Domain-Oriented Knowledge Transfer for Cross-Domain Recommendation

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Abstract

Cross-Domain Recommendation (CDR) aims to alleviate the cold-start problem by transferring knowledge from a data-rich domain (source domain) to a data-sparse domain (target domain), where knowledge needs to be transferred through a bridge connecting the two domains. Therefore, constructing a bridge connecting the two domains is fundamental for enabling cross-domain recommendation. However, existing CDR methods often overlook the valuable of natural relationships between items in connecting the two domains. To address this issue, we propose DKTCDR: a Domain-oriented Knowledge Transfer method for Cross-Domain Recommendation. In DKTCDR, We leverages the rich relationships between items in a cross-domain knowledge graph as bridges to facilitate both intra- and inter-domain knowledge transfer. Additionally, we design a cross-domain knowledge transfer strategy to enhance inter-domain knowledge transfer. Furthermore, we integrate the semantic modality information of items with the knowledge graph modality information to enhance item modeling. To support our investigation, we construct two high-quality cross-domain recommendation datasets, each containing a cross-domain knowledge graph. Our experimental results on these datasets validate the effectiveness of our proposed method. Source code is available at https://github.com/zxxx1123/DKTCDR.

1 Introduction

A recommendation system plays a vital role in analyzing user preferences using their profiles and historical data. By doing so, it tailors content recommendations to align with users' interests Wang et al. [2022], Jiang et al. [2020]. However, the performance of a recommendation system is significantly hindered when dealing with new users or items with limited historical data. This predicament is commonly referred to as the cold-start problem in recommendation systems. Existing research primarily addresses the cold-start problem through techniques such as data augmentation or the introduction of external knowledge, such as multi-sampling-based recommendation Tang et al. [2023], knowledge graph-based recommendation Li et al. [2020], multimodal recommendation Wei et al. [2019], Liu et al. [2019], Wei et al. [2020], Xiao et al. [2022], Chen et al. [2022a], Wu et al. [2023], Wang et al. [2015], Tao et al. [2023], Du et al. [2023], cross-domain recommendation Zheng et al. [2022], Nie et al. [2023], Sang et al. [2018], Chen et al. [2022b], and others Wei et al. [2021]. Cross-domain recommendation methods Berkovsky et al. [2007] can effectively address the cold-start problem by

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transferring information from the data-rich domain (source domain) to the data-sparse domain (target domain).

Cross-domain recommendation methods rely on transferring information through bridges that connect different domains. These bridges fall into three categories: 1) Common users shared between different domains Man et al. [2017], Zhu et al. [2021, 2022]; 2) Common items shared between different domains Zhu et al. [2018, 2020]; 3) Common content shared between different domains, including user and item attributes, interactions between them, and introduction of themselves Yuan et al. [2019], Zhao et al. [2020], Zhu et al. [2020]. However, existing methods do not utilize the natural relations of items, which may be valuable for cross-domain knowledge transfer and for mining potential relations between items in the source and target domains. Natural relations between items refer to the 1-hop or 2-hop connection between items in the knowledge graph. 1-hop connection means a direct relation, such as a book and the movie adapted from it, they are connected by the adaptation relation. 2-hop connection means a connection generated through a shared attribute, such as books written by the same author are connected by the author attribute. Knowledge Graph contains information about items and their rich attributes, which has rich natural relations of items, therefore it is well suited for uncovering potential relations between items and facilitating knowledge transfer. Potential relations between items refer to the 3-hop or more-hop connection between items in the knowledge graph. Additionally, there is a challenge that enabling the target domain to efficiently acquire knowledge from the source domain, as nodes in a knowledge graph may have numerous neighbors, potentially leading to a dilution of knowledge during the transfer process. To summarize, the problems with existing methods can be categorized into the following two challenges:

1. *How can effective cross-domain knowledge transfer be achieved?* Some methods Zhu et al. [2020], Ouyang et al. [2021] employ cross-domain knowledge transfer by constructing a cross-domain user-item interaction graph. However, there are currently no methods that utilize a cross-domain knowledge graph for cross-domain knowledge transfer. Furthermore, within a cross-domain knowledge graph, most nodes possess a considerably larger number of intra-domain relations in comparison to their inter-domain relations. Directly aggregating all neighbors of a node may potentially compromise the efficacy of cross-domain knowledge transfer. Hence, it is essential to devise an effective strategy for intra-domain and inter-domain knowledge transfer.
2. *There is currently no open-source cross-domain recommendation dataset that includes a cross-domain knowledge graph.* The commonly used open-source cross-domain recommendation datasets, such as the Amazon dataset Ni et al. [2019] and the Douban dataset Zhu et al. [2019], lack associated knowledge graphs. Existing open-source knowledge graphs, such as Freebase and Wikidata, are excessively large to be employed directly and necessitate a method to align the knowledge graph entities with the recommendation dataset items. Consequently, they cannot be readily applied for cross-domain recommendation purposes.

To solve the above challenges, we propose a Domain-oriented Knowledge Transfer method for Cross-Domain Recommendation, called DKTCDR. For challenge one, an item is an entity that exists in the real world and has rich attributes and relational information. Based on this, DKTCDR introduces the cross-domain knowledge graph to help the intra-domain and inter-domain knowledge transfer. Compared with the traditional single-domain knowledge graph, user-item graph, item-item graph, or item-label graph, the cross-domain knowledge graph we constructed contains items and their attributes from multiple domains. Compared to traditional single-domain knowledge graph, cross-domain knowledge graph has natural relations between items from different domains. Such as the natural relation between a book and the movie adapted from it, and the natural relation between books and movies with the same categories. Therefore, we can perform cross-domain knowledge transfer by these natural relations that connect different domains and learn items' high-quality embedding representations. Additionally, we design a Cross-domain Knowledge Transfer Strategy(CKTS), which can further improve the efficiency of cross-domain knowledge transfer. For challenge two, we construct two datasets based on the original data from Amazon Book&Movie, Douban Book&Movie, and Freebase. There are three main problems when constructing the datasets: 1) How to map items in recommendation datasets to the open source knowledge graph entity; 2) How to build a knowledge graph containing only the items from the cross-domain recommendation datasets based on the open source large-scale knowledge graph; 3) How to identify different names for the same person in the original data and how to unify a person's name. Details of dataset construction are given in the dataset construction section.

Moreover, to better model items, we design a semantic embedding module to introduce the information of the semantic modality, which fuses with the knowledge graph modality to jointly model the embedding of items, so that items with similar semantic information can be recommended with higher probability. To learn the user's comprehensive preference, we design a user preference extraction module. The user preference extraction module first maps the user's embedding in the source domain to the target domain, then concatenates it with items the user has interacted with in the source domain, and finally feeds them into the transformer encoder Vaswani et al. [2017] to generate the user's comprehensive preference in the target domain.

In summary, our contributions are as follows:

- We propose a cross-domain knowledge graph-based recommendation method. We propose a novel method using a cross-domain knowledge graph to improve cross-domain knowledge transfer efficiency.
- We propose a cross-domain knowledge transfer strategy (CKTS) for cross-domain knowledge graph-based recommendation to improve cross-domain knowledge transfer performance. Additionally, we introduce the semantic information of items to increase the recommendation probability of semantically similar items.
- We propose two cross-domain recommendation datasets, each equipped with a cross-domain knowledge graph, tailored for common cross-domain recommendation scenarios. They provide more information than existing cross-domain recommendation datasets. Our method significantly outperforms other methods and achieves top performance on the Douban dataset.

2 Related Work

2.1 Cross Domain Recommendation

Cross-domain recommendation can effectively solve the cold-start problem by transferring information from the data-rich to data-sparse domains. At the beginning, it mainly relies on collaborative filtering and matrix factorization, which transfer cross-domain information by constructing matrices. CMF Singh and Gordon [2008] realizes cross-domain knowledge transfer by constructing multiple information matrices and sharing user embedding in multiple domains.

