This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TKDE.2022.3151986, IEEE Transactions on Knowledge and Data Engineering

Cross-domain knowledge graph chiasmal embedding for multi-domain item-item recommendation

Jia Liu, Wei Huang, Tianrui Li, *Senior member, IEEE,* Shenggong Ji, and Junbo Zhang *Member, IEEE*

Abstract—Recommender system can provide users with the required information accurately and efficiently, playing a very important role in improving users' life experience. Although knowledge graph-based recommender system can solve the sparsity and cold start problems faced by traditional recommender system, it cannot handle the cross-domain cold start problem and cannot provide multi-domain recommendations. Therefore, this paper focuses on multi-domain item-item (I2I) recommendation based on cross-domain knowledge graph embedding by analyzing the association between items of the same domain and the interaction between items of diverse domains with the aid of knowledge graph that contains rich information. Firstly, a cross-domain knowledge graph chiasmal embedding approach is proposed to efficiently interact all items in multiple domains. To help achieve both homo-domain embedding and hetero-domain embedding of items, a binding rule is put forward. Secondly, a multi-domain I2I recommendation method is presented to efficiently recommend items in multiple domains, which is a recommendation method based on link prediction of knowledge graph. Finally, the proposed methods are compared and analyzed with some benchmark methods using two datasets. The experimental results show that the proposed methods achieve better link prediction results and multi-domain recommendation results.

Index Terms—Recommender system, Multi-domain recommendation, Item-item recommendation, Knowledge graph embedding.

1 Introduction

With the explosion of data on the Internet, recommendation system is playing a crucial role in a wide variety of information domains, such as e-commerce (e.g. Alibaba and Amazon), multi-media (e.g. MovieLens and Douban), and social network (e.g. Twitter and Facebook). Recommender system not only enhances users' life experience, but also facilitates commerce business. Recommendation algorithm is the core of recommendation system. As a basic research mode of recommendation algorithm, item-item (I2I) recommendation tackles the problem of how to recommend items with high relevance for a given item [1]. I2I recommendation is widely used in real life, for instance, when a user has clicked/downloaded an item on a multi-media platform, the "You may also like" will appear on the platform to make recommendations for the user.

For I2I recommendation, the two most classical approaches are the collaborative filtering approach [2], [3] and the content-based approach [4], [5]. Item-based collaborative filtering methods recommend similar items to users based on their historical behavior (clicks, ratings, etc.) on the items. The drawback of this approach is that there is a cold start problem for new items, i.e., new items cannot be recommended. On the other hand, content-based methods directly recommend items with high similarity for users by calculating the similarity of between items. Although these methods can avoid the cold-start problem for new items, the similarity between items is difficult to be accurately defined. To address the above problem, some approaches use knowledge graph as supplementary information for recommendation [6], [7]. Recommender systems that incorporate knowledge graphs containing large-scale information can not only alleviate the cold start problem for new items, but also accurately measure the similarity between items by analyzing knowledge graphs, such as knowledge graph embedding.

However, these recommendation methods are single-domain recommendations, which suffer from cross-domain cold start problem. Specifically, the single-domain recommendation cannot recommend the item from another domain for a user based on the his/her preferences in a domain. For instance, a novel cannot be recommended to a user based on the his/her music listening records. Therefore, some multi-domain recommendation methods have been proposed to study the mutual enhancement of knowledge between different domains [8], [9]. Figure 1 shows an example of a recommendation with items from multiple domains, namely music, movie and fiction. For the man, I:Music3, I:Movie2 and I:Fiction3 are recommended to him based on his favorite movie I:Movie*. The immediate reason is that I:Movie* and I:Movie2 are both science fiction films and use the same music I:Music3, and I:Movie2 is a film adaptation of I:Fiction3. Similarly, we recommend to a woman I:Fiction2, I:Fiction3, I:Movie2 and I:Movie3 based on her preferred novel I:Fiction* on similar grounds. The existing multi-domain recommendation methods are based on the extension of single-domain recommendation methods, which ignore the distinction and association of items between various domains in the real world. For example, a social media content enhanced framework based on the underlying assumption of collaborative filtering was proposed to perform multi-domain recommendation [8].

To address the above problems, the main goal of this paper is to study multi-domain I2I recommendation based on

- *Jia Liu, Wei Huang, Tianrui Li(the corresponding author) are with Institute of Artificial Intelligence, School of Computing and Artificial Intelligence, Southwest Jiaotong University, Chengdu 611756, China. E-mails: xiaoke92@foxmail.com, huangweifujian@126.com, trli@swjtu.edu.cn.*
- *Shenggong Ji is with Tencent Inc., Shenzhen, China. E-mail:shenggongji@163.com.*
- *Junbo Zhang is with JD Intelligent Cities Research, China & JD iCity, JD Tech, China. E-mail:msjunbozhang@outlook.com.*

Manuscript received 12 Sep, 2021; accepted 13 Feb, 2022.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TKDE.2022.3151986, IEEE Transactions on Knowledge and Data Engineering

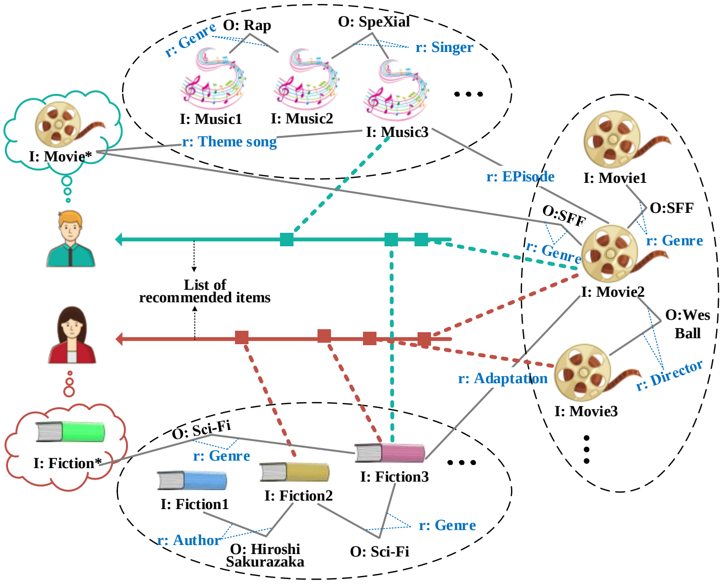


Fig. 1. An example of multi-domain recommendation. * stands for items that the user likes or has interacted with. I: denotes the item, O: indicates other information such as the attributes of the item, and r: shows the relation between the item and the item or the relation between the item and other information. Sci-Fi is an abbreviation for science fiction and SFF is science fiction film.

cross-domain knowledge graph embedding. It not only can explore the similarity between items, but also can tackle the new items cold-start and cross-domain cold-start problems. However, multi-domain I2I recommendation based on cross-domain knowledge graph embedding faces two challenges. One challenge is how to embed cross-domain knowledge graph? Specifically, entity embedding and relation embedding in cross-domain knowledge graph should contain information of multiple domains, and the information of different domains can be distinguished. For example, in Figure 1, how can the embedding of the entity I:Fiction3 be enhanced by using the music information I:Music3 and the movie information I:Movie3? Another challenge is how to design a reasonable multi-domain I2I recommendation method based on knowledge graph embedding. Specifically, for a seed item, how to establish a reasonable connection between it and other items in multiple domains for recommendation decision rather than simply calculating the inner product between item vectors. For instance, in Figure 1, although the embeddings of I:Music2 and I:Fiction3 have low similarity, there may exist a link (relation) to connect them together.

To meet these challenges, we design a novel cross-domain knowledge graph embedding method and a multi-domain I2I recommendation method. In summary, our contributions are shown below.

- A cross-domain knowledge graph chiasmal embedding (CDKG-CE) method is proposed to efficiently distinguish and associate all items in multiple domains. Besides, a binding rule is proposed to achieve the interaction between multiple domains, thereby reaching the goal of homo-domain embedding and hetero-domain embedding.
- The link prediction of knowledge graph is applied to recommendation method and a multi-domain I2I recommendation (MD-I2IR) is proposed. First, this is the first time that knowledge graph is applied to solve the multi-domain I2I recommendation problem; second, link prediction is a downstream application of knowledge graph, and this is the first time that link prediction is applied to implement a specific recommendation process.
- Experiments are conducted on two datasets to evaluate the performance of the proposed CDKG-CE and M-DI2IR. The experimental results show that CDKG-CE and MDI2IR are better than the corresponding benchmark methods in terms of knowledge graph embedding and recommendation methods respectively. Moreover, the proposed MDI2IR method demonstrates the superiority of cross-domain recommendation over the recommended items distribution of the benchmark methods.

The remaining of the paper is organized as follows. Related work on knowledge graph embedding, knowledge graph-based recommendation and multi-domain recommendation are presented in Section 2. Section 3 presents some definitions and task description. Section 4 details the proposed CDKG-CE and Section 5 provides the algorithm of MD-I2IR. The experimental results of CDKG-CE and MD-I2IR on two datasets are discussed in Section 6. Conclusion and future work are given in Section 7.

2 Related Work

2.1 Knowledge graph embedding

Knowledge graph (KG) is a practical method that can denote large-scale information from multiple fields. Specifically, the KG is a set consisting of numerous knowledge triples $< e_h, r, e_t >$, i.e., $KG = \{< e_h, r, e_t > | e_h, e_t \in E, r \in R\}$, where e_h and e_t are head entity and tail entity in the knowledge triple, and r is the relation in the knowledge triple, E represents the set of entities and R shows the set of relations. Each knowledge triple $< e_h, r, e_t >$ means a fact of the relation r from entity e_h to entity e_t. For example, $< Da\ Vinci, painted, Mona\ Lisa >$ describes the case that Mona Lisa is painted by Da Vinci. Due to its strong expressive ability and flexibility in reuse, knowledge graph is widely employed in many application fields, such as natural language understanding [10], [11], question answering systems [12], [13] and recommendation systems [14], [15].

