Enhanced Knowledge Graph Embedding for Multi-Task Recommendation via Integrating Attribute Information and High-Order Connectivity

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ABSTRACT

Recently, knowledge graph (KG) has been introduced into recommender systems as side information to mitigate problems of sparsity and cold start, which attracts growing attention. Among these works, the multi-task learning methods that learn KG-related tasks and recommendation tasks have greatly enhanced the effectiveness of the recommendation. However, existing works tend to ignore attribute triples in the real knowledge graph, which makes the research affected by the sparsity of KGs. General knowledge graph embedding methods in multi-task recommendation barely take direct relations between entities into account, that leads to the ignorance of rich information in high-order relations. In addition, the lack of consideration on the user attribute information makes recommendation less than satisfactory. In order to relieve these issues, we propose a model of enhanced knowledge graph embedding for recommendation based on the multi-task learning, HMKR. Our method alternately trains recommendation task considering user-side information and enhanced knowledge graph embedding task integrating attribute information and high-order connectivity. The experiments on the real dataset MovieLens verify the effectiveness of HMKR. Even in the sparse data scenarios, the performance of our model is also satisfactory.

CCS CONCEPTS

• **Information systems** → **Recommender systems**.

KEYWORDS

Recommender Systems; Knowledge Graph; Multi-Task Learning; Graph Neural Network

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1 INTRODUCTION

Currently, recommender systems are widely utilized to provide service for users through interacting with them. The recommender systems based on collaborative filtering have been extensively used [14]. They model user preferences through the resemblance of users or interactive items [17]. However, recommender systems based on collaborative filtering face sparsity and cold start problems [36]. To overcome the challenges, researchers have explored various types of side information. Recently, knowledge graph is introduced into the recommender systems as side information to relieve sparsity and cold start, which has caused growing attention.

Knowledge graph is a heterogeneous graph composed of entities, relations and attributes. The entity is the object of the real-world and the conceptual abstraction, relations represent the relationships between entities or the attributes of entities [11]. Attributes are inherent characteristics of entities. The KGs are usually encoded in the form of triples. The triples have two types [18], one is relation triples, e.g.,(*Li Bai*, *Friendof*, *Du Fu*), another is attribute triples, e.g.,(*Li Bai*, *Born*, *"701 A.D."*). The existing KG-based recommender systems adopt KG through three ways: embedding-based method, path-based method, and unified method [8]. Among them, the multi-task learning methods can learn KG-related tasks and recommendation tasks jointly so that knowledge graph can effectively enhance recommendation. Multi-task learning is a valuable learning method. It uses mutually significative information included in related tasks to help increase performance [35]. Papers [24], [2], [28] apply multi-task learning strategies to train recommendation and KG-related tasks jointly and find that joint learning improves performance and recommendation quality compared with individual learning.

However, the existing works tend to ignore massive attribute triples in the real knowledge graph [18], which makes the research affected by the sparsity of the KG. Knowledge graph embedding is a key foundation for various applications. The general knowledge graph embedding methods in multi-task recommendation barely take the direct relations between entities into consideration, but ignore the high-order structural relations, that will lead to the ignorance of rich information [15]. Meanwhile, user-side information is very significant [33], existing works lack consideration of user attribute information such as age and gender, and make recommendation less than satisfactory, especially when the user has very little interaction.

To relieve these issues, we propose a model of enhanced knowledge graph embedding for recommendation based on the multi-task learning [24], HMKR. Our method shares features between items and entities, and alternately trains recommendation and enhanced knowledge graph embedding. We consider the attribute triples which encode rich semantic information, and employ the idea of embedding propagation [13, 20, 29] based on the graph neural network (GNN) architecture to capture the high-order connectivity between entities. We also extract features of user attributes to consider user-side information. The experiments on the real dataset verify the effectiveness of HMKR.

The main contributions of this work are summarized as follows:

- We highlight the significance of attribute triples and high-order connectivity of KG for knowledge graph embedding and recommendation.
- We process the user attributes to provide more reliable recommendation.
- We propose the method HMKR, which conducts multi-task training to improve recommendation with the enhanced knowledge graph embedding integrating the attribute information and high-order information.
- We conduct experiments on the real dataset, and HMKR is proved to be effective.

2 RELATED WORK

2.1 Embedding-based Methods for Recommendation

In recent years, embedding has gained many application and development [3]. Most embedding-based methods [36], [10], [24], [22], [30], [2], [12], [28], [31] use various forms of item side information to construct KGs so that the presentation of items can be enriched. And this information can be utilized to build user representation accurately. Some models [34], [16], [1], [21], [5] construct user preferences directly by drawing users into graph to build user-item interaction. Our work can be regarded as a especial embedding-based methods for recommendation.

