Virtual Relational Knowledge Graphs for Recommendation

Lingyun Lu, Bang Wang*
School of Electronic Information and Communications, Huazhong University of Science and Technology (HUST), Wuhan, China
lulingyun@hust.edu.cn, wangbang@hust.edu.cn

ABSTRACT

Incorporating knowledge graph as side information has become a new trend in recommendation systems. Recent studies regard items as entities of a knowledge graph and leverage graph neural networks to assist item encoding, yet by considering each relation type individually. However, relation types are often too many and sometimes one relation type involves too few entities. We argue that it is not efficient nor effective to use every relation type for item encoding. In this paper, we propose a VRKG4Rec model (Virtual Relational Knowledge Graphs for Recommendation), which explicitly distinguishes the influence of different relations for item representation learning. We first construct virtual relational graphs (VRGs) by an unsupervised learning scheme. We also design a local weighted smoothing (LWS) mechanism for encoding nodes, which iteratively updates a node embedding only depending on its own embedding and its neighbors’, but involve no additional training parameters. We also employ the LWS mechanism on a user-item bipartite graph for user representation learning, which utilizes items’ encodings with relational knowledge to help train users’ representations. Experiment results on two public datasets validate that our VRKG4Rec model outperforms the state-of-the-art methods.

KEYWORDS

recommendation system; knowledge graph; graph neural network

1 INTRODUCTION

Recommender system (RS) as an information filtering tool plays an important role in our daily life. Traditional RS mainly depends on collaborative filtering of user-item interaction records, which suffers from the data sparsity problem. Recently, knowledge graph (KG) with entities and rich relation connections has been exploited to enhance the representation learning of users and items [9]. Generally speaking, a KG consists of many knowledge triplets \((h, r, t)\), where \(h\) and \(t\) are a head entity and a tail entity respectively, and \(r\) is the relation from \(h\) to \(t\). For example, \((Leonardo, \text{star}, \text{Titanic})\) states the fact that Leonardo is the star of the movie Titanic. A knowledge graph can contain multiple types of relations, and more than one type of relation can exist between \(h\) and \(r\) in a knowledge graph.

The main challenge of KG-based recommendation is how to extract useful information from structured knowledge triplets for better learning user and item representation. Some researches [1, 7, 10] first learn entity representation in a KG by some knowledge representation learning method (e.g., the TransX series) and use the learned embeddings as pre-trained features in a follow-up recommendation task. Although these methods can well model knowledge triplet relationships in a KG, they mainly focus on the first-order connectivity but ignore the global relationships of entities. Some researches [2, 4] explore a kind of meta-path connecting history entity and the candidate entity. However, these methods suffer from two main problems: (1) Devising such meta-path requires strong expertise, which has poor transfer capability. (2) It is labor-intensive and time-consuming when applying on the KGs of large scale.

Recently, some researches [6, 8] use graph neural networks (GNNs) for encoding knowledge in terms of entities and their relations into item representation learning. Despite their significant performance improvements, they equally treat all relations in a knowledge graph and encode each relation individually into an entity representation. This approach, we argue, is not efficient and maybe not effective too. On the one hand, a KG often contains many different relation types. Although each of them is unique, some of them may be with similar contribution to a recommendation task. On the other hand, some relation type only involves a very few of connections connecting only a small subset of entities. Such a relation type may be of little contribution to entity representation learning for recommendation.

In this paper, we propose to discriminate relations for encoding a kind of aggregated knowledge into representation learning and design a Virtual Relational Knowledge Graph for Recommendation model (VRKG4Rec). We first construct virtual relational knowledge graphs (VRGks) from an unsupervised learning approach. We next devise a local weighted smoothing (LWS) mechanism on each VRKG to learn aggregated relational knowledge for item encoding and fuse item encodings from all VRGks to obtain its final representation. We also employ the LWS mechanism on a user-item bipartite graph to learn user representation, which utilizes items’ encodings with relational knowledge to help train users’ representations. Experiment results on two public datasets validate that our VRKG4Rec model outperforms the state-of-the-art methods.