To efficiently apply the knowledge graph to various fields, the knowledge graph embedding (KGE) method is commonly used to embed KG into a low-dimensional space. KGE can quantify KG by its semantic meaning or high-order proximity, while retaining its inherent characteristics [16]. The existing knowledge graph embedding methods can be roughly divided into geometry-based method and deep learning-based method. The geometry-based method interprets the relation as the geometric transformation of the entity in the latent space. Specifically, TransE regards the relation r as the translation between the head entity e_h and the tail entity e_t in Cartesian coordinates [17]. After that, a large number of variant methods based on TransE are introduced to improve the effect of knowledge graph embedding. For example, TransH deals with one-to-many, many-to-one, and many-to-many complex relations [18] and TransD enables each entity to have a different representation under diverse relations [19]. The deep learning-based method learns the representation of the head entity and relation to make it closer to the representation of the tail entity. Dettmers et al. propose ConvE based on 2D convolutional neural network to predict the relation of the knowledge graph [20]. Based on the ConvE method, ConvKB is put to perform representation learning for each item of knowledge triple [21], and CapsE is presented to generate a continuous vector to measure the credibility of knowledge triple [22].

Some well-known knowledge bases, such as YAGO [23], Freebase [24] and DBpedia [25] are cross-domain knowledge graphs, and they all contain thousands of knowledge. However, these knowledge bases include too many domains and the knowledge in each domain is unevenly distributed. None of the existing methods consider the differences and similarities between domains when embedding these knowledge triples. Therefore, cross-domain knowledge graph representation remains to be studied.

2.2 Knowledge graph-based recommendation

In recent years, a large quantity of methods that utilize knowledge graphs as additional information for recommendation have been presented [6], [7], [26]. These methods not only alleviate the data sparsity and cold start problems in recommender systems, but also achieve more accurate and interpretable recommendations [16]. Knowledge graph-based recommendation can be broadly considered into two categories, i.e., knowledge graph embedding-based approach and meta-path-based approach.

The knowledge graph embedding-based approach can be regarded as a multi-task learning approach to some extent, which considers knowledge graph embedding and recommendation as two tasks. The knowledge graph embedding can improve the accuracy and interpretability of the recommendation system, while the recommendation system can help the knowledge graph achieve further completeness [27]. Some methods learn these two tasks sequentially. Wang et al. propose a deep knowledge-aware network for recommending news, which first extracts the features of the knowledge graph through KGE and then constructs a recommendation model based on convolutional neural network (CNN) and attention mechanism [28]. Some methods perform joint learning for these two tasks. Specifically, these methods incorporate users and items as entities in the knowledge graph to form a heterogeneous knowledge graph and embed them in the heterogeneous knowledge graph. Sun et al. design a multi-modal knowledge graph attention network to better enhance the recommender system by exploiting multi-modal knowledge [14]. The approach applies a multi-modal graph attention technique to propagate information over the knowledge graph and then uses an aggregated embedding representation to make recommendations. Some methods learn alternatively for these two tasks. Considering the overlap between the entities of the knowledge graph and the items of the recommender system, a multi-task learning approach, which is a deep end-to-end framework, is employed for knowledge graph-enhanced recommendation [29].

Meta-path-based approach designs pre-defined format and length meta-paths on heterogeneous knowledge graph to capture the diverse semantics carried by the knowledge graph. Some studies exploit the relationships between items to improve recommendation quality. Yu et al. present a recommendation framework based on matrix decomposition (Hete-MF), which extracts multiple different meta-paths and calculates item-item similarity in each meta-path [30]. Some studies model user-user or user-item relationships through meta-paths. Luo et al. propose a collaborative filtering recommendation method based on heterogeneous social network, which models user-item, user-user, and item-item connections by meta-path based similarity [31]. Subsequently, considering that meta-path-based approach relies heavily on hand-crafted feature and domain knowledge, some studies have combined knowledge graph embedding-based approach with meta-path-based approach to avoid this problem. Sun et al. introduce a recursive knowledge graph embedding approach (RKGE) for automatically learning semantic representations of entities and inter-entity paths to characterize users' preferences for products, which employs a novel recurrent network architecture to model the semantics of paths connecting the same entity pairs [32].

Although many knowledge graph-based recommendation models have been proposed, there are still some further challenges. For example, multi-domain recommendation based on knowledge graph and dynamic recommendation based on knowledge graph are still to be studied. In this paper, we focus on applying cross-domain knowledge graphs to achieve multi-domain recommendations to users.

2.3 Multi-domain recommendation

Single-domain recommendation usually suffers from sparsity and cold-start problems. To solve the above problems, researches on mutual enhancement of knowledge between different domains have been performed [8], [33], [34], which are called multi-domain recommendation method. Multi-domain recommendation recommends multiple items from various domains to the user, which is different from cross-domain recommendation.

Cross-domain recommendation recommends items from the source domain to users in the target domain. Assuming that I_i^A is the i^{th} item in the domain A, the cross-domain recommendation will recommend user an item in the domain B that is different from the domain A. State-of-the-art cross-domain recommendation methods usually learns the features of items in different domains separately, and then performs feature interaction on these items to achieve inter-domain associations [35], [36]. The interaction step in these methods is often computed using item similarity [37]. Zhong et al. design an autoencoder framework with an attention mechanism for cross-domain recommendation [38]. The framework uses autoencoder, multilayer perceptron, and self-attention to extract user and item features, and fuse user-latent factors from different domains. Man et al. study the cross-domain recommendation problem from the perspective of embedding and propose an embedding-and-mapping framework, which can learn cross-domain mapping function and clearly distinguish between domain-specific factor and domain-sharing factor [39]. In order to avoid leaking user privacy during data sharing, Gao et al. design a new neural attention transfer recommendation model, which only shares the information of the project party and does not share user behavior data [40].

However, the goal of multi-domain recommendation is to leverage the shared knowledge of multiple domains to alleviate data sparsity in all domains [33]. Assuming that I_i^A is the i^{th} item in domain A, multi-domain recommendation will recommend both the non-i^{th} item in domain A and the item in domain B to users. Zhang et al. propose an active learning recommendation strategy that considers both domain-specific and independent knowledge of all domains to alleviate data sparsity in multi-domain scenarios [33]. Liao et al. present a multi-domain topic-guided session recommender that incorporates

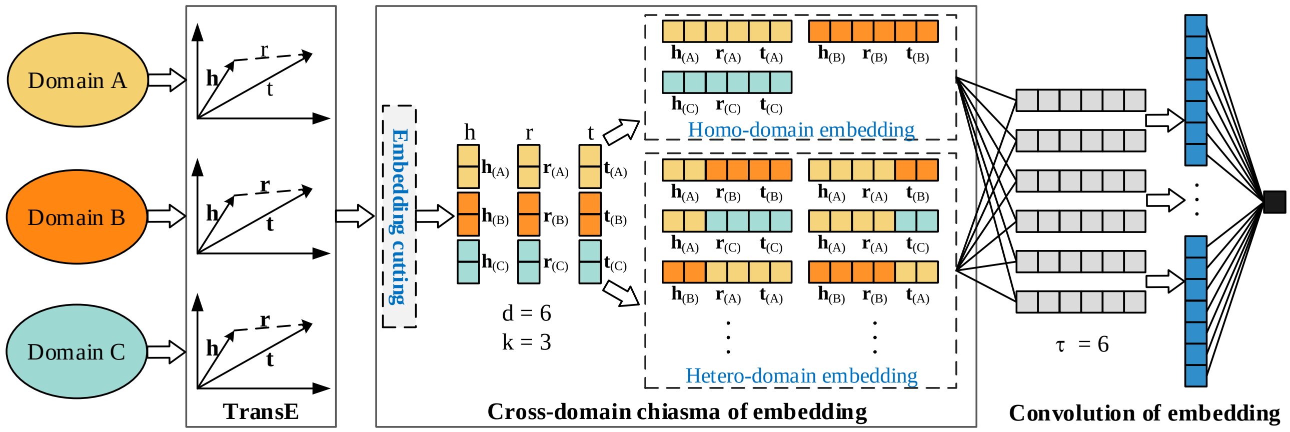


Fig. 2. The proposed cross-domain knowledge graph chiasmal embedding method.

a neural latent topic component in the sequence-to-sequence model to better guide response generation [41]. A convolutional neural network based multi-domain product recommendation algorithm is proposed to achieve better recommendations by leveraging user reviews and multi-domain co-consumption patterns [42].

In general, existing works on multi-domain recommendation are based on extensions of classical single-domain recommendation methods, i.e., collaborative filtering and content-based approaches. Factually, the items between different domains are correlated in the real world. Considering that knowledge graph can effectively represent large-scale information from multiple domains, we apply knowledge graphs of diverse domains to effectively distinguish and connect all items in multiple domains to achieve accurate item-item recommendation in this paper.

3 Preliminary

In this section, we provide the definitions of cross-domain knowledge graph, cross-domain knowledge graph embedding, multi-domain recommendation and the description of the task. We set the number of domains k to 3 to present the proposed approach more briefly and clearly. These $k = 3$ domains are denoted by (A), (B) and (C) respectively.

3.1 Definition

Definition1 Cross-domain knowledge graph (CDKG). Distinguishing from large-scale cross-domain knowledge graphs such as YAGO [23], Freebase [24] and DBpedia [25], we define the cross-domain knowledge graph with clearer domain information. A cross-domain knowledge graph is a collection of knowledge triples with entities and relations from multiple deterministic domains, i.e., $CDKG = \{< h, r, t > | h, t \in E, r \in R, E = E_{(A)} \bigcup E_{(B)} \bigcup \cdots, R = R_{(A)} \bigcup R_{(B)} \bigcup \cdots\}$. $E_{(A)}$ and $R_{(A)}$ denote the set of entities and the set of relations of the domain (A), respectively. E and R represent the set of entities and the set of relations of all domains, respectively. h, t and r refer to head entity, tail entity as well as relation, respectively.

