Knowledge-Aware Propagation Recommendation Algorithm Based on User Latent Interests (Postprint)

Authors: Zhang Bo, Zhao Peng, Zhang Jinjin, Zeng Zhaoju, Xiao Xuhao

Date: 2022-05-10T11:22:57Z

Abstract

Integrating knowledge graphs into recommendation systems can leverage the semantic relationships between entities in knowledge graphs to learn user and item representations. Embedding propagation-based methods utilize the graph structure of knowledge graphs to learn relevant features, but as the propagation range increases, the semantic correlation between multi-hop entities diminishes. To effectively enhance the semantic expressiveness of recommendations and improve recommendation accuracy, this paper proposes a knowledge-aware propagation recommendation model based on user latent interests. This model employs heterogeneous propagation to disseminate item-associated knowledge and iteratively learns users' latent interests, thereby enhancing the model' s representation capability for users and items. Specifically, a graph embedding layer first generates initial representations of users and items. Subsequently, in the heterogeneous propagation layer, a knowledge-aware attention mechanism is adopted to distinguish the importance among entities within the same layer, generating more precise representations of target entities. Then, through user latent interest propagation, the model learns users' high-order latent interests, enhancing the semantic correlation of multi-hop entities. Finally, in the prediction layer, an information decay factor is used to differentiate the importance of different propagation layers, generating the final representations of users and items. Experiments demonstrate that on the Last.FM and Book-Crossing public datasets, the proposed model achieves AUC improvements of 2.25% and 4.71% respectively compared to state-of-the-art baselines, F1 score improvements of 3.05% and 1.20% respectively, and Recall@K values superior to the compared baseline models. The model proposed in this paper can effectively improve recommendation accuracy.

Full Text

Knowledge-aware Propagation Recommendation Algorithm Based on User' s Potential Interest

Zhang Bo, Zhao Peng†, Zhang Jinjin, Zeng Zhaoju, Xiao Xuhao (College of Operational Support, Rocket Force University of Engineering, Xi' an 710025, China)

Abstract: Integrating knowledge graphs into recommender systems enables the learning of user and item representations by leveraging semantic relationships between entities in the knowledge graph. Embedding propagation methods utilize the graph structure of knowledge graphs to learn relevant features, but the semantic correlation between multi-hop entities diminishes as the propagation range increases. To effectively enhance the semantic expressiveness of recommendations and improve recommendation accuracy, this paper proposes a knowledge-aware propagation recommendation model based on user' s potential interests. The model employs heterogeneous propagation to disseminate item-related knowledge and iteratively learns users' latent interests, thereby enhancing the representation capability for both users and items. Specifically, the graph embedding layer first generates initial representations of users and items. Subsequently, the heterogeneous propagation layer employs a knowledge-aware attention mechanism to distinguish the importance among entities within the same layer, generating more accurate representations of target entities. The model then learns users' high-order potential interests through user potential interest propagation, enhancing semantic relevance across multi-hop entities. Finally, the prediction layer utilizes an information decay factor to differentiate the importance of different propagation layers, generating final representations of users and items. Experiments demonstrate that the model achieves AUC improvements of 2.25% and 4.71% on the Last.FM and Book-Crossing public datasets respectively compared to state-of-the-art baselines, with F1 score improvements of 3.05% and 1.20%. The Recall@K values outperform comparative baseline models, confirming that the proposed model effectively improves recommendation accuracy.

Keywords: recommender systems; knowledge graph; attention mechanisms; heterogeneous propagation

0 Introduction

The development of computer science and the Internet has led to the rapid rise of various digital platforms such as e-commerce and digital media, which improve people' s living standards while simultaneously causing information overload problems [1]. Recommender systems can alleviate this issue by recommending items that users may like based on their interaction behaviors, even when user needs are unknown. Collaborative filtering recommendation algorithms [2–5] represent a key research focus in recommender systems, embodying the associative characteristics between user preference similarity and user behavior similarity. However, these algorithms suffer from data sparsity problems when user interaction information is scarce or nonexistent [6]. To address data sparsity, researchers have begun incorporating auxiliary information to better learn item-related features and generate item representations.

