Information Processing and Management 61 (2024) 103636

Contents lists available at ScienceDirect

Information Processing and Management

journal homepage: www.elsevier.com/locate/ipm

An adaptive category-aware recommender based on dual knowledge graphs

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ARTICLE INFO

Keywords:
Social network
Knowledge graph
Category-aware
Recommendation

ABSTRACT

Combining the knowledge graph (KG) with the personalized item recommendation has become an important method to improve user experience. In the personalized item recommendation, users have their preferences on categories that influence their choices of items. In order to fully use category information, we explicitly focus on their impact on user preference and run through the whole recommendation process. We construct two dual knowledge graphs (KG-UI and -UC). Based on them, we propose KG-CICEF, a recommendation system based on knowledge graph aggregation and user preference modeling. Our model effectively captures user preferences for explored and unexplored item categories by aggregating information from two types of knowledge graphs. We convert user preference over unexplored item categories to the cross-item-category exploration factor (CEF). We utilize CEF to build a category-wise loss function for the item recommendation. For consistency, we also propose a category-based negative sampling mechanism to optimize this loss function. Experimental results on three benchmark datasets demonstrate that KG-CICEF achieves significant improvements over the state-of-the-art methods, and the case study validates the effectiveness of CEF in item recommendations.

1. Introduction

Item recommendation can serve in every field of life, such as fashion items (Chen, Chen et al., 2019; Li et al., 2020), scenic spots (Dadoun et al., 2019), food (Chen et al., 2021; Elsweiler et al., 2017), music (Hong et al., 2020; Liu & Miyazaki, 2022), news (Chen et al., 2023; Lee et al., 2020; Qiu et al., 2022), literature (Vatturi et al., 2008), finance (Liu, Ma et al., 2021). The main task of a recommendation system is to obtain user preference accurately and then use the preference information to predict some items that the user may be interested in. Users keep certain preferences for the interaction between different categories of items (Liang et al., 2021). For example, some users prefer to try different items in Clothing, while others prefer to stick to their styles and choose items from categories they have purchased before (as shown in Fig. 1), where the latent space of category is different from item. This rule applies to Music, Movies, News, Food, and other fields. We can roughly divide users into different user type groups by their user preference on different categories of items. Fig. 2(a–c) statistics the distribution of different user types on three datasets from different domains, which conforms to the logic of life. In the field of Clothing (a), most users keep neutral to exploring clothing categories. In the field of Movie (c), more users have their own fixed styles of movies,i.e., they easily reject new types of movies. In the field of Music (b), the user type is evenly distributed, meaning the user type in this field is more diverse than others. The user preference for categories will greatly impact the selection of item categories, but some recommendation system models

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https://doi.org/10.1016/j.ipm.2023.103636
Received 25 June 2023; Received in revised form 7 November 2023; Accepted 29 December 2023
Available online 6 February 2024

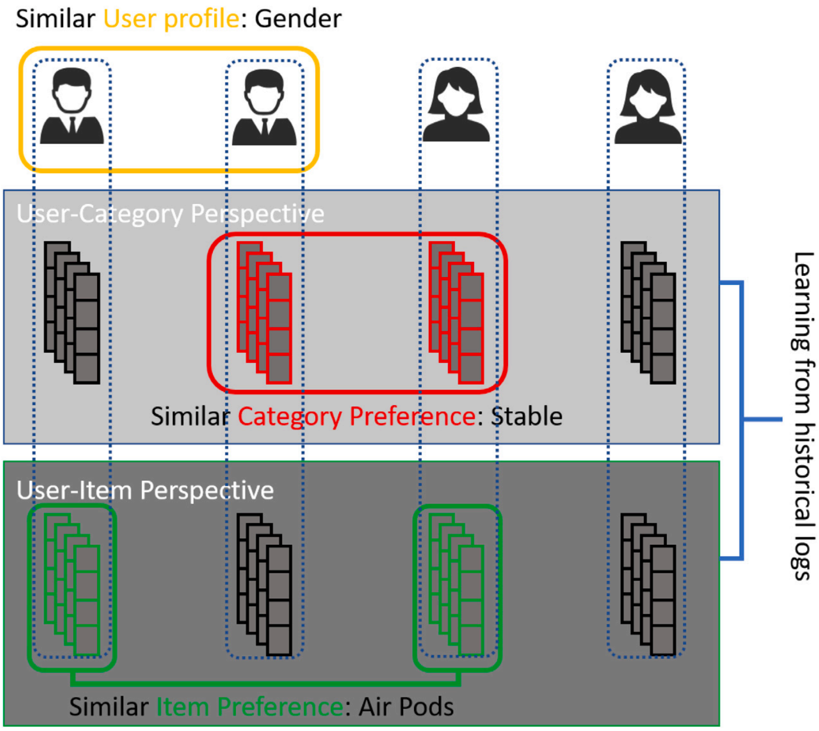
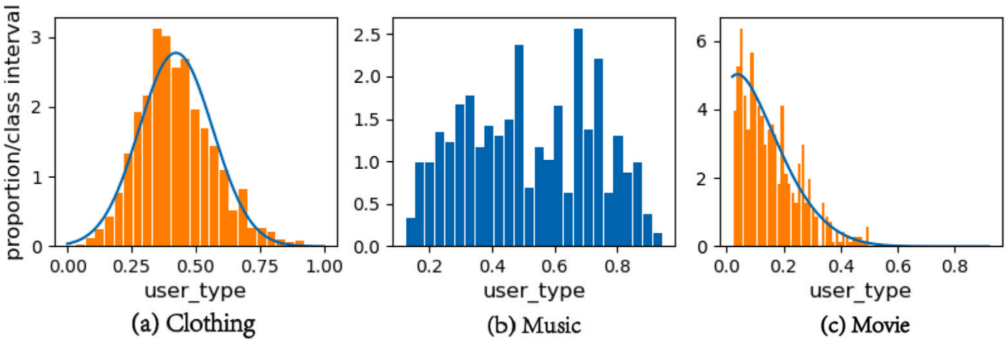

Similar User profile: Gender
User-Category Perspective
Similar Category Preference: Stable
User-Item Perspective
Similar Item Preference: Air Pods
Learning from historical logs

Fig. 1. A toy example to indicate the issues with utilizing category and item explicitly. We could find that (1) the similarities from different perspectives are different (user profile, category perspective, and item perspective) and (2) the latent space for the user's category preference and item preference are different.



(a) Clothing (b) Music (c) Movie

Fig. 2. Distribution of user type on three datasets. We classify users according to their initial values of the cross-item-category exploration factor (CEF, introduced in Section 1 and formulated in Section 3.1). The user preference over explored item categories is proportional to the initial values of CEF.

(He et al., 2017; Yu, Ren, Sun et al., 2013) did not fully use it. In addition, item recommendation lists generated by some existing recommendation models cannot adapt to users' styles. Particularly, if a recommendation system only focuses on accuracy blindly, it will result in the simplicity of the recommendation list.