Definition2 Cross-domain knowledge graph embedding (CD-KGE). Without loss of generality, the CD-KGE embeds the cross-domain knowledge graph into a low-dimensional space, and the embedded entity vector $\mathbf{e} \in \mathbb{R}^d$, and the relation vector $\mathbf{r} \in \mathbb{R}^d$ both contain information about k domains. In this paper, we use d to express the vector dimensionality of CD-KGE.

Definition3 Multi-domain item-item recommendation (MD-I2IR). Multi-domain recommendation recommends items of multiple domains to the user. Specifically, based on the seed item I_u that the user u prefers to, the multi-domain item-item recommendation method recommends to the user the set of items that are similar to I_u from multiple domains.

3.2 Task Description

The multi-domain recommendation task in this paper is formulated as follows. **Input:** Knowledge graph of multiple domains $KG_{(A)}$, $KG_{(B)}$ and $KG_{(C)}$, seed item $I_u \in E$ and the set of target items to be recommended $\mathcal{I}_{target} \subset E$. **Output:** Based on I_u, the scores are computed for the triples formed by $\forall r \in R$ and $\forall I_i \in \mathcal{I}_{target}$, and the set $\mathcal{I} = \{I_i\}_{top@m}$ of the top m items with the highest scores is outputted.

4 Cross-domain knowledge graph chiasmal embedding

This section presents the proposed cross-domain knowledge graph chiasmal embedding (CDKG-CE) method in detail, which is capable of fusing single-domain and cross-domain information of knowledge graphs. Figure 2 illustrates the framework of CDKG-CE method, which consists of three main components: 1) initialization of embedding; 2) cross-domain chiasma of embedding; and 3) convolution of embedding.

4.1 Initialization of embedding

TransE is a knowledge representation learning method based on translation model, which considers the relation r as a translation relation between the head entity h and the tail entity t, i.e., $h + r \approx t$ [17]. Firstly, TransE made up for the weaknesses of the traditional method that training is complicated and not easy to expand. Secondly, TransE, as the basis of knowledge base vectorization, has derived many variants, such as TransH [18] and TransD [19]. In this paper, we use TransE to initialize the embedding of the knowledge triples for each domain. Compared to random initialization, this not only speeds up the convergence of the proposed CDKG-CE method, but also improves the performance of embedding. It is worth noting that if an entity e or relation r appears in multiple domains at the same time, there are multiple embeddings of it that will be output after the initialization embedding. We use average fusion

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TKDE.2022.3151986, IEEE Transactions on Knowledge and Data Engineering

to fuse multiple initialization embeddings of entity e or relation r.

$$\mathbf{e} = \frac{1}{k}(\mathbf{e}_{(A)}^{ini} + \mathbf{e}_{(B)}^{ini} + \cdots), \quad \mathbf{r} = \frac{1}{k}(\mathbf{r}_{(A)}^{ini} + \mathbf{r}_{(B)}^{ini} + \cdots), \tag{1}$$

where $\mathbf{e}_{(A)}^{ini}$ and $\mathbf{r}_{(A)}^{ini}$ denote the initialized embedding of entity and relation in the knowledge graph $KG_{(A)}$, respectively.

4.2 Cross-domain chiasma of embedding

In the cross-domain knowledge graph, each entity $e \in E$ can exist in diverse domains, and each relation $r \in R$ can link not only two entities in the same domain but also two entities in different domains. Hence, the main goal of cross-domain knowledge graph embedding is to explore entity embedding and relation embedding that can contain information from multiple domains, and each domain information of the embedding can be distinguished and interacted. To address this challenge, we propose a cross-domain chiasmal embedding approach for cross-domain knowledge graph, which mainly consists of two steps: embedding cutting and embedding chiasmal.

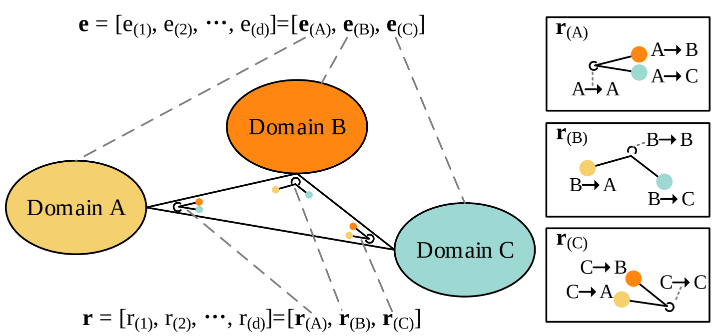


Fig. 3. Embedding cutting and the meaning of segmented embeddings in cross-domain knowledge graph.

Embedding cutting. The embedding cut method has been applied to knowledge graph embedding [43] by Xu et al. Inspired by the SEEK method [43], we cut the entity vector $\mathbf{e}$ and the relation vector $\mathbf{r}$ into k segments with equal number of elements, as shown in Figure 3. Each segment vector of entity e denotes information in a domain, e.g., $\mathbf{e}_{(A)}$ represents the segment embedding of entity e in the domain (A). Obviously, the embedding $\mathbf{e} = [\mathbf{e}_{(A)}, \mathbf{e}_{(B)}, \mathbf{e}_{(C)}]$ of the entity e contains the information of all domains. Each segment vector of the relation r stands for both intra-domain linking information and inter-domain linking information. For example, $\mathbf{r}_{(A)}$ not only denotes links between entities in domain (A), but also links between entities of domain (A) and domain (B), and entities of domain (A) and domain (C).

Embedding chiasma. Embedding chiasma enable interaction of information between diverse domains. The embedding chiasma process is shown in Figure 4. In fact, only two domains are involved in one chiasma. Specifically, there is no chiasma among domain (A), domain (B) and domain (C) at the same time, i.e., $[\mathbf{h}_{(A)}, \mathbf{r}_{(B)}, \mathbf{t}_{(C)}]$ is a non-existent chiasma. Therefore, we propose binding rules to constrain the chiasma between multiple domains. The binding rules include relation-tail entity binding and head entity-relation binding. The chiasmas generated by the binding rules are shown in the bottom part of Figure 4. In the same domain, the chiasmas generated by the two rules are consistent, e.g. $[\mathbf{h}_{(A)}, \mathbf{r}_{(A)}, \mathbf{t}_{(A)}]$. In the embedding process, we use a chiasma as an information embedding in the same domain. In different domains, the chiasmas generated by the two rules are inconsistent. In the embedding process, we use the sum of two chiasmas as the information embedding in the hetero-domain. Specifically, in cross-domain embedding, $\mathbf{r}_{(B)}$ denotes the link between domain (B) and domain (C), and also the link between domain (B) and domain (A); Similarly, $\mathbf{r}_{(A)}$ indicates the link between domain (A) and domain (B), and the link between domain (A) and domain (C). When domain (A) interacts with domain (B), $\mathbf{r}_{(B)}$ is combined with $\mathbf{r}_{(A)}$ to show the association between domain (A) and domain (B), e.g. $[\mathbf{h}_{(A)}, \mathbf{r}_{(B)}, \mathbf{t}_{(B)}]$ and $[\mathbf{h}_{(A)}, \mathbf{r}_{(A)}, \mathbf{t}_{(B)}]$. This embedding chiasma process is similar to chromosome chiasma in the medical field, so we call it cross-domain chiasmal embedding. More, in the whole embedding chiasma process, there are k chiasmas in the same domain and $2k(k-1)$ chiasmas in various domains, and the total number of chiasmas is $2k^2 - k$. As shown in Figure 4, when $k = 3$, the total number of chiasmas is 15.

Given the number of domains k, the number of segmented embedding chiasma in Figure 4 is calculated as shown below. For the number of homo-domain chiasmas, under the relation-tail entity binding rule, the head entity ($\mathbf{h}_{(A)}$) interacts only with the relation-tail entity pair ($\mathbf{r}_{(A)}$-$\mathbf{t}_{(A)}$) in the same domain, with a number of chiasmas of k. Under the header entity-relational binding rule, we drop these chiasmas since the segmented embedding chiasmas are the same as the previous ones. In summary, the number of same-domain chiasmas is k. For the number of hetero-domain chiasmas, under the relation-tail entity binding rule, for k domains, $\forall$ head entity ($\mathbf{h}_{(x)}$) interacts only with the relation-tail entity pair ($\mathbf{r}_{(\neg x)}$-$\mathbf{t}_{(\neg x)}$) of the hetero-domain, with a number of chiasmas of $k(k-1)$. Similarly, segmented embeddings also interact $k(k-1)$ times under the head entity-relational binding rule. In summary, the number of hetero-domain chiasmas is $2k(k-1)$. (x) denotes the x-domain, and $\neg(x)$ denotes a domain except for the x-domain. Overall, the number of segmented embedding chiasmas is $k + 2k(k-1) = 2k^2 - k$.

4.3 Convolution of embedding

ConvKB is a knowledge graph embedding method applying convolutional neural networks [21]. In this method, each knowledge triple $< h, r, t >$ is represented as a matrix of dimension $d \times 3$, where each column vector denotes an element of the knowledge triple. Then, this matrix is convolved by multiple filters to generate different feature maps. Finally, these feature maps are concatenated into a single feature vector that represents the knowledge triple, and the feature vector is multiplied by the weight vector via dot product to return a score. This score is used to predict the validity of the knowledge triple $< h, r, t >$. Formally, the score function of ConvKB is defined as [21]:

$$f_{ConvKB}(h, r, t) = concat(g([\mathbf{h}, \mathbf{r}, \mathbf{t}] * \Omega)) \cdot \mathbf{w}, \tag{2}$$

where Ω and $\mathbf{w}$ indicate the set of filters and the weight vector, respectively. $*$ denotes the convolution operation and $concat(\bullet)$ denotes the concatenation operation. $g(\bullet)$ is the activation function.