2.2 Graph Neural Network for Recommendation

Our work applies the idea of GNN. GNN is increasingly utilized for recommendation. It improves the model from the traditional convolution network. The recommender systems based on GNN are mainly collaborative filtering. The specific problems include Web-Scale Recommender Systems [32], GC-MC [19] and so on [26], [9]. In later research, the collaborative filtering applies secondary information. It builds models from two perspectives, one is Social Recommendation [6], [7], the other one is Knowledge-graph-aware Recommendation [23], [25].

3 OUR APPROACH

As shown in Figure 1, HMKR consists of four sub-modules: recommendation module, enhanced knowledge graph embedding module, cross-compress unit and user feature extraction unit.

3.1 User Feature Extraction Unit

Inspired by the existing work [27], we process all user attributes by multi-layer perceptron to output the user feature vectors.

We use $x : \{\mathrm{x}_1, \mathrm{x}_2 \ldots \mathrm{x}_\mathrm{m}\}$ to express the attributes of the user, where x_i means the user attributes. We input user attributes into the user feature extraction unit to obtain the user attributive feature vector X:

$$X = f\left(w_1 x + b_1\right) \tag{1}$$

Where w_1 represents the weight, b_1 represents the bias, and $f(\cdot)$ means the activation function.

We get the embedding of the user after the full connection layer:

$$u = \text{concatenate}(X) \tag{2}$$

3.2 Recommendation Module

The module input is the feature vector $\mathbf{u}$ of user u and the feature vector $\mathbf{v}$ of the item v. Vector $\mathbf{u}$ is the output result of the user feature extraction unit. The vector $\mathbf{v}$ is the original feature of item.

In recommendation module, we use L-layers multi-layer perceptron to extract the user feature:

$$u_L = M(M(\cdots M(u))) = M_L(u) \tag{3}$$

Formula 3 is the extraction of u's feature, where $\mathrm{M}(\mathrm{x}) = \sigma(\mathrm{Wx} + \mathrm{b})$ is a fully-connected neural network layer. W is weight, b is bias, and $\sigma(\cdot)$ is nonlinear activation function.

We extract the feature of item v by applying the cross-compress unit:

$$vL = E_{e \sim S(v)}\left[Cross^L[v]\right] \tag{4}$$

Where $S(v)$ is the associated entity set of item v. More details of cross and compress will be presented in section 3.4.

We predict the probability result of user u participating in item v by using the prediction function after obtaining the latent features of user u and item v:

$$\hat{y}_{\mathrm{uv}} = \sigma f_{\mathrm{RS}}\left(M_L(\text{ concatenate }(X)), vL\right) \tag{5}$$

3.3 Enhanced Knowledge Graph Embedding Module

The module encodes attribute triples and captures the high-order connectivity between entities.

3.3.1 Attribute Embedding. We encode the words or sentences of attribute triples as vectors of fixed length. After studying, we apply LSTM networks to encode attributes into vectors which can conquer the defect of Bag-of-Word encoder [15].

$$\mathbf{a} = f_{lstm}\left(\mathbf{c}_1, \mathbf{c}_2, \ldots, \mathbf{c}_n\right) \tag{6}$$

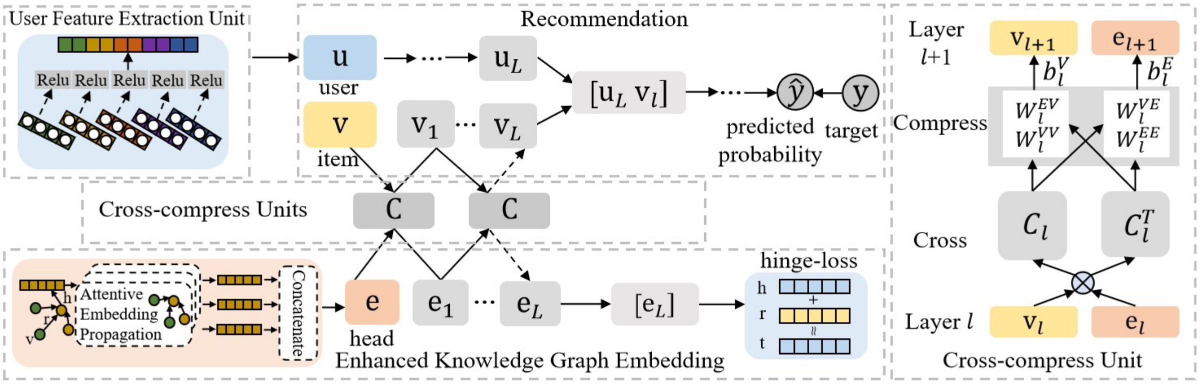


Figure 1: Illustration of the HMKR model.

Where f_{lstm} represents the Long-Short Term Memory network.