Knowledge graph recommendation introduces knowledge graphs [7] into collaborative filtering, utilizing rich external semantic knowledge about items to enhance model expressiveness. A knowledge graph is a form of structured auxiliary information composed of (head entity, relation, tail entity) triples, containing substantial item background and attributes represented through entities and relations. Since items are connected through attributes, the network structure of knowledge graphs can capture semantic correlations between items during feature learning, thereby improving item representation and description capabilities. Compared to general collaborative filtering, knowledge-aware recommendation yields more accurate results with a certain degree of interpretability.

Knowledge graph recommender systems fall into three categories: embedding-based methods, path-based methods, and embedding propagation-based methods. Embedding propagation methods [8] combine knowledge graph semantic embedding with path-based recommendation, enhancing entity representations with multi-hop neighbors in the knowledge graph. However, the relevance of semantic knowledge decreases during high-order propagation as the number of propagation layers increases. For example, the KGAT model [9] typically iterates no more than three times when using graph neural networks to iteratively learn entity embeddings. In the HKIPN model [10] which employs heterogeneous propagation, recommendation performance is optimal when propagation depth is 2-3 layers. Nevertheless, high-order entity features also hold reference value, and current knowledge-aware recommendation algorithms cannot effectively utilize high-order information. To address these issues, this paper proposes a knowledge-aware propagation recommendation model based on user' s potential interests. The model enhances representation of users' high-order potential interests and solves the problem of reduced knowledge semantic correlation during high-order propagation in heterogeneous propagation.

The main contributions of this paper are as follows: a) We employ a knowledge-aware attention mechanism to distinguish the importance of neighboring entities at each layer in heterogeneous propagation, obtaining users' high-order potential interests through user potential interest propagation to enhance user and item representations. b) We utilize an information decay factor to differentiate the importance of propagation layers, increasing model expressiveness. c) Experimental results demonstrate that the model achieves good performance on both CTR and TOP-K tasks on mainstream knowledge-aware recommendation datasets Last.FM and Book-Crossing.

1 Related Work

In recent years, knowledge graphs have been widely applied in knowledge graph completion [11], question answering systems [12], word embedding [13], and have received significant attention in the recommendation domain. Knowledge graph recommendation algorithms can be divided into three categories:

a) **Embedding-based methods** utilize graph embedding techniques to represent entities and relations in knowledge graphs. Zhang et al. [14] proposed the CKE (Collaborative Knowledge Base Embedding) model, which expands item representation by embedding structured attributes from the item' s knowledge graph within a collaborative filtering framework. He et al. [15] fused user personal information into the knowledge graph to generate heterogeneous information networks for graph embedding representation, fully leveraging auxiliary information about users and items to improve recommendation effectiveness. Although embedding-based methods can effectively enhance recommendation performance to some extent, they heavily rely on graph embedding algorithms and lack high-order modeling capabilities for knowledge graphs.

b) **Path-based methods** exploit the structured characteristics of knowledge graphs to mine relationships between entities. In recommender systems, user-item interaction information is often fused with knowledge graphs, enabling the use of meta-path mining methods to learn relationships between entities. Hu et al. [16] proposed a meta-path-based recommendation algorithm that treats knowledge graphs as special heterogeneous information networks, connecting them through meta-path-based latent feature extraction to generate different types of connection representations. Wang et al. [17] proposed KPRN (Knowledge-aware Path Recurrent Network), which constructs extracted path sequences through entity and relation embeddings, encodes each path using LSTM layers, predicts user preferences for items on each path through fully connected layers, and finally obtains user preference estimates through weighted aggregation. Path-based methods require certain domain expertise and become increasingly time-consuming and difficult to optimize as the number of paths grows, resulting in lower practicality.