Inspired by ConvKB [21], this paper extracts and fuses the homogeneous and heterogeneous information by convolving the homo-domain embedding and hetero-domain embedding

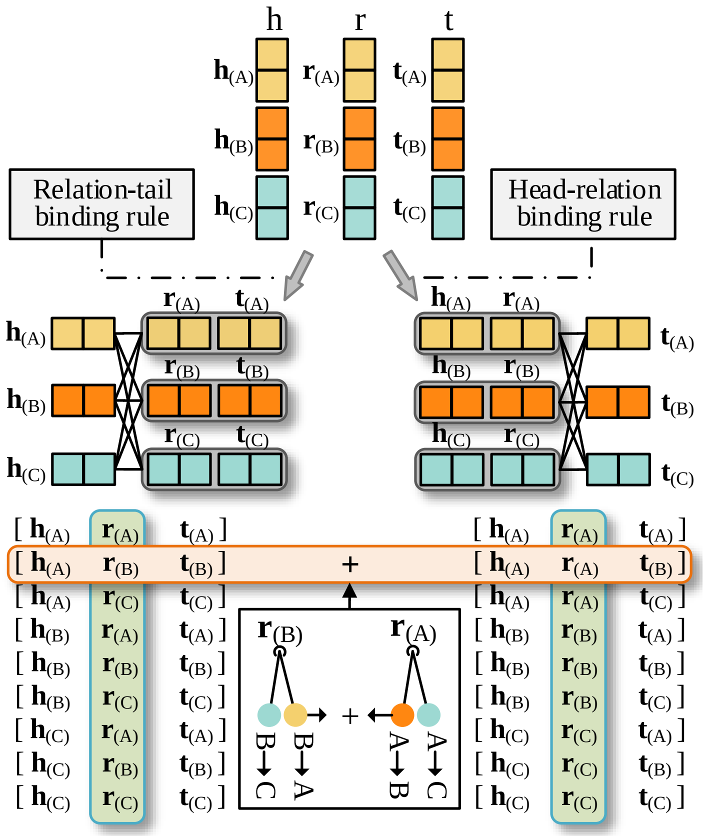


Fig. 4. Binding rules and segmented embedding chiasma.

with τ convolution kernels. The network structure is shown in the right part of Fig. 2. First, for each knowledge triple $< h, r, t >$, a vector matrix of dimension $(2k^2 - k) \times d$ is generated by cross-domain interaction operations. This vector matrix is then fed to a convolutional layer with τ convolutional kernels of size $1 \times d$. By repeatedly convolving each row of the vector matrix, different feature maps are generated. Finally, these feature maps are concatenated into a single feature vector and combined with the weight vector **w** to compute the score of the knowledge triple $< h, r, t >$ by the dot product operation. Formally, the score function of CDKG-CE is defined as:

$$
\begin{aligned}
f_{CDKG-CE}(h,r,t) = \\
& concat(g(\\
& concat([\mathbf{h}_{(x)}, \mathbf{r}_{(y)}, \mathbf{t}_{(z)}]^{homo}, [\mathbf{h}_{(x)}, \mathbf{r}_{(y)}, \mathbf{t}_{(z)}]^{hetero}) * \Omega \\
&)) \cdot \mathbf{w}, \\
& \begin{cases} [\mathbf{h}_{(x)}, \mathbf{r}_{(y)}, \mathbf{t}_{(z)}]^{homo}, & x = y = z; \\ [\mathbf{h}_{(x)}, \mathbf{r}_{(y)}, \mathbf{t}_{(z)}]^{hetero}, & x \neq y = z \;\; or \;\; x = y \neq z, \end{cases}
\end{aligned} \tag{3}
$$

where $x, y, z \in \{A, B, C\}$. $[\mathbf{h}_{(x)}, \mathbf{r}_{(y)}, \mathbf{t}_{(z)}]^{homo}$ and $[\mathbf{h}_{(x)}, \mathbf{r}_{(y)}, \mathbf{t}_{(z)}]^{hetero}$ denote homo-domain embedding and hetero-domain embedding, respectively, as shown in the middle part of Figure 2.

Certainly, the proposed CDKG-CE method can also be utilized for embedding of generic knowledge graphs. When the input is a generic knowledge graph, CDKG-CE can be viewed as an extension of ConvKB [21] and SEEK-1 [1]. For ConvKB, CDKG-CE segments and interacts the embedding. Each segment represents a semantic meaning of the entity, e.g., the segmented embedding of the entity "apple" can represent multiple semantics, i.e., apple company, fruit, and movie name, etc. For SEEK-1, CDKG-CE uses τ convolutional kernels for feature extraction instead of simple dot-product for the interactions of the segmented embedding.

1. There are four score functions proposed in the paper [43], and we use SEEK-1 to denote the first score function.

4.4 Loss function

Without loss of generality, we train the proposed CDKG-CE method using the set of valid triples $CDKG$ and the set of invalid triples $CDKG'$ as input, which is a general learning method for knowledge graph embedding.

Generation of invalid triples. For each valid triple $< h, r, t > \in CDKG$, randomly replace the head entity h or the tail entity t with other entity to obtain the invalid triple $< h', r, t >$ or $< h, r, t' >$, where h' and t' are other entities that replace the head entity h and the tail entity t, respectively. Formally, the set of invalid triples is represented as

$$
\begin{aligned}
CDKG' = \\
& \{< h', r, t > | h', t \in E, r \in R\} \\
& \cup \\
& \{< h, r, t' > | h, t' \in E, r \in R\}.
\end{aligned} \tag{4}
$$

For simplicity, $< h', r, t' >$ is used to denote the invalid triple, including $< h', r, t >$ and $< h, r, t' >$.

Loss function. During the training process, the loss function L and the regularization term on the weight vector **w** are minimized. Formally, the loss function is

$$
\begin{aligned}
L = & \sum_{<h,r,t> \in CDKG} \; \sum_{<h',r,t'> \in CDKG'} \\
& log(exp(f_{CDKG-CE}(h,r,t) - f_{CDKG-CE}(h',r,t')) + \gamma) \\
& + \lambda \|\mathbf{w}\|_2^F,
\end{aligned} \tag{5}
$$

where $\gamma > 0$ is a hyperparameter which serves as a boundary between a valid triplet and an invalid triplet. $\lambda \|\mathbf{w}\|_2^F$ is the regularization term on the weight vector **w**.

5 Multi-domain I2I Recommendation

Link prediction is a downstream application of knowledge graph embedding. Based on link prediction, we design a novel recommendation method. The method can be used as a multi-domain I2I recommendation method based on knowledge graphs. In this section, we present link prediction and the designed novel multi-source I2I recommendation method.

5.1 Link prediction

Link prediction is generally the task of predicting another entity that has a specific relationship with a given entity, i.e., predicting t by given $< h, r, ? >$ and predicting h by given $<?, r, t >$ [44]. In matter of fact, a triple $< h, r, t >$ in the knowledge graph describes a fact in the real world. In the link prediction, if $\exists\, h^* \in E$ (or $\exists\, t^* \in E$) such that the newly composed triple $< h^*, r, t >$ (or $< h, r, t^* >$) has a score $f_{CDKG-CE}(h^*, r, t)$ (or $f_{CDKG-CE}(h, r, t^*)$) higher than $f_{CDKG-CE}(h, r, t)$, which means that $< h^*, r, t >$ (or $< h, r, t^* >$) is also a fact in the real world.

5.2 Recommendation based on link prediction

In multi-domain I2I recommendation, given a seed item $I_u \in E$, explore that whether $\exists\ r \in R$ and $\exists\ I^* \in \mathcal{I}_{target}$ makes the newly composed triple $< I_u, r, I^* >$ have a score $f_{CDKG-CE}(I_u, r, I^*)$ higher than $f_{CDKG-CE}(I_u, r, e)$. Where $< I_u, r, e > \in CDKG$ is a real existing triple, and $e \in E$. If it holds, the term I^* can be treated as the recommended term for the seed item I_u.

The algorithm 1 demonstrates a multi-domain I2I recommendation algorithm based on link prediction. The input of the algorithm 1 consists of the seed items $I_u \in E$, the set of target items to be recommended $\mathcal{I}_{target} \subset E$, and the CDKG after embedding through the CDKG-CE method. The output is the set of the top m items with the highest score, i.e., $\mathcal{I} = \{I_i\}_{top@m}$. Step 1, the set of recommended items is initialized to be empty. Step 2, if $\exists\ < I_u, r, e > \in CDKG$, the entity-relation pair $< I_u, r >$ will be fetched to be used as the object of link prediction. Since there exist multiple relations r forming entity-relation pairs with I_u, we denote the set of entity-relation pairs of the seed item $I_u \in E$ by $\{< I_u, r >\}$. $\{< r, I_u >\}$ is obtained by the same way. In steps 3-8, item recommendation is performed with I_u as the head entity. First, calculate the score $f_{CDKG-CE}(I_u, r, e)$ of the triple $< I_u, r, e >$ with I_u as the head entity and r as the relation in $CDKG$, and obtain the highest score $max_{<I_u,r>}$. Then, the score $f_{CDKG-CE}(I_u, r, I^*)$ of the triple $< I_u, r >$ with each element I^* in $\mathcal{I}_{target}$ is calculated, and the term I^* with a score higher than $max_{<I_u,r>}$ is put into the recommended set of items $\mathcal{I}$. Steps 9-14, I_u is used as the tail entity for item recommendation. The detailed steps are similar to steps 3-8. Steps 15-16, elements in $\mathcal{I}$ are sorted by score in descending order, and extract the set $\mathcal{I} = \{I_i\}_{top@m}$ of the top m items with the highest score if the number of elements in $\mathcal{I}$ is greater than m. Step 17, return the set of recommended items $\mathcal{I} = \{I_i\}_{top@m}$.