In this paper, we explicitly focus on the impact of item categories on user preference and run through the whole recommendation process. Specifically, we construct two KGs to obtain users' entity representations from different angles. KG-UI is the regular user-item KG containing information between all kinds of entities. It focuses more on the global information between users and other entities than on the interaction between users and categories, so we built KG-UC. KG-UC is the user-category KG that directly selects the users' historical categories interaction logs further to enhance the user preference for these explored item categories. Based on them, we propose a *knowledge graph model based on the user's cross-item category exploration factor* (KG-CICEF) to get user preference and entity representations effectively. Technically, we design a novel **information aggregation framework** that can aggregate user-item, user-category, and item-category information from two kinds of KGs. In particular, adding information about users and categories of items strengthens the user preference for items of different categories, which enriches entity representations. Our aggregation is divided into two stages: (1) aggregation on KG-UC and KG-UI; (2) fusion of entity representations on the two kinds of KGs. We consider the different influences of various relationships for the entity in the aggregation process, adding the attention mechanism to aggregation stage one. Specifically, we explore **the independence and the correlation** among various categories in users' historical purchasing logs. Thus, it benefits the user preference learning for the recommendation. In addition, we convert user preference over unexplored item categories to the cross-item-category exploration factor (CEF). The more item categories the user interacts with, the greater the corresponding CEF value will be; Otherwise, the user's CEF value will decrease. Then, we adopt **a novel negative sampling mechanism** combining conventional negative sampling with category-based negative sampling mechanism and integrating the category-based negative sampling mechanism with the CEF to refine the representation of each entity. The category-based negative sampling mechanism selects negative items from some categories that the user unexplored. Different users have different preferences over item categories, which means users have their repulsive forces over item categories that they have unexplored before, so we combine users' CEF with the category-based negative sampling mechanism to enhance user preference over unexplored item categories. Experimental results indicate that our KG-CICEF outperforms the state-of-the-art methods such as KGIN (Wang et al., 2021), KGAT (Wang, He et al., 2019), and CKEKGAT (Zhang et al., 2016).

We summarize the contributions of this work as follows:

- Proposing a novel information aggregation framework. The framework aggregates the information on two kinds of KGs and strengthens the user preference over these explored item categories.
- Designing a novel category-based negative sampling mechanism and combining it with the CEF to enhance user preference over unexplored item categories while considering the impact of category independence and correlation on category entity representations.
- Conducting empirical studies on three benchmark datasets to demonstrate the superiority of KG-CICEF. A case study is also provided to validate our proposed method.

2. Related work

In the early research on recommendation systems, most models only used a user-item bipartite graph to predict user preference, such as collaborative filtering (CF) (Hofmann, 2004; Islam et al., 2021; Kim & Li, 2004; Xu, Wang et al., 2022, 2023; Xu, Yu et al., 2023) and matrix decomposition (MF) (Li et al., 2023; Rendle et al., 2009). The emergence of graph-based neural network (GNN) provides a new idea for recommendation systems (Gao et al., 2021; Huang et al., 2020; Yang et al., 2021). GNN uses an informative graph-based network structure to improve the performance of recommendation systems. Graph convolution network (GCN) (Liu, Cheng et al., 2021; Zhang et al., 2020) aggregates neighbor information through convolution operation, which adds graph structural features into node representation to improve model performance. However, these methods are highly dependent on data feature extraction and have the defect of sparse data, which will have a great impact on the prediction effect (Xu et al., 2020; Zhu et al., 2022). The recommendation system based on knowledge graph (Liu, Cheng et al., 2021) avoids the above defects to some extent. It adds the auxiliary information into the knowledge graph in the form of triplets to enrich the information of entities. A recommender system based on knowledge graphs can improve the accuracy of entity representation and alleviate the problem of data sparsity to a certain extent. In addition, the path of KG from a user to an item provides interpretability for the recommendation system.

The recommendation system based on the knowledge graph can be divided into two types: the embedding-based method and the path-based method. The embedding-based method (Bordes et al., 2013; Lin et al., 2017; Liu et al., 2022; Wang et al., 2014) mainly maps the distance between the head entity and tail entity of each triplet into the relational space and use this distance to modify the representation of the entity. The representatives of this kind of method are Trans series models, such as TransE (Bordes et al., 2013), TransH (Wang et al., 2014), TransR (Lin et al., 2017), and TransD (Ji et al., 2015), which verify the validity of methods based on the knowledge graph. However, there are still some deficiencies in the aggregation of higher-order information and the connectivity expression of the knowledge graph. The path-based method (Luo et al., 2014; Yu et al., 2014; Yu, Ren, Sun et al., 2013) uses the connectivity on user-item graph to aggregate information, such as Hete-MF (Yu, Ren, Gu et al., 2013), HeteRec (Yu, Ren, Sun et al., 2013). In contrast, their performance is highly dependent on the quality of the path, which determines the accuracy of the representation. In order to make full use of the advantages of the above two methods, KGCN (Wang, Zhao et al., 2019) combines them to guide the recommendation jointly. It aggregates neighbor information and considers the path relationship between nodes, making entity representation more accurate.

More and more models combine application scenarios and user characteristics to improve the performance of recommendation systems based on the knowledge graph. TEKGR (Lee et al., 2020) considers the user's dependence on news headlines when browsing news, so it extracts semantic information by using the words in the headlines and their contexts to enrich the expression of users and news further. KGIN (Wang et al., 2021) believes that users always have their intention when they click on an item. Then, they simplify this intent to an attention set of relationships in the knowledge graph and add it to the user's representation. EDUA (Liang et al., 2021) uses a bilateral branch network to balance the diversity and accuracy of the recommendation list. TGT (Xia et al., 2023) captures dynamic short-term and long-range user-item interactive patterns to solve the awareness of multi-behavior interactive patterns by exploring the evolving correlations across different types of behaviors. In addition, KEGNN (Lyu et al., 2023) designs a graph neural networks based user behavior learning and reasoning model to perform both semantic and relational knowledge propagation and reasoning over the user behavior graph for a comprehensive understanding of user behaviors.

However, to our knowledge, the previous recommendation system models use category information as an external information-rich entity representation. However, there are many kinds of users in life, and they have their own styles when buying items. The item categories have a great impact on users' choices. Different from theirs, explicitly focus on the impact of item categories on user preference and run through the whole recommendation process.

Table 1
Symbol list.

Symbols	Descriptions
$\mathcal{U}$	User set
$\mathcal{I}$	Item set
$\mathcal{C}$	Category set
R_{ui}	Feedback set of user u on item i
R_{uc}	Feedback set of user u on category c
(h, r, t)	Triplet from graphs, h, t are head and tail, respectively
KG-UI/KG-UC	user-item/user-category knowledge graph, respectively
cef_u	User u's cross-item category exploration factor
$\mathbf{e}_u, \mathbf{e}_i, \mathbf{e}_c$	Embeddings of user u, item i, and category c
O^+, O^-	Positive/negative sample set
$\mathcal{D}_{cate}, \mathcal{C}_{cate}$	Distance score and category score
$d,\ n$	Embedding dimension, aggregation layer
$\hat{y}_{ui}$	Predicted click score of user u on item i
In_c	Category indicator
$\alpha()$	Attention calculation
$W,\ \lambda$	Hyperparameters

3. Problem definition

We first introduce the structural data: user-item interactions and knowledge graphs. Then, we formulate our tasks. All the important symbols are listed in Table 1.

