulated:
\[
\mathcal{L}_{SP} = \sum_{o \in \{U \cup I\}} \sum_{s=1}^{\vert S \vert} (1 - P(\gamma_o)_s(0)).
\]
(24)
Here the notation $\mathbb{P}(\gamma_x) \sim (0)$ denotes the cumulative distribution function (CDF) of the rescale scalar $(\gamma_x)$. And thus Equation (24) provides the equivalent functionality of penalty on the number of non-zero entries that is originally posted in Formulation (23). Moreover, as shown in [20], the probability distribution function (PDF) and CDF of unrescaled scalar $(\gamma_x)_{x}$ are respectively derivatived as:

$$ p(\gamma_x) = \frac{\tau(\beta_o) x_{r-x}(1-r)^{r-1}}{((\beta_o) x_{r-x} + (1-r)^{r})^2} \quad \mathbb{P}(\gamma_x) = \sigma((\log r - log(1-r))\tau - log(\beta_o)) .$$

Due to the monotonicity of the rescaling operation in Equation (13) letting notation $g(r) = (1 - \eta) r + \eta$, the PDF of $(\gamma_x)$ can be derived as:

$$ p(\gamma_x) = p(\gamma_x) \cdot \frac{\partial}{\partial \eta} g^{-1}(r)$$

$$ = (1 - \eta) \tau(\beta_o) x_{r-x} (r-\eta)^{-1} (1-r)^{-r} \quad \mathbb{P}(\gamma_x) = \sigma((\log r - log(1-r))\tau - log(\beta_o)) .$$

Similarity, the CDF of $(\gamma_x)$ is:

$$ \mathbb{P}(\gamma_x) = \mathbb{P}(\gamma_x) \cdot \frac{\partial}{\partial \eta} g^{-1}(r)$$

By setting $r = 0$, $L_{SP}$ can be finally reformulated as:

$$ L_{SP} = \sum_{o \in \{(U \cup I) \}} \sum_{i=1}^{S} \sigma(\log(\beta_o) - \tau \log(\eta)) .$$

### 6 Experiments

We formally evaluate our proposed KPER model with the aim of answering the following research questions:

**RQ1**: How does KPER perform compared to the state-of-the-art counterparts in general recommendation scenarios?

**RQ2**: How does KPER specialize in the cold-start scenario?

**RQ3**: How does our proposed Personalized Feature Reference Mechanism strengthen KPER’s performance?

**RQ4**: What is the effect of each model component?

**RQ5**: How do hyper-parameter settings affect KPER?

### 6.1 Datasets

We include four public real-life datasets from: Last.FM for music recommendation, Book-Crossing for book recommendation, MIND for news recommendation, and Dianping-Food for restaurant recommendation. These four datasets are widely evaluated in recent works [31, 4, 10, 50] and we report the dataset statistics in Table 2.

| Music | Book | News | Restaurant |
|-------|------|------|------------|
| # users | 1,872 | 1,960 | 299,955 | 2,298,698 |
| # items | 3,846 | 14,967 | 47,034 | 1,362 |
| # interactions | 42,346 | 139,746 | 5,090,654 | 23,416,418 |

**MIND** (News) [3] is collected from anonymized behavior logs of Microsoft News website. The construction of MIND’s KG is based on [spacy-entity-linker](https://spacy.io/) tool and [Wikidata](https://www.wikidata.org/).

**Dianping-Food (Restaurant)** [10] is provided by Dianping.com, which including over 10 million interactions (including clicks, purchases, and adding to favorites) between around two million users and one thousand restaurants. The corresponding KG is constructed by the internal toolkit of Meituan-Dianping Group.

### 6.2 Baselines

We compare KPER with two streams of recommender models: previous non-KG CF-based models (BPRMF, NFM, LightGCN) and recent KG-based recommender models (CNE, RippleNet, KGAT, CKAN, CG-KGR, KGPL, MetaKG).