In recent years, methods based on deep neural networks have become the mainstream Elkahky et al. [2015], Zhang et al. [2020], Xie et al. [2021], Li et al. [2021b], Min et al. [2015]. EMCDR Man et al. [2017] first uses matrix factorization on the rating matrix of each domain to obtain the embedded representation of each entity in the domain, and then learns a cross-domain mapping network through the overlapping entities of each domain, so as to realize cross-domain knowledge transfer. DARec Yuan et al. [2019] utilizes the rating matrix to model both users and items, it predicts user ratings for items in both the source and target domains simultaneously by transferring the rating pattern. Additionally, DARec predicts the domain to which the item belongs simultaneously. DTCDR Zhu et al. [2019] utilizes both rating information and content information. The two are combined across domains via the binding layer and ultimately recommended through an MLP. GA-DTCDR Zhu et al. [2020] is an improved version of DTCDR, which introduces the user-item interaction graph to transfer the interaction relations between users and items in multiple domains. CATN Zhao et al. [2020] uses user comment information and proposes aspect-level preference matching to better transfer user preference across domains. DASL Li et al. [2021a] introduces sequential learning, which learns user preference from historical interaction sequences of users, and proposes dual embedding and dual attention mechanisms for cross-domain knowledge transfer. PTUPCDR Zhu et al. [2022] introduces meta-learning and proposes to generate a personalized cross-domain mapping function for each user by learning a meta-network. DDGHM Zheng et al. [2022] models source-target interactions by constructing local and global dynamic graphs, and introduces metric learning to alleviate the problem of data sparsity.

2.2 Knowledge Graph-based Recommendation

The knowledge graph is a type of entity-relation graph that contains abundant attribute relations between items. It facilitates the exploration of users' interests on a deeper level. At the beginning,

CKE Zhang et al. [2016] combines knowledge graph and collaborative filtering to jointly train its models. RippleNet Wang et al. [2018] simulates the propagation process of user interests on the knowledge graph and aggregates the information of multi-hop neighbors. KGCN Wang et al. [2019a] uses GCN Kipf and Welling [2017] for knowledge graph, where it learns knowledge graph embeddings by recommendation tasks and uses the learned knowledge graph embeddings as item embeddings. KGAT Wang et al. [2019b] proposes a Knowledge Graph Attention Network, which is used to capture the multi-hop connection between users and items based on the knowledge graph. QKGN Li et al. [2020] proposes a quaternion-based knowledge graph network, which explores the complex potential relationships between entities and relations by representing users and items with quaternion embeddings. MD-I2IR Liu et al. [2022] proposes a multi-domain recommendation method based on the item-item link prediction task within a cross-domain knowledge graph. This method stitches together items from different domains and their relations on the knowledge graph, and scores the constructed relations to decide whether to recommend the item.

2.3 Differences with existing methods

For cross-domain recommendation methods, they do not effectively utilize the attribute information of items, and the cross-domain knowledge transfer through user-item graph is also limited, e.g. CGKT Ouyang et al. [2021]. For knowledge graph-based recommendation methods, most of them are single-domain recommendation methods. Although MD-I2IR Liu et al. [2022] achieves multi-domain recommendation by doing cross-domain item-item link prediction on cross-domain knowledge graph, it partially ignores important short-term preferences of users, and intra-domain knowledge is not effectively transferred across domain. Unlike the above methods, in this paper, we propose a cross-domain recommendation method based on cross-domain knowledge graph. Firstly, we achieve cross-domain knowledge transfer through cross-domain knowledge graph. Secondly, we design a cross-domain knowledge transfer strategy to improve the efficiency of cross-domain knowledge transfer. Finally, we model user's comprehensive preference by using transformer encoder, and introduce semantic information of item to improve the quality of item embedding.

3 Methodologies

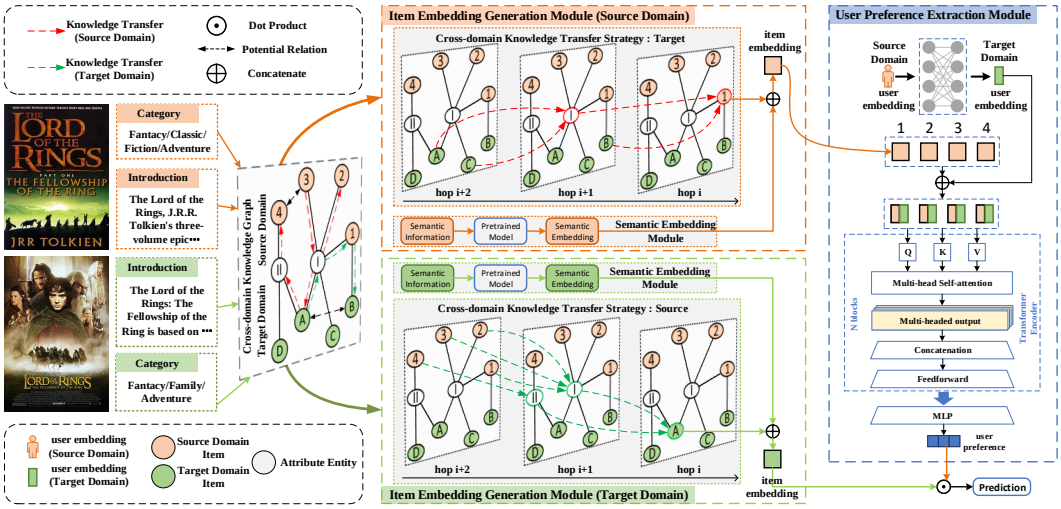


Figure 1: The architecture of DKTCDR. Because B is adapted from 1, there is an edge "adaptation relation" between node 1 and node B. The **Item Embedding Generation Module** utilizes the item's description to generate its semantic embedding, which is then concatenated with the graph embedding to form the item embedding. For historical interactions [1,2,3,4] in the source domain, their respective item embeddings are concatenated with the **user embedding(target domain)**. These combined embeddings are subsequently input into the transformer encoder of the **User Preference Extraction Module**, which is responsible for extracting **user preference**. For an item denoted as 'A' in the target domain, DKTCDR predicts the user's click-through rate by computing the dot product between its item embedding and the **user preference**.

In this section, we will introduce our proposed method DKTCDR, Figure 1 provides an overview of DKTCDR.

Problem Definition. We formalize the cross-domain recommendation problem based on a cross-domain knowledge graph. Given two related domains, our model input includes the user set of the source domain:$U^s = [u_1^s, u_2^s, ..., u_m^s]$, the item set $I = [i_1, i_2, ..., i_n]$ of both domains and the knowledge graph G contains all items of both domains, where u_i^s also denotes the user embedding of user i in this paper. We use $E = [e_1, e_2, ..., e_v]$ to denote the entity embedding set of G and $E_r = [e_{r_1}, e_{r_2}, ..., e_{r_k}]$ to denote the relation embedding set of G. Let $S_i^s = [s_{s_1}^i, s_{s_2}^i, ..., s_{s_q}^i]$ and $S_i^t = [s_{t_1}^i, s_{t_2}^i, ..., s_{t_p}^i]$ denote the historical interaction sequence of user i in source domain and target domain, respectively. $s_{s_i}^i \in I$ and $s_{t_i}^i \in I$ represent the ith clicked item of user i, n is the length of the interaction sequence. When the model is trained in the source domain, given a prefix of the interaction sequence at time t, $S_{i_t}^s = [s_{s_{t-4}}^i, s_{s_{t-3}}^i, ..., s_{s_t}^i], t \in (5, q)$, the goal of the proposed model is to predict the next click item $s_{s_{t+1}}^i$. When the model is trained in the target domain, the interaction sequence is S_i^s, and the goal of the proposed model is to predict all items in S_i^t. To be exact, the proposed model learns to generate a click-through rate $\hat{y_j}$ of user i to the target item j.

3.1 Item Embedding Generation Module

In this module, we design a Cross-domain Knowledge Graph(CKG) and a Semantic Embedding Module(SEM) to fuse the information of knowledge graph modality and semantic modality, and ultimately generate item embedding.

3.1.1 Cross-domain Knowledge Graph

We introduce the Cross-domain Knowledge Graph(CKG) to enhance the cross-domain transfer ability of domain knowledge, where knowledge is transferred as nodes aggregate information from their neighbors. However, nodes and their neighbors may have different relations which contain different information. To simultaneously learn information from neighbors and relations, inspired by KGCN Wang et al. [2019a], we incorporate relation embeddings and entity embeddings into the aggregation process, thereby enhancing the quality of entity embeddings. Below is an introduction to the aggregation process.