3.1. Interaction definition

We mainly focus on these items clicked (browsed or purchased) by users, i.e., the implicit feedback (Rendle et al., 2009) in the recommendation system. The interactions between users and items can reflect their preferences about items. Let $\mathcal{U}$ be a set of users, $\mathcal{I}$ be a set of items, and $\mathcal{C}$ be a set of item categories. $R_{ui} = \left\{ r_{ui} | u \in \mathcal{U}, i \in \mathcal{I} \right\}$ is a set of observed feedback, where each (u, i) pair denotes user u has interacted with item i; $R_{uc} = \left\{ r_{uc} | u \in \mathcal{U}, c \in \mathcal{C} \right\}$ is a set of observed feedback, where each (u, c) pair denotes user u has interacted with category c. Correspondingly, there are two triplets: $(u, |r_{ui}|, i)$ and $(u, |r_{uc}|, c)$, where $|.|$ is a binary indicator to represent the relation existing.

3.2. Knowledge graph definition

There are some preparations for constructing a KG to convert all the information into triplets. Let $\mathcal{V}$ be a set of entities and $\mathcal{R}$ be a set of relations. $G = \{(h, r, t) | h, t \in \mathcal{V}, r \in \mathcal{R}\}$ is a set of triplets, where each (h, r, t) triplet indicates that a relation r exists from head entity h to tail entity t. Fig. 3 indicates two kinds of KGs: KG-UI and KG-UC. KG-UI can add all kinds of triplets according to external information. For example, the $(o, \text{contains}, i)$ triplet denotes that the outfit o contains item i. It uses this external information to describe the global characteristics of users, items, and categories so that the representation of each entity contains abundant structural information. KG-UC separates the interaction information between users and categories of items, helping us better represent user preference for item categories. Besides, most existing methods treat items and categories as coupling factors, lacking the explanation of item/category effect on user's click actions. With KG-UC and KG-UI, we can extract the effect of the item and category independently, which benefits the recommender system.

3.3. Task definition

Given the interaction data R_{ui}, R_{uc}, and the two kinds of KGs, our task is to learn a function to predict the score $\hat{y}_{ui}$ that a user u may click an item i.

4. Methodology for category-aware recommendation

We now introduce the proposed knowledge graph-based on the user's cross-item-category exploration factor (KG-CICEF). Fig. 4 indicates the workflow for KG-CICEF. It focuses on user preferences over explored and unexplored item categories, hoping to extract well-explained user preferences through aggregation operation on two KGs. In addition, it tries to learn users' exploration factors for different item categories and combine them with the category-based negative sampling mechanism to improve the personalized service of item recommendation.

4.1. Parameter initialization

Initialization of parameters is mainly divided into two components: (1) The initialization of the users' cross-item category exploration factor. (2) The initialization of entities on two KGs. Reasonable initialization can help the model to converge more quickly and accurately.

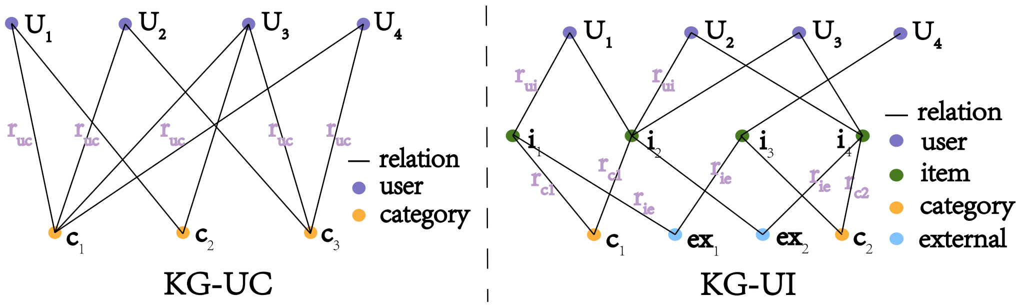


Fig. 3. Two kinds of KGs. In KG-UI, we enrich the entity representations with external information.

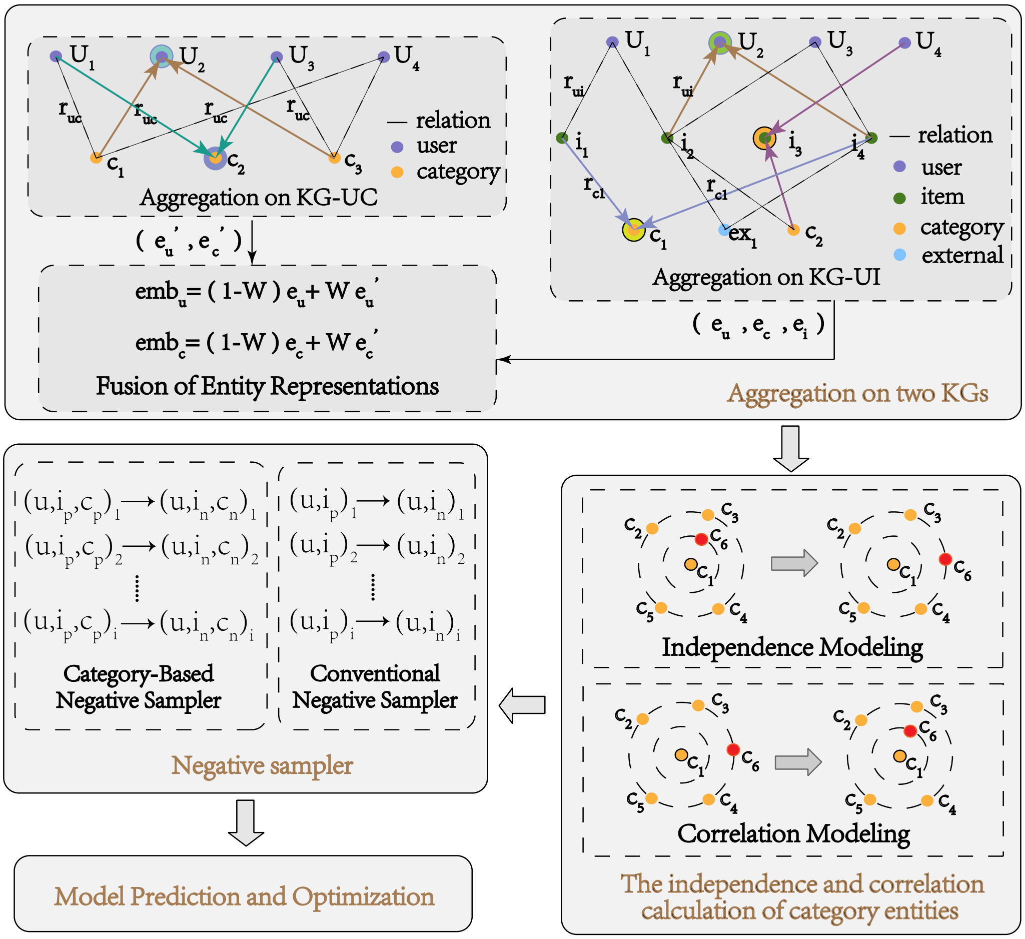

Aggregation on KG-UC
(e_u' , e_c')
emb_u = (1-W) e_u + W e_u'
emb_c = (1-W) e_c + W e_c'
Fusion of Entity Representations
Aggregation on KG-UI
(e_u , e_c , e_i)
Aggregation on two KGs
(u,i_p,c_p)_1 ⟶ (u,i_n,c_n)_1
(u,i_p,c_p)_2 ⟶ (u,i_n,c_n)_2
(u,i_p,c_p)_i ⟶ (u,i_n,c_n)_i
Category-Based Negative Sampler
(u,i_p)_1 ⟶ (u,i_n)_1
(u,i_p)_2 ⟶ (u,i_n)_2
(u,i_p)_i ⟶ (u,i_n)_i
Conventional Negative Sampler
Negative sampler
Independence Modeling
Correlation Modeling
The independence and correlation calculation of category entities
Model Prediction and Optimization

Fig. 4. Illustration of the proposed KG-CICEF framework.