- **BPRMF** [52] is a classical CF-based method that performs matrix factorization with a pairwise ranking loss.
- **NFM** [53] is a neural factorization machine model for collaborative filtering which utilizes the multi-layer perceptrons to model the feature interaction.
- **LightGCN** [19] is a recent recommender model that achieves the state-of-the-art performance. It learns user-item representations with graph convolution networks and omits feature transformation and nonlinear activation, making it easier to be trained and more effective.
- **CNE** [33] is a representative KG-based model. It applies TransR [54] to extract semantic representations from structural, textual and visual knowledge. These semantic representations are jointly learned in a unified framework.
- **RippleNet** [3] is a classical work that automatically propagates users’ potential preferences along the links in KGs.
- **KGAT** [4] is one representative model that extends graph convolutions on KGs with an attention mechanism to jointly trained with KG embeddings with interaction embeddings.
- **CKAN** [5] is one of the latest model that explicitly encodes collaborative signals from user-item interactions and combines them with KG associations for better recommendation.
- **CG-KGR** [20] is another state-of-art recent method which encodes the collaborative signals as guidance in KGs for personalized recommendation.
In Top-K recommendation, we apply the trained model to select K items for each user in the test set. We rescale the estimated score \( \hat{y}_{u,i} \) via the sigmoid function and assign the click rate to 0 or 1 with the threshold 0.5. We choose AUC as the evaluation metric.

To present reproducible and stable results, we follow the previous work \[20\] to randomly split each dataset 4 times into training, validation, and test sets with the ratio of 6:2:2. Our proposed KPER is implemented under Python 3.8 and Pytorch 1.7.1 with non-distributed training. The experiments are conducted on a server with Intel(R) Xeon(R) Platinum 8276, 2.20GHz CPU, 256GB RAM, and 4 NVIDIA A100 GPUs. For all the baselines, the hyper-parameter settings follow the original papers/codes by default or are tuned from the empirical studies. In our KPER, the learning rate is tuned among \( \{10^{-3}, 5 \times 10^{-3}, 10^{-2}, 5 \times 10^{-2}\} \). And we search \( \eta, \lambda_1, \lambda_2 \) within the range of \( \{-1.0, -0.9, \ldots, 0.1\}, \{10^{-4}, 10^{-3}, 10^{-2}\}, \) and \( \{10^{-5}, 10^{-4}, 10^{-3}\} \), respectively. We initialize and optimize all models with default Xavier initializer \[58\] and Adam optimizer \[59\].

#### 6.3 Evaluation Metrics and Experiment Setup

We consider two evaluation tasks. (1) Top-K recommendation, and (2) Click-through rate (CTR) prediction.

- **In Top-K recommendation**, we apply the trained model to select K items from the test set. We rescale the estimated score \( \hat{y}_{u,i} \) via the sigmoid function and assign the click rate to 0 or 1 with the threshold 0.5. We choose AUC as the evaluation metric.

- **In CTR prediction**, we use the trained model to predict the binary matching decision of each user-item pair from the test set. We rescale the estimated score \( \hat{y}_{u,i} \) via the sigmoid function and assign the click rate to 0 or 1 with the threshold 0.5. We choose AUC as the evaluation metric.

To present reproducible and stable results, we follow the previous work \[20\] to randomly split each dataset 4 times into training, validation, and test sets with the ratio of 6:2:2. Our proposed KPER is implemented under Python 3.8 and Pytorch 1.7.1 with non-distributed training. The experiments are conducted on a server with Intel(R) Xeon(R) Platinum 8276, 2.20GHz CPU, 256GB RAM, and 4 NVIDIA A100 GPUs. For all the baselines, the hyper-parameter settings follow the original papers/codes by default or are tuned from the empirical studies. In our KPER, the learning rate is tuned among \( \{10^{-3}, 5 \times 10^{-3}, 10^{-2}, 5 \times 10^{-2}\} \). And we search \( \eta, \lambda_1, \lambda_2 \) within the range of \( \{-1.0, -0.9, \ldots, 0.1\}, \{10^{-4}, 10^{-3}, 10^{-2}\}, \) and \( \{10^{-5}, 10^{-4}, 10^{-3}\} \), respectively. We initialize and optimize all models with default Xavier initializer \[58\] and Adam optimizer \[59\].
- Incorporating KGs is effective to improve the model performance in general Top-K recommendation. The performance comparison between KG-based models and non-KG based counterparts confirms the helpfulness of incorporating KGs to compensate for semantic features in collaborative filtering. (1) On one hand, for non-KG based methods, NFM and LightGCN outperform BPRMF in the most of datasets, mainly because their neural networks can effectively capture higher-order interaction information and thus facilitate the performance improvement. (2) On the other hand, while several knowledge-aware methods (i.e., KGAT, CKAN and CG-KGR) perform well among all the baselines, the recent work KGPL performs the best in Music and Book datasets. One explanation is that KGPL is capable of giving higher credits to the Top-K positive samples in sparse and small-scaled datasets, via their proposed pseudo-labelling approach, as we introduced in §2. However, for larger datasets, i.e., News and Restaurant, such exhaustive label assignments is inefficient and may be difficult to guarantee the validity of the labels.