At First, we sample the neighbors of a node using a specific sampling strategy, which is detailed in the section on Cross-domain Knowledge Transfer Strategy. Then, for the sampled neighbors, we adopt the idea of KGCN for node aggregation, which aggregates neighbors based on their weights. To illustrate, for a user i and node i with k neighbors in the source domain, we denote the set of (neighbors, relations) of node i as $N_i = [(e_{i,1}, r_{i,1}), (e_{i,2}, r_{i,2}), ..., (e_{i,k}, r_{i,k})]$. For a neighbor $e_{i,j}$, its importance score π_j^i to u_i^s is defined as follows:

$$\pi_j^i = u_i^s \odot e_{r_{i,j}} \tag{1}$$

where $\odot$ denotes the dot product. $e_{r_{i,j}}$ denotes the embedding of the relation $r_{i,j}$ between node i and its neighbour j. The importance scores of all neighbors are normalized as the weight coefficients $W_i = [w_{i,1}, w_{i,2}, ..., w_{i,k}]$. Formally, $w_{i,j}$ is denoted as follows:

$$w_{i,j} = \frac{exp(\pi_j^i)}{\sum_{t=1}^{k} exp(\pi_t^i)} \tag{2}$$

The weighted sum of all neighbor embeddings is used as the aggregated neighbor embeddings, and then add it with e_i as the knowledge graph embedding e_{g_i} of node i. Formally, e_{g_i} is defined as follows:

$$e_{g_i} = \sum_{j=1}^{j \leq k} w_{i,j} * e_{i,j} + e_i \tag{3}$$

3.1.2 Semantic Embedding Module

The semantic information of an item is crucial for users when deciding whether to click on it. For instance, when users are deciding whether to read a book or watch a movie, they typically start by

looking at the introduction. Therefore, recommending other books with a similar introduction to the one they like can significantly improve the click-through rate of users.

Based on the analysis above, we utilized the 2017-EnWiki-dataset[2] to pretrain a Doc2Vec Le and Mikolov [2014] model. To expedite the training of the Doc2Vec model, we employ the publicly available English wiki corpus[3]. Subsequently, for a given item description list $D = [d_1, d_2, ..., d_n]$, the pre-trained Doc2Vec model is used to generate a corresponding list of semantic embeddings $E_s = [e_{s_1}, e_{s_2}, ..., e_{s_n}]$ based on d_i. Specifically, for item i where $i \in [1, 2, ..., n]$, its description is fed into Doc2vec to obtain a 200-dimensional preliminary embedding e_{d_i}. This preliminary embedding is then dimensionally reduced using a two-layer MLP to yield its semantic embedding e_{s_i}. The calculation of e_{s_i} is as follows:

$$e_{s_i} = W_{d_2} * (W_{d_1} * e_{d_i} + bias_{d_1}) + bias_{d_2} \tag{4}$$

where W_{d_1}, W_{d_2}, $bias_{d_1}$ and $bias_{d_2}$ are parameters. Then semantic embedding e_{s_i} is concatenated with knowledge graph embedding e_{g_i} to obtain the final item embedding e_i of item i. Formally, e_i is generated as follows:

$$e_i = concat(e_{s_i}, e_{g_i}) \tag{5}$$

where $concat(\cdot)$ denotes concatenate each term at the last dimension.

3.2 Cross-domain Knowledge Transfer Strategy

We introduce a Cross-domain Knowledge Transfer Strategy(CKTS) for cross-domain knowledge graph, which facilitates the efficient transfer of valuable knowledge from the source domain to the target domain, thereby enhancing the effectiveness of inter-domain knowledge transfer.

Specifically, for the cold-start problem of cross-domain recommendation, we divide the model training process into two stages: 1)The learning stage in the source domain, and 2)The cold-start stage in the target domain. Each stage focuses on learning the embedding representations of two types of items: the user's historical interaction sequence Seq and the target item. Our CKTS is designed to handle these two types of items in each of the two stages, resulting in a total of four item categories depending on the respective stage.

For the sake of clarity, we represent CKTS in the format *[*$\mathcal{D}_t^s$,$\mathcal{D}_{Seq}^s$,$\mathcal{D}_t^t$,$\mathcal{D}_{Seq}^t$*]*, where each term represents the knowledge transfer strategy of the target item in the source domain, the historical interaction sequence when at the learning stage, the target item in the target domain, the historical interaction sequence when at the cold-start stage in order.

We use the format *[first-hop target neighbor of an entity, second-hop target neighbor of an entity]* to represent the knowledge transfer strategy for each type of item, where the optional values for each term are: 1)*random*, which indicates random neighbor sampling; 2)*source*, which indicates the sampling of neighbors from the source domain as much as possible; 3)*target*, which indicates the sampling of neighbors from the target domain as much as possible.

The CKTS used in our method is denoted as C:*[[random, random], [random, random], [source, source], [target, target]]*, and its illustration is shown in Figure 2. The figure demonstrates that our method is capable of acquiring knowledge about Movie B during the learning stage and subsequently utilizing it during the cold-start stage.

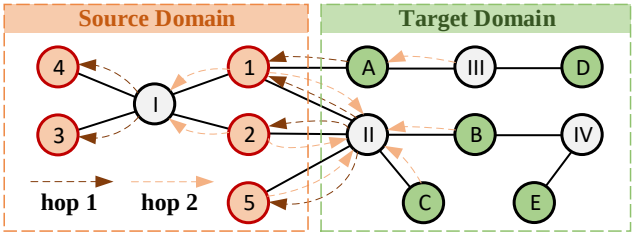
Based on the three optional values of the knowledge transfer strategy mentioned above, we explored three variants of C, namely: 1) C_1:*[[target, target], [target, target], [source, source], [target, target]]*; 2) C_2:*[[target, source], [target, target], [source, target], [source, source]]*; 3) C_3:*[[random, random], [target, target], [source, target], [target, target]]*. The experimental results and discussion of these four strategies are provided in the experiments section.

3.3 User Preference Extraction Module

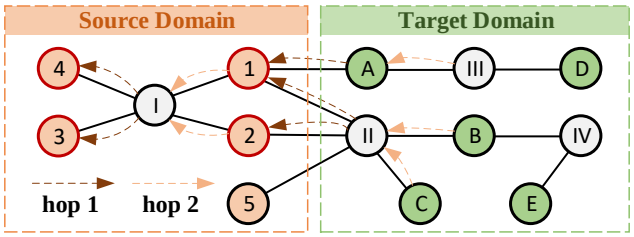
We design the User Preference Extraction Module to extract users' comprehensive preferences from their long-term preferences and historical interactions in the source domain.

[2]https://dumps.wikimedia.org/enwiki/20171001

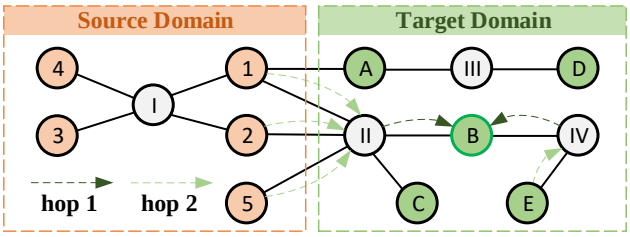
[3]https://github.com/RaRe-Technologies/gensim-data/releases/tag/wiki-english-20171001



(a) Sampling strategy for $\mathcal{D}_t^s$ and $\mathcal{D}_{Seq}^s$. The target of knowledge transfer is the click sequence and item 5. Their knowledge transfer strategy is *[random, random]*, which means sampling neighbors randomly for both the first hop and the second hop as much as possible.



(b) Sampling strategy for $\mathcal{D}_{Seq}^t$. The target of knowledge transfer is click sequence. Their knowledge transfer strategy is *[target, target]*, which means sampling neighbors from the target domain for both the first hop and the second hop as much as possible.



(c) Sampling strategy for $\mathcal{D}_t^t$. The target of knowledge transfer is Movie B. Its knowledge transfer strategy is *[source, source]*, which means sampling neighbors from the source domain for both the first hop and the second hop as much as possible.

Figure 2: An illustration of our cross-domain knowledge transfer strategy C: *[[random, random], [random, random], [source, source], [target, target]]*. Where [1,2,3,4] represents a user's click sequence in the source domain, source domain item 5 is the target item of the learning stage, and target domain item B is the target item of the cold-start stage.