4.1.1. *Users' cross-item category exploration factor initialization*

The user's exploration factor reflects his preference for unexplored item categories. Based on the previous work, we initialize the cross-item category exploration factor of user u as follows:

$$cef_u = \frac{\text{count}(C_u)}{\text{count}(\mathcal{I}_u)}, \tag{1}$$

where count(A) calculates the element number in A set, C_u, $\mathcal{I}_u$ denote the set of items and categories interacted by user u respectively. We simplify the category information of an item, i.e., an item can only belong to one category, so the $cef_u \in (0, 1]$, which means a higher value indicates that the user is more likely to try more items in new categories. In other words, cef_u is negatively correlated with the repulsive force of category items with which the user u has not interacted.

4.1.2. KG-UI and KG-UC initialization

The entities on two KGs can be divided into user, item, and category. We use their IDs for initialization. More formally, we denote IDs initialization of user u, item i and category c separately as $\mathbf{e}_u^0 \in \mathbb{R}^d$, $\mathbf{e}_i^0 \in \mathbb{R}^d$, $\mathbf{e}_c^0 \in \mathbb{R}^d$ where d is the embedding size.

4.2. Aggregation on KG-UI and KG-UC

In order to enhance the representation capability of entities, we aggregate internal information on two KGs. First, we separate the user-category triplet to construct KG-UC and aggregate it to obtain the user preference over these explored item categories. In this way, the user preference over explored item categories can be more clearly and directly obtained without being affected by other entities. At the same time, the representation of category entities also collects information from different users themselves. KG-UI consists of user-item, item-category, and category-item triplets, so it contains richer global information than KG-UC. The different triplets in the two KGs lead to their different features, so the entity representation obtained by aggregation on different KGs also has different meanings. Finally, we fuse the entity representations in the two KGs to jointly guide the final recommendation.

4.2.1. Aggregation on users

The nodes on the two KGs consist of three parts: user, item, and category. Furthermore, each node aggregates information about its neighbors. The user aggregates on both KGs in the same way, but just with different neighborhood information. Now, we take the aggregation on KG-UI as an example to illustrate the aggregation process. We use $\mathbf{e}_u^1$ and $\mathbf{e'}_u^1$ to represent the first-order aggregate representation of user u on KG-UI and KG-UC, respectively, and $\mathbf{e}_u^1$ is defined as follows:

$$\mathbf{e}_u^1 = \frac{1}{|\mathcal{I}_u|} \sum_{j \in \mathcal{I}_u, (u,r,j) \in G} \alpha(u,j) \mathbf{e}_j^0 \odot \mathbf{e}_r^0, \tag{2}$$

where $\mathcal{I}_u$ is the item set interacted with user u; $\odot$ denotes the element-wise product. There is a relational message (Wang et al., 2021) $\mathbf{e}_j^0 \odot \mathbf{e}_r^0$ by modeling the relation $\boldsymbol{r}$ as the projection or rotation operator for each triplet $(\boldsymbol{u}, \boldsymbol{r}, \boldsymbol{j})$; different items have different effects on a user, so we add the attention score $\alpha(u,j)$ to quantify its importance, formally :

$$\alpha(u,j) = \frac{\exp\left(\sigma\left(x_{uj}\right)\right)}{\sum_{j \in \mathcal{I}_u} \exp\left(\sigma\left(x_{uj}\right)\right)}, \tag{3}$$

where x_{uj} is a trainable weight for user u and item j; $\sigma(\cdot)$ is the sigmoid function. Therefore, the representation of user u after n-layer aggregation on KG-UI is defined as follows:

$$\mathbf{e}_u^n = \frac{1}{|\mathcal{I}_u|} \sum_{j \in \mathcal{I}_u, (u,r,j) \in G} \alpha(u,j) \mathbf{e}_j^{(n-1)} \odot \mathbf{e}_r^{(n-1)}, \tag{4}$$

4.2.2. Aggregation on items

The item nodes are only in KG-UI, and their neighborhood information is from nodes of users and categories. The representation of item i after first-order aggregation is defined as follows:

$$\begin{aligned} \mathbf{e}_i^1 = \left(\frac{1}{|\mathcal{U}_i|} + \frac{1}{|C_i|}\right) \Bigg(& \sum_{j \in \mathcal{U}_i, (i,r,j) \in G} \alpha(i,j) \mathbf{e}_j^0 \odot \mathbf{e}_r^0 \\ & + \sum_{j' \in C_i, (i,r,j') \in G} \alpha(i,j') \mathbf{e}_{j'}^0 \odot \mathbf{e}_r^0 \Bigg), \end{aligned} \tag{5}$$

where $\mathcal{U}_i$ and C_i are the user set and category set interacted with the item i, respectively; $\alpha(i,u)$ and $\alpha(i,c)$ are corresponding attention scores to reflect the different effects on item i. They are similar to the definition of Eq. (3). The n-order aggregation mode of the category is the same with users.

4.2.3. Aggregation on categories

The category aggregates on both KGs similarly but with different neighborhood information, the same as users' nodes. On the KG-UI, the category node aggregates information from neighboring items, while on the KG-UC, it aggregates information from users. We use $\mathbf{e}_c^1$ and $\mathbf{e'}_c^1$ to represent the first-order aggregate representation of category c on KG-UI and KG-UC respectively, and use $\mathbf{e}_c^n$ and $\mathbf{e'}_c^n$ to represent the corresponding n-order aggregate representation.

4.2.4. Entity representation fusion

After aggregating the two KGs separately, we fuse the n-order aggregation representation of user u and category c. Their fusion methods are the same, so we take the fusion of user nodes as an example. Therefore, the final n-layer aggregation of user u is expressed as:

$$\mathbf{emb}_u^n = (1 - W_1)\mathbf{e}_u^n + W_1 \mathbf{e'}_u^n, \tag{6}$$

where W_1 is a hyperparameter that reflects the proportion of category information in the user representation u, a larger value of W_1 indicates that category information is more important. The final n-layer aggregation of category c is expressed as $\mathbf{emb}_c^n$, similar to user u.

4.3. Independence and correlation modeling

We retain the independence and correlation between categories to improve the accuracy of categories' representations. Specifically, **independence** can be treated as the deviation between different categories. The diverse items in categories lead to differences, so we must formulate this difference deviation between categories to achieve better embeddings. On the contrary, there exists **correlations**, which can be treated as the similarity between categories. A user is interested in one category because of his interactions with other previous categories, so we can say there are correlations between these categories. To simplify the model, we use statistics to reserve the most relevant category for each category. A more detailed category correlation will be carried out in our next section.

First, the independence between different categories of entities can be represented by the distance between the entities. The greater the distance between the two categories, the greater their independence. We describe the distance score between entities of various categories as follows:

$$\mathcal{D}_{cate} = -\sum_{i,j \in C, i \neq j} \text{distance}(\mathbf{emb}_i^n, \mathbf{emb}_j^n), \tag{7}$$

where distance($\mathbf{emb}_i^n, \mathbf{emb}_j^n$) calculates the distance between two categories' embedding.