The link prediction-based recommendation approach is different from both classical I2I recommendation and knowledge graph-based recommendation approaches. The classical I2I recommendation approach performs recommendation by calculating the similarity between items, such as local I2I recommendation [1] and hybrid I2I recommendation [45]. The knowledge graph-based recommendation approaches calculate the inner product between the user vector and the item vector as the probability of recommendation after the knowledge graph embedding, such as the knowledge graph attention network-based recommendation [46] and the collaborative knowledge base embedding-based recommendation [47]. And the link prediction-based recommendation method designed in this paper draws on the application of link prediction in knowledge graphs to make recommendations. The predicted triples represent an objective fact in the real world, and thus there is a certain rationality of the link prediction-based recommendation approach.

6 Experiments

In this section, to validate the effectiveness of the proposed CDKG-CE method and the multi-domain I2I recommendation algorithm, we compare with some benchmark methods on two knowledge graph datasets. All experiments are carried out with Python 3.5 and torch 0.4.1 on a PC server configured with Intel(R) Core(TM) i7-8700 CPU 3.20GHz, 4 GPUs of 12G NVIDIA Tesla K80C, and 128GB of RAM.

Algorithm 1: Multi-domain I2I recommendation algorithm (MD-I2IR)

Input: Seed item I_u, the set of target items to be recommended $\mathcal{I}_{target}$, the embedded $CDKG$
Output: The set of recommended items $\mathcal{I} = \{I_i\}_{top@m}$

1 $\mathcal{I} \leftarrow \emptyset$
2 Get $\{< I_u, r >\}$ and $\{< r, I_u >\}$ in CDKG
3 **for** *each* $< I_u, r >$ **do**
4   Compute the score $f_{CDKG-CE}(I_u, r, e)$ of the triple $< I_u, r, e >$ with I_u as the head entity and r as the relation in $CDKG$
5   Get the highest score $max_{<I_u,r>}$ of the fact triple according to $f_{CDKG-CE}(I_u, r, e)$
6   Compute the score $f_{CDKG-CE}(I_u, r, I^*)$ of the triple $< I_u, r, I^* >$ formed by $< I_u, r >$ with each element I^* in $\mathcal{I}_{target}$
7     $\mathcal{I} \leftarrow I^*$ if $f_{CDKG-CE}(I_u, r, I^*) > max_{<I_u,r>}$
8 **end**
9 **for** *each* $< r, I_u >$ **do**
10   Compute the score $f_{CDKG-CE}(e, r, I_u)$ of the triple $< e, r, I_u >$ with r as the relation and I_u as the tail entity in $CDKG$
11   Get the highest score $max_{<r,I_u>}$ of the fact triple according to $f_{CDKG-CE}(e, r, I_u)$
12   Calculate the score $f_{CDKG-CE}(I^*, r, I_u)$ of the triple $< I^*, r, I_u >$ formed by $< r, I_u >$ with each element I^* in $\mathcal{I}_{target}$
13     $\mathcal{I} \leftarrow I^*$ if $f_{CDKG-CE}(I^*, r, I_u) > max_{<r,I_u>}$
14 **end**
15 Sort the elements in $\mathcal{I}$ by score in descending order
16 Extract the set $\mathcal{I} = \{I_i\}_{top@m}$ of the top m items with the highest score if the number of elements in $\mathcal{I}$ is greater than m
17 **return** $\mathcal{I} = \{I_i\}_{top@m}$.

6.1 Datasets

Two knowledge graph datasets are adopted to evaluate our proposed CDKG-CE method and multi-domain I2I recommendation algorithm. The details of the two datasets are shown in Table 1. FB15K-237 is a subset of FB15k and is introduced by Toutanova et al. [48]. Relative to FB15k, the inverse relations of FB15K-237 are removed. There are a total of 310,116 knowledge triples, 14,541 entities and 237 relations in FB15K-237.

TABLE 1
Statistics of the experimental datasets. $\#Triples$, $|E|$ and $|R|$ denote the number of triples, entities and relations, respectively.

Dataset	$\#Triples$	$\lvert E\rvert$	$\lvert R\rvert$
FB15K-237 [48]	310,116	14,541	237
KG3Domain	78,032	9,282	445
KG3Domain-1	25,450	3,557	177
KG3Domain-2	30,072	5,300	262
KG3Domain-3	22,510	3,127	140

KG3Domain is a knowledge graph containing information of three domains, which is obtained by the Knowledge Base Cloud Service Platform API [2]. First, we manually give the seed

2. http://kw.fudan.edu.cn/, the Knowledge Works platform provides large-scale, high-quality knowledge graphs that can meet the needs of machine language understanding [49].

entities (called mentions) of multiple identified domains. Then, the 'mention2entity' API is applied to search the set of entities associated with each seed entity. Then, the knowledge triples related to the entities are collected utilizing the 'entity2triple' API. Finally, the knowledge triples of each domain are cleaned. KG3Domain includes 78,032 triples, 9,282 entities and 445 relations. And KG3Domain consists of three sub-knowledge graphs of diverse domains, i. e., KG3Domain-1, KG3Domain-2 and KG3Domain-3. The total number of entities in the three sub-knowledge graphs is 11,984, while the number of entities in KG3Domain is 9,282, which indicates that some entities exist in multiple domains at the same time. Similarly, relations exist in multiple domains simultaneously.

6.2 Evaluation mechanism

To evaluate the proposed CDKG-CE method and the novel multi-domain I2I recommendation method, we apply two evaluation mechanisms, link prediction and recommendation quality assessment, as shown in Table 2.

TABLE 2
Evaluation mechanism.

Evaluation mechanism	Target	Dataset	Evaluation metric
Link prediction	Evaluating the performance of knowledge graph embedding method.	FB15K-237, KG3Domain	MR, MRR, $hits$@10
Recommendation quality assessment	Evaluating the performance of the recommended method.	KG3Domain	HR@10, $NDCG$@10

Link prediction. Link prediction is a classical and effective method for evaluating the performance of knowledge graph embedding. We perform link prediction on FB15K-237 and KG3Domain. Specifically, the head or tail entity in a triple is randomly replaced with other entity. The score of the triple is then calculated by $f_{CDKG-CE}$ and ranked in ascending order. We evaluate the performance of the knowledge graph embedding method by calculating the mean ranking (MR), mean reciprocal ranking (MRR) as well as the proportion of its ranking in the top 10 ($hits$@10) of the correct entity. Lower MR, higher MRR and $hits$@10 indicate better performance of the knowledge graph embedding method.

Recommendation quality assessment. Without loss of generality, we evaluate the performance of the recommendation method on the KG3Domain dataset using the evaluation metric hit rate (HR@10) and the normalized discounted cumulative gain ($NDCG$@10) for the top 10. Given a seed item I_u and a recommended item I^*, we follow the evaluation strategy [45], [50] by mixing the real item I^* and 100 randomly sampled items from $\mathcal{I}_{target}$, sorting the real item and the 100 items and measuring HR@10 and $NDCG$@10. The higher the HR@10 and $NDCG$@10, the better the performance of the recommended method. It is worth noting that although HR@10 and $hits$@10 are computed similarly, they aim at different targets. The $NDCG$@10 takes into account not only the relevance of the recommended item to the seed item, but also the effect of ranking position.

6.3 Baselines

In link prediction, we compare the proposed CDKG-CE method with representatives of two categories of knowledge graph embedding methods: distance-based methods and deep learning-based methods.

TransE [17]. TransE is the most representative distance-based method. Its score function is $\|\mathbf{h}+\mathbf{r}-\mathbf{t}\|_{1/2}$.

SEEK-1 [43]. SEEK-1 calculates the multi-linear dot product of the head entity vector, the relation vector and the tail entity vector. Its score function is $\sum_{(i)} \mathbf{h}_{(i)} \cdot \mathbf{r}_{(i)} \cdot \mathbf{t}_{(i)}$, where $\mathbf{h}_{(i)}$ refers to the i^{th} vector segment after vector cutting, and $\cdot$ stands for dot product operation.

ConvE [20]. ConvE is a knowledge graph embedding method based on 2D convolutional neural network. It has a score function of $f(vec(f([\mathbf{h};\mathbf{r}]*\Omega))\mathbf{w})\mathbf{t}$, where f is a nonlinear function and vec is used to vectorize the tensor.

ConvKB [21]. ConvKB explores the global relationships between entity embedding and relations embedding with the same dimension by convolutional neural network. Its score function is shown in Equation 2.

In the recommendation quality assessment, we compare the proposed multi-domain I2I recommendation method (MD-I2IR) with representatives of multi-class recommendation methods.

NeuMF [50]. NeuMF is a collaborative filtering method based on neural network and matrix decomposition. It is used to represent a collaborative filtering based recommendation method.

SPE [45]. SPE is a tightly coupled hybrid semi-parametric embedding framework. It is used to represent both hybrid methods and I2I recommended methods. We initialize the terms with TransE and use the initialization vector of the terms as the meta-information vector of the terms.

Content+topology_KNN.Content_KNN is a classical I2I recommendation method. It evaluates the relationship between a pair of items by analyzing their contents. We extend Content_KNN to Content+topology_KNN. Content+topology_KNN considers both content information and the topology of two items in the knowledge graph, i.e. $\frac{cos(I_u,I_i)}{\mu}$, where $cos(I_u, I_i)$ is the cosine similarity between I_u and I_i, and μ indicates that I_i is a μ-order neighbour of I_u.

DeepICF [3].DeepICF is an item-based collaborative recommendation employing deep neural network. In this paper, the seed entity I_u is considered as the user and the neighbors within the 2 order ($\mu \leq 2$) of I_u as its interactive items, and a multi-hot representation is used. Each item in $\mathcal{I}_{target}$ is represented by one-hot.

MD-I2IR(ip). MD-I2IR(ip) performs recommendation after the knowledge graph embedding by computing the inner product between the item vectors, which is a common method for knowledge graph-based recommendation. It is used to represent the knowledge graph based recommendation method.

