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The Recommendation Method Based on GRU and Knowledge Graph

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Abstract

With the development of information technology, people enter the era of big data, and one of the problems they face is information overload, and recommendation systems are an effective means to solve information overload. Recently, many deep learning-based web embedding methods have been applied to the recommendation field. However, these methods still have some limitations, such as data sparsity and interpretability problems. This paper reviews the application of knowledge graphs to solve the problems of sparsity and interpretability in recommender systems.

Keywords

Knowledge graph; recommendation system; deep learning.

1. Introduction

With the explosive growth of information on the Internet, the total amount of information is growing exponentially, and it is difficult for people to get useful information from the huge amount of information, resulting in a difficult situation when people are faced with information choices, called information overload. In order to effectively filter information for users, recommendation systems have been proposed, and after 20 years of development, they are now known as a hot research topic. The goal is to predict users' preferences for items based on their historical behavioral data and thus recommend suitable items for them. Unlike search engines, recommendation systems present users with personalized information, which can achieve the effect of a thousand people, while search engines present information based on keyword matching, which is a kind of mass information.

The goal of recommendation algorithms, as the core of recommendation systems, is to model users' interest preferences by learning user information and user behavior. They can be divided into three main categories: content-based recommendation methods, collaborative filtering-based recommendation methods, and hybrid recommendation methods. Among them, content-based recommendation is to select items with similar characteristics to the user's preferred items. Collaborative filtering uses the feature of similar interest preferences among similar users to discover the potential preferences of users for items, with the advantage that it does not require complex feature extraction for the items. Collaborative filtering is simple and effective because it only needs to utilize users' historical rating data. However, there are also problems of data sparsity and cold start. In order to solve the sparsity problem, the research community firstly, clustering is used to dimension the original data; secondly, auxiliary information such as text comment information and contextual information is introduced to increase the diversity of data sources and improve the recommendation effect; thirdly, deep learning is introduced to enhance the extraction of implicit features of user-item interactions, thus alleviating data sparsity. However, because deep learning is usually regarded as a "black box", it lacks interpretability for recommendation results, and how to make users trust the

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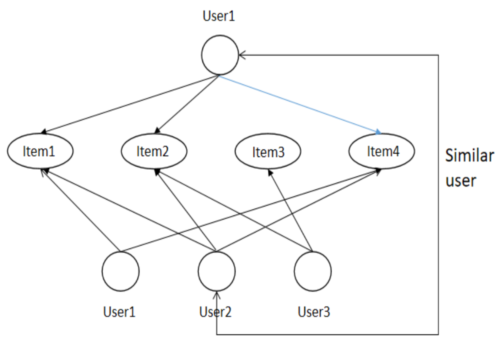
recommendation system is not convincing. In recent years, the research of knowledge graph in search engines and natural language processing has attracted the attention of scholars. A knowledge graph is a heterogeneous network structure graph containing rich speech information. The multi-source information it contains provides unique auxiliary information for recommendation systems, thus alleviating data sparsity, and its semantic paths provide logical inference support for recommendation results. This paper classifies and reviews the literature on knowledge graphs applied to recommender systems.

2. Recommendation system algorithm

Recommender system algorithm is a new research area combining various disciplines such as data mining, prediction algorithm, and machine learning. The earliest definition of recommendation system is that in daily life whether it is an understood event or an unknown event, people are always required to make decisions, and in the face of familiar things, people can often rely on past experience to make reasonable decisions, however, in the face of unknown things, people need others' verbal advice, book reviews, movie reviews, recommendations, etc. to make judgments, and the literature considers the significance of recommendation systems as being able to establish an appropriate matching relationship between recommended items and users. With the development over time, it is believed that recommendation systems are matching different users with items that match their interest preferences from a large number of items but are not observed by the users, and it is believed that recommendation systems are becoming an important business with significant economic impact