2 THE VRKG4REC MODEL

Fig. 1 presents the architecture of our VRKG4Rec model, which consists of (1) virtual relational knowledge graph (VRKG) construction; (2) item representation learning; (3) user representation learning; (4) model prediction.

2.1 VRKG Construction

We construct virtual relational knowledge graphs to distinguish entities contributing to different aspect of item encoding by clustering all types of relations into \(K\) virtual relations. The representations of such virtual relations are initialized as a virtual centroid matrix \(V \in \mathbb{R}^{K \times d}\)

\[
V = (v_1, v_2, ..., v_K)^T, \tag{1}
\]

where the \(k\)-th row \(v_k \in \mathbb{R}^d\) is the representation of the \(k\)-th virtual relation. On basis of this, we compute the similarities between
each relation with the virtual relations. For the $i$-th relation $r_i$, we construct its similarity vector $s_i \in \mathbb{R}^K$ by

$$s_i = (g(r_i, v_1), g(r_i, v_2), ..., g(r_i, v_K)),$$

where $r_i$ is the embedding of relation $r_i$, and $g(\cdot)$ is a similarity function, e.g., an inner product function. The relation $r_i$ is replaced with a virtual relation $v_r$ with the highest similarity.

$$k' = \text{arg max}_{k=1,2,\ldots,K} (g(r_i, v_k)),$$

with

$$k = \text{arg max}_{k=1,2,\ldots,K} (g(r_i, v_k)),$$

we can also stack multiple layers of LWS to explore high-order connectivity information from high-order neighbors into a center node. Technically, we formulate the representation of an entity $e_i$ after $l$ layers as follows:

$$e_i^{(l+1)} = \sum_{k=1}^{K} f_{LWS} \left( \{ (e_i^{(l)}, e_j^{(l)}) \mid e_j \in N_k(i) \} \right),$$

where $e_i^{(0)}$ denotes the ID embedding of entity $e_i$. 

2.3 User Representation Learning

To leverage collaborative information, we first construct a user-item bipartite graph based on the user-item interaction record, and then apply the LWS the same way as that in item representation learning to learn user representation:

$$e_u^{(l+1)} = f_{LWS} \left( \{ (e_u^{(l)}, e_i^{(l)}) \mid e_i \in N_u(i) \} \right),$$

where $e_u^{(0)}$ denotes the ID embedding of the user $u$. $N_u(i)$ is a set of items that a user $u$ has interacted. By stacking multiple LWS layers,
To train this model, we construct the BPR loss function
\[
\mathcal{L}_{\text{BPR}} = \frac{1}{|O|} \sum_{(u, i, j) \in O} - \ln \sigma(\tilde{u}_i - \tilde{u}_j),
\]
where \(O = \{(u, i, j) \mid (u, i) \in O^+, (u, j) \in O^-\}\) is the training set, \(O^+\) is the observed interactions; While \(O^-\) is the unobserved interactions. \(\sigma(\cdot)\) is the sigmoid function.

The objective function for training model parameters is:
\[
\mathcal{L} = \mathcal{L}_{\text{BPR}} + \lambda \|\Theta\|_2^2,
\]
where \(\Theta = \{e_u, e_i, V \mid u \in \mathcal{U}, i \in \mathcal{E}\}\) is the model parameter set. \(\mathcal{E}\) is the entity set containing item set \(\mathcal{I}\), and generally \(\mathcal{I} \subseteq \mathcal{E}\). \(\lambda\) is a hyperparameter controlling \(L_2\) regularization to prevent overfitting.

### 3 EXPERIMENTS

#### 3.1 Experiment settings

**Datasets:** We conduct our experiments on two public datasets: LastFM\(^1\) and MovieLens-1M\(^2\). Following [6, 7], we use Microsoft Satori to construct knowledge graph for each dataset by matching the item IDs with the head of all triplets.

**Competitors:** We compare with the following algorithms that also exploit graph knowledge for recommendation.

- **FM** [5] is a factorization model, which considers second-order feature interactions between items and a KG.
- **NFM** [3] is a state-of-the-art factorization model, which modifies FM by using a neural network.
- **CKE** [10] is an embedding-based method, which incorporates knowledge into the MF framework.
- **KGAT** [8] designs the knowledge graph attention network to model high-order conductivities in a KG.
- **KGIN** [9] applies a GNN to explore user-item interactions by using auxiliary item knowledge.