At first, when addressing users' long-term preferences, we utilize user embedding to represent their long-term preferences. We take users' embedding from the source domain and process them through a two-layer MLP. The output of this process serves as their long-term preference in the target domain, denoted as $U^t = [u_1^t, u_2^t, ..., u_m^t]$. For example, the long-term preference of user i in the target domain is generated as follows:

$$u_i^t = W_{m_2} * (W_{m_1} * u_i^s + bias_{m_1}) + bias_{m_2} \tag{6}$$

where W_{m_1}, W_{m_2}, $bias_{m_1}$ and $bias_{m_2}$ are parameters. Subsequently, drawing inspiration from SASRec Kang and McAuley [2018] and BST Chen et al. [2019], we introduce a transformer encoder to extract users' comprehensive preferences. Specifically, for user i's click sequence S_i^s in the source domain, the corresponding item embedding sequence is denoted as $E_{S_i}^s = [e_{s_1}^i, e_{s_2}^i, ..., e_{s_q}^i]$. We begin by separately concatenating each term in $E_{S_i}^s$ with u_i^t. We then feed these concatenated representations into a transformer encoder with n blocks and h headers, and the output is used to represent the user's comprehensive preference P_i^t in the target domain. Formally, P_i^t is denoted as follows:

$$P_i^t = TF([concat(e_{s_1}^i, u_i^t), ..., concat(e_{s_q}^i, u_i^t)]) \tag{7}$$

where $TF(\cdot)$ denotes transformer encoder.

3.4 Prediction and Loss Function

In the preceding module, we have acquired the comprehensive preferences of users in the target domain and the final representation of items. To illustrate this, let's consider user i and item j in the target domain as an example. In DKTCDR, the first step involves performing a dot product between P_i^t and e_j, then summing the results. Subsequently, the user bias b_i^u and item bias b_j^i are added to yield the prediction for the click rate of item j. Formally, the final click-through rate $\hat{y_j}$ of item j is defined as follows:

$$\hat{y_j} = sigmoid((e_j \odot P_i^t) + b_i^u + b_j^i) \tag{8}$$

where $sigmoid(\cdot)$ denotes the sigmoid function, b_i^u denotes the user bias, b_j^i denotes the item bias. For $\hat{y_j}$, $j \in (1, n)$, if the real label is y_j, The loss function $\mathcal{L}$ of DKTCDR is defined as follows:

$$\mathcal{L} = \sum_{j=1}^{n} -(y_j * log(\hat{y_j}) + (1 - y_j) * log(1 - \hat{y_j})) \tag{9}$$

Datasets	domain	reviewer	asin	rating	timestamp	reviewText
Amazon	Book	A1GNQOCSTACJY9	0670922013	5.0	1379808000	I consider myself a proponent ...
	Movie	A1GNQOCSTACJY9	B002BFBAWO	4.0	1375228800	like that movie is included ...
Douban	Book	Frida_Wu	19898714	3.0	2013-05-23	It's too serious.
	Movie	Frida_Wu	5397782	3.0	2013-04-11	She's not the Kai I had in mind.

Table 1: Rating sample of the Amazon and Douban datasets

title	author	tag	doubanID
The Mystery of Edwin Drood	Charles Dickens	mystery,England,horror, detective	6885356

Table 2: Book metadata sample of the Douban dataset

title	actor	editor	director	category	country	language	doubanID
A Christmas Carol	Reginald Owen, Gene Lockhart, Kathleen Lockhart	Charles Dickens, Hugo Butler	Edwin L. Marin	Drama, Fantacy	America	English	3278804

Table 3: Movie metadata sample of the Douban dataset

4 Datasets Construction

4.1 Construction of Amazon Dataset

For the Amazon dataset, we utilize the (entity1, relation, entity2) triplet in Freebase to construct our knowledge graph. The entities in Freebase have a unique identifier, Freebase ID, and the items in the original Amazon book and movie dataset have a unique identifier, ASIN. Most of the items have titles. Since some of these ASINs have no matching Freebase ID, we choose to find the matching Freebase ID of the item first, and then proceed to the next step for these items.

Firstly, there is no open-source dataset that provides the mapping of ASIN to Freebase ID. We discover that Google provides a partial mapping of Wiki ID to Freebase ID, where Wiki ID serves as the unique identifier for entities in Wikidata. Some of Wikidata's books and movies also have corresponding Freebase IDs. To address this, we utilize the Wikidata open query interface to retrieve all book and movie titles, along with their associated Wiki IDs and Freebase IDs. For items lacking a Freebase ID in Wikidata, we employ the Wiki ID as a public identifier to establish the connection between the book or movie title and its Freebase ID. Subsequently, the title is utilized as a public identifier to establish the correspondence between ASIN and the Freebase ID of the Amazon item.

Secondly, for the construction of the cross-domain knowledge graph, we download the latest Freebase dataset and filter the triples that contain the Freebase IDs acquired through the aforementioned process. Subsequently, we eliminate triples in which an entity has a relation with only one item and triples in which an entity has a relation with almost all items within a domain. These exclusions are deemed necessary as they do not significantly contribute to the facilitation of cross-domain knowledge transfer. Consequently, we derive a cross-domain knowledge graph that centers its focus on all items within the Amazon book and movie categories.

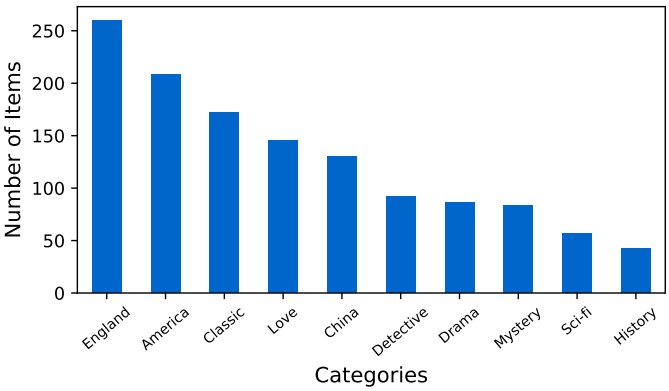


Figure 3: Statistics of Main Categories for Douban Book

Finally, in the process of preparing data for general cross-domain recommendation tasks, we filter the reviews and metadata for the Amazon items mentioned above from the original Amazon review dataset and Amazon metadata. While filtering the reviews, we discovered that the open-source 2018 version of the Amazon dataset does not fully encompass the 2014 version. As a solution, we merge both the 2014 and 2018 versions. A review includes reviewer ID, ASIN, review content, rating, and timestamp.

Furthermore, while processing item metadata, we have encountered instances where the description information for certain items is not found in the metadata but is available on the Amazon website [4]. Consequently, we conduct web crawling to retrieve the English description information of these items from the Amazon website, which we then use to generate semantic embedding through our Doc2Vec model trained on English Wikipedia.

4.2 Construction of Douban Dataset

For the Douban dataset, we construct a cross-domain knowledge graph based on information such as basic attributes, categories, and tags of items. Each item in Douban is assigned a unique identifier called subjectID.

Firstly, we identify several problems with the existing open-source Douban dataset. For instance, the reviews in the Book field of AO2EFM Shu [2018] lack reviewer identifiers, some books lack introductions, some tags are corrupted, and there are inaccuracies in the listed authors of certain books. To address these problems, we perform a re-crawl of user reviews and profiles for all books from the Douban website. This process involved retrieving user information, subjectID, reviews, ratings, timestamps, and book introductions. The comments in the movie field of our dataset and the derived relations between books and movies are referenced from the AO2EFM dataset.

Secondly, during the construction of the cross-domain knowledge graph, we encounter instances where individuals on the Douban website may have multiple names. For example, the Russian writer Lev Tolstoy is associated with two appellations on Douban: 'Lev Tolstoy' and 'Tolstoy'. We also encounter some issues, such as metadata not being presented in a unified language (some in English, some in Chinese, and some in other languages). To address the challenge of dealing with multiple names or the mixing of Chinese and English, which makes it impossible to distinguish them as the same entity, we initiate a preliminary name unification process by conducting similarity calculations on the text. Since IMDb's person names and introductions are uniformly presented in full English, we perform web crawling to extract actor, director, editor, and introduction information from IMDb. Subsequently, we replace the corresponding content in the Douban movie dataset with IMDb's data and establish a mapping between the Chinese and English names of each individual. We utilize both the established Chinese and English name mapping relationships and Google Translate to replace the Chinese author names in Douban books with a unified English name. In cases where names cannot be unified automatically, we manually standardize them to achieve a consistent naming convention in both the book and movie domains.