3.3.2 Embedding Propagation. Next we conduct embedding propagation based on the architecture of graph convolution network and the idea of graph attention network. Our embedding propagation consists of attentive embedding propagation and embedding aggregation.

The input of our embedding propagation is a set of entities, relations and attribute value embeddings. We employ $\mathbf{h} \in R^k$ to express the embedding of entity h. The neighbor of h is defined as $\mathcal{N}_h = \{t, a \mid (h, r, t) \in T_R \cup (h, r, a) \in T_A\}$. We obtain the vector $\mathbf{H}$ as the improved embedding of entity h through attentive embedding:

$$\mathbf{H} = \sum_{t \in \mathcal{N}_h} \pi(h, r, t)\mathbf{W}(\mathbf{r} + \mathbf{t}) \tag{7}$$

Where $\mathbf{W} \in R^{k' \times k}$ is one learnable linear transformation, $\pi(h, r, t)$ means the significance of entity t to entity h.

We use softmax function on the triples connected with h:

$$\pi(h, r, t) = \frac{\exp(\pi(h, r, t))}{\sum_{t' \in \mathcal{N}_h} \exp\left(\pi\left(h, r', t'\right)\right)} \tag{8}$$

$\pi(h, r, t)$ is realized by a simply feedforward neural network:

$$\pi(h, r, t) = \text{LeakyRelu}\left((\mathbf{W}\mathbf{h})^T \mathbf{W}(\mathbf{r} + \mathbf{t})\right) \tag{9}$$

We use concatenation aggregator to concatenate all embeddings of multi-head graph attention for more stable learning and transform it through LeakyReLu:

$$\mathbf{H}' = \text{LeakyReLu}\left(\mathbf{W}\left(\|_{i=1}^{m} \sum_{t \in \mathcal{N}_h} \pi(h, r, t)^i \mathbf{W}^i(\mathbf{r} + \mathbf{t})\right)\right) \tag{10}$$

Where $\|$ represents concatenation, $\pi(h, r, t)^i$ is i-th normalized attention coefficient and $\mathbf{W}^i$ denotes the linear transformation.

We utilize embedding propagation layers to gather the deeper information of the neighbors so that we can obtain the high-order connectivity information in KGs. The l-th layer embedding of entity h is stated as follows:

$$\mathbf{H}^{(l)} = \sum_{t \in \mathcal{N}_h} \pi(h, r, t)\mathbf{W}\left(\mathbf{r}^{(l-1)} + \mathbf{t}^{(l-1)}\right) \tag{11}$$

After the propagation and aggregation, we extract the feature of entity h by applying the cross-compress unit:

$$\mathbf{e}_L = \mathbb{E}_{v \sim \mathcal{S}(h)}\left[Cross^L[\mathbf{e}]\right] \tag{12}$$

Where $\mathcal{S}(h)$ is the set of relevant items of entity h.

3.4 Cross-compress Unit

The cross-compress unit consists of two operations, cross and compress. The unit interacts the items in the recommendation with the entities in the KG so that features can be shared.

We construct cross feature matrix C_l of layer l. This is the cross operation.

$$C_l = v_l e_l^T = \begin{bmatrix} v_l^{(1)} e_l^{(1)} & \cdots & v_l^{(1)} e_l^{(d)} \\ \vdots & & \vdots \\ v_l^{(d)} e_l^{(1)} & \cdots & v_l^{(d)} e_l^{(d)} \end{bmatrix} \tag{13}$$

Where $\mathbf{v}_l \in R^d$, $\mathbf{e}_l \in R^d$ and d is the dimension of hidden layers.

Follwing the cross operation, we conduct compress operation to get the next layer feature vectors. We project the cross feature matrix into vectors of items and entities in their latent representation spaces:

$$\begin{aligned} \mathbf{v}_{l+1} &= \mathbf{v}_l \mathbf{e}_l^\top \mathbf{w}_l^{VV} + \mathbf{e}_l \mathbf{v}_l^\top \mathbf{w}_l^{EV} + \mathbf{b}_l^V \\ \mathbf{e}_{l+1} &= \mathbf{v}_l \mathbf{e}_l^\top \mathbf{w}_l^{VE} + \mathbf{e}_l \mathbf{v}_l^\top \mathbf{w}_l^{EE} + \mathbf{b}_l^E \end{aligned} \tag{14}$$

Where $w_l \in R^d$ is weight and $b_l \in R^d$ is bias.

Cross-compress units help both tasks adjust and learn automatically.