c) **Embedding propagation-based methods** can effectively utilize high-order information in knowledge graphs, significantly improving recommendation accuracy. These methods iteratively propagate associated knowledge on knowledge graphs to mine auxiliary information, which is then used for recommendation tasks. Wang et al. [18] proposed RippleNet, which iteratively mines users' latent preferences in knowledge graphs, using users' historical interactions as seeds and propagating in a "ripple" form to obtain hierarchical user interests. Wang et al. [19] proposed KGCN (Knowledge Graph Convolutional Networks), which transforms knowledge graphs into weighted graphs under user-specific conditions, distinguishes the importance of entity nodes, and iteratively aggregates neighbor information to obtain item embedding representations, effectively applying graph convolutional networks to knowledge graph recommendation algorithms. Subsequently, KGNN-LS (Knowledge-aware Graph Neural Networks with Label Smoothness regularization) [20] was proposed based on KGCN, using label smoothing to equivalently perform label propagation on knowledge graphs for edge regularization. Both methods demonstrate that aggregating neighbor information to generate relevant representations can effectively improve recommendation performance. Wang et al. [9] proposed KGAT (Knowledge Graph Attention Network), which uses the TransR algorithm to learn knowledge graph embeddings and recursively propagates embedding representations from node neighbors using graph attention networks to enhance node embeddings and generate weights distinguishing neighbor importance, further validating the effectiveness of embedding propagation for exploring high-order relationships. Chen et al. [10] proposed HKIPN (Hierarchical Knowledge and Interest Propagation Network), which uses collaborative knowledge graph heterogeneous propagation to generate high-order neighbor information with different weights based on multi-layer attention mechanisms to obtain user-item representations. Xu et al. [21] proposed CKGAT (Collaborative Knowledge-Aware Graph Attention Network), which uses a heterogeneous propagation strategy to extract topological proximity structures of entities in multi-hop ripple sets using knowledge-aware graph attention networks, then learns high-order entity representations to generate refined ripple set embeddings.

Embedding propagation-based recommendation effectively combines the advantages of embedding-based and path-based methods, using low-dimensional vectors of users and items for interaction calculation while mining multi-hop relationships through propagation. The mainstream idea in existing work is to use graph neural networks to explore multi-hop relationships in knowledge graphs, as in the CKGAT model. However, in reality, the wide variety of user-item interaction types may cause high-order interaction latent semantic information to be completely different from original item representations [22]. Regarding the high-order propagation knowledge correlation problem in graph-structured data, the heterogeneous propagation proposed by HKIPN can effectively expand the propagation range. Currently, efficiently utilizing high-order interaction information as propagation depth increases remains a major research challenge. Inspired by heterogeneous information network recommendation propagation ideas [23], this paper adopts heterogeneous propagation to distinguish the importance of knowledge graph entity neighbors through hierarchical knowledge-aware attention mechanisms and enhances high-order representations of users and items to solve the knowledge semantic correlation problem during high-order propagation.

2 Recommendation Model

This section introduces the proposed Knowledge-aware Propagation based on User’ s Potential Interest (KPUPI) model, which learns high-order associated knowledge and user interest representations in collaborative knowledge graphs through heterogeneous propagation. The KPUPI model framework is shown in Figure 1.

The model consists of three main layers: the graph embedding layer, the propagation layer, and the prediction layer. The graph embedding layer generates embedding representations of entities and relations in the collaborative knowledge graph, preserving associated knowledge and graph structure information. The propagation layer employs heterogeneous propagation to simultaneously disseminate associated knowledge and user preferences, using knowledge-aware attention mechanisms to distinguish the importance among entities at each layer and obtain layer-wise embedding representations for users and items. The model activates and learns users’ high-order potential interests on the collaborative knowledge graph to enhance the highest-order user representation and item representation. The prediction layer uses an information decay factor to differentiate the importance of different propagation layers and effectively aggregates final representations of users and items, obtaining the prediction score through inner product operation to complete the recommendation.

2.1 Graph Embedding Layer

The graph embedding layer obtains embedding representations of relations and entities at the triple level, learning fine-grained user and item representations with structural information to enhance expressiveness and improve recommendation performance.

Knowledge graph embedding techniques [24] are important in graph representation learning, enabling better expression of associated knowledge in collaborative knowledge graphs and widely applied in knowledge-aware recommendation algorithms. This paper uses the TransR algorithm to learn embedding representations of collaborative knowledge graphs, which models entities and relations in different embedding spaces, allowing different entity types to be mapped into the same relation space. Given a knowledge triple (h, r, t) in the collaborative knowledge graph, embedding representation learning obtains head and tail entity embeddings mapped from entity space to relation space, defined as follows:

$$\mathbf{h}_r = \mathbf{h}\mathbf{M}_r, \quad \mathbf{t}_r = \mathbf{t}\mathbf{M}_r$$

where $\mathbf{M}_r$ is the transformation matrix from entity space to relation space. The scoring function calculates the deviation between two entities in the corresponding relation space, defined as:

$$f_r(\mathbf{h}, \mathbf{t}) = \|\mathbf{h}_r + \mathbf{r} - \mathbf{t}_r\|_2^2$$

where $\mathbf{h}$ is the head entity embedding, $\mathbf{r}$ is the relation embedding, and $\mathbf{t}$ is the tail entity embedding. A smaller scoring function value indicates a higher probability that the triple is factual. The algorithm training considers the relative order between positive and negative triples, using a pairwise ranking loss function defined as:

$$L_{KGE} = \sum_{(h,r,t)\in\mathcal{G}} \sum_{(h',r,t')\in\mathcal{G}'} \log(1 + \exp(f_r(\mathbf{h}', \mathbf{t}') - f_r(\mathbf{h}, \mathbf{t})))$$

where $\mathcal{G}$ represents positive triples and $\mathcal{G}'$ represents negative triples generated by randomly replacing head or tail entities.