Then, we can extract the correlation between categories through KG-UC. It can be shown simply by the number of interactions between users and categories. Therefore, we describe the correlation scores between categories as follows:

$$\mathcal{C}_{cate} = \sum_{c \in C} \text{distance}(\mathbf{emb}_c^n, \mathbf{emb}_{\text{find}(c)}^n), \tag{8}$$

where $find(c)$ searches the category for c with the highest correlation among the other $|C-1|$ categories, and it is defined as follows:

$$\text{find}(c) = \text{max}_c \left(\sum_{u \in \mathcal{U}_c} \frac{1}{|C_u|} \text{In}_c \right), \tag{9}$$

where $\text{max}_c(c)$ returns the category c's representation with the highest correlation score; C_u is the set of categories that interacted with user u, and $\mathcal{U}_c$ is the set of users interacted with category c; In_c is an indicator, $\text{In}_c = \{(1/0) | c \in C_u / c \notin C_u\}$. Category independence requires the distance between category entities as far as possible, while the correlation is contrary.

4.4. Negative sampling

Our sampling mechanism is divided into conventional and category-based negative sampling mechanisms. The conventional negative sampler selects negative samples from items that the user unexplored. In contrast, category-based negative sampling selects negative items from the categories the user unexplored, and it can train an exploration factor for each user to capture the user preference over unexplored item categories. We use $O_{con} = \left\{O_{con}^+, O_{con}^-\right\}$ to represent the result of conventional negative sampling, where O_{con}^+ is the positive sample and O_{con}^- is the negative sample. The result of the category-based negative sampling is $O_{cate} = \left\{O_{cate}^+, O_{cate}^-\right\}$. For example, $o_i = (u,i) \in O_{con}^+$ indicates an interaction record between user u and item i in the user purchase logs, i.e., a positive sample. Otherwise, $o_j = (u,j) \in O_{con}^-$ indicates no interaction between user u and item j in the user purchase logs, i.e., a negative sample. The definition of O_{cate} is similar to O_{con}.

4.5. Model prediction and optimization

After n-layer aggregations of user u and item i, we sum the representations of different layers to get the final representation:

$$\mathbf{e}_u = \sum_{0 \le k \le n} \mathbf{emb}_u^k; \quad \mathbf{e}_i = \sum_{0 \le k \le n} \mathbf{e}_i^k. \tag{10}$$

Then, we use the conventional inner product method to express the click score of user u on item i, which is defined as follows:

$$\hat{y}_{ui} = \mathbf{e}_u^\top \mathbf{e}_i, \tag{11}$$

Table 2
Statistics of the datasets.

Dataset	#user	#item	#category	#interactions	Sparsity
Movie	592	7310	19	49,304	98.86%
Music	1416	82,44	488	51,525	99.56%
Clothing	46,932	205,084	74	997,490	98.96%

For model optimization, we ensure that the probabilities clicked by the user of negative samples are less than the positive samples (Rendle et al., 2009), so the optimization function obtained based on conventional sampling can be expressed as follows:

$$\mathcal{Y}_{con} = \sum_{(\boldsymbol{u},\boldsymbol{i},\boldsymbol{j})\in O_{con}} -\ln\sigma(\hat{y}_{ui} - \hat{y}_{uj}), \tag{12}$$

where $O_{con} = (\boldsymbol{u},\boldsymbol{i},\boldsymbol{j})|(\boldsymbol{u},\boldsymbol{i}) \in O^{+}_{con}, (\boldsymbol{u},\boldsymbol{j}) \in O^{-}_{con}$ and $\sigma(\cdot)$ is the sigmoid function. The optimization function of category-based negative sampling is similar, but the difference is that users have different repulsion forces for items in unexplored categories, which depends on the value of the user's exploration factor. The optimization function of category-based negative sampling is defined as follows:

$$\mathcal{Y}_{cate} = \sum_{(\boldsymbol{u},\boldsymbol{i},\boldsymbol{j})\in O_{cate}} -\ln\sigma(\hat{y}_{ui} - cef_u\hat{y}_{uj}), \tag{13}$$

where cef_u is a training parameter that reflects the user u's repulsion force for the item in the category unexplored by him.

In addition, we also consider the independence and correlation between categories to improve the accuracy of entity representations. Therefore, the optimization equation of the model can be expressed as follows:

$$\mathcal{L}_{CICEF} = \mathcal{Y}_{con} + \mathcal{Y}_{cate} + \left(\mathcal{D}_{cate} + \mathcal{C}_{cate}\right) + \lambda\|\Theta\|^2, \tag{14}$$

where $\Theta = \left\{\mathbf{e}_v, \mathbf{e}_r, w | v \in \mathcal{V}, r \in \mathcal{R}\right\}$ is the set of model parameters; λ is the regularization term in (0,1).

5. Experiment

We present a series of experimental results to demonstrate the effectiveness of KG-CICEF. The experimental results mainly answer the following three questions:

- **RQ1:** How does KG-CICEF perform compared to state-of-the-art knowledge-aware recommendation models?
- **RQ2:** How do some special designs (e.g., the aggregation layer and the weights of the representations on the two KGs at the time of fusion) affect KG-CICEF?
- **RQ3:** Can KG-CICEF's recommendation list be expanded to these less popular items?

5.1. Experimental settings

5.1.1. Dataset description

To better verify KG-CICEF's performance in different recommendation domains, we use three benchmark datasets for Movie, Music, and Clothing recommendation. The Movie[1] dataset is the MovieLens, which is the stable benchmark dataset with 25 million movie ratings. 25 million ratings and one million tag applications applied to 62,000 movies by 162,000 users. Includes tag genome data with 15 million relevance scores across 1129 tags. The Music[2] datasets is the hetrec-2011. The 2nd International Workshop on Information Heterogeneity and Fusion in Recommender Systems (HetRec 2011, http://ir.ii.uam.es/hetrec2011) has released datasets from Delicious, Last.fm Web 2.0, MovieLens, IMDb, and Rotten Tomatoes. These datasets contain social networking, tagging, and resource consuming (Web page bookmarking and music artist listening) information from sets of around 2000 users. For the Clothing recommendation dataset, we randomly select 46,932 user records according to the proportion of user type and construct a small dataset on the premise of maintaining the user type distribution of the Alibaba-iFashion dataset (Chen, Huang et al., 2019). To ensure data quality, we remove the items clicked by only one user in each dataset. In addition, we delete user records with less than eight interaction records (8-core setting) for the Movie and Music datasets while we adopt a 10-core setting for the Clothing dataset. We use implicit feedback, i.e., only need to pay attention to whether the user interacts with the item. Therefore, we only retain movies with user ratings greater than or equal to 3 in the Movie dataset. In particular, we maintain that each item belongs to one category on each dataset. For the Movie dataset, we assign items to the first category of their original category, while for the Music dataset, the category of items is determined by the mode of the category selected by users when it is clicked. The statistics of our final data set are summarized in Table 2.

[1] https://grouplens.org/datasets/movielens/.

[2] https://grouplens.org/datasets/hetrec-2011/.

Table 3
Overall performance comparison.