[4] https://www.amazon.com/

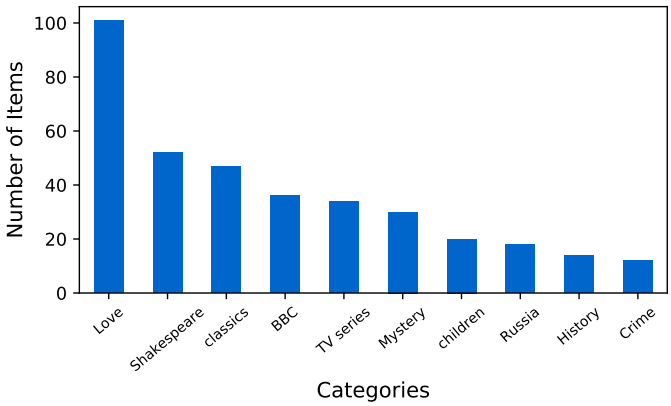


Figure 4: Statistics of Main Categories for Douban Movie

Finally, we process the list of tags for the items in the existing dataset AO2EFM. The tags that are subdividable are further segmented using the Jieba subword database. Tags that appear only once in the entire dataset are eliminated, and synonyms or different words indicating the same meaning are manually combined. Consequently, our Douban mapping consists of triples corresponding to the attribute information mentioned above. For example, for 'Richard II' by Shakespeare, which has the labels: England, History, Drama and Culture. We generate the following triplets: (Richard II, Author, Shakespeare), (Richard II, Label, England), (Richard II, Label, History), (Richard II, Label, Drama), (Richard II, Label, Culture).

Furthermore, for data used in general cross-domain recommendation tasks, we extract the reviewer, subjectID, comment, rating, and timestamp from the raw comment information that is crawled. Then, we isolate the comments of overlapping users from this data. Considering that our Doc2Vec model is trained for English text, the item introductions in the Douban dataset must be also provided in English. In the book domain, we utilize Google Translate to translate item introductions from other languages into English and then use Doc2Vec to generate semantic embedding. In the movie domain, we use the item introductions obtained from IMDb and subsequently employ Doc2Vec to generate the semantic embedding.

In summary, the final Amazon and Douban datasets we have built consist of two parts: general cross-domain recommendation data and a cross-domain knowledge graph. The general cross-domain recommendation data includes user reviews (userId, itemId, review, rating, timestamp) and item metadata (itemId, title, category, tag, description). The cross-domain knowledge graph comprises triples (entity1, relation, entity2).

A sample of reviews from both the Amazon and Douban datasets is provided in Table 1. Additionally, metadata samples from both domains of the Douban dataset are presented in Table 2 and Table 3. The main categories of Douban books and movies can be found in Figure 3 and Figure 4. For more detailed information about the Amazon and Douban datasets, please refer to our GitHub repository.

5 Experiments

5.1 Datasets

Dataset	Amazon		Douban	
Domain	Book	Movie	Book	Movie
Users	175110	175110	38721	38721
Items	21908	8619	1136	1349
Interactions	589205	493419	187933	203150
Entities	53767		10819	
Relations	261		6	
Triplets	565279		22854	

Table 4: The general statistics of the datasets

The cross-domain datasets we have built include the common Amazon Book&Movie dataset, as well as the Douban Book&Movie dataset. For the Amazon dataset, the cross-domain knowledge graph is constructed using data from Freebase. For the Douban dataset, We crawl user comments and ratings from the Douban website[5]. We utilize additional sources such as Wikipedia[6], Goodreads[7], and IMDB[8] to rectify and enhance tags, categories, labels, authors, directors, and other information that are of poor quality or missing in the raw crawl data of books and movies. We use the information queried from Goodreads to rectify and enhance book details. We use the information queried from IMDB to rectify and enhance movie details. Then we use the information queried from Wikipedia to rectify and enhance items we cannot queried in the previous process. Subsequently, the cross-domain knowledge graph for the Douban dataset is constructed based on the improved information. In summary, our datasets encompass not only the cross-domain knowledge graph but also user comments, ratings, tags, timestamps, categories, and semantic information related to the items.

We provide essential details about these two datasets in Table 4. Our method is designed to enhance the quality of cross-domain recommendations for users who overlap in both domains, and it does not take into account users who only appear in one domain. Such users are excluded during the dataset construction process. To simulate cold-start scenarios, the dataset is divided by user, with test users representing 20% of the total user population. To mitigate the impact of excessive interaction samples from certain users in the datasets, we keep users fixed in all experiments for both training and testing, thus ensuring unbiased model performance evaluation.

5.2 Baselines and Metrics

We compare our DKTCDR with nine baseline methods in both single-domain and cross-domain recommendation methods. Cross-domain recommendation methods include DARec Yuan et al. [2019], DASL Li et al. [2021a], CATN Zhao et al. [2020], EMCDR Man et al. [2017], PTUPCDR Zhu et al. [2022], GA-DTCDR Zhu et al. [2020], and COAST Zhao et al. [2023]. Single-domain recommendation methods include xDeepFM Lian et al. [2018] and DcN Wang et al. [2017].

We choose four metrics for the evaluation to comprehensively evaluate the model, namely Area Under Curve(AUC), Root Mean Square Error(RMSE), Mean Absolute Error(MAE), and Logloss.

5.3 Parameter Settings

For the semantic embedding module, we set the embedding dimensions of Doc2vec to 200, which is the default setting. The final dimension for semantic embedding is tuned in [8, 16, 32, 64], and we select 32. The learning rate is tuned in [0.01, 0.05, 0.1, 0.2], and we select 0.1. The batch-size is tuned in [128×5, 128×10, 128×15, 128×20], and we select 128×10. The block number of the transformer encoder is tuned in [1, 2, 4], and we select 1. The head number of the transformer encoder is tuned in [1, 2, 4, 8], and we select 4. The number of neighbors nn for node aggregation on the knowledge graph is tuned in [2, 4, 8, 16, 32], and we select 16. The parameters of our model are initialized by the Glorot normal distribution initializer. Our model is optimized by the gradient descent optimizer. The training epoch is tuned in [50, 100, 150], and we set it to 150. The embedding dimensions for both users and items are tuned in [32, 64, 128, 256], and we set it to 64. The regularization coefficient is set to 0.00001. Following the method presented in Wang et al. [2019a], we apply L2 regularization loss to entities and relations in the cross-domain knowledge graph to prevent potential issues with gradient explosion. The weight of this regularization is set to 1×10^{-7}.

5.4 Results and Discussions

We compare our DKTCDR with other methods in the cold-start scenario to demonstrate the effectiveness of our proposed model. The comparison experimental results on our datasets are shown in Table 5.

Firstly, COAST, GA-DTCDR, PTUPCDR, EMCDR, CATN, DASL, and DARec are all cross-domain recommendation methods. COAST is the latest in comparison methods, which attempts to utilize

[5]https://www.douban.com/
[6]https://wikipedia.org/
[7]https://www.goodreads.com/
[8]https://www.imdb.com/

Datasets	$\mathcal{D}_s \rightarrow \mathcal{D}_t$	Metrics	DcN	xDeepFM	DARec	DASL	CATN	EMCDR	PTUPCDR	GA-DTCDR	COAST	**DKTCDR**
Amazon	*Book→ Movie*	AUC	0.7967	0.8211	0.8105	0.7764	0.6980	0.7950	0.8129	0.7903	0.7911	**0.8268**
		RMSE	0.6308	0.4707	0.4257	0.4762	**0.4110**	0.4364	0.4235	0.4315	0.4366	0.4121
		MAE	0.4734	0.4677	0.3417	0.4732	0.3290	0.3463	0.3383	0.3616	0.3387	**0.2756**
		Logloss	1.2055	0.6359	0.6563	0.6461	0.6640	0.6555	0.6491	0.6617	0.6471	**0.5165**
	Movie→ Book	AUC	0.7514	0.7701	0.7417	0.6146	0.6550	0.7339	0.7483	0.7287	**0.7706**	0.7679
		RMSE	0.5133	0.4846	0.4614	0.4936	**0.4123**	0.4700	0.4571	0.4618	0.4445	0.4436
		MAE	0.4290	0.4802	0.3821	0.4927	**0.3310**	0.3871	0.3856	0.3895	0.3676	0.3351
		Logloss	0.7404	0.6621	0.6732	0.6803	0.7100	0.6719	0.6690	0.6741	0.6582	**0.5778**
Douban	*Book→ Movie*	AUC	0.8457	0.8258	0.8484	0.8449	0.6530	0.8297	0.8427	0.8567	0.8545	**0.8611**
		RMSE	0.4228	0.4575	0.3862	0.4441	0.4790	0.4056	0.3897	0.3821	0.3833	**0.3811**
		MAE	0.3972	0.4536	0.3042	0.4363	0.4110	0.2989	0.2867	0.2861	0.2844	**0.2430**
		Logloss	0.5373	0.6111	0.6363	0.5858	0.7440	0.6385	0.6337	0.6296	0.6268	**0.4524**
	Movie→ Book	AUC	0.7476	0.7709	0.7884	0.7777	0.6630	0.7531	0.7718	0.7880	0.7874	**0.8004**
		RMSE	0.4799	0.4378	0.4296	0.4584	0.4450	0.4523	0.4387	0.4302	0.4322	**0.4250**
		MAE	0.4572	0.3760	0.3662	0.4454	0.3770	0.3781	0.3670	0.3672	0.3630	**0.3125**
		Logloss	0.6520	0.5628	0.6719	0.6094	0.6440	0.6713	0.6662	0.6642	0.6577	**0.5364**