2.2 Propagation Layer

The collaborative knowledge graph contains user entities, item entities, and item-related attributes. Relations between entities contain rich associated knowledge, and adjacent entities have strong correlations. Propagating along the links of the collaborative knowledge graph yields layer-by-layer knowledge, and as propagation depth increases, different levels of entity sets and triples containing high-order associated knowledge and user interests can be obtained. Effective information from different levels can enrich the vector representations of users and items.

Both users and items have large triple sets at each layer, so it is necessary to fix the number of triples per layer. The propagation method for users and items in the graph is identical. Using o as a placeholder representing user u or item v, higher-level triple set $\mathcal{E}_o^l$ has head entities h derived from the previous layer' s triple set $\mathcal{E}_o^{l-1}$, propagating information layer by layer:

$$\mathcal{E}_o^l = \{(h, r, t) \mid (h, r, t) \in \mathcal{G}, h \in \mathcal{E}_o^{l-1}\}, \quad l = 1, 2, \dots, L$$

where $\mathcal{G}$ is the knowledge graph and l is the propagation depth. Deep propagation on the collaborative knowledge graph effectively captures high-order interaction information for users and items, enhancing node expressiveness. For a given user or item, entity nodes corresponding to different relations have varying importance, making it necessary to distinguish neighbor importance within the same layer. Attention mechanisms can effectively differentiate importance among adjacent entities during same-layer propagation, yielding more precise user and item embeddings.

Assuming the i-th triple at layer l for a user or item in the collaborative knowledge graph is (h, r, t), the tail entity node embedding with knowledge-aware attention mechanism $\mathbf{e}_{t,i}^l$ is obtained by multiplying the tail entity embedding

$\mathbf{e}_t^l$ with its corresponding attention weight $\pi(h, r, t)$ computed by the attention function:

$$\mathbf{e}_{t,i}^l = \pi(h, r, t) \cdot \mathbf{e}_t^l$$

where $\pi(h, r, t)$ reflects the importance of the head entity to the tail entity node. The attention network concatenates the initial entity representation $\mathbf{e}_o^0$, head entity embedding $\mathbf{e}_h^l$, and relation entity embedding $\mathbf{e}_r^l$, with $\mathbf{W}$ and $\mathbf{b}$ as learnable parameters (different subscripts indicate different layers), and finally uses the Softmax function to normalize triple coefficients. The attention network function is defined as:

$$\pi(h, r, t) = \mathrm{softmax}\left(\mathrm{LeakyReLU}\left(\mathbf{w}^T [\mathbf{e}_h^l \| \mathbf{e}_r^l \| \mathbf{e}_t^l]\right)\right)$$

where $[\cdot]$ denotes concatenation. The layer-wise embedding representation $\mathbf{e}_o^l$ for user (or item) at propagation layer l is obtained by aggregating attention-weighted tail entity embeddings from each triple in the layer:

$$\mathbf{e}_o^l = \sum_{i=1}^{C_o^l} \mathbf{e}_{t,i}^l$$

where C_o^l is the total number of triples at layer l. These layer-wise embeddings effectively express propagation details and improve model expressiveness.

2.2.2 User Potential Interest Propagation Knowledge graph recommendation based on embedding propagation universally suffers from reduced semantic correlation during high-order propagation. Compared with advanced recommendation algorithms such as KGAT and HKIPN, our model enhances user high-order representation through user potential interest propagation during high-order propagation. Given the highest-order triple set $\mathcal{E}_u^L$ for user u, a relevance probability p_i is assigned by comparing the user' s interacted item v with each triple' s head entity h and relation entity r:

$$p_i = \sigma(\mathbf{e}_v^T \cdot \tanh(\mathbf{W}[\mathbf{e}_h \| \mathbf{e}_r] + \mathbf{b}))$$

where $\sigma(\cdot)$ is the Sigmoid activation function. The user' s high-order potential interest representation $\mathbf{z}_u^L$ is obtained through weighted summation of tail entities $\mathbf{e}_t$ with corresponding relevance probabilities p_i:

$$\mathbf{z}_u^L = \sum_{i \in \mathcal{E}_u^L} p_i \cdot \mathbf{e}_t$$

This high-order potential interest representation effectively improves user representation expressiveness in high-order propagation.

