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A Survey on Knowledge Graph-Based Recommender Systems

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***Abstract*—To solve the cognitive overlord problem and information explosion, recommender systems have been using to model the user interest. Although recommender systems have been developed for decades, there still exists many problems such as cold start and data sparsity. Thus, the knowledge graph is introduced into the recommendation domain to alleviate these problems. We collect papers related to the knowledge graph-based recommender systems in recent years to summarize their fundamental knowledge and main ideas, including the usage of the knowledge graph in the recommender systems and user interest models. Finally, we propose several future directions aiming to make some progress.**

Keywords—knowledge graph; graph structure; interest model; recommendation system

I. INTRODUCTION

Nowadays Internet carrying a variety of information resources, the volume of the data is in the exponential growth. When facing a huge number of Internet resources, the user is unable to grasp all the knowledge, also the lack of professional guidance to overcome the "cognitive overload" problem. To prevent users from losing themselves in the data sea, we need the recommendation system to assist user find what they really need in the scenarios, such as movie recommendation, news recommendations and so on.

As a recommender system (RS), the main purpose is to recommend the suitable items for users. The traditional recommendation system, like collaborative filtering-based recommender systems and content-based recommender systems, have excessively played an important role in the recommendation fields for the convenience and easy deployment. However, the RS's needs to capture the user changing interests is beyond the capacity of the traditional RS. In recent years, the knowledge graph is introduced into the recommendation fields as the side information, which can find out the change of the user interests and provide the more explanation for recommendations.

The paper is organized as follows. In Section 2, we introduce the foundation of the knowledge graphs and recommender systems; in Section 3, we review the key methods of the recommender systems based on the KG; in Section 4, we give a brief outlook on the future research directions in the fields; finally, we conclude this survey in Section 5.

II. RELATED WORK

This section mainly introduce the fundamental knowledge and related work about the knowledge graph and recommender systems。

A. Knowledge Graphs

Knowledge graph (KG) was first proposed by Google[1] in May.17th, 2012. After that, many companies and organizations started their own knowledge graphs, such as YAGO, Freebase, Wikidata, DBpedia. Especially, CN-DBpedia is the largest Chinese knowledge graph. Though KG has developed for several years, it hardly has a specific definition yet. A widely accepted definition is a graph of data intended to accumulate and convey knowledge of the real world, whose nodes represent entities of interest and whose edges represent relations between these entities[2]. In general, KG is represented by triple [3]

$$\mathrm{G} = \{(h, r, t)\} \tag{1}$$

In formula (1), h refers to the head entities, r the relations and t the tails entities.

With the development of the knowledge graph, it can contain a huge amount of the information. Thus, it is necessary to abstract the knowledge, which is also called the knowledge graph embedding. The knowledge graph embedding aims to encode the semantics of entitle and relations in a continuous vector space, which can efficiently measure semantic correlations of entities and relations, alleviate sparsity issue, and significantly improve the performance of knowledge acquisition, fusion, and inference. According to the sources of the information, we can divide the knowledge graph into two types[4], one is the representation learning, which is carried out by using triples in the knowledge graph, the other one is the representation learning with additional information. The first one can also be divided into two types: Translational Distance Models and Semantic Matching Models. Translational Distance Models use the distance-based scoring function to measure the confidence of triples by the distance between the head entity and the tail entity after the transfer, TransE [5], TransH [6] and TransR [7]

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are these typical models. Semantic Matching Models use the matching-based scoring function to the confidence of triples by calculating the similarity of entities and relationships in vector space. RESCAL [8], DistMult [9] and HolE [10] are the typical models. The second type of the representation learning convinces that the knowledge graph is incomplete in fact. We need additional information to complete the semantic information of the KG. In this way, we named models: the relational-path-based model, the triplet-context-based model text-based model and so on.