Table 5: Comparison experiment results on Amazon and Douban datasets. The best results are highlighted in boldface, and the second best results are underlined.

rich content information and user interest alignment for bidirectional knowledge transfer. COAST shows similar performance to GA-DTCDR on the Douban dataset, and achieves the best result in the AUC metric of the second task. GA-DTCDR introduces a User-Item Interaction Graph to transfer the interaction between users and items in multiple domains. GA-DTCDR shows better performance than most of the latest methods on the Douban dataset, but performs mediocrely on the Amazon dataset. PTUPCDR primarily leverages the concept of meta-learning, and its performance is between COAST and GA-DTCDR on the Amazon dataset, but not as good as GA-DTCDR on the Douban dataset. While CATN demonstrates strong results in terms of RMSE and MAE, it performs poorly on AUC and Logloss, indicating a limitation in distinguishing between positive and negative samples. DARec performs well on the Douban dataset, even better than PTUPCDR, but not better than PTUPCDR on the Amazon dataset. This suggests that methods solely relying on rating matrices may struggle to capture complex user preferences in larger datasets. About DASL, which introduces dual embedding and dual attention mechanisms, it performs poorly on all four metrics. This may be due to that in our experimental setting, we deal with a fully cold-start scenario, where users have data only in one domain, while the other domain is entirely cold-start. However, DASL requires historical interactions from users in both domains, making it unable to perform effectively in our scenario, resulting in poor performance on all four metrics. EMCDR serves as a common baseline for cross-domain recommendation, and its performance on both pairs of cross-domain datasets is middling. Notably, all seven methods exhibit poor results in Logloss. Experimental results on these seven methods show that they do not distinguish well between positive and negative samples compared to our method, and also have a higher probability of giving predictions opposite to the actual. This demonstrates the effectiveness of our cross-domain knowledge graph.

Secondly, the last two methods, xDeepFM and DcN, are both single-domain recommendation methods. Notably, xDeepFM demonstrates superior AUC and Logloss performance on the Amazon dataset when compared to certain cross-domain recommendation methods. In contrast, DcN is inferior to all other baseline methods. In summary, when it comes to cold-start scenarios, it becomes evident that single-domain recommendation methods do not perform as well as cross-domain recommendation methods.

Finally, our DKTCDR outperforms all other methods. Both single-domain and cross-domain learning of DKTCDR are based on a cross-domain knowledge graph. DKTCDR transfers user and item information learned from the source domain to the target domain through a mapping network and rich inter-domain relations, which significantly improves the recommendation performance of the method in the target domain.

Additionally, COAST shows strong competitiveness, but our model still achieves the best overall results. Our model could discover more relations between items from the cross-domain knowledge graph than the user-item interaction graph. Additionally, our model can better facilitate cross-domain knowledge transfer, thereby learning higher-quality item embeddings.

5.4.1 Ablation Study

We conduct ablation experiments on three main modules: Semantic Embedding Module(SEM), Cross-domain Knowledge Transfer Strategy(CKTS), and Cross-domain Knowledge Graph(CKG). Table 6 shows the results of ablation experiments, where a checkmark indicates that the module is

Datasets	Modules				$\mathcal{D}_s \rightarrow \mathcal{D}_t$				$\mathcal{D}_s \rightarrow \mathcal{D}_t$			
					Book→ Movie				*Movie→ Book*			
	base	CKG	CKTS	SEM	AUC	RMSE	MAE	Logloss	AUC	RMSE	MAE	Logloss
Amazon	✓				0.8150	0.4200	0.2857	0.5321	0.7460	0.4517	0.3597	0.5937
	✓	✓			0.8162	0.4185	0.2872	0.5290	0.7493	0.4516	0.3463	0.5936
	✓	✓	✓		0.8172	0.4179	0.2866	0.5273	0.7503	0.4515	0.3452	0.5935
	✓	✓		✓	0.8242	0.4140	0.2804	0.5203	0.7600	0.4475	0.3363	0.5885
	✓	✓	✓	✓	**0.8268**	**0.4121**	**0.2756**	**0.5165**	**0.7679**	**0.4436**	**0.3351**	**0.5778**
Douban	✓				0.8510	0.3861	0.2591	0.4596	0.7920	0.4294	0.3204	0.5461
	✓	✓			0.8507	0.3856	0.2507	0.4584	0.7925	0.4292	0.3151	0.5450
	✓	✓	✓		0.8507	0.3854	0.2436	0.4580	0.7936	0.4291	0.3135	0.5441
	✓	✓		✓	0.8597	0.3822	0.2507	0.4542	0.7976	0.4259	0.3143	0.5383
	✓	✓	✓	✓	**0.8611**	**0.3811**	**0.2430**	**0.4524**	**0.8004**	**0.4250**	**0.3125**	**0.5364**

Table 6: Ablation results on Amazon and Douban datasets

in use. The base module represents our method without the SEM, CKTS, and CKG modules. It's important to note that both SEM and CKTS depend on the CKG module in our method. Consequently, ablation experiments involving SEM and CKTS inherently include the CKG module.

The results indicate that the base module yields the poorest performance. The inclusion of the CKG module leads to significant improvements in almost all metrics across both datasets, with the most notable enhancement observed in MAE on the Amazon dataset, exhibiting an average improvement of 9.3%. This highlights the substantial impact of a cross-domain knowledge graph on model performance. Further incorporation of CKG and SEM modules results in additional enhancements across almost all metrics for both datasets, underscoring the value of conveying semantic information about the item through the cross-domain knowledge graph in addressing the cold-start problem. On the other hand, substituting the SEM module with the CKTS module does not bring about a significant improvement in model performance. Ultimately, the best results across all metrics for both datasets are achieved when CKG, SEM, and CKTS are combined, signifying that CKTS plays a beneficial role in facilitating cross-domain knowledge transfer within the knowledge graph.

5.4.2 Effect of the cross-domain knowledge transfer strategy

	Datasets	Amazon				Douban			
$\mathcal{D}_s \rightarrow \mathcal{D}_t$	Metrics	C	C_1	C_2	C_3	C	C_1	C_2	C_3
Book→ Movie	AUC	**0.8268**	0.8257	0.8256	0.8250	**0.8611**	0.8596	0.8604	0.8581
	RMSE	**0.4121**	0.4139	0.4134	0.4135	**0.3811**	0.3817	0.3825	0.3823
	MAE	**0.2756**	0.2813	0.2834	0.2788	**0.2430**	0.2453	0.2471	0.2471
	Logloss	**0.5165**	0.5198	0.5203	0.5201	**0.4524**	0.4527	0.4564	0.4525
Movie→Book	AUC	0.7679	0.7647	0.7661	**0.7680**	**0.8004**	0.7987	0.7976	0.7991
	RMSE	**0.4436**	0.4450	0.4448	0.4456	**0.4250**	0.4258	0.4261	0.4254
	MAE	**0.3351**	0.3353	0.3359	0.3367	**0.3125**	0.3150	0.3145	0.3175
	Logloss	**0.5778**	0.5812	0.5816	0.5840	0.5364	0.5380	0.5377	**0.5362**

Table 7: Different cross-domain knowledge transfer strategy results

We conduct experiments to investigate the impact of various cross-domain knowledge transfer strategies. DKTCDR's CKTS is employed in the item's node aggregation phase, where each node aggregates its neighboring nodes within two hops. In the cross-domain knowledge transfer strategy module introduced earlier in this paper, we provide the design details of our strategy denoted as C and explore its three variants: C_1, C_2, and C_3.