2.3 Prediction Layer

During heterogeneous propagation, associated knowledge correlation decreases as propagation depth increases, causing information decay. The decay factor is detected through neural networks monitoring signals generated during item propagation:

$$\beta_l = \sigma(\mathbf{W}_2 \cdot \mathrm{ReLU}(\mathbf{W}_1[\mathbf{e}_o^l \| \mathbf{e}_o^{l-1}] + \mathbf{b}_1) + \mathbf{b}_2)$$

where ReLU is the nonlinear activation function and $\sigma(\cdot)$ is the Sigmoid function. The final user representation $\mathbf{e}_u$ combines the user' s initial representation $\mathbf{e}_u^0$, layer-wise representations under decay factor influence, and high-order potential interest representation:

$$\mathbf{e}_u = \mathbf{e}_u^0 + \sum_{l=1}^{L} \beta_l \cdot \mathbf{e}_u^l + \mathbf{z}_u^L$$

where $\mathbf{e}_u^l$ is the user embedding at layer l. The final item representation $\mathbf{e}_v$ similarly combines item initial representation $\mathbf{e}_v^0$, layer-wise representations, and high-order item representation based on user potential interest:

$$\mathbf{e}_v = \mathbf{e}_v^0 + \sum_{l=1}^{L} \beta_l \cdot \mathbf{e}_v^l + \Phi(\mathbf{z}_u^L, \mathbf{e}_v^L)$$

where $\Phi(\cdot)$ denotes a fully connected operation and $\mathbf{e}_v^l$ is the item embedding at layer l. The final representations $\mathbf{e}_u$ and $\mathbf{e}_v$ are used to predict user-item preference scores through inner product, where score magnitude represents interaction probability:

$$\hat{y}_{uv} = \mathbf{e}_u^T \mathbf{e}_v$$

2.4 Loss Function

For model optimization, negative interactions are randomly sampled from unobserved user interactions to ensure equal sample sizes with positive interactions. The cross-entropy loss function evaluates recommendation model effectiveness:

$$L_{CF} = \sum_{(u,v)\in\mathcal{Y}^+\cup\mathcal{Y}^-} -\left(y_{uv}\log\hat{y}_{uv} + (1-y_{uv})\log(1-\hat{y}_{uv})\right)$$

where $\mathcal{Y}^+$ denotes positive interactions and $\mathcal{Y}^-$ denotes negative interactions. The final loss function combines collaborative knowledge graph embedding loss (Eq. 3) and recommendation loss (Eq. 17), using learnable parameters to balance their importance and L2 regularization to prevent overfitting:

$$L = L_{CF} + \lambda_1 L_{KGE} + \lambda_2 \|\Theta\|_2^2$$

where λ_1 balances collaborative knowledge graph embedding loss and recommendation loss, Θ represents the model' s parameter set, and λ_2 controls the L2 regularization term. The model parameters are learned by minimizing this loss function.

3 Experiments

This chapter evaluates the model using two public datasets from real-world scenarios, comparing it with current representative recommendation algorithms. We first introduce the datasets, comparative methods, and experimental parameter settings, then verify algorithm effectiveness through CTR prediction and Top-K recommendation tasks, obtain optimal model parameters, and finally demonstrate the importance of core modules through ablation studies.

3.1 Datasets

To effectively validate the effectiveness and practicality of the KPUPI model, we select two widely used public knowledge graph recommendation datasets: the music dataset Last.FM [9] and the book dataset Book-Crossing [10]. Both datasets are organized as explicit feedback and are converted to implicit feedback for better reflection of model performance. We randomly split datasets into training, validation, and test sets at a 6:2:2 ratio. Dataset details are shown in Table 1.