3.5 Optimization

The loss of HMKR is as follows:

$$\mathcal{L} = \mathcal{L}_{RS} + \mathcal{L}_{KG} + \lambda_2 \|W\|_2^2 \tag{15}$$

$$\mathcal{L}_{RS} = \sum_{u \in \mathcal{U}, v \in \mathcal{V}} \mathcal{J}\left(\hat{y}_{uv}, y_{uv}\right) \tag{16}$$

$$\mathcal{L}_{KG} = \sum_{(h,r,e) \in T} \sum_{(h',r,e') \in T'} \left[\gamma + d(h + r, e) - d\left(h' + r, e'\right)\right]_+ \tag{17}$$

Where $\mathcal{L}_{RS}$ is the loss of recommendation, $\mathcal{L}_{KG}$ is the loss of enhanced KGE, $\lambda_2\|W\|_2^2$ is the regularization term for preventing overfitting.

4 EXPERIMENTS

4.1 Datasets

We utilize MovieLens dataset in our experiments. MovieLens-1M is a dataset widely applied in recommendation. The set has approximately 1 million explicit ratings and contains 6036 users, 2347 items, 753772 ratings and 20195 knowledge graph triples.

4.2 Baselines

We make comparisons with the following four baselines. The settings of the various models remain unchanged.

- **MKR** [24] is one of the inspiration ideas of our method. In the experiment, the inner product is f_{RS}. High-level layer is $K = 1$ and $\lambda_1 = 0.5, \lambda_2 = 10^{-6}, L = 1, d = 8$, t = 3.
- **Wide&Deep** [4] is a deep recommendation method that combines wide and deep channels. In the experiment, the dimensions of user, item and entity are 64, the dimension of deep channel is 100, and the dimension of wide channel is 50.
- **DKN** [22] combines entity embedding and word embedding as multiple channels for prediction. In the experiment, the dimensions of word and entity embedding are 64, and the filters with different window sizes are 128.
- **SI-MKR** [27] is an alternate training recommendation model based on MKR that extracts valuable external information. In the experiment, $\lambda_2 = 10^{-8}$, learning rate of recommendation and embedding are $2e - 4$ and $2e - 5$.

4.3 Experiments setup

The training, validation and test sets in our HMKR is 6:2:2. We conduct every experiment 3 times and take the average result. We evaluate HMKR in two experimental scenarios. One is the click-through rate (CTR) prediction in which we use AUC and ACC to evaluate the result. Another scenario is the top-K recommendation in which we evaluate the result through the set of Precision@K and Recall@K.

4.4 Performance

Table 1 is the AUC and ACC of HMKR and other baselines in CTR prediction. Figure 2 is the result of Recall@K and Precision@K in top-K recommendation.

We can observe that Wide&Deep splices the attributes simply, so the performance is ordinary. DKN performs poorly because it is more suitable for long text recommendation such as news recommendation. SI-MKR performs better than MKR as it considers user attributes, item text and multi-value attributes based on MKR. Our method performs best because we consider the high-order connectivity of entities, attribute triples with rich semantics and user attributes.

Table 2 is the performance of different models in different ratios of the training set. We test the proportions of the training set as

Table 1: Results of AUC and ACC in CTR prediction.

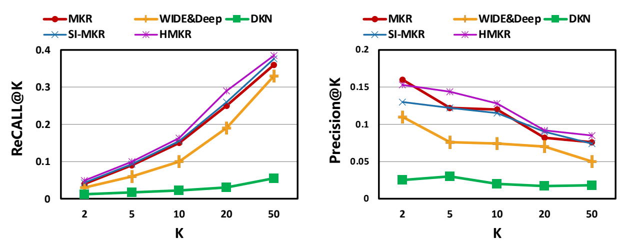
Model	AUC	ACC
MKR	0.917	0.843
Wide&Deep	0.898	0.820
DKN	0.655	0.589
SI-MKR	0.921	0.845
HMKR	0.924	0.847

Table 2: Results of AUC in CTR prediction with different ratios of training set r.

Model	20%	40%	60%	80%	100%
MKR	0.874	0.882	0.897	0.908	0.917
Wide&Deep	0.802	0.815	0.840	0.876	0.898
DKN	0.582	0.601	0.620	0.638	0.655
SI-MKR	0.876	0.884	0.898	0.900	0.921
HMKR	0.877	0.886	0.899	0.910	0.923

100%, 80%, 60%, 40%, 20% respectively to explore the performance in sparse scenarios.

From the experimental results, we can know that our model further relieves the sparsity problem and improve the effectiveness of the recommender systems on the basis of existing research.



(a) Recall@K (b) Precision@K

Figure 2: The results of Recall@K and Precision@K in top-K recommendation.

5 CONCLUSIONS

In this work, we propose HMKR. Our model takes attribute triples that encode rich semantic information into consideration, uses the idea of GNN to capture high-order connections between knowledge graph entities and takes user-side information into account. HMKR shares high-order features of items and entities, and alternately trains recommendation and knowledge graph embedding. The user feature extraction and enhanced knowledge graph embedding further relieve the sparsity and cold start problems of the recommendation. Experiments on the MovieLens dataset prove that the HMKR model has reached better performance than other models.

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