The experimental results of these four strategies are shown in Table 7. We observe that strategy C yielded the most favorable evaluation results across most metrics for all four tasks. The results may indicate that random sampling is needed in the learning stage of the source domain, which allows entities in the source domain to comprehensively acquire knowledge from the source domain, thereby enhancing effective knowledge transfer during the cold-start stage of the target domain.

5.4.3 Effect of the number of blocks and heads

To investigate the effect of the number of blocks and heads on the performance, we consider the candidate set 1, 2, 4 for the number of blocks and the candidate set 1, 2, 4 for the number of heads. We

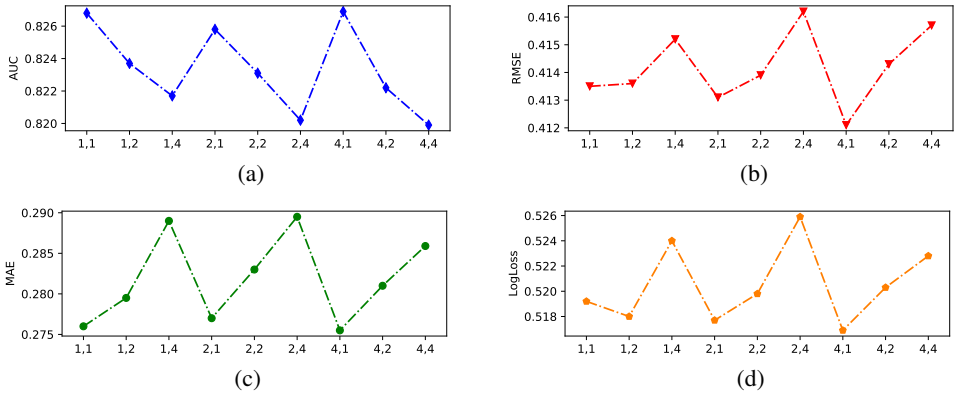


Figure 5: Effect of the number of blocks and heads, where the horizontal coordinates indicate [head num, block num].

then conducted experiments for all possible combinations of these elements. The experimental results are illustrated in Figure 5, indicating a significant decrease in model performance as the number of blocks increases, with a slight improvement as the number of heads increases. Overall, the model's performance is optimal when head=4 and block=1.

5.4.4 Effect of the number of neighbors for nodes aggregation

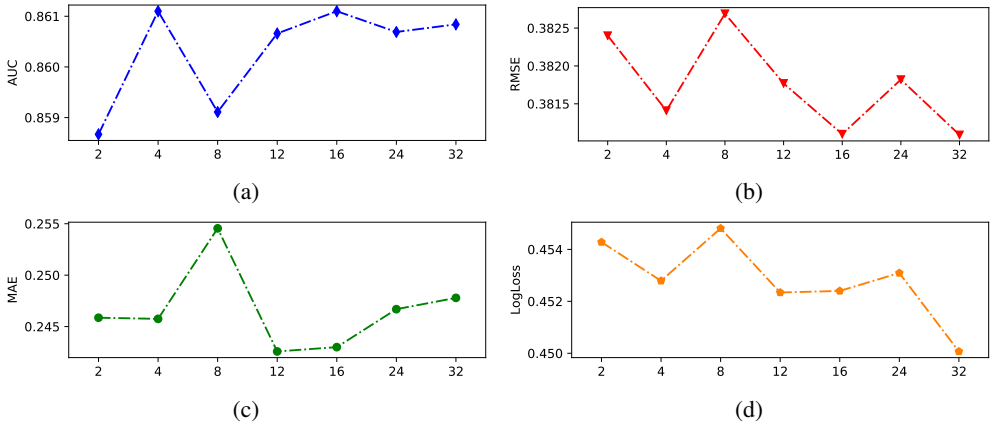


Figure 6: Effect of the sampling number of neighbors. (Transformer Encoder)

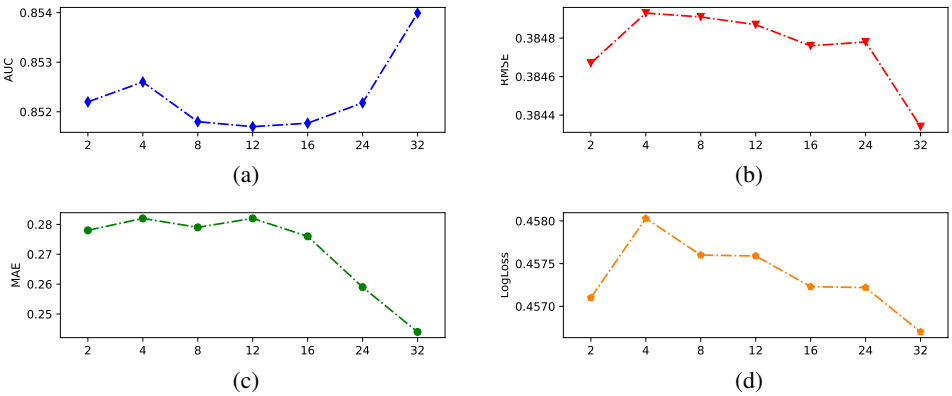


Figure 7: Effect of the sampling number of neighbors. (GRU)

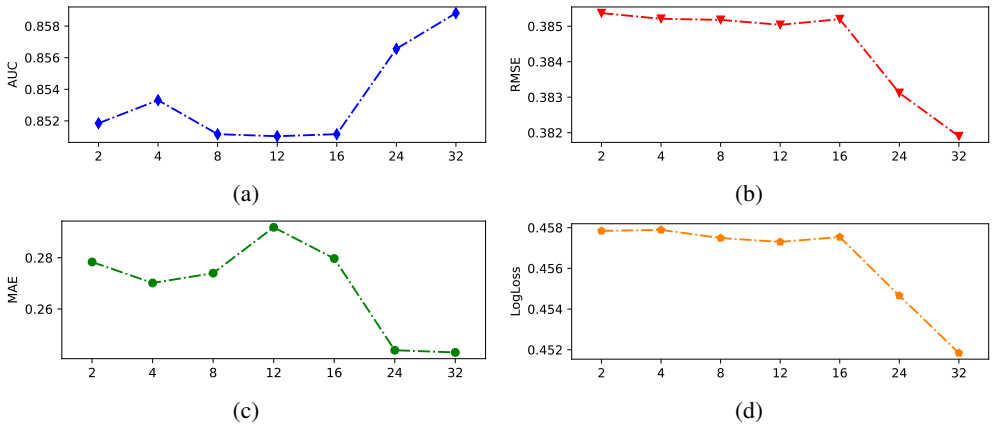


Figure 8: Effect of the sampling number of neighbors. (Bi-LSTM)