	Movie		Music		Clothing	
	recall	ndcg	recall	ndcg	recall	ndcg
BPR	0.0340	0.0276	0.0840	0.0941	0.0037	0.0024
NFM	0.0435	0.0375	0.1121	0.1012	0.0041	0.0034
CKE	0.0452	0.0488	0.1009	0.1079	0.0045	0.0028
CFKG	0.0451	0.0448	0.1135	0.1043	0.0041	0.0022
KGAT	0.0468	0.0496	0.1036	0.1114	0.0044	0.0028
KGIN	0.0490	0.0516	0.1403	0.0920	0.0052	0.0032
CoCoRec	0.0481	0.0510	0.1387	0.1001	0.0047	0.0031
CMHGNN	0.0463	0.0491	0.1266	0.0916	0.0043	0.0029
DGCN	0.0451	0.0509	0.1464	0.1077	0.0042	0.0027
KG-CICEF	0.0605	0.0537	0.1810	0.1137	0.0056	0.0035
% Imp.	23.47	4.07	23.63	2.06	7.69	2.94

5.1.2. Evaluation metrics

In order to evaluate the performance of top-K, we select two common evaluation indicators in recommendation systems (Li et al., 2020):

- **Recall@K** is defined as how many positive samples are predicted to be true, i.e., how many positive samples appear in top-K.
- **NDCG@K** further evaluates the quality of the recommendation list by considering the correlation between the positive and negative samples in top-K.

We set K as 20 by default and use the average results of all users in the training set.

5.1.3. Baselines

To demonstrate the effectiveness, we compare KG-CICEF with the state-of-the-art methods, covering methods KG-free (BPR and NFM), embedding-based (CKE and CFKG), GNN-based (KGAT) method, and path-based (KGIN), as follows:

- **BPR** (Rendle et al., 2009) only utilizes user-item interaction data without constructing KG and adopts the Matrix Factorization (FM) for the recommendation.
- **NFM** (Li et al., 2020) is a state-of-the-art factorization model. It combines traditional MF with Deep Neural Network (DNN) to obtain the ability of FM to model low-order feature interaction and the ability of DNN to learn high-order feature interaction and nonlinearity.
- **CKE** (Zhang et al., 2016) is a representative recommendation method based on KG. It uses TransR to fuse KG and MF for joint training and sends features extracted from KG into MF for recommendations.
- **CFKG** (Ai et al., 2018) integrates the embedding of traditional collaborative filtering (CF) and KG-based to preserve the knowledge structure of users, items, and other heterogeneous entities and further help generate personalized recommendations.
- **KGAT** (Wang, He et al., 2019) is an advanced GNN-based recommendation model that propagates the embedding recursively from the node's neighbor to refine the node's embedding and uses the attention mechanism to distinguish the importance of the neighbor.
- **KGIN** (Wang et al., 2021) refines GNN-based relationship modeling at the level of the user's intentions, recursively extracting information from the relationship path.

Besides, to our knowledge, we are the first KG-based model explicitly utilizing category information to build a complete category-aware KG and enhance user and item representations. However, we have added several SOTA category-aware baselines for a plain comparison, including:

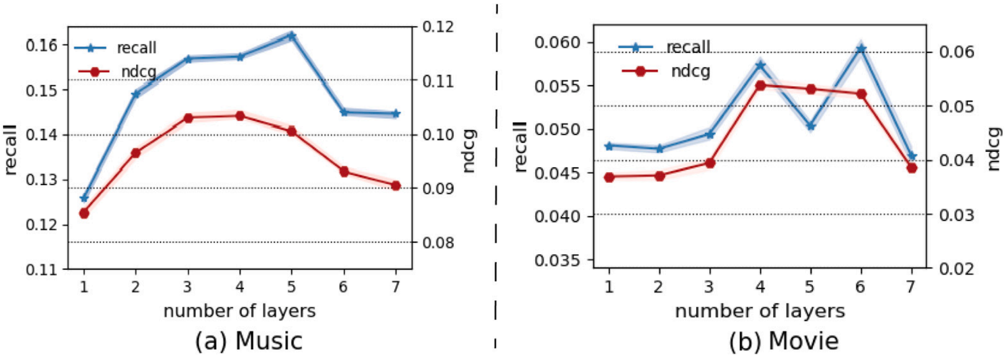
- **CoCoRec** (Cai et al., 2021) utilizes self-attention to capture inner-category transition patterns and make accurate recommendations with users' recent actions.
- **CMHGNN** (Xu, Yang et al., 2022) regards category as input for traditional item recommendation, by constructing an ICHG, a session-level KG.
- **DGCN** (Zheng et al., 2021) analyzes the effect of existing diversification algorithms and combines diversification with matching by utilizing category-aware negative sampling to enhance GCN performance for recommendations.

5.2. Performance comparison (RQ1)

We compared the performance of KG-CICEF to the baseline, and the results are shown in Table 3. The experimental results are the average of all user results. We find that:

Table 4
Ablation results on three datasets.

	Movie		Music		Clothing	
	recall	ndcg	recall	ndcg	recall	ndcg
w/o uc	0.0482	0.0433	0.1409	0.0924	0.0054	0.0034
w/o ui	0.0557	0.0450	0.1686	0.1058	0.0037	0.0022
w/o cns-cef	0.0464	0.0364	0.1649	0.0966	0.0050	0.0032
w/o catt	0.0571	0.0480	0.1609	0.0949	0.0052	0.0032



(a) Music

(b) Movie

Fig. 5. Impact of different aggregation layers. The proportions of aggregation results on KG-UI and KG-UC are fixed at 0.3 and 0.7.

- KG-CICEF consistently outperforms all baselines across three datasets regarding all measures. More specifically, it achieves significant improvements over the strongest baselines w.r.t. recall@20 by 23.47%, 23.63%, and 7.69% in Movie, Music, and Clothing, respectively, which demonstrates the effectiveness of KG-CICEF. We attribute this superiority over baseline to three reasons : (1) KG-CICEF extracts additional user preference over the explored and unexplored item category and forms more powerful representations of users and categories. Compared with other baselines, KG-CICEF focuses more specifically on user preference for categories. (2) We encourage the independence and relevance between categories, making the representations of categories more accurate, and then we can enhance the representation for users. (3) Our aggregation scheme can extract the features of various entities and effectively capture the correlation between different entities. In addition, it combines the information from two KGs to collect the information of users and categories from different perspectives and jointly guide the final recommendation.
- By analyzing and comparing the results of KG-CICEF in three datasets, we found that the effects of KG-CICEF in Music and Movie are better than that in the Clothing dataset. This is reasonable because the Clothing dataset is only a sub-dataset of Alibaba-Ifashion. Although we retain the distribution characteristics of user type in the original dataset, the interaction information between users and items becomes more sparse due to the narrowing of the user set. We supplement the data to some extent by constructing other forms of triplets, e.g., $(o, contains, i)$, but it can only alleviate the problem and cannot completely solve it.
- By analyzing the results of each model, it can be found that the performance of the models based on the KG (e.g., CKE, CFKG, KGAT, KGIN) is better than that of BPR. Specifically, CKE fuses the features extracted from KG into MF, then the performance is greatly improved, which indicates the importance of edge information in the KG for feature extraction.
- The effectiveness of GNN-based KG methods can be proved. The performance of KGAT is superior compared to CKE and CFKG in Movie and Clothing datasets, which illustrates the necessity of aggregating higher-order neighbor information in the KG. CFKG performs better than KGAT on the Music dataset, which is possible that the GNN-based method contains additional nonlinear transformation, then reduces performance due to heavy training.