6.4 Hyperparameter

TransE is utilized to initialize the knowledge triples, and its hyperparameters are shown below. The learning rate is 0.01, the optimizer is stochastic gradient descent (SGD), the number of training rounds is 3000, and the dimension d of the embedding is 60. The hyperparameters of the proposed CDKG-CE method are shown below. The learning rate is 0.0005, the number of convolutional kernels τ is 256, the optimizer is adaptive gradient

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TKDE.2022.3151986, IEEE Transactions on Knowledge and Data Engineering

algorithm (Adagrad), the number of training rounds is 300, and the dimensionality of the embedding d is 60. The hyperparameters of the baselines used for comparison are set according to the corresponding papers.

6.5 Performance evaluation of knowledge graph embedding

The performance of the proposed CDKG-CE method is evaluated by comparing it with some baseline methods for knowledge graph embedding. The results of link prediction are shown in Table 3. First, the performance of CDKG-CE is higher than TransE on both two datasets, as evidenced by the fact that CDKG-CE has lower MR, higher MRR and $Hits@10$. This demonstrates that the deep features extracted using the neural network are effective. Secondly, the performance of SEEK-1 is the lowest on two datasets, which shows that the embedding capability of the method for the knowledge graph is still insufficient. For the deep learning-based method, the performance of CDKG-CE is improved relative to both ConvE and ConvKB in evaluating the metrics MRR and $Hits@10$. For the metric MR, CDKG-CE's MR value is slightly higher than ConvE and ConvKB on dataset FB15K-237, and slightly higher than ConvE and slightly lower than ConvKB on dataset KG3Domain. Nevertheless, their performance on the metric MR is similar.

TABLE 3
Link prediction results and performance comparison of different methods. The • indicates that the experimental results are from the paper [21], because the actual experimental results are slightly lower than those in the paper [21].

KGE methods	FB15K-237 [48]			KG3Domain		
	MR	MRR	$Hits@10$	MR	MRR	$Hits@10$
TransE [17]•	347	0.294	0.465	216	0.146	0.332
SEEK-1 [43]	408	0.283	0.451	260	0.139	0.320
ConvE [20]•	246	0.316	0.491	149	0.156	0.351
ConvKB [21]•	257	0.396	0.517	159	0.196	0.378
CDKG-CE	264	0.464	0.523	152	0.206	0.431

6.6 Performance evaluation of I2I recommendation

On the dataset KG3Domain, we validate the performance of the proposed MD-I2IR by comparing the experimental results of multiple I2I recommended methods. The detailed experimental results are shown in Table 4. First, MD-I2IR has better performance on both metrics $HR@10$ and $NDCG@10$ relative to NeuMF, SPE, Content+topology_KNN and DeepICF methods. And the performance of MD-I2IR(ip) is slightly better than that of SPE. This implies that the knowledge graph-based approach is more suitable to be applied to I2I recommendation. The possible reason is that the knowledge graph embedding approach provides a good representation of the information of items and the relationship between them, which makes it easier to identify items with similar features. Second, MD-I2IR performs better than MD-I2IR(ip). This demonstrates the effectiveness of the link prediction-based recommendation method. The items recommended by this method are more like a fact with the seed items on a certain relation r.

TABLE 4
I2I recommended results and performance comparison of different methods.

I2I recommendation methods	$HR@10$	$NDCG@10$
NeuMF [50]	0.3681	0.1416
SPE [45]	0.5654	0.3336
Content+topology_KNN	0.3471	0.2085
DeepICF [3]	0.3791	0.2567
MD-I2IR(ip)	0.5796	0.3388
MD-I2IR	0.6038	0.3583

6.7 Comparison of the distribution of the recommended items in different domains

In order to verify the performance of the recommendation algorithm to be able to recommend items in various domains, we analyze and discuss the distribution of the recommended items in different domains. Specifically, for the m items recommended by the recommendation algorithm, i.e., $HR@10$, we analyze the proportion of these m items in each of the three domains. We evaluate the proportion of the three domains using the standard deviation, which is most frequently used as a measure of the degree of statistical dispersion. Formally,

$$\sigma = \sqrt{\frac{1}{k}\sum_{i=1}^{k}(x_i - \overline{x})^2}, \tag{6}$$

where σ is the standard deviation of the distribution of the recommended items in various domains. x_i denotes the number of recommended items in the i^{th} domain, and $\overline{x}$ stands for the average number of recommended items in each domain. In particular, the smaller the σ, the stronger the ability of the recommendation algorithm to recommend items from multiple domains.

Figure 5 shows the distribution and standard deviation of the items recommended by multiple recommendation algorithms in different domains. From the Figure 5, we can notice that when the number of recommendations is $m = 10$, the items recommended by NeuMF, SPE, Content+topology_KNN, DeepICF and MD-I2IR(ip) methods come from the same domain, while the items recommended by the proposed MD-I2IR come from domain (A) and domain (C). When the number of recommendations is $m = 20$, SPE, Content+topology_KNN and DeepICF recommends items from the same domain, NeuMF and MD-I2IR(ip) recommend items from domains (A) as well as domain (C), and MD-I2IR recommends items from three domains. When the number of recommendations is $m = 30$, the items recommended by the Content+topology_KNN method come from two domains, while the items recommended by the other five recommendation methods all come from three domains. And NeuMF, SPE and DeepICF have relatively few items from domain (B) and domain (C). When the number of recommendations is $m = 40$, the items recommended by MD-I2IR are more evenly distributed in each domain compared to the other recommendation methods. When $m > 40$, the items ranked greater than 40 are unsuitable to be recommended to users considering the low score. As the number of items recommended increases, the standard deviation of the distribution of the items recommended by the proposed MD-I2IR in various

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TKDE.2022.3151986, IEEE Transactions on Knowledge and Data Engineering

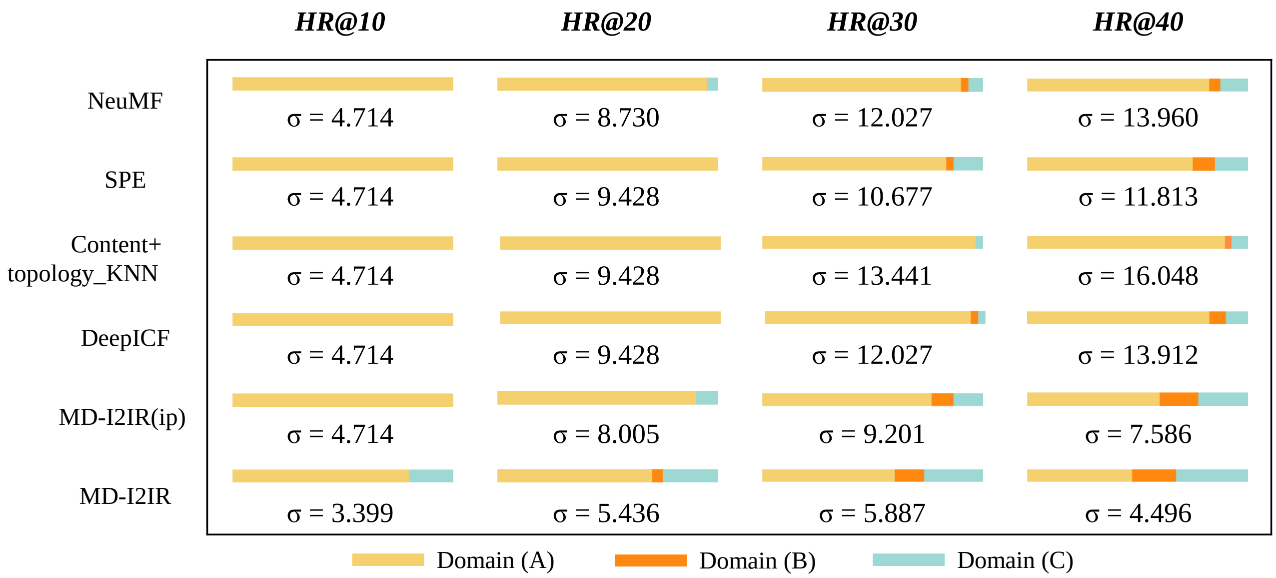


Fig. 5. The distribution and standard deviation of items recommended by different recommendation algorithms in diverse domains.

domains is the lowest, which demonstrates the good ability of the method to recommend items from multiple domains.

Figure 6 illustrates the distribution and standard deviation of the items recommended in different domains by MD-I2IR based on multiple knowledge graph embedding methods. From the Figure 6, we can see that MD-I2IR(TransE) and MD-I2IR(SEEK-1) can recommend items from all three domains at the same time only if the number of recommendations reaches 40. This indicates that these methods have difficulty in capturing the connection between different domains in embedding. MD-I2IR(ConvE) and MD-I2IR(ConvKB) are able to recommend items from all three domains when the number of recommendations is 30 and 40. This demonstrates that the deep learning-based method has some ability to capture the connection between different domains. The proposed MD-I2IR (CDKG-CE) considers both same-domain embedding and cross-domain embedding, and it has better performance in multi-domain recommendation. To a certain extent, this indicated the good ability of CDKG-CE to embed cross-domain knowledge graphs. As the number of recommendations increases, the standard deviation of the distribution of the items recommended by MD-I2IR (CDKG-CE) across domains is the lowest, which also demonstrates that the method has good ability to recommend items from multiple domains.

Further, we analyze the tendency of the standard deviation of the distribution with the growth of the number of recommended terms, as shown in Figure 7. In Figure 7(a), the standard deviations of the distribution of NeuMF, SPE, Content+topology_KNN and DeepICF increase with the increase of the number of recommended terms m, which indicates that the distribution of their recommended terms in different domains becomes more and more unbalanced. The standard deviations of the distribution of MD-I2IR(ip) and MD-I2IR increase and then decrease with the increase of the number of recommended terms m, which reflects that the distribution of their recommended terms in different domains can remain stable. In Figure 7(b), the standard deviations of the distribution of MD-I2IR(TransE), MD-I2IR(SEEK-1) and MD-I2IR(ConvE) increase with the increase of the number of recommendations m, which shows that the distribution of the recommended terms in different domains is relatively unstable. In the case that the number of recommendations exceeds 20, MD-I2IR (ConvKB) can keep the standard deviation of the recommended distribution in a stable state. Compared with other methods, the proposed MD-I2IR(CDKG-CE) has a lower distribution standard deviation as the number of recommendations m increases, and can maintain the stability of the distribution standard deviation.