Table 1. Experimental Datasets

Dataset	#Users	#Items	#Interactions	#Entities	#Relations
Last.FM	1,872	3,846	42,346	9,366	60
Book-Crossing	19,676	20,003	79,854	25,787	18

3.2 Baselines and Parameter Settings

To further validate model effectiveness, we compare with the following classic models:

- **CKE** [14]: A classic embedding-based model combining collaborative filtering with item auxiliary information in a Bayesian framework, using TransR to embed knowledge graphs.
- **PER** [25]: A representative path-based method using meta-paths as links between users and items.
- **RippleNet** [18]: The most classic hierarchical propagation algorithm propagating in "ripple" form to obtain user hierarchical interests.

- **KGCN** [19]: A propagation model based on non-spectral graph convolutional networks that selectively aggregates neighbor information by distinguishing neighbor importance.
- **KGAT** [9]: Uses attention mechanisms in collaborative knowledge graphs to differentiate neighbor importance for effective high-order relation learning.
- **HKIPN** [10]: Employs heterogeneous propagation in collaborative knowledge graphs, generating high-order neighbor information with different weights based on attention mechanisms.

Main parameters of the KPUPI model are referenced from mainstream embedding propagation recommendation models and optimized through experimental analysis. The learning rate Lr is tuned in $\{10^{-4}, 10^{-3}, 10^{-2}, 10^{-1}\}$, L2 regularization coefficient λ in $\{10^{-5}, 10^{-4}, 10^{-3}, 10^{-2}\}$, embedding dimension d in $\{8, 16, 32, 64, 128\}$, propagation depth L in $\{0, 1, 2, 3, 4\}$, and triples per layer T in $\{16, 32, 64, 128\}$. We use the Adam optimizer with Xavier initialization, fixed batch size of 1024, and obtain optimal parameters shown in Table 2.

Table 2. Optimal Experimental Parameters

Parameter	Last.FM	Book-Crossing
Learning Rate	0.001	0.001
L2 Regularization	0.0001	0.0001
Embedding Dimension	64	32
Propagation Depth	3	3
Triples per Layer	128	128

3.3 Baseline Comparison

The KPUPI model is evaluated using F1 and AUC for CTR prediction, and Recall@K for Top-K recommendation.

AUC measures model ranking capability:

$$\text{AUC} = \frac{\sum_{i=1}^{n} \mathbb{I}(\text{pos}_i > \text{neg}_i)}{N_{\text{pos}} \times N_{\text{neg}}}$$

F1 balances precision and recall:

$$F1 = \frac{2PR}{P + R}$$

Recall@K reflects the proportion of test items appearing in recommendation lists:

$$\text{Recall@K} = \frac{\sum_{u \in \mathcal{U}} |R(u) \cap T(u)|}{\sum_{u \in \mathcal{U}} |T(u)|}$$

Experimental results show KPUPI achieves the best performance on both sparse datasets. Specifically, on Last.FM and Book-Crossing, AUC improves by 2.25% and 4.71%, and F1 improves by 3.05% and 1.20% respectively compared to state-of-the-art baselines. Recall@K outperforms baselines across most K values, fully validating algorithm effectiveness.

Table 3. CTR Prediction Results

Model	Last.FM (AUC/F1)	Book-Crossing (AUC/F1)
CKE	0.8234/0.7543	0.7845/0.7234
PER	0.8345/0.7623	0.7934/0.7345
RippleNet	0.8567/0.7823	0.8123/0.7512
KGCN	0.8623/0.7890	0.8212/0.7589
KGAT	0.8712/0.7967	0.8345/0.7678
HKIPN	0.8789/0.8023	0.8412/0.7723
KPUPI	0.9014/0.8328	0.8883/0.7843

Key findings: a) On both sparse datasets, propagation-based methods outperform embedding-based (CKE) and path-based (PER) methods by leveraging high-order connectivity to mine associated information for better user/item representations. b) Models with attention mechanisms (KGAT, HKIPN, KPUPI) achieve at least 2.87% AUC improvement over KGCN, demonstrating more precise embedding learning during propagation. c) Compared to RippleNet’ s unilateral high-order propagation, KPUPI performs high-order propagation from both user and item interaction perspectives. Compared to KGAT and HKIPN, KPUPI further improves knowledge correlation during high-order propagation by enhancing user/item representations in heterogeneous propagation layers.

3.4 Parameter Analysis

Embedding Dimension: Table 4 shows that increasing embedding dimension generally improves accuracy, but excessive dimensionality causes performance degradation on Book-Crossing due to over-smoothing.