5.3. Aggregation design (RQ2)

5.3.1. Ablation study

To verify the efficacy of each part in KG-CICEF, we conducted the ablation experiment, and the results are shown in Table 4. The ablation experiment mainly verifies the effectiveness of the corresponding part from the following four aspects : (1) w/o uc: discard the aggregation for users' nodes and categories on KG-UC. (2) w/o ui: discard aggregation for nodes of users and categories on kG-UI. (3) w/o cns-cef: discard the category-based negative sampling mechanism and user exploration factor. The users' exploration factors can only work based on the category negative sampling mechanism, so we bundle them together to verify the effect. (4) w/o catt: discard the category attributes, i.g., remove the independence and relevance between categories. The independence and correlation of category have a uniform effect on the model, so we consider them together.

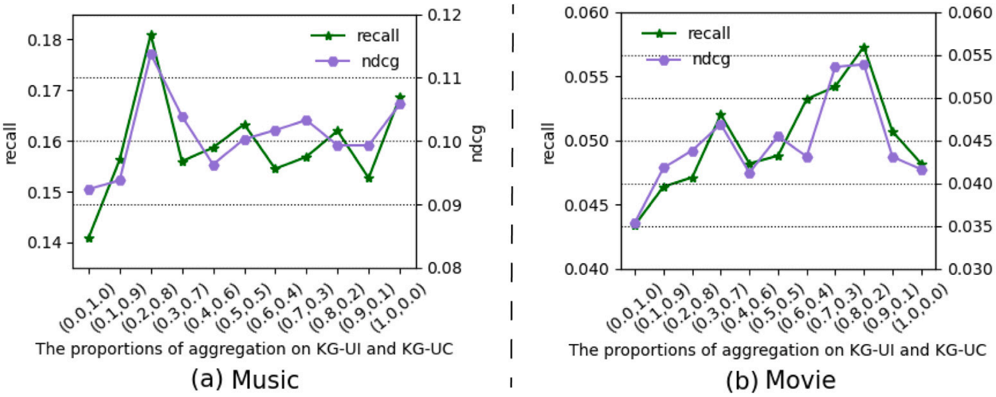


Fig. 6. Impact of different proportions of fusion results on KG-UI and KG-UC. The horizontal axis represents the weights of the fusion results on the two KGs on the final entity representations, e.g., (0.3,0.7) indicates that the proportion of the fusion results on KG-UI in the final entity representations is 0.3, while the proportion on KG-UC is 0.7.

According to the results of the ablation experiment, each part plays a different role in the datasets distributed by different user types. On the Movie and Music datasets, the aggregation portion on KG-UC significantly impacts the final performance, demonstrating the importance of information between the users and the categories of items to the final result. In Clothing, the aggregated results in KG-UI have the most significant influence on the final performance, which further indicates the complexity of information on each fashion item in the Clothing dataset, leading to a more substantial effect of the characteristics of the item on users' decision-making.

5.3.2. Effect of model depth

Next, we consider the impact of changing the number of aggregation layers on performance. Stacking more aggregation layers can cover more nodes in the KG, so the representation of nodes contains more information. However, as the number of layers increases, the representations of different nodes will become similar, i.e., the problem of excessive smoothing, resulting in performance degradation. Here, we compare the performance of aggregation layers with $\{1, 2, 3, 4, 5, 6, 7\}$, and the results are shown in Fig. 5. More specifically, the performance of KG-CICEF indicates a trend of first increasing and then decreasing with the increase of the aggregation layers. When the number of stacking layers reaches 4–6, the model performance reaches a high level or even a peak. As more layers are added, the performance of the model plummets.

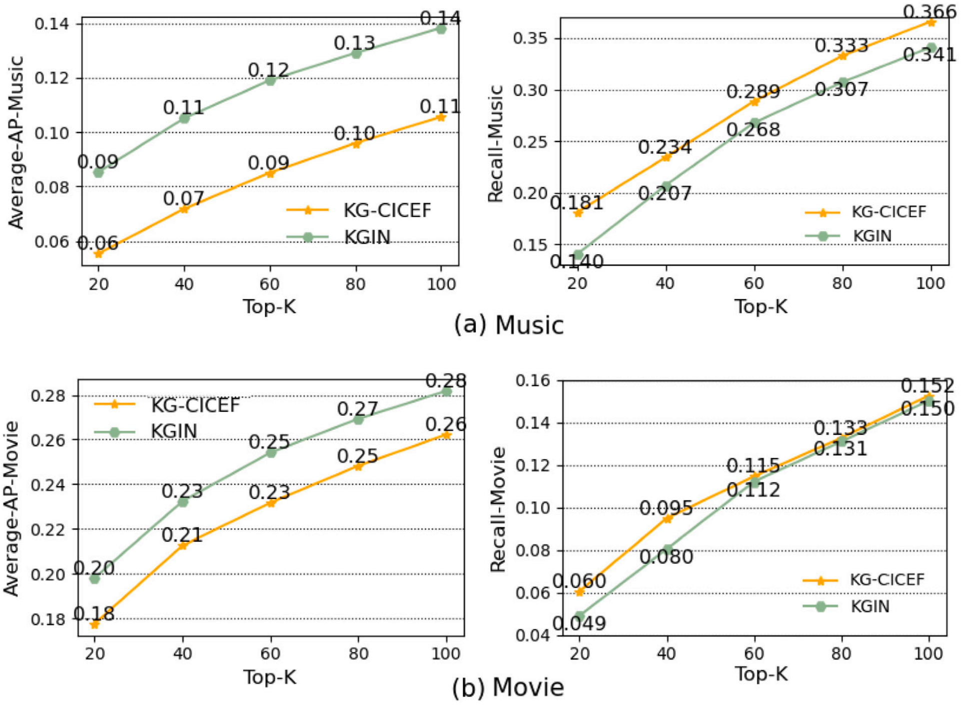
5.3.3. Effect of different proportions of aggregation results on KG-UI and KG-UC

The aggregation results on KG-UI represent global information for each entity, i.e., focusing on structural information between users and items, items, and categories. In contrast, aggregation on KG-UC captures local information about users and categories, focusing on user preference about categories. Therefore, the aggregation results on the two KGs are of different importance in representing the final entity features. Theoretically, if a user pays more attention to the item categories when selecting items, the importance of the aggregated results on KG-UC for the final representation of the user will also increase, i.e., the proportion of KG-UC polymerization results in the final fusion is relatively high. Otherwise, the weight will be low. Fig. 6 indicates the influence of the weight of aggregation results of the two KGs on performance. In the field of Music, user type is complex because there are significant differences in users' attention to categories. Therefore, when aggregating neighbor users' interaction content, the noise influence among users with different exploration styles should be reduced as much as possible. Specifically, in the field of Music, KG-UC should account for a higher proportion of aggregation results than KG-UI. Fig. 6 indicates it peaks at (0.2,0.8). However, in the field of Movies, the user type is relatively fixed, and the neighbors found in the aggregation are most likely users of the same exploration style. At this point, there is no necessity to pay too much attention to the user preference on categories, i.e., the aggregation result of KG-UC should account for less than that of KG-UI. The model peaks at (0.8,0.2) in the Movie domain, which is consistent with our idea. At the same time, the variation of the model performance caused by the change in the weight of the two kinds of KGs can also prove the validity and difference of the information extracted from these two KGs.