- The results of Top-10 recommendation prove that KPER achieves significant and stable performance improvement. (1) As shown in Table 3 on Music, Book, News, and Restaurant datasets, KPER improves over the state-of-the-art methods w.r.t. Recall@10 by 3.90%, 13.06%, 0.81%, and 16.08%, as well as Precision@10 by 5.53%, 14.49%, 1.01%, and 4.13%. The corresponding standard deviations suggest that our model's results are on the same level of stability as these baselines. (2) Moreover, the Wilcoxon signed-rank tests also verify that the KPER's improvement over the second-best model across most datasets are statistically significant over 95% confidence level.

- As K increases, KPER consistently shows the competitive performance compared to the baselines. (1) By performing our proposed candidate probing in the embedding space, where both structural and semantic information are well encoded, our model KPER is proved to be effectively capable of learning representative feature enrichment for to user-item interactions. (2) Furthermore, we notice that the improvement of KPER on Book and Restaurant datasets are higher than that of on Music and News datasets. This demonstrates the effectiveness of our proposed model for “cold” user recommendation with sparse interactions, i.e., \( \frac{\text{#interactions}}{\text{#users}} \). For example, users in Book and Restaurant present 7.82 and 10.19 average interactions, while for the other two dataset Music and News, the average interactions are 22.62 and 16.97. In §6.5, we formally analyze KPER performance in cold-start recommendation scenario.

6.4.2 CTR Prediction

In addition, we also validate the performance of our model on the CTR prediction task and present the results in Table 4. (1) Compared to these state-of-the-art baselines, KPER achieves strongly competitive and stable performance. Specifically, KPER improves the baselines on Music and Book datasets w.r.t. AUC by 3.61% and 4.24% with low variance, respectively. (2) On News and Restaurant datasets, KPER achieves the second-best performance and slightly underperforms CG-KGR by -0.46% and -0.61%. (3) Compared to Top-K recommendation task, this performance difference on CTR prediction is much smaller than that in Top-K recommendation. This is because our KPER so far is trained for ranking tasks, i.e., Top-K recommendation, via encouraging model to learn the ranking, especially for Top-K recommendation. On the contrary, The model CTR prediction capability can be generally trained towards the pairwise classification problem, by making the judgement whether a user-item interaction exists. (4) To further improve the CTR prediction performance as future work, one promising direction would be integrating curriculum learning paradigm to gradually improve the classification capability especially for hard negative samples.

### Table 4

| Model | Music AUC(%) | Book AUC(%) | News AUC(%) | Restaurant AUC(%) |
|-------|--------------|-------------|-------------|-------------------|
| BPRMF | 79.49 ± 0.11 | 65.12 ± 0.51 | 93.85 ± 0.05 | 81.81 ± 0.03     |
| NFM   | 80.09 ± 0.26 | 73.75 ± 0.61 | 94.69 ± 0.02 | 87.26 ± 0.01     |
| CKE   | 83.16 ± 0.18 | 64.40 ± 0.07 | 94.33 ± 0.01 | 85.14 ± 0.09     |
| RippleNet | 81.00 ± 0.49 | 71.44 ± 1.03 | 94.68 ± 0.03 | 85.54 ± 0.17     |
| KGAT  | 83.38 ± 0.26 | 71.19 ± 0.27 | 94.78 ± 0.08 | 87.22 ± 0.15     |
| CKAN  | 83.86 ± 0.20 | 74.63 ± 0.27 | 93.25 ± 0.09 | 87.77 ± 0.01     |
| CG-KGR | 82.52 ± 0.42 | 75.73 ± 0.31 | 95.28 ± 0.02 | 89.58 ± 0.04     |
| LightGCN | 84.10 ± 0.14 | 67.02 ± 0.25 | 93.70 ± 0.01 | 89.28 ± 0.05     |
| MetaKG | 84.24 ± 0.19 | 71.13 ± 0.43 | 93.50 ± 0.03 | 86.65 ± 0.77     |
| KGPL  | 84.40 ± 0.38 | 73.64 ± 0.47 | 94.46 ± 0.09 | 84.83 ± 0.09     |

6.5 Comparison in Cold-Start Scenario (RQ2)

6.5.1 Analysis on Cold Users

To investigate the performance of “cold” users with limited interactions, we split all users into three groups based on descending popularity, while keeping the total number of interactions for each group the same. The sparsity decreases from group-1 to group-3. We consider users in group-3 as cold users, group-2 for normal users, and group-1 for warm users. We evaluate on the task of Top-K recommendation. On the contrary, The model CTR prediction capability can be generally trained towards the pairwise classification problem, by making the judgement whether a user-item interaction exists. (4) To further improve the CTR prediction performance as future work, one promising direction would be integrating curriculum learning paradigm to gradually improve the classification capability especially for hard negative samples.
indicating that a straightforward model adaptation may not be effective.