The algorithms of recommendation systems can be divided into content-based recommendation algorithms, collaborative filtering-based recommendation algorithms, and hybrid recommendation algorithms. Content-based recommendation, based on the metadata of items or contents, discovers the relevance of items or contents, and then based on users' historical behaviors (such as ratings, likes, etc. based on display feedback and search, click, purchase, etc. based on implicit feedback), obtains users' interest preferences and thus recommends to them items similar to their previously purchased items. Collaborative filtering algorithms, which have been widely studied by various research institutions and industries, have been applied in practice. There are two main types of collaborative filtering: (i) item-based approach and (ii) user-based approach. The two approaches are shown in Figure 1. The recommendation systems of many online shopping platforms (Taobao, Jingdong, etc.) are built based on collaborative filtering algorithms. The algorithm principle is to predict user preferences for candidate items based on the user-item interaction history matrix. Hybrid recommendation algorithms, which refer to recommendation algorithms that combine content-based recommendation algorithms and collaborative filtering algorithms, are used to avoid the limitations of either approach.



(a) Methods of collaborative user-based filtering

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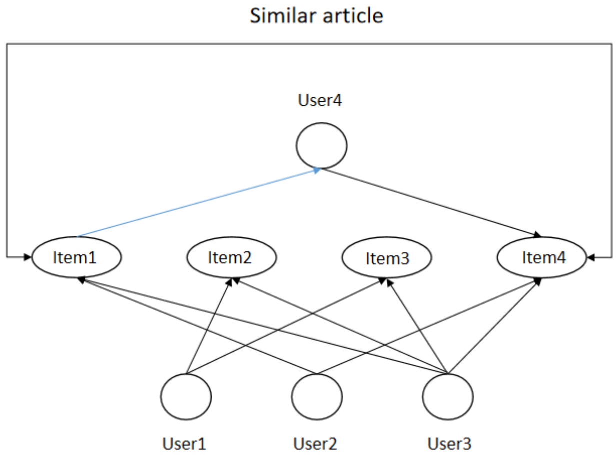

(b) Item-based collaborative filtering methods

Figure 1 (a) (b) shows two collaborative filtering methods respectively

3. Interpretability of recommendation algorithms

Explainable recommendations are recommendation algorithms that explain the recommendation reasoning problem, providing the user with the recommendation result along with an explanation to clarify the reason for the recommendation. This helps to improve the variety, effectiveness, and accuracy of recommendation algorithms and facilitates users to understand and adopt the recommendation results. Most of the early recommendations were content-based recommendations or collaborative filtering-based recommendations. Content-based recommendation methods model information about the attributes of users or items and are based on intuitive explanations of features. The collaborative filtering approach has to be interpreted through explicit or implicit feedback from users. Collaborative filtering of items is more intuitive because the user is familiar with the item he previously liked and the user can understand it more easily. The explanation of user collaborative filtering may be less convincing because the target user may not know anything about other "similar" users, which may reduce the credibility of the explanation. Traditional recommendation algorithms often generate recommendation explanations that are limited to one of item-mediated, user-mediated, or feature-mediated, and do not sufficiently explore the connections between these three types of media. Knowledge graphs, as structured knowledge bases possessing knowledge representation capabilities, contain rich information about users and items that can help provide informed explanations about recommended items. The potential relationships between users and items are reflected by exploring the connectivity of entities within the knowledge graph. The connected paths from users to recommended items on the knowledge graph give the recommendation algorithm the ability to reason and interpret.