**Evaluation metrics:** We adopt the widely-used evaluation protocols: recall@20, NDCG@20, precision@20 and HR@20. We report the average results from all users.

**Parameter setting:** The embedding dimension \(d = 64\), LWS iterations \(T = 3\), LWS layers \(L = 3\). The number of VRKGs \(K = 3\). The mini-batch size is set as 1024 for all datasets. We adopt the Adam optimizer with the initial learning rate \(lr = 10^{-4}\) and set \(L_2 = 10^{-4}\).

#### 3.2 Experiment results

Table 1 presents the overall performance comparison for recommendation length of 20, and Fig 2 compares the performance for different recommendation lengths. Our VRKG4Rec outperforms the competitors on both two datasets in most of cases. We attribute its superiority to two reasons: (1) our conversion of many relations of a knowledge graph into a few virtual relations. Such virtual relations can not only improve the efficiency of entity representation learning, but also help encode those relational knowledge more relevant to the downstream recommendation task. (2) our LWS for encoding an item merely from its neighbors’ embeddings. Such an encoding mechanism focuses on converting local relational knowledge into neighboring items’ encodings, as it tries to ensure relational knowledge-connected entities with closer distances in an embedding space.

From Table 1, it can be observed that the relational information of knowledge graph can generally improve recommendation performance (c.f., the FM and NFM without using relational knowledge vs. the others). The CKE utilizes TransR to encode the first-order information of a KG for entity representation learning. While the KGAT and KGIN design graph neural models so as to capture high-order neighbors’ information. This operation, however, can be either constructive or destructive to recommendation. It can be observed that the KGAT performs rather worse on the Last-FM dataset. We note that the KG for this dataset contains 60 relation types and about 155K knowledge triplets; While the MovieLens-1M contains only 15 relation types and about 200K knowledge triplets. Furthermore, both items and entities are fewer in the MovieLens-1M dataset. The worse performance of KGAT on the Last-FM dataset suggests that

### Table 1: Overall comparison of performance

| Dataset | Model | recall | NDCG | precision | HR |
|---------|-------|--------|------|-----------|----|
| Last    | FM    | 0.1402 | 0.0772 | 0.0169    | 0.2810 |
|         | NFM   | 0.1497 | 0.0805 | 0.0187    | 0.2990 |
|         | CKE   | 0.2695 | 0.1625 | 0.0333    | 0.4611 |
|         | KGAT  | 0.0526 | 0.0295 | 0.0064    | 0.1169 |
|         | KGIN  | 0.3549 | 0.2169 | 0.0443    | 0.5907 |
|         | proposed | 0.3726 | 0.2320 | 0.0467 | 0.6004 |
| ML      | FM    | 0.2911 | 0.2798 | 0.1610    | 0.8510 |
|         | NFM   | 0.2759 | 0.2484 | 0.1340    | 0.8430 |
|         | CKE   | 0.3130 | 0.2918 | 0.1603    | 0.8651 |
|         | KGAT  | 0.2637 | 0.2305 | 0.1320    | 0.8215 |
|         | KGIN  | 0.3150 | 0.1935 | 0.0395    | 0.5322 |
|         | proposed | 0.3328 | 0.3125 | 0.1736 | 0.8743 |

#### Table 2: Impact of VRKG construction and LWS mechanism

| Dataset | KG      | recall | NDCG | precision | HR |
|---------|---------|--------|------|-----------|----|
| Last    | Raw     | 0.3616 | 0.2231 | 0.0452    | 0.5583 |
|          | Each    | 0.3701 | 0.2313 | 0.0462 | 0.5986 |
|          | VRKG    | 0.3726 | 0.2320 | 0.0467 | 0.6004 |
| ML      | Raw     | 0.3314 | 0.3095 | 0.1711    | 0.8708 |
|          | Each    | 0.3319 | 0.3095 | 0.1705 | 0.8720 |
|          | VRKG    | 0.3328 | 0.3125 | 0.1736 | 0.8743 |

\(^1\)https://grouplens.org/datasets/hetrec-2011/

\(^2\)https://grouplens.org/datasets/movielens/1m/
in a sparse KG but with many relation types, it is not wise to consider all relations in item encoding. We note that our VRKG4Rec is robust to different KG scales for its conversion of virtual relations.