### 6.5.2 Analysis on Cold Items

We also justify the effectiveness of KPER for “cold” items with limited popularity, we follow [60] to adopt Popularity Stratified Recall@K (denoted as $PSR@K$) metric as follows:

$$\frac{\sum_{u \in U} \sum_{i \in T_u^{rec} \cap T_u^{test}} \left( \frac{1}{N_i^u} \right)^{\beta}}{\sum_{u \in U} \sum_{i \in T_u^{test}} \left( \frac{1}{N_i^u} \right)^{\beta}},$$

where $T_u^{rec}$ and $T_u^{test}$ are user $u$'s predicted items in the Top-K recommendation list and historical interacted items, respectively. $N_i^u$ is the number of relevant ratings for item $i$, and $\beta$ is a hyperparameter that adjusts for the popularity bias. Higher values of $PSR@K$ indicate that more relevant cold items are recommended. In our experiments, we used $\beta = 0.1$. The corresponding results are reported in Table 5 where the Top-K PSR values on four datasets are respectively denoted by M-$PSR@10$, B-$PSR@10$, N-$PSR@10$, and R-$PSR@10$.

As shown in Table 5, graph-based methods (e.g., LightGCN, KAG, CG-KGR, and KGPL) generally achieve competitive performance. This is because the graph neural networks are able to capture higher-order node proximity and thus are beneficial to model implicit relations in the cold-start scenario. But most importantly, compared to these baseline models, KPER significantly improves the performance w.r.t. $PSR@10$ by 5.36%, 13.33%, 1.20%, and 17.80%, respectively. This shows that KPER is capable to retrieve those temporarily less popular actually relevant items to users, demonstrating its superiority in alleviating the cold-start problem.

### 6.6 Personalized Feature Referencing Analysis (RQ3)

We formally investigate the effectiveness of our Personalized Feature Reference Mechanism. We first provide a detailed ablation study and then give a case study for visualization.

#### 6.6.1 Ablation Study

To differentiate the effect of our personalized seed probing, we provide the following analysis:

- We first set three variants KPER$_{Random}$, KPER$_{Kmeans}$, and KPER$_{All}$. KPER$_{Random}$ randomly samples the nodes from seed pool $S$ (84). KPER$_{Kmeans}$ employs K-means as the seed probing method. KPER$_{All}$ brutally takes all nodes in $S$ for computation. We fix $|S| = 128$ for fair comparison. From the results in Table 6, we observe that KPER$_{Kmeans}$ performs better than KPER$_{Random}$ in most cases. This generally follows the intuition that centroids-nearby nodes are usually more representative to present unique semantics than other randomly selected ones. Furthermore, although KPER$_{All}$ performs slightly better than KPER$_{Random}$ on Music and Book datasets, it underperforms others on larger datasets, i.e., News and Restaurant, while not only may introduce noise but also increase the heavy computational burden to the model training. By contrast, our proposed adaptive approach makes a good balance between performance stability across different datasets and seed allocation concision for computation ease.

- We also study how the encoded information affects the seed probing process. We introduce two variants, i.e., KPER$_{Partial-inter}$ and KPER$_{Partial-KG}$, by partially using one side of information, i.e., from interaction side only and KG side only. As we can observe from Table 6, partially utilizing information may lead to the sup-optimal model learning and thus impede KPER performance.

#### 6.6.2 Case Study

To visualize the effect of our proposed Adaptive Seed Probing, we take a real case from Book dataset in Fig. 5. By adaptive seed probing, our model can well customize to find 334 and 382 candidates for item $i_{3826}$ and item $i_{10121}$, respectively. By assignatively assigning the weight 0.011 item $i_{3826}$ to seed $i_{407}$, KPER highlights the strong confidence of information referencing and pays a less attention to seed $i_{5405}$ with a lower weight 0.00097. This example visually shows that, endorsed by our proposed Adaptive Seed Probing approach, KPER can well distinguish the semantically similar nodes (i.e., seed $i_{407}$) out of dissimilar one (i.e., seed $i_{3826}$). As for the item $i_{10121}$, the weights regarding to three seeds (i.e., $i_{2487}$, $i_{1998}$, and $i_{4864}$) show the similar confidences and thus these three seeds equally contribute to information reference for the item $i_{10121}$.
6.7 Ablation Study of KPER (RQ4)
To validate the effectiveness of different parts in KPER, we conduct a comprehensive ablation study on the task of Top-K recommendation task and report the results in terms of Recall@10 and Precision@10 on four datasets.