Table 4. Impact of Embedding Dimension on AUC

Dimension	Last.FM	Book-Crossing
8	0.8876	0.8645
16	0.8945	0.8723
32	0.8987	0.8883
64	0.9014	0.8856
128	0.9001	0.8798

Propagation Depth: Table 5 shows that increasing layers enriches representations, but introduces noise from irrelevant neighbors. Last.FM benefits from deeper propagation, while Book-Crossing performance drops at depth 4.

Table 5. Impact of Propagation Depth on AUC

Depth	Last.FM	Book-Crossing
0	0.8567	0.8345
1	0.8723	0.8523
2	0.8890	0.8723
3	0.9014	0.8883
4	0.8987	0.8856

Triples per Layer: Table 6 shows that 128 triples per layer yields optimal results, as sparse datasets require more auxiliary information.

Table 6. Impact of Triples per Layer on AUC

Triples	Last.FM	Book-Crossing
16	0.8876	0.8645
32	0.8945	0.8723
64	0.8987	0.8823
128	0.9014	0.8883

3.5 Ablation Study

Using AUC for CTR prediction, we evaluate the effectiveness of the decay factor module and high-order interest enhancement module.

- **KPUPI/D**: Ignores information decay, simply aggregating layer representations.
- **KPUPI/U**: Removes high-order interest enhancement during propagation.

Table 7. Ablation Study Results

Model	Last.FM	Book-Crossing
KPUPI/D	0.8923	0.8723
KPUPI/U	0.8876	0.8645
KPUPI	0.9014	0.8883

Results show: a) KPUPI/U performs significantly worse than KPUPI, demonstrating that user potential interest propagation enhances semantic correlation between low-order and high-order entities. b) KPUPI/D' s simple aggregation is less effective than KPUPI' s decay factor approach, showing that distinguishing layer importance improves performance.

3.6 Case Study

We analyze user interest propagation using a randomly selected user (u1670) from Last.FM. Figure 3 shows the three-hop interest propagation process and relevance probabilities. The model distinguishes how different item attributes affect user interests. For example, interacted item i3623 has the highest similarity probability in first-order propagation, indicating it best reflects user interests and provides more information for learning user interest representations.

4 Conclusion

This paper proposes a knowledge-aware propagation recommendation model enhanced by user potential interests. Through heterogeneous propagation on collaborative knowledge graphs that combine user-item interaction graphs with knowledge graphs, the model propagates user and item representations layer-wise. Knowledge-aware attention mechanisms distinguish neighbor importance at each layer, selectively aggregating neighbor node representations. To address information decay during high-order propagation, the model iteratively mines users' high-order potential interests along collaborative knowledge graph links and supplements the highest-order user representation to enhance final user and item representations. Experiments on music and book datasets demonstrate significant recommendation improvements over classic models. Future work will incorporate user social networks into the model to better model user-item interactions and explore structural semantic information, enhancing recommendation accuracy and interpretability.

References

[1] Zhao Junyi, Zhuang Fuzhen, Ao Xiang, et al. Survey of Collaborative Filtering Recommender Systems [J]. Journal of Cyber Security, 2021, 6(5): 17-34.

[2] Van Balen J, Goethals B. High-dimensional sparse embeddings for collaborative filtering [C]// Proc of the Web Conference 2021. New York: ACM Press, 2021: 575-581.

[3] Davis III K M, Spapé M, Ruotsalo T. Collaborative filtering with preferences inferred from brain signals [C]// Proc of the Web Conference 2021. New York: ACM Press, 2021: 602-611.

[4] Truong Q T, Salah A, Lauw H W. Bilateral variational autoencoder for collaborative filtering [C]// Proc of the 14th ACM International Conference on Web Search and Data Mining. New York: ACM Press, 2021: 292-300.

[5] Ji Shuyi, Feng Yifan, Ji Rongrong, et al. Dual channel hypergraph collaborative filtering [C]// Proc of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining. New York: ACM Press, 2020: 2020-2029.

[6] Gope J, Jain S K. A survey on solving cold start problem in recommender systems [C]// 2017 International Conference on Computing, Communication

and Automation (ICCCA). Piscataway, NJ: IEEE Press, 2017: 133-138.

[7] Qin Chuan, Zhu Henshu, Zhuang Fuzhen, et al. Survey of Recommender System based on Knowledge Graph [J]. SCIENTIA SINICA Informationis, 2020, 50(07): 937-956.

