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Recommender Systems Based on Knowledge Graph

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1 Introduction

The recommender system is a kind of information filtering system. It solves the information overload problem for users through generating recommendation content based on user’s preference. It is widely used in various fields including entertainment, service, e-commerce, social media and so on. The recommender system uses data about users and items to generate recommendation content. The existing recommender algorithms include content-based, collaborative filtering-based, and hybrid methods. Although the recommender system has been widely applied and deeply explored, the inherent sparsity problem and the cold start problem have limited its effectiveness. Knowledge graphs provides a new way to improve recommendation systems. Knowledge Graphs contain rich side information about entities, so as to enhance accuracy and diversity of recommender system, and bring interpretability for recommendation.

2 literature review

Existing recommender systems exploit knowledge graph information in three different ways: embedding-based methods [1], path-based methods [2], and hybrid methods[3]. The embedding-based methods pre-process a KG with knowledge graph embedding algorithms and incorporates the learned entity embeddings into a recommendation framework. Embedding-based methods are usually more suitable for in-graph applications such as link prediction than for recommendation, thus the learned entity embeddings are less intuitive and effective to characterize inter-item relations. Path-based methods explore the various patterns of connections among items in KG to provide additional guidance for recommendations, but they rely heavily on manually designed meta-paths, which is hard to optimize in practice.[3] Hybrid methods integrates both KGE and path-based methods.

3 Methods

To illustrate the idea of KG-aware recommender systems, we take an typical embedding-based methods to illustrate. A typical user-item interaction matrix is defined according to user’s feedback, where the element equals one when the corresponding user has interacted with the corresponding item, zero otherwise (Fig.1). A knowledge graph is a heterogeneous graph where nodes correspond to entities and edges correspond to relations. A KG usually consists of triples (head, relation, tail). Items in recommender system are also nodes in KGs. Given interaction matrix as well as KG, we aim to predict whether user has potential interest in item with which he has had no interaction before. The KG-aware recommender framework mainly consists of two steps in [1]. 1) knowledge base embedding and 2) collaborative joint learning (Fig.2). In the knowledge base embedding step, item entity’s three embedding vectors are extracted from structural knowledge, textual knowledge and visual knowledge, respectively. An item’s latent vector is finally represented as the integration of three embedding vectors from the knowledge base as well as a latent offset vector. Then collaborative filtering is used by optimizing the pair-wise ranking between items to learn both user latent vectors and item latent vectors. Final recommendation is generated from these user latent vectors and item latent vectors.

	$user_1$	$user_2$	…	$user_n$
$item_1$	1	?	1	0
$item_2$	?	0	?	?
…	?	?	1	?
$item_m$	?	0	?	?

Fig.1 user-item interaction matrix

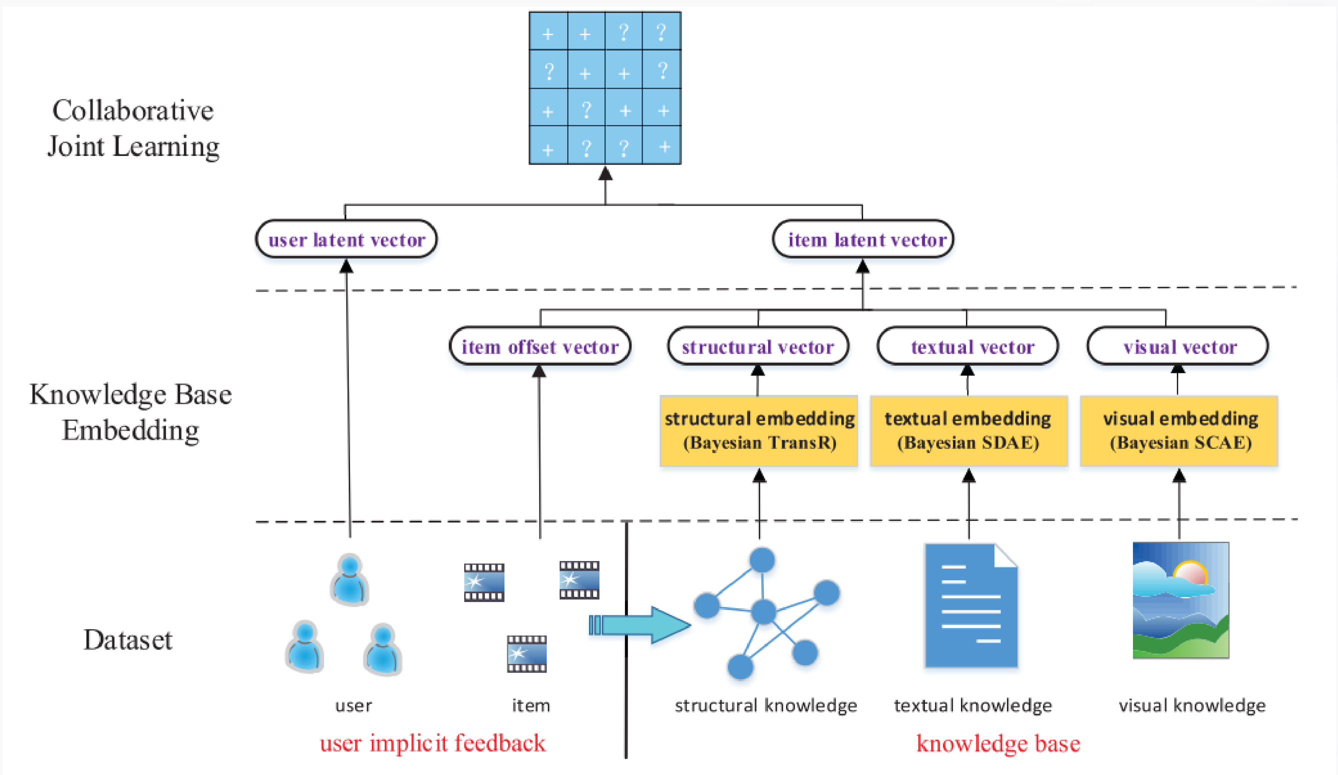

Fig.2 The framework for KG-aware recommender systems[1]

4 Future Work

Future work can be expanded in the following aspects. Firstly, existing KG-aware recommender systems do not consider the situation where an item corresponds to multiple entities such as news recommendation. The different weights of entities related to a same item and the interaction between these entities should be taken into consideration in this situation. Secondly, fusing other information such as user’s social network, user’s profile, entity type and relation type into KG-aware recommender systems is a promising direction. Thirdly, Consider the different weights/confidence coefficient of the edge in KG, for instance, the trust coefficient in the user's social network and the edge weight in KG. Fourthly, fuse the chronological order of user click behavior information. Fifthly, consider the updating characteristics over time of knowledge in the knowledge graph when recommending.

5 Reference

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