B. Recommender Systems

With the human getting into the Big Data Time, the information is too big for human to deal with it. That is why the recommender system (RS) is invented. According to users' click history, the RS applied in the e-commerce platform, can model users' preferences and assist users to find out the interested information. There are two main approaches to recommend, as described below.

(1) **Collaborative Filtering.** CF can be divided into item-based CF and user-based CF. Item-based CF assumes that the item is the attribution of the user. The system tends to recommend items, which is similar with users' clicked items. user-based CF assumes that users have the similar taste with the one who has the same click history. Thus, the system is more likely to recommend others' favorite items for users who share the same items. CF, as one of the most popular recommender systems, has widely used on the website for its simpleness and interpretability. On the other hand, its efficiency depends on users' comments and cannot deal with the cold start problem.

(2) **Content-based Filtering.** Compared with CF-based models, Content-based models take attributions and the content of items into account. According to the click history, the system can recommend items with similar contents for users. To some extent, Content-based models solve the cold start problem. However, it can only apply to a specific scene, while lack of the ability to help users to explore new items and to provide sufficient surprises.

III. Key Methods of Recommender Systems with Knowledge Graph

In this section, we introduce the usage of the knowledge graph in the recommender systems and user interest models. We review the key methods that related to KG-based recommender systems in recent years and summarize them.

A. Usage of Knowledge Graph in Recommender Systems with

(1) **Path-based Methods.** Path-based Methods generally build a user-item graph, whose nodes mean users or items and edges means the interactions between users and items. One of the greatest advantages is that the user-item graph has included the potential information between users and items, which carries complete information, especially semantic information, into the graph. Also, these models provide explanations for recommended items. However, the user-item graph contains no timestamp, which is important for system to confirm the order of users clicked sequence. Thus, path-based methods can seldom model the dynamic preferences of users [11]. For instance, Wang *et al*. proposed NGCF [12], which embed both users and items into the same space by using the user-item interaction graph with the CF method, as shown in Fig.1. Wang *et al*. proposed LightGCN [13], which improve GCN model and make it more suitable for recommendation.

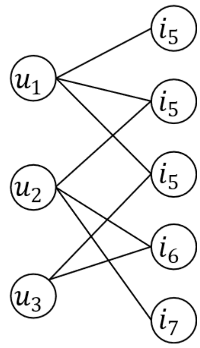

Fig. 1. The user-item graph in NGCF

(2) **Embedding-based Methods.** Embedding-based Methods generally based on the item/user graph, which can be divided into two classes. The first class is based on the item KG, which assumes that nodes are items connected by the relations of items, such as the same tag or attributions, in the homogeneous network. Similarly, the second class is based on the user KG, which assumes that nodes are users connected by the relations among users, such as relation of friends, colleague and so on. In fact, the item/user KG can contain all the knowledge about the item/user. Thus, the main goal of embedding-based methods is to create a dense representation of the item/user graph in a continuous, low-dimensional vector space that can be used in the recommend fields.

For instance, Zhang *et al* [14] proposed CKE with multi-information sources, such as texts, pictures, KG and so on. Especially, the structure information of the KG enhances the semantic information of the item embedding and improves the accuracy of recommendation. However, the model needs too much additional information outside, which is a difficult condition for most fields. Similarly, Wang *et al* proposed DKN [15] with news entity KG in news recommendation, which extracts entities from the news title to obtain the entity embeddings, content embeddings and word embeddings. These three classes embeddings are input by three channels of CNN. Also, Wang [16] used the KG as the additional information to propose RippleNet [16]. Wu [17] proposed SR-GNN, which make a session to sort user clicked item history by time. However, SR-GNN regards each user as an

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anonymous user without taking the interaction among users into account.