| Dataset | w/o Inter | w/o KG-att | w/o Ref | KPER |
|---------|-----------|-------------|---------|------|
| M-R@10(%) | 18.64 (9.16%) | 17.49 (4.47%) | 19.10 (4.92%) | 20.32 |
| M-P@10(%) | 4.35 (2.03%) | 4.20 (1.66%) | 4.34 (1.36%) | 4.96 |
| B-R@10(%) | 7.16 (3.15%) | 6.49 (3.09%) | 2.90 (0.41%) | 7.27 |
| B-P@10(%) | 1.45 (0.82%) | 1.27 (0.45%) | 0.72 (0.20%) | 1.58 |
| N-R@10(%) | 4.47 (0.42%) | 4.68 (0.42%) | 3.20 (0.30%) | 4.99 |
| N-P@10(%) | 0.95 (5.06%) | 0.96 (4.00%) | 0.76 (2.00%) | 1.00 |
| R-R@10(%) | 13.15 (29.66%) | 16.02 (44.3%) | 15.47 (37.2%) | 18.70 |
| R-P@10(%) | 3.63 (9.86%) | 3.58 (9.17%) | 3.60 (9.67%) | 4.03 |

Effect of Interactive Information Encoding. We first verify the effectiveness of interactive information encoding (§4.2). The variant w/o Inter, discards our attentive approach to simply average the historical interacted embeddings in aggregation. As shown in Table 7, the performance degradation of w/o Inter justifies the effectiveness of interactive information in improving KPER performance across all datasets.

Effect of Attentive Knowledge Encoding. We move on to studying the effect of our knowledge-aware attentive encoding module (§4.3) by replacing the original attention mechanism to force the knowledge triples to contribute equally. We denote it as w/o KG-att. As we can observe, variant w/o KG-att confronts a conspicuous performance decay, which shows that our knowledge-aware attentive encoding provides an effective approach to extract knowledge from KGs and thus benefits the recommendation performance.

Effect of Personalized Feature Referencing Mechanism. We use a variant, i.e., w/o Ref, To substantiate the impact of our Personalized Feature Referencing (§4.4), by totally removing this module in model training. From Table 7 we find that the performance of w/o Ref dramatically degrades across all datasets. This supports that our proposed feature referencing is a powerful determinant, enabling KPER to detect potential similar candidates for each user/item, and further improve the recommendation performance.

6.8 Hyper-parameter Analysis (RQ5)
Sampling in Interactive Information Encoding. We investigate the effect of neighbor sampling in interactive information encoding, and take user nodes are examples to conduct the experiments. The results are presented in the left-part of Table 8. We notice that: a larger number of sample size, denoted as l, (or even the whole node neighborhood) is not a guarantee for a better performance. The best performance is obtained when l is 16, 8, 8, 16, respectively. One reasonable explanation is that heavy repetitive sampling on sparse datasets leads to overfitting, which has the negative impact on the model training.

| Dataset | l = 8 | l = 16 | l = 32 |
|---------|------|------|------|
| M-R@10(%) | 19.58 | 20.52 | 19.40 |
| M-P@10(%) | 4.25 | 4.96 | 4.51 |
| B-R@10(%) | 7.27 | 6.14 | 7.19 |
| B-P@10(%) | 1.58 | 1.12 | 1.42 |
| N-R@10(%) | 4.99 | 4.86 | 4.14 |
| N-P@10(%) | 1.00 | 0.96 | 0.71 |
| R-R@10(%) | 18.11 | 18.70 | 17.36 |
| R-P@10(%) | 3.89 | 4.03 | 3.79 |

Depth of Attentive Knowledge Encoding. In the second part of Table 8 we further present the evaluation results of different knowledge extraction depths, by varying K from 0 to 3 and 0 means no information aggregated from KGs. KPER achieves the best performance when K is 2, 2, 1, and 1 for all benchmarks, respectively. One possible reason for this phenomenon is that a longer distance information propagation may incur more noise, especially on large datasets and
maintaining a appropriate depth of knowledge encoding can ultimately maximize the recommendation performance.

7 Conclusion & Future Work

In this paper, we propose a novel knowledge-graph-based recommender model KPER, towards the alleviation of cold-start problem. The core mechanism, namely Personalized Feature Referencing, enables an effective latent feature enrichment to user-item representations, while getting rid of the interaction sparsity constraint. The extensive experiments well demonstrate the model effectiveness in both general and cold-start recommendation scenarios.