We also conduct experiments to evaluate the effectiveness of virtual relation clustering and the proposed LWS mechanism for item encoding. To this end, we consider the following two KG variants: (1) Raw: The LWS is directly applied on the raw KG without discriminating relation types; (2) Each: For each relation type, we construct one relational knowledge graph, on which the LWS is applied.

Table 2 presents the experiment results. We can observe that the VRKG4Rec achieves the best performance. On the one hand, the VRKG4Rec outperforms VRKG4Rec-Raw, which indicates the effectiveness of clustering virtual relations. On the other hand, the VRKG4Rec outperforms VRKG4Rec-Each, which indicates that not every relation for item encoding is constructive to recommendation. From Table 2, we can also observe that even the VRKG4Rec-Raw outperforms all the competitors. This validates the effectiveness of the proposed LWS mechanism for node encoding.

4 CONCLUSION

Although knowledge graph is helpful for enriching item and user representation, we argue that it is not wise to directly exploit all relations of a raw KG without considering a particular downstream task. In this work, we have proposed a VRKG4Rec model to first construct VRKGs to learn a kind of virtual relational knowledge for item encoding. We have designed the LWS, a new graph neural model, for node encoding in a graph, which has been applied in each VRKG for item encoding. A fusion mechanism is used to learn final item representation. Experiments on two datasets have shown that the proposed VRKG4Rec outperforms the state-of-the-art methods. We notice that besides enriching representation, a knowledge graph can also be used to infer latent reasons for recommendation. Our future work shall investigate how to combine the inference capability of a KG for recommendation.

REFERENCES

[1] Q. Ai, V. Azizi, X. Chen, and Y. Zhang. 2018. Learning heterogeneous knowledge base embeddings for explainable recommendation. Algorithms 11, 9 (2018), 137.
[2] R. Catherine and W. Cohen. 2016. Personalized recommendations using knowledge graphs: A probabilistic logic programming approach. In Proceedings of the 10th ACM conference on recommender systems. 325–332.
[3] X. He and T. Chua. 2017. Neural Factorization Machines for Sparse Predictive Analytics. In Proceedings of the 40th International ACM SIGIR Conference on Research and Development in Information Retrieval. 355–364.
[4] W. Ma, M. Zhang, Y. Cao, W. Jin, C. Wang, Y. Liu, S. Ma, and X. Ren. 2019. Jointly learning explainable rules for recommendation with knowledge graph. In The World Wide Web Conference. 1210–1221.
[5] S. Rendle, Z. Gantner, C. Freudenthaler, and L. Schmidt-Thieme. 2011. Fast Context-Aware Recommendations with Factorization Machines. In Proceedings of the 34th International ACM SIGIR Conference on Research and Development in Information Retrieval. 635–644.
[6] H. Wang, F. Zhang, M. Zhang, J. Leskovec, M. Zhao, W. Li, and Z. Wang. 2019. 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. 968–977.
[7] H. Wang, F. Zhang, M. Zhao, W. Li, X. Xie, and M. Guo. 2019. Multi-task feature learning for knowledge graph enhanced recommendation. In The World Wide Web Conference. 2000–2010.
[8] X. Wang, X. He, Y. Cao, M. Liu, and T. Chua. 2019. Kgat: Knowledge graph attention network for recommendation. In Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining. 950–958.
[9] X. Wang, T. Huang, D. Wang, Y. Yuan, Z. Liu, X. He, and T. Chua. 2021. Learning Intents behind Interactions with Knowledge Graph for Recommendation. In Proceedings of the Web Conference 2021. 878–887.
[10] F. Zhang, N. J. Yuan, D. Lian, X. Xie, and W. Ma. 2016. Collaborative Knowledge Base Embedding for Recommender Systems. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. 355–362.