7 Conclusion

In this paper, we proposed a cross-domain knowledge graph chiasmal embedding approach to effectively associate and interact items in multiple domains. In the interaction between multiple domains, a binding rule was put forward to help achieve both homo-domain embedding and hetero-domain embedding. Then, a multi-domain I2I recommendation algorithm was presented to recommend items from multiple domains simultaneously, which is a method based on link prediction of knowledge graph. Finally, experiments were conducted on two datasets to validate the proposed approaches for their knowledge graph embedding and cross-domain recommendation capabilities.

In the future, we can improve the research in the following aspects. First, users' information or historical interactions can be joined to study personalized multi-domain recommendation, which can highly enhance users' personalized experience. Second, connectionless cross-domain knowledge graphs are explored to make multi-domain recommendation to users, such as the movie domain and the clothes domain. Third, information from one domain is transferred to another domain to enable recommendation of items from another.

Acknowledgments

This research was supported by the National Key R&D Program of China (2019YFB2101802) and the National Natural Science Foundation of China (61773324).

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TKDE.2022.3151986, IEEE Transactions on Knowledge and Data Engineering

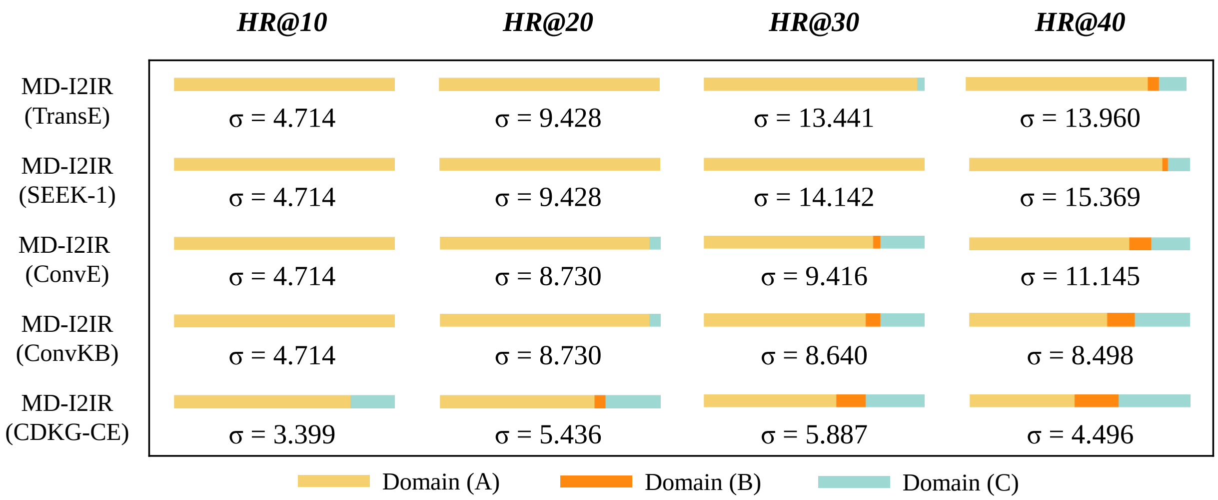
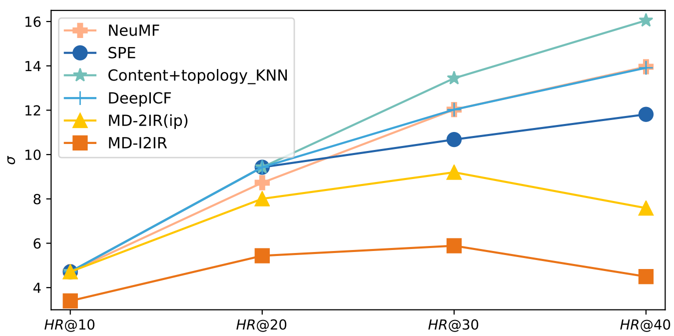
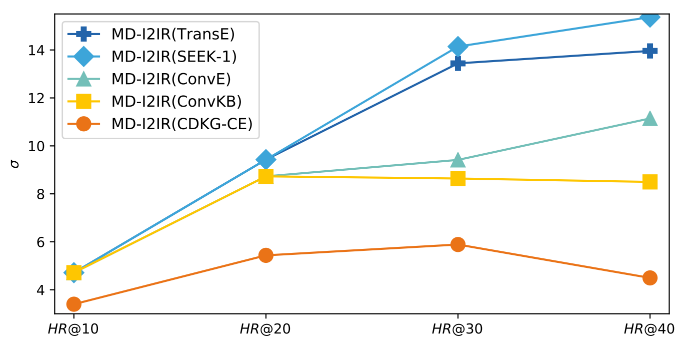


Fig. 6. Distribution and standard deviation of items in diverse domains by MD-I2IR based on different knowledge graph embedding methods.



(a) Recommended items based on different recommendation approaches.



(b) Recommended items based on different knowledge graph embedding methods.

Fig. 7. The tendency of the standard deviation of the distribution with the increase of the number of recommended terms.

REFERENCES

[1] E. Christakopoulou, G. Karypis, Local item-item models for top-n recommendation, in: Proceedings of the 10th ACM Conference on Recommender Systems, 2016, pp. 67–74.

[2] B. Sarwar, G. Karypis, J. Konstan, J. Riedl, Item-based collaborative filtering recommendation algorithms, in: Proceedings of the 10th International Conference on World Wide Web, 2001, pp. 285–295.

[3] F. Xue, X. He, X. Wang, J. Xu, K. Liu, R. Hong, Deep item-based collaborative filtering for top-n recommendation, ACM Transactions on Information Systems 37 (3) (2019) 1–25.

[4] M. J. Pazzani, D. Billsus, Content-based recommendation systems, in: The Adaptive Web, Springer, 2007, pp. 325–341.

[5] C. Wang, T. Zhou, C. Chen, T. Hu, G. Chen, Camo: a collaborative ranking method for content based recommendation, in: Proceedings of the AAAI Conference on Artificial Intelligence, 2019, pp. 5224–5231.

[6] V. W. Anelli, Y. Deldjoo, T. Di Noia, E. Di Sciascio, F. A. Merra, Sasha: Semantic-aware shilling attacks on recommender systems exploiting knowledge graphs, in: European Semantic Web Conference, Springer, 2020, pp. 307–323.

[7] X. Wang, D. Wang, C. Xu, X. He, Y. Cao, T.-S. Chua, Explainable reasoning over knowledge graphs for recommendation, in: Proceedings of the AAAI Conference on Artificial Intelligence, 2019, pp. 5329–5336.

[8] W. Ma, M. Zhang, C. Wang, C. Luo, Y. Liu, S. Ma, Your tweets reveal what you like: introducing cross-media content information into multi-domain recommendation, in: Proceedings of the 27th International Joint Conference on Artificial Intelligence, 2018, pp. 3484–3490.

[9] L. Liu, J. Cui, W. Song, H. Wang, Multi-domain collaborative recommendation with feature selection, China Communications 14 (8) (2017) 137–148.

[10] X. Chen, M. Chen, C. Fan, A. Uppunda, Y. Sun, C. Zaniolo, Multilingual knowledge graph completion via ensemble knowledge transfer, in: Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: Findings, 2020, pp. 3227–3238.

[11] W. Liu, P. Zhou, Z. Zhao, Z. Wang, Q. Ju, H. Deng, P. Wang, K-bert: Enabling language representation with knowledge graph, in: Proceedings of the AAAI Conference on Artificial Intelligence, 2020, pp. 2901–2908.

[12] A. Saha, V. Pahuja, M. Khapra, K. Sankaranarayanan, S. Chandar, Complex sequential question answering: Towards learning to converse over linked question answer pairs with a knowledge graph, in: Proceedings of the AAAI Conference on Artificial Intelligence, 2018, pp. 705–713.

[13] Y. Zhang, H. Dai, Z. Kozareva, A. Smola, L. Song, Variational reasoning for question answering with knowledge graph, in: Proceedings of the AAAI Conference on Artificial Intelligence, 2018, pp. 6069–6076.

[14] R. Sun, X. Cao, Y. Zhao, J. Wan, K. Zhou, F. Zhang, Z. Wang, K. Zheng, Multi-modal knowledge graphs for recommender systems, in: Proceedings of the 29th ACM International Conference on Information & Knowledge Management, 2020, pp. 1405–1414.

[15] H. Wang, F. Zhang, M. Zhang, J. Leskovec, M. Zhao, W. Li, Z. Wang, Knowledge-aware graph neural networks with label smoothness regularization for recommender systems, in: Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, 2019, pp. 968–977.

[16] C. Qin, H. Zhu, F. Zhuang, Q. Guo, Q. Zhang, L. Zhang, C. Wang, E. Chen, H. Xiong, A survey on knowledge graph-based recommender systems, Scientia Sinica Informationis 50 (7) (2020) 937–956.

[17] A. Bordes, N. Usunier, A. Garcia-Duran, J. Weston, O. Yakhnenko, Translating embeddings for modeling multi-relational data, in: Neural Information Processing Systems (NIPS), 2013, pp. 1–9.

[18] Z. Wang, J. Zhang, J. Feng, Z. Chen, Knowledge graph embedding by translating on hyperplanes, in: Proceedings of the AAAI Conference on Artificial Intelligence, 2014, pp. 1112–1119.

[19] G. Ji, S. He, L. Xu, K. Liu, J. Zhao, Knowledge graph embedding via dynamic mapping matrix, in: Proceedings of the 53rd Annual

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TKDE.2022.3151986, IEEE Transactions on Knowledge and Data Engineering

Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing, 2015, pp. 687–696.