In the future, we plan to investigate two major possible directions. (1) It is worth further improving KPER by adopting different learning paradigms, e.g., curriculum learning. (2) We may extend our methodology to session recommendation or sequential recommendation, in which modeling the sequential interactive trajectory may be harder to capture and predict in cold-start scenarios.

References

[1] R. Ying, R. He, K. Chen, P. Eksombatchai, W. L. Hamilton, and J. Leskovec, “Graph convolutional neural networks for web-scale recommender systems,” in 24th ACM SIGKDD, 2018, pp. 974–983.

[2] A. Pfafleder, H. Zhao, J. Wang, L. Wang, P. Huang, and D. L. Lee, “Billion-scale recommendation with heterogeneous side information at taobao,” in 36th IEEE ICDE, 2020, pp. 1667–1676.

[3] H. Wang, F. Zhang, J. Wang, M. Zhao, W. Li, X. Xie, and M. Guo, “RippleNet: Propagating user preferences on the knowledge graph for recommender systems,” in 27th ACM CIKM, 2018, pp. 417–426.

[4] Y. Wang, X. He, Y. Cao, M. Liu, and T.-S. Chua, “Kgat: Knowledge graph attention network for recommendation,” in 25th ACM SIGKDD, 2019, pp. 950–958.

[5] Z. Wang, G. Lin, H. Tan, Q. Chen, and X. Liu, “Ckan: Collaborative knowledge-aware attentive network for recommender systems,” in 43rd ACM SIGIR, 2020, pp. 219–228.

[6] Y. Chen, M. Yang, Y. Zhang, M. Zhao, Z. Meng, J. Hao, and I. King, “Modeling scale-free graphs with hyperbolic geometry for knowledge-aware recommendation,” in 15th ACM WSDM, 2022, pp. 94–102.

[7] R. Togashi, M. Otani, and S. Satoh, “Alleviating cold-start problems in recommendation through pseudo-labelling over knowledge graph,” in 14th ACM WSDM, 2021, pp. 931–939.

[8] Y. Du, L. Zhu, L. Chen, Z. Fang, and Y. Guo, “Meta-learning on knowledge graph for cold-start recommendation,” IEEE TKDE, 2022.

[9] Y. Lu, Y. Fang, and C. Shi, “Meta-learning on heterogeneous information networks for cold-start recommendation,” in 26th ACM SIGKDD, 2020, pp. 1563–1573.

[10] C. start (recommender systems), 2022, https://en.wikipedia.org/wiki/Cold_start (recommender systems).

[11] B. Hu, C. Shi, W. X. Zhao, and P. S. Yu, “Leveraging meta-path based context for top-n recommendation with a neural co-attention model,” in 24th ACM SIGKDD, 2018, pp. 1531–1540.

[12] Y. Cao, X. Wang, X. He, Z. Hu, and T.-S. Chua, “Unifying knowledge graph learning and recommendation: Towards a better understanding of user preferences,” in WWW, 2019, pp. 151–161.

[13] W. Ma, M. Zhang, Y. Cao, W. Jin, C. Wang, Y. Liu, S. Ma, and X. Ren, “Jointly learning explainable rules for recommendation with knowledge graph,” in WWW, 2019, pp. 1210–1221.

[14] H. Wang, F. Zhang, X. Xie, and M. Guo, “Dkn: Deep knowledge-aware network for news recommendation,” in WWW, 2018, pp. 1835–1844.

[15] H. Huang, W. X. Zhao, H. Dou, J.-R. Wen, and E. Y. Chang, “Improving sequential recommendation with knowledge-enhanced memory networks,” in 41st ACM SIGIR, 2018, pp. 505–514.

[16] H. Wang, M. Zhao, X. Xie, W. Li, and M. Guo, “Knowledge gcns for recommender systems,” in WWW, 2019, p. 3307–3313.

[17] H. Wang, F. Zhang, M. Zhang, J. Leskovec, M. Zhao, W. Li, and Z. Wang, “Knowledge-aware gnn with label smoothness regularization for recommender systems,” in 25th ACM SIGKDD, 2019, p. 968–977.

[18] Y. Chen, H. Guo, Y. Zhang, C. Ma, R. Tang, J. Li, and I. King, “Learning binarized graph representations with multi-faceted quantization reinforcement for top-k recommendation,” in 28th ACM SIGKDD, 2022, p. 168–178.