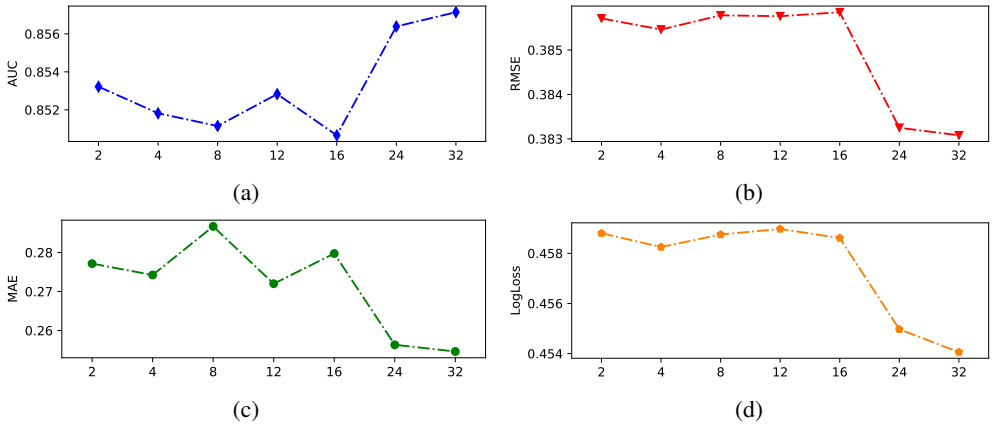
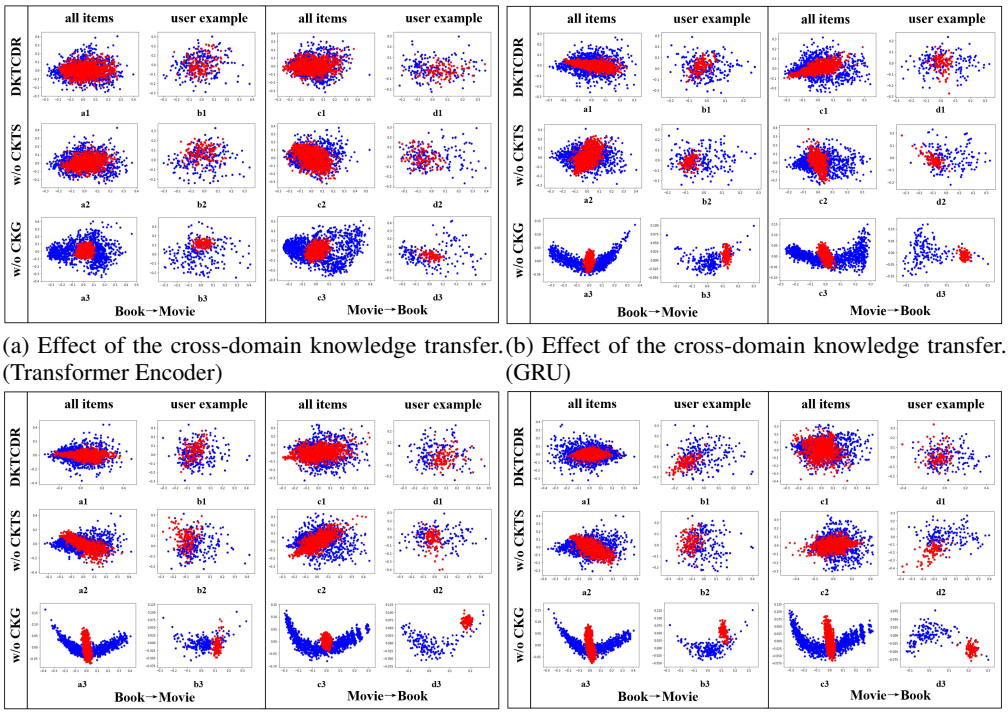


Figure 9: Effect of the sampling number of neighbors. (LSTM)

The cross-domain knowledge graph performs knowledge transfer by nodes aggregating their neighbors. To investigate the effect of the number of sampled neighbors on performance, we conduct experiments with various neighbor counts and sequential modeling methods. The neighbor counts is ranging from [2, 4, 8, 12, 16, 24, 32], and the sequential modeling method is selected from [LSTM, GRU, Bi-LSTM, Transformer Encoder]. The experimental results are shown in Figure 6, Figure 7, Figure 8 and Figure 9. Overall, the number of neighbors aggregated by nodes has a limited effect on model performance, although it still demonstrates some improvement as the number of aggregated neighbors increases. For Transformer Encoder, the model performs best when the node aggregates 16 neighbors. For GRU, LSTM, and Bi LSTM, the model performs best when the node aggregates 32 neighbors. Unfortunately, due to hardware limitations, we are unable to conduct experiments with larger values.

5.4.5 Effect of Our Proposed Cross-domain Knowledge Transfer Strategy to similar items

To assess whether our proposed method enhances the proximity of similar items, we design the present discussion experiment, which visualizes the distribution of items in both the source and target domains within the feature space. We choose the Douban dataset for this analysis due to most of the books and movies in our Douban dataset have a one-to-one adaptation relation. From a feature perspective, the alignment between items of the two domains should also be relatively good, resulting in similar item distributions in the vector space of the two domains. Hence, intuitively, the higher the overlap in the node distribution of the two domains, the better the model learns. In this experiment, we evaluate our DKTCDR, DKTCDR with the CKTS module removed(**w/o CKTS**), and DKTCDR with the CKG module removed(**w/o CKG**) using the Douban dataset. We also experiment many different sequential modeling methods, which is selected from [Transformer Encoder, GRU, Bi-LSTM, LSTM]. Figure 10a, Figure 10b, Figure 10c, and Figure 10d shows the distribution of all



(a) Effect of the cross-domain knowledge transfer. (Transformer Encoder)

(b) Effect of the cross-domain knowledge transfer. (GRU)

(c) Effect of the cross-domain knowledge transfer. (Bi-LSTM)

(d) Effect of the cross-domain knowledge transfer. (LSTM)

Figure 10: Effect of the cross-domain knowledge transfer, where the blue dot and red dot represent source domain item and target domain item respectively. High overlap of node distribution in two domains indicates good model performance.

items in the two domains(as shown in the 'all items' column) and the distribution of all items that are interacted with by the same user(as shown in the 'user example' column) for the three methods, respectively (we believe that most items of source and target domains interacted by the same user should be partially similar).

The results of **w/o CKTS** and **w/o CKG** demonstrate that the cross-domain knowledge graph can significantly enhance the distribution of items in both the source and target domains, reducing the gap between similar items in these domains. The results of DKTCDR and **w/o CKTS** reveal that the item distribution of the source and target domains in DKTCDR exhibits greater convergence and overlap. DKTCDR (i.e. using CKTS) makes the feature distributions of two domains more smilar than w/o CKTS. For example, in the "all items" column in Figure 10, the distribution of blue dots is always horizontal. When using CKTS, the distribution of red dots also changes to horizontal. This clearly demonstrates that CKTS effectively improves the representation of nodes.

In summary, the results in this section prove the effectiveness of the cross-domain knowledge graph and cross-domain knowledge transfer strategy.

5.4.6 Effect of different sampling neighbours' hops

To investigate the effect of high hop information on the model performance on the cross-domain knowledge graph, we conduct experiments on the case of sampling different hops of neighbors.

The results are shown in Table 8, where "hop i" denotes the aggregation of neighbors from hop 1 to hop i. Table 8 shows that on the Amazon dataset, the model performance first improves and then declines with the number of hops increases. On the Douban dataset, the MAE metric improves with the number of hops, while other metrics significantly decrease. Overall, the model performs best at hop 2, and then performance decreases with increasing hops. This may be because there's too much information to aggregate at higher hops, diluting the effective information from lower hop neighbors. Similar results appear in KGCN Wang et al. [2019a], where the authors also experimented from hops

Datasets	$\mathcal{D}_s \rightarrow \mathcal{D}_t$	Metrics	hop 1	hop 2	hop 3	hop 4
Amazon	*Book*→ *Movie*	AUC	0.8183	**0.8268**	0.8235	0.8212
		RMSE	0.4172	**0.4121**	0.4145	0.4152
		MAE	0.3185	0.2756	**0.2732**	0.2801
		Logloss	0.5264	**0.5165**	0.5218	0.5223
	Movie→ *Book*	AUC	0.7492	**0.7679**	0.7651	0.7504
		RMSE	0.4518	**0.4436**	0.4478	0.4531
		MAE	0.3793	**0.3351**	0.3352	0.3405
		Logloss	0.5954	**0.5778**	0.5887	0.5979
Douban	*Book*→ *Movie*	AUC	0.8501	**0.8611**	0.8559	0.8480
		RMSE	0.3849	**0.3811**	0.3866	0.3872
		MAE	0.2796	0.2430	0.2250	**0.2215**
		Logloss	0.4574	**0.4524**	0.4645	0.4625
	Movie→ *Book*	AUC	0.7855	**0.8004**	0.7928	0.7877
		RMSE	0.4305	**0.4250**	0.4294	0.4305
		MAE	0.3649	0.3125	0.3133	**0.3053**
		Logloss	0.5453	**0.5364**	0.5451	0.5466

Table 8: Effect of different sampling neighbours' hops

1 to 4, as shown in Table 4 below. The results show that considering 1-hop and 2-hop information is sufficient, as too many hops can lead to a significant performance decline.

6 Conclusion

In this paper, we propose a Domain-oriented Knowledge Transfer method for Cross-Domain Recommendation, called DKTCDR. We first introduce a cross-domain knowledge graph for intra-domain and inter-domain knowledge transfer. We then fuse semantic information of items in the knowledge graph and design a cross-domain knowledge transfer strategy called CKTS to enhance inter-domain knowledge transfer. Experiments conducted across four cross-domain recommendation scenarios demonstrate that our proposed method can leverage cross-domain knowledge transfer to significantly improve the quality of recommendation for cold-start users.

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