[20] T. Dettmers, P. Minervini, P. Stenetorp, S. Riedel, Convolutional 2d knowledge graph embeddings, in: 2018 AAAI Conference on Artificial Intelligence, 2018, pp. 1811–1818.

[21] D. Q. Nguyen, T. D. Nguyen, D. Q. Nguyen, D. Phung, A novel embedding model for knowledge base completion based on convolutional neural network, in: 16th Annual Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, 2018, pp. 327–333.

[22] D. Q. Nguyen, T. Vu, T. D. Nguyen, D. Q. Nguyen, D. Phung, A capsule network-based embedding model for knowledge graph completion and search personalization, in: 2019 Annual Conference of the North American Chapter of the Association for Computational Linguistics, 2019, pp. 2180–2189.

[23] F. M. Suchanek, G. Kasneci, G. Weikum, Yago: a core of semantic knowledge, in: Proceedings of the 16th International Conference on World Wide Web, 2007, pp. 697–706.

[24] K. Bollacker, C. Evans, P. Paritosh, T. Sturge, J. Taylor, Freebase: a collaboratively created graph database for structuring human knowledge, in: Proceedings of the 2008 ACM SIGMOD International Conference on Management of Data, 2008, pp. 1247–1250.

[25] J. Lehmann, R. Isele, M. Jakob, A. Jentzsch, D. Kontokostas, P. N. Mendes, S. Hellmann, M. Morsey, P. Van Kleef, S. Auer, et al., Dbpedia–a large-scale, multilingual knowledge base extracted from wikipedia, Semantic Web 6 (2) (2015) 167–195.

[26] H. Wang, M. Zhao, X. Xie, W. Li, M. Guo, Knowledge graph convolutional networks for recommender systems, in: The World Wide Web Conference, 2019, pp. 3307–3313.

[27] Y. Cao, X. Wang, X. He, Z. Hu, T.-S. Chua, Unifying knowledge graph learning and recommendation: Towards a better understanding of user preferences, in: The World Wide Web Conference, 2019, pp. 151–161.

[28] H. Wang, F. Zhang, X. Xie, M. Guo, Dkn: Deep knowledge-aware network for news recommendation, in: Proceedings of the 2018 World Wide Web Conference, 2018, pp. 1835–1844.

[29] H. Wang, F. Zhang, M. Zhao, W. Li, X. Xie, M. Guo, Multi-task feature learning for knowledge graph enhanced recommendation, in: The World Wide Web Conference, 2019, pp. 2000–2010.

[30] X. Yu, X. Ren, Q. Gu, Y. Sun, J. Han, Collaborative filtering with entity similarity regularization in heterogeneous information networks, IJCAI HINA 27.

[31] C. Luo, W. Pang, Z. Wang, C. Lin, Hete-cf: Social-based collaborative filtering recommendation using heterogeneous relations, in: 2014 IEEE International Conference on Data Mining, IEEE, 2014, pp. 917–922.

[32] Z. Sun, J. Yang, J. Zhang, A. Bozzon, L.-K. Huang, C. Xu, Recurrent knowledge graph embedding for effective recommendation, in: Proceedings of the 12th ACM Conference on Recommender Systems, 2018, pp. 297–305.

[33] Z. Zhang, X. Jin, L. Li, G. Ding, Q. Yang, Multi-domain active learning for recommendation, in: Proceedings of the AAAI Conference on Artificial Intelligence, 2016, pp. 2358–2364.

[34] I. Cantador, M. Szomszor, H. Alani, M. Fernández, P. Castells, Enriching ontological user profiles with tagging history for multi-domain recommendations, Proceedings of the 1st International Workshop on Collective Intelligence and the Semantic Web (2008) 5.

[35] F. Zhu, Y. Wang, J. Zhou, C. Chen, L. Li, G. Liu, A unified framework for cross-domain and cross-system recommendations, IEEE Transactions on Knowledge and Data Engineering (2021) 1–14.

[36] P. Li, A. Tuzhilin, Dual metric learning for effective and efficient cross-domain recommendations, IEEE Transactions on Knowledge and Data Engineering (2021) 1–14.

[37] Q. Zhang, J. Lu, D. Wu, G. Zhang, A cross-domain recommender system with kernel-induced knowledge transfer for overlapping entities, IEEE Transactions on Neural Networks and Learning Systems 30 (7) (2018) 1998–2012.

[38] S.-T. Zhong, L. Huang, C.-D. Wang, J.-H. Lai, S. Y. Philip, An autoencoder framework with attention mechanism for cross-domain recommendation, IEEE Transactions on Cybernetics (2020) 1–13.

[39] T. Man, H. Shen, X. Jin, X. Cheng, Cross-domain recommendation: an embedding and mapping approach, in: Proceedings of the 26th International Joint Conference on Artificial Intelligence, 2017, pp. 2464–2470.

[40] C. Gao, X. Chen, F. Feng, K. Zhao, X. He, Y. Li, D. Jin, Cross-domain recommendation without sharing user-relevant data, in: The World Wide Web Conference, 2019, pp. 491–502.

[41] L. Liao, R. Takanobu, Y. Ma, X. Yang, M. Huang, T.-S. Chua, Topic-guided relational conversational recommender in multi-domain, IEEE Transactions on Knowledge and Data Engineering.

[42] Y. Cai, S. Dong, J. Hu, Jointly modeling user and item reviews by cnn for multi-domain recommendation, in: China Conference on Information Retrieval, Springer, 2018, pp. 237–248.

[43] W. Xu, S. Zheng, L. He, B. Shao, J. Yin, T.-Y. Liu, Seek: Segmented embedding of knowledge graphs, in: Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, 2020, pp. 3888–3897.

[44] Q. Wang, Z. Mao, B. Wang, L. Guo, Knowledge graph embedding: A survey of approaches and applications, IEEE Transactions on Knowledge and Data Engineering 29 (12) (2017) 2724–2743.

[45] P. Hu, R. Du, Y. Hu, N. Li, Hybrid item-item recommendation via semi-parametric embedding, in: Proceedings of the 28th International Joint Conference on Artificial Intelligence, 2019, pp. 2521–2527.

[46] X. Wang, X. He, Y. Cao, M. Liu, T.-S. Chua, Kgat: Knowledge graph attention network for recommendation, in: Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, 2019, pp. 950–958.

[47] F. Zhang, N. J. Yuan, D. Lian, X. Xie, W.-Y. Ma, Collaborative knowledge base embedding for recommender systems, in: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 2016, pp. 353–362.

[48] K. Toutanova, D. Chen, Observed versus latent features for knowledge base and text inference, in: Proceedings of the 3rd Workshop on Continuous Vector Space Models and Their Compositionality, 2015, pp. 57–66.

[49] B. Xu, Y. Xu, J. Liang, C. Xie, B. Liang, W. Cui, Y. Xiao, Cn-dbpedia: A never-ending chinese knowledge extraction system, in: International Conference on Industrial, Engineering and Other Applications of Applied Intelligent Systems, Springer, 2017, pp. 428–438.

[50] X. He, L. Liao, H. Zhang, L. Nie, X. Hu, T.-S. Chua, Neural collaborative filtering, in: Proceedings of the 26th International Conference on World Wide Web, 2017, pp. 173–182.

Jia Liu received the B.S. and M.S. degrees from Xihua University, Chengdu, China in 2015 and 2018 respectively. He is a Ph. D. candidate at Southwest Jiaotong University. His reseach interests include machine learning, data mining, and knowledge graph, etc. He has published several papers in journals such as IEEE Transactions on Knowledge and Data Engineering, Information Fusion etc.

Wei Huang received the B.S. degree from Fujian University of Technology, Fuzhou, China in 2016. She received M.S. degree from Fujian Normal University, Fuzhou, China in 2019. She is a Ph. D. candidate at Southwest Jiaotong University, Chengdu, China. Her reseach interests include federated learning, deep learning, data mining, and urban computing, etc.

Tianrui Li received the B.S., M.S., and Ph.D. degrees from the Southwest Jiaotong University, Chengdu, China in 1992, 1995, and 2002, respectively. He was a postdoctoral researcher with SCK CEN, Belgium from 2005 to 2006, and a visiting professor with Hasselt University, Belgium, in 2008, the University of Technology, Sydney, Australia, in 2009, and the University of Regina, Canada, 2014. He is currently a Professor and the Director of the Key Laboratory of Cloud Computing and Intelligent Techniques, Southwest Jiaotong University. He has authored or coauthored more than 300 research papers in refereed journals and conferences. His research interests include big data, cloud computing, data mining, granular computing and rough sets. He is a fellow of IRSS and senior member of ACM and IEEE.

Shenggong Ji is received the Ph.D. degrees from the Southwest Jiaotong University, Chengdu, China in 2020. He is currently working at Tencent Inc., Shenzhen, China. His major research interests include data mining, reinforcement learning, and urban computing.

Junbo Zhang is a Senior Researcher of JD Intelligent Cities Research and the Head of AI Department, JD Intelligent Cities Business Unit, JD Digits. Prior to that, he was a researcher at MSRA from 2015 - 2018. His research interests include urban computing, machine learning, data mining, and big data analytics. He currently serves as Associate Editor of ACM Transactions on Intelligent Systems and Technology. He has published over 30 research papers (e.g. AI Journal, IEEE TKDE, KDD, AAAI, IJCAI) in refereed journals and conferences, among which one paper was selected as the ESI Hot Paper, three as the ESI Highly Cited Paper. He received the ACM Chengdu Doctoral Dissertation Award in 2016, the Chinese Association for Artificial Intelligence (CAAI) Excellent Doctoral Dissertation Nomination Award in 2016, the Si Shi Yang Hua Medal (Top 1/1000) of SWJTU in 2012, and the Outstanding Ph.D. Graduate of Sichuan Province in 2013. He is a member of IEEE, ACM, CAAI and China Computer Federation.