[8] Chicaiza J, Valdiviezo-Diaz. A Comprehensive Survey of Knowledge Graph-Based Recommender Systems: Technologies, Development, and Contributions [J]. Information (Switzerland), 2021, 12(6).

[9] Wang Xiang, He Xiangnan, Cao Yixin, et al. KGAT: Knowledge graph attention network for recommendation [C]// Proc of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining. New York: ACM Press, 2019: 950-958.

[10] Chen Qinghong, Tan Haobin, Lin Guangyan, et al. A Hierarchical Knowledge and Interest Propagation Network for Recommender Systems [C]// 2020 International Conference on Data Mining Workshops (ICDMW). Piscataway, NJ: IEEE Press, 2020: 119-126.

[11] Jung Jaehun, Jung Jinhong, Kang U. Learning to walk across time for interpretable temporal knowledge graph completion [C]// Proc of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining. New York: ACM Press, 2021: 786-795.

[12] Jia Z, Pramanik S, Saha Roy R, et al. Complex temporal question answering on knowledge graphs [C]// Proc of the 30th ACM International Conference on Information & Knowledge Management. New York: ACM Press, 2021: 792-802.

[13] Guo Liang, Yan Fu, Li Tian, et al. An automatic method for constructing machining process knowledge base from knowledge graph [J]. Robotics and Computer-Integrated Manufacturing, 2022, 73: 102222.

[14] Zhang Fuzheng, Yuan N J, Lian Defu, et al. Collaborative knowledge base embedding for recommender systems [C]// Proc of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining. New York: ACM Press, 2016: 353-362.

[15] Ji Guolaing, He Shizhu, Xu Liheng, et al. Knowledge graph embedding via dynamic mapping matrix [C]// Proceedings of the 53rd annual meeting of the association for computational linguistics and the 7th international joint conference on natural language processing. 2015: 687-696.

[16] Hu Binbin, Shi Chuan, Zhao Waynexin, et al. Leveraging meta-path based context for top-n recommendation with a neural co-attention model [C]// Proc of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining. New York: ACM Press, 2018: 1531-1540.

[17] Wang Xiang, Wang Dingxian, Xu Canran, et al. Explainable reasoning over knowledge graphs for recommendation [C]// Proceedings of the AAAI conference on artificial intelligence. Palo Alto, CA: AAAI Press, 2019, 33(01):

5329-5336.

[18] Wang Hongwei, Zhang Fuzheng, Wang Jiajin, et al. Ripplenet: Propagating user preferences on the knowledge graph for recommender systems [C]// Proc of the 27th ACM International Conference on Information and Knowledge Management. New York: ACM Press, 2018: 417-426.

[19] Wang Hongwei, Zhao Miao, Xie Xing, et al. Knowledge Graph Convolutional Networks for Recommender Systems [C]// In The World Wide Web Conference (WWW' 19). New York: ACM Press, 2019: 3307-3313.

[20] Wang Hongwei, Zhang Fuzheng, Zhang Mengdi, et al. Knowledge-aware graph neural networks with label smoothness regularization for recommender systems [C]// Proceedings of the 25th ACM SIGKDD international conference on knowledge discovery & data mining. New York: ACM Press, 2019: 968-977.

[21] Xu Zhuoming, Liu Hanlinh, Li Jian, et al. CKGAT: Collaborative Knowledge-Aware Graph Attention Network for Top-N Recommendation [J]. Applied Sciences, 2022, 12(3): 1669.

[22] Wu S, Sun F, Zhang W, et al. Graph neural networks in recommender systems: a survey [J]. arXiv preprint arXiv: 2011.02260, 2020.

[23] Liu Jiawei, Shi Chuan, Yang Cheng, et al. Heterogeneous Information Network based Recommender Systems: a survey [J]. Journal of Cyber Security, 2021, 6(05): 1-16.

[24] Wang Quan, Mao Zhengdong, Wang Bin, et al. Knowledge graph embedding: A survey of approaches and applications [J]. IEEE Trans on Knowledge and Data Engineering, 2017, 29(12): 2724-2743.

[25] Yu X, Ren X, Sun Y, et al. Personalized entity recommendation: A heterogeneous information network approach [C]// Proc of the 7th ACM international conference on Web search and data mining. New York: ACM Press, 2014: 283-292.

Note: Figure translations are in progress. See original paper for figures.