(3) **Hybrid Methods.** As mentioned above, path-based Methods use the semantic connection information, while embedding-based methods extract the implicit information from the item/user KG. To exploit the information in the KG, the hybrid methods integrate both methods above together to get better recommendations. For instance, Wang *et al*. proposed KGAT [18] to utilize item KG to obtain the representations of the item and integrate the user-item interaction graph. Besides, the model aims to complete the information of the high order node information by using entities as intermediary nodes in the user-item interaction graph. Also, Kang *et al*. [19] proposed HCKDC, which uses the similar methods combined with deep learning to obtain the reasoning paths.

B. The User Interest Model

The user interest model is the key technique in the recommendation. Most modes are based on the sequential recommendation, which regards users' click history as a sequence order by time. So, the sequence S_t at t time can be defined as follow:

$$\mathrm{S}_t = \{x_1, x_2, ..., x_t\} \tag{2}$$

In formula (2), x_t represents the item that user clicked at the time t.

Thus, the mission of the system is predicting the item at the time, which means what is the next item the user will click. To some extent, the sequence can be link to the natural language process (NLP) which is like words in the sentence. Thus, some effective solutions to NLP are implied to model user behaviors, which is aimed to obtain the rules of the user preference changed with the time. Generally, according to the change of the user preferences, we can divide the preferences into the long-term and short-term preferences. The long-term preferences pay more attention on the whole preference in the sequence, while the short-term preferences force on the temporary preference of the user, which have the weak relationship with the preference before. Traditional sequence recommendation is based on the Markov chains and factorization and tends to capture the user short-term preferences. For instance, paper [20] bases on the one or more user-item interaction to recommend. With the development of deep learning, NLP is more closely related to sequence recommendation. Transformer and Bert in NLP have also been successfully extended to sequential recommendation. For instance, SASRec [21] bases on the encoder part of Transformer model and

BERT4Rec [22] applies the bi-direction model on the sequential recommendation, which balance of long-term and long-term preferences very well. The main idea assumes BERT4Rec use the Transformer to predict the last item masked, final we can obtain the recommendation result. Recently, with the considering the complex relationship between users and items, models, such as YoutubeNet [23] and DeepFM [24] to enrich the semantic embedding by adding the user profile and item attributes. Also, the attention mechanism has been applied in the recommendation. DIN [25] utilizes the attention mechanism first to capture the user's preference, which assumes that the same items may have different effects on different recommendation purposes. With the development of the graph neutral network (GNN), some paper transfers the sequence into graph to use the Gated graph neutral network (GGNN), which can also obtain better results. For instance, SR-GNN forces on the transition among the clicked items, as shown in Fig.2, while GNN-TA-SR [26] utilizes the time attention factors to obtain the user interest model based on SR-GNN.

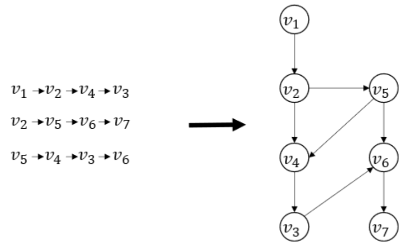

Fig. 2. The transition from the user clicked history into the directed graph

IV. Future Directions

Combination with graph neural network. User clicked sequences can be transitioned to directed graphs order by time to enhance the explanation of the RS.

Enhance the representation of the KG. Although existing KG representation methods can extract the nodes and edges information into vector, the processing is still inevitably making the information loss. Also, the negative samples in the training process will inevitably introduce errors cases. Therefore, further studies need to KG embedding way.

KG completion and correction. Currently, most KG-based recommender systems build for the item side information to obtain the semantic information. However, the incorrect entities and relationships in the knowledge graph can be included in the processing of building. Thus, the KG should be in a dynamic updating state to complete and correct.

V. Conclusions

In this paper, we do a survey about the knowledge graph-based recommendation systems and review the key methods of the knowledge graph-based recommender systems. This survey summarizes several recent approaches to utilize the knowledge graph and user interest model to improve the system interpretability and recommendation results. Finally, we propose the future research directions and hope to promote the development of the recommendation fields.

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