5.4. Recommendation analysis (RQ3)

The popularity of items in the user recommendation list is one of the indicators to evaluate a recommendation result. A recommendation system recommending the current hottest or most popular items to all users will exacerbate the two-tier differentiation. That means that items ignored initially are less likely to be noticed, which can exacerbate unfair recommendations.

To test whether a user's recommendation list can focus on a broader range of items, we evaluate it using an average of the popularity (AP) of items from each user's recommendation list. The popularity of an item is the ratio of the number of times it is recommended to all users to the number of recommended places for all users. The smaller the average AP of all user recommendation



(a) Music

(b) Movie

Fig. 7. The average popularity of user-recommended lists. The smaller the average AP of all user recommendation lists, the more items the model can cover. To ensure accuracy, we improve the popularity of items in the user-recommended list.

lists, the more items the model can cover. Finally, we compared AP with the most powerful baseline, as shown in Fig. 7. We calculated the average popularity of individual items in user-recommended lists on Music and Movie datasets. As we can see, due to our explicit attention to user preference for these explored and unexplored item categories, KG-CICEF is more sensitive to item categories than KGIN, allowing it to focus on more different categories. Furthermore, we did not sacrifice accuracy to achieve smaller popularity in the recommended list. The results indicate that our model can focus on a wider range of items while maintaining accuracy.

We conduct a case study as in Fig. 8. We choose user u_1 and u_2 with different cef_u as examples. According to the definition of CEF, a high cef_u indicates that the user prefers to explore different categories in our framework, while a low cef_u indicates that the user prefers to stay in the categories he/she has clicked/bought. If we drop the CEF in our proposed method (cef_u = null), we notice that both users cannot achieve satisfying recommendation lists. Specifically, when applying cef_u, our proposed method can provide a diverse category recommendation list for the user u_1 with high CEF and a relatively stable category recommendation list for the user u_2 with low CEF.

6. Concluding remarks

Differences from existing work. Our research distinguishes itself in the following ways compared to existing studies. Firstly, we introduce the user's cross-item category exploration factor (KG-CICEF) as a key factor in the personalized recommendation, enabling us to capture user preferences for different item categories accurately. Secondly, we construct two knowledge graphs (KG-UI and KG-UC) to represent the relationships between users and items and users and categories, respectively. We then fuse the entity representations from both knowledge graphs using an information aggregation framework, improving model performance. Lastly, we propose a category-based negative sampling mechanism and a cross-item category exploration factor to enhance user preference learning further. Through these novel contributions, our research demonstrates higher accuracy and practicality in personalized recommendations compared to existing studies.

In this work, we not only extract user preference for items but also pay extra attention to user preference for items over explored and unexplored item categories. We propose a KG-CICEF to obtain user preference effectively. Through a novel information aggregation framework, we aggregate information simultaneously on two kinds of KGs to learn the entity representations jointly. On the one hand, we explicitly extract the user preference for explored categories on the user-category KG. On the other hand, we define CEF and combine it with a category-based negative sampling mechanism to extract the user preference for unexplored categories. For consistency, we also propose a category-based negative sampling mechanism to optimize this loss function. The experimental results indicate that our model, e.g., KG-CICEF is superior in performance. In future work, we will pay more attention to the feature representations of categories, e.g., refining the correlation feature of the category to obtain better performance.

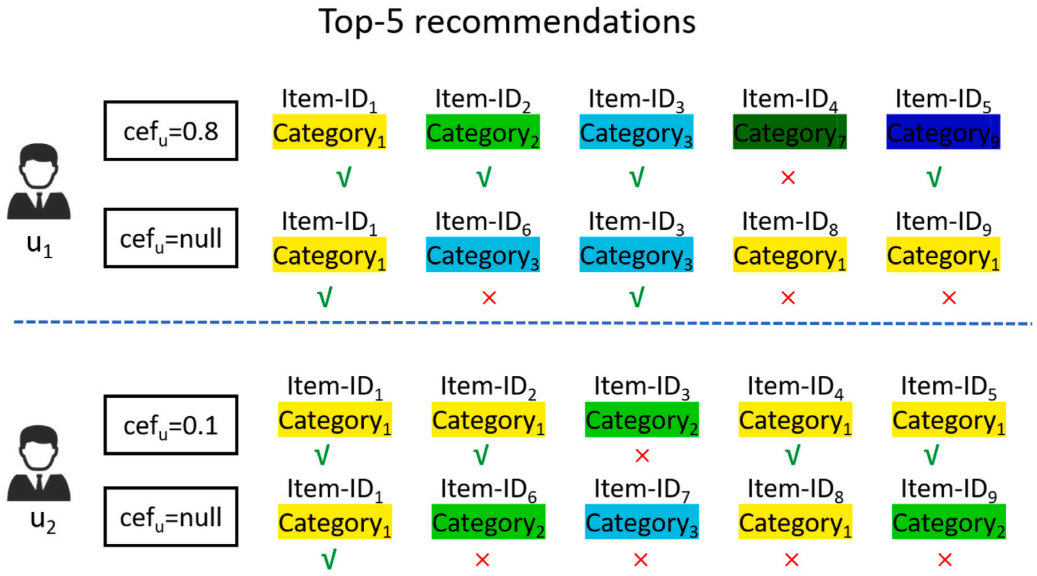

Top-5 recommendations
u_1
cef_u=0.8
Item-ID$_1$ Category$_1$ √
Item-ID$_2$ Category$_2$ √
Item-ID$_3$ Category$_3$ √
Item-ID$_4$ Category$_7$ ×
Item-ID$_5$ Category$_9$ √
cef_u=null
Item-ID$_1$ Category$_1$ √
Item-ID$_6$ Category$_3$ ×
Item-ID$_3$ Category$_3$ √
Item-ID$_8$ Category$_1$ ×
Item-ID$_9$ Category$_1$ ×
u_2
cef_u=0.1
Item-ID$_1$ Category$_1$ √
Item-ID$_2$ Category$_1$ √
Item-ID$_3$ Category$_2$ ×
Item-ID$_4$ Category$_1$ √
Item-ID$_5$ Category$_1$ √
cef_u=null
Item-ID$_1$ Category$_1$ √
Item-ID$_6$ Category$_2$ ×
Item-ID$_7$ Category$_3$ ×
Item-ID$_8$ Category$_1$ ×
Item-ID$_9$ Category$_2$ ×

Fig. 8. A case study to indicate the effectiveness of CEF in recommender systems.

CRediT authorship contribution statement

Yuanbo Xu: Conceptualization, Methodology. **Tian Li:** Validation, Writing – original draft, Visualization. **Yongjian Yang:** Resources, Supervision. **Weitong Chen:** Writing – review & editing. **Lin Yue:** Writing – review & editing.

Data availability

The data that has been used is confidential.

Acknowledgments

This work was supported by the National Natural Science Foundation of Youth Fund, China under Grant 62002123, the Key Project of Science and Technology Development Plan of Jilin Province, China Grant 20210201082GX, Jilin Education Science Foundation, China JJKH20221010KJ. Jilin Science and Technology Research Project, China 20230101067JC.

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