[19] X. He, K. Deng, X. Wang, Y. Li, Y. Zhang, and M. Wang, “Lightgcn: Simplifying and powering graph convolution network for recommendation,” in 43rd ACM SIGIR, 2020, pp. 639–648.

[20] Y. Chen, Y. Yang, W. J. Bai, X. Song, and I. King, “Attentive knowledge-aware graph collaborative networks with collaborative guidance for personalized recommendation,” in 38th IEEE ICDE, 2022.

[21] M. Yang, M. Zhou, J. Liu, D. Lian, and I. King, “Hcfr: Enhancing collaborative filtering via hyperbolic geometric regularization,” in WWW, 2022, pp. 2462–2471.

[22] M. Yang, Z. Li, M. Zhou, J. Liu, and I. King, “Hcfr: Hyperbolic informative collaborative filtering,” in 28th ACM SIGKDD, 2022, pp. 2212–2221.

[23] M.-H. Namidah-Shahrami and M. Bahadourpour, “Cold-start problem in collaborative recommender systems: Efficient methods based on ask-to-rate technique,” Journal of computing and information technology, vol. 22, no. 2, pp. 105–113, 2014.

[24] A. M. Rashid, G. Karypis, and J. Riedl, “Learning preferences of new users in recommender systems: an information theoretic approach,” ACM SIGKDD Explorations Newsletter, vol. 10, no. 2, pp. 90–100, 2008.

[25] A. M. Rashid, I. Albert, D. Cosley, S. K. Lam, S. McNee, J. A. Konstan, and J. Riedl, “Getting to know you: learning new user preferences in recommender systems,” in 7th IUI, 2002, pp. 127–134.

[26] E. Aimeur and F. S. M. Onana, “Better control on recommender systems,” in CEC/IEEE. IEEE, 2006, pp. 38–38.

[27] D. Agarwal and B.-C. Chen, “Regression-based latent factor models,” in ACM SIGKDD, 2009, pp. 19–28.

[28] C. Wang and D. M. Blei, “Collaborative topic modeling for recommending scientific articles,” in 17th ACM SIGKDD, 2011, pp. 448–456.

[29] H. Wang, N. Wang, and D.-Y. Yeung, “Collaborative deep learning for recommender systems,” in 21th ACM SIGKDD, 2015, pp. 1230–1244.

[30] P. K. Gopalan, L. Charlin, and D. Blei, “Content-based recommendations with poisson factorization,” NeuroIPS, vol. 27, 2014.

[31] M. Volkovs, G. Yu, and T. Poutanen, “a: Addressing cold start in recommender systems,” NeuroIPS, vol. 30, 2017.

[32] S. Shi, M. Zhang, X. Yu, Y. Zhang, B. Hao, Y. Liu, and S. Ma, “Adaptive feature sampling for recommender systems with missing feature values,” in 30th ACM CIKM, 2019, pp. 1451–1460.

[33] C. Luo, W. Pang, Z. Wang, and C. Lin, “Hete-cf: Social-based collaborative filtering recommendation using heterogeneous relations,” in IEEE ICDM, 2014, pp. 917–922.

[34] H. Zhao, Q. Yao, J. Li, Y. Song, and D. L. Lee, “Meta-graph based recommendation fusion over heterogeneous information networks,” in 23rd ACM SIGKDD, 2017, pp. 635–644.

[35] F. Zhang, N. J. Yuan, D. Lian, X. Xie, and W.-Y. Ma, “Collaborative knowledge base embedding for recommender systems,” in 22nd ACM SIGKDD, 2016, pp. 353–362.

[36] C. Shi, B. Hu, W. X. Zhao, and S. Y. Philip, “Heterogeneous information network embedding for recommendation,” IEEE TKDE, vol. 31, no. 2, pp. 357–370, 2018.

[37] Q. Wang, Z. Mao, B. Wang, and L. Guo, “Knowledge graph embedding: A survey of approaches and applications,” IEEE TKDE, vol. 29, no. 12, pp. 2724–2743, 2017.

[38] G. Ji, S. He, L. Xu, K. Liu, and J. Zhao, “Knowledge graph embedding via dynamic mapping matrix,” in ACL, 2015, pp. 687–696.

[39] A. Bordes, N. Usunier, A. Garcia-Duran, J. Weston, and O. Yakhnenko, “Translating embeddings for modeling multi-relational data,” NeurIPS, vol. 26, 2013.

[40] Z. Wang, J. Zhang, J. Feng, and Z. Chen, “Knowledge graph embedding by translating on hyperplanes,” in AAAI, vol. 28, no. 1, 2014.

[41] X. Glorot, A. Bordes, and Y. Bengio, “Deep sparse rectifier neural networks,” in 14th AISTATS, 2011, pp. 315–323.
[42] J. MacQueen et al., “Some methods for classification and analysis of multivariate observations,” in Proceedings of the fifth Berkeley symposium on mathematical statistics and probability, vol. 1, no. 14, 1967, pp. 281–297.
[43] Y.-J. Park and A. Tuzhilin, “The long tail of recommender systems and how to leverage it,” in RecSys, 2008, pp. 11–18.
[44] J. Wu, X. Wang, F. Feng, X. He, L. Chen, J. Lian, and X. Xie, “Self-supervised graph learning for recommendation,” in 44th ACM SIGIR, 2021, pp. 726–735.
[45] J. Weston, S. Chopra, and A. Bordes, “Memory networks,” arXiv preprint arXiv:1410.3916, 2014.
[46] S. Shi, W. Ma, M. Zhang, Y. Zhang, X. Yu, H. Shan, Y. Liu, and S. Ma, “Beyond user embedding matrix: Learning to hash for modeling large-scale users in recommendation,” in 43rd ACM SIGIR, 2020, p. 319–328.
[47] C. Louizos, M. Welling, and D. P. Kingma, “Learning sparse neural networks through $\ell_0$ regularization,” in ICLR, 2018.
[48] D. Luo, W. Cheng, W. Yu, B. Zong, J. Ni, H. Chen, and X. Zhang, “Learning to drop: Robust graph neural network via topological denoising,” in 14th ACM WSDM, 2021, pp. 779–787.
[49] J. Chung, C. Gulcehre, K. Cho, and Y. Bengio, “Empirical evaluation of gated recurrent neural networks on sequence modeling,” arXiv preprint arXiv:1412.3555, 2014.
[50] C. J. Maddison, A. Mnih, and Y. W. Teh, “The concrete distribution: A continuous relaxation of discrete random variables,” in ICLR, 2017.
[51] F. Wu, Y. Qiao, J.-H. Chen, C. Wu, T. Qi, J. Lian, D. Liu, X. Xie, J. Gao, W. Wu et al., “Mind: A large-scale dataset for news recommendation,” in 58th ACL, 2020, pp. 3597–3606.
[52] S. Rendle, C. Freudenthaler, Z. Gantner, and L. Schmidt-Thieme, “Bpr: Bayesian personalized ranking from implicit feedback,” in 25 UIAI, 2009, pp. 452–461.
[53] X. He and T.-S. Chua, “Neural factorization machines for sparse predictive analytics,” in 40th ACM SIGIR, 2017, pp. 355–364.
[54] Y. Lin, Z. Liu, M. Sun, Y. Liu, and X. Zhu, “Learning entity and relation embeddings for knowledge graph completion,” in 29th AAAI, 2015.
[55] R. v. d. Berg, T. N. Kipf, and M. Welling, “Graph convolutional matrix completion,” arXiv preprint arXiv:1706.02263, 2017.
[56] R. Ying, R. He, K. Chen, P. Eksombatchai, W. L. Hamilton, and J. Leskovec, “Graph convolutional neural networks for web-scale recommender systems,” in 24th ACM SIGKDD, 2018, pp. 974–983.
[57] J. Zhang, X. Shi, S. Zhao, and J. King, “Star-gcn: Stacked and reconstructed graph convolutional networks for recommender systems,” in 28th IJCAI, 2019, pp. 4264–4270.
[58] X. Glorot and Y. Bengio, “Understanding the difficulty of training deep feedforward neural networks,” in AISTATS, 2010, pp. 249–256.
[59] D. Kingma and J. Ba, “Adam: A method for stochastic optimization,” in ICLR, 2014.
[60] S. A. Puthiya Parambath, N. Usunier, and Y. Grandvalet, “A coverage-based approach to recommendation diversity on similarity graph,” in 10th ACM RecSys, 2016, pp. 15–22.
[61] L. Yang, L. Luo, X. Zhang, F. Li, X. Zhang, Z. Jiang, and S. Tang, “Why do semantically unrelated categories appear in the same session? a demand-aware method,” in 45th ACM SIGIR, 2022, p. 2065–2069.
[62] T. Chen, H. Yin, Q. V. H. Nguyen, W.-C. Peng, X. Li, and X. Zhou, “Sequence-aware factorization machines for temporal predictive analytics,” in 36th IEEE ICDE, 2020, pp. 1405–1416.