4. Knowledge graph

The knowledge graph was proposed by Google in 2012 to improve the performance of search engines, and it usually consists of a heterogeneous graph composed of multiple triples (head entities, relations, and tail entities), where the nodes of the graph represent entities and the edges between nodes represent relations. The entities in the graph correspond to multiple relationships between them, and a relationship can be considered as a fact of the objective world. By introducing the knowledge graph into the recommendation system, firstly, by mapping the objects (users or items) of the recommendation system and the entities in the knowledge graph to each other, the connection between items can be enhanced and the relationship between users and items can be captured more accurately, thus alleviating data sparsity. Second, based on the logical reasoning of the knowledge graph, the user's history is connected with the recommended results, providing interpretability for the recommended results. As in Figure 2, a graph network structure about movies is represented. In this structure, firstly, by using movie names as attributes such as the following two, "Police Story" and "Plan A", the cold-start problem and data sparsity problem can be mitigated to some extent. Then more relevant information such as category, lead actor and other attributes can also be utilized in this structure to be able to understand its similarity, which also alleviates the shortcomings of traditional algorithms and improves the recommendation accuracy. And we can recommend "Joey Wong" as the producer or "Jackie Chan" as the lead actor to users who prefer "Plan A" by virtue of the film title attribute, such as "Police Story". The recommendation content is enriched by the related movies starring "Jackie Chan". In addition, "Shen Teng" starred in both "Charlotte's Trouble" and "Hello Li Huan Ying", and both movies are classified as action movies, so the movie " Police Story" to users who prefer "Plan A", it makes more sense and increases user satisfaction.

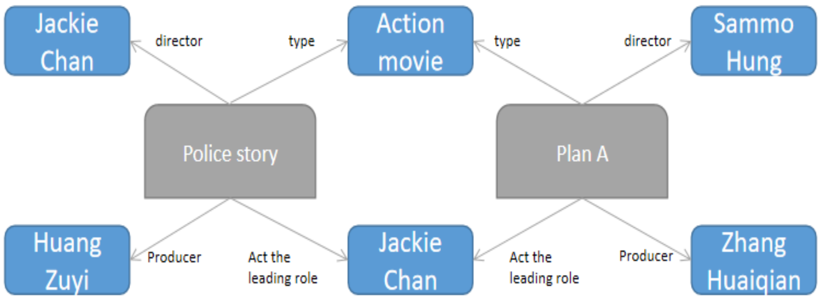

Figure 2 Example of knowledge graph

4.1. Knowledge Graph-based Recommendation Algorithm

With the introduction of the auxiliary information of knowledge graphs, recommendation algorithms can learn the potential connectivity between users and items, which can capture user preferences more accurately and improve the recommendation effect. This chapter presents research related to knowledge graph-based recommendation algorithms, which can be classified into three categories according to the different forms of applied knowledge graphs: embedding-based approaches, path-based approaches, and propagation-based approaches.

Table I summarizes the main studies in the user short-term preference sequence recommendations in this paper.

4.1.1. Embedding-based recommendation method

The embedding-based approach uses the information in the knowledge graph to enrich the representation of users or items, and the knowledge graph embedding characterizes the entities and relationships in the knowledge graph as low-dimensional vectors, preserving the original structure of the knowledge graph. The method of knowledge graph embedding is mainly based on the translational distance model for feature representation. The translational distance model uses distance-based scoring functions to measure the reasonableness of facts by the distance between two entities. The main ones include TransE, TransR, etc. The basic principle is to embed the head entity, tail entity, and relationship of each triad into the vectors h, t, and r such that they satisfy $h + r \approx t$ The truthfulness of the triad can be calculated using an evaluation function defined as the distance between $h+r$ and t under L_1 parametric or L_2 parametric constraints. Its mathematical expression is as follows Equation(1):

$$d(h+r,t)=\|h+r-t\|_{L_1/L_2} \quad (1)$$

The goal is to make the distance between related entities as small as possible, and the distance between unrelated entities as large as possible.

Wang et al. proposed a deep knowledge-aware network DKN that introduces knowledge graph representation into news recommendation.The model extracts entities from news headlines using Kim CNN with entity linking, constructs feature vectors from the relation link subgraphs of entities extracted from the original knowledge graph by TransD, and also extracts contextual information of entities using their nearest neighbor entities. Finally, a knowledge-aware convolutional neural network KCNN with multi-channel and word-entity alignment is used to combine word semantics and entity information to generate the knowledge-aware embedding vector. In addition, the model is designed with an attention module to capture the dynamic preferences of users on news and get the influence weight of history on users.

4.1.2. Path-based recommendation method

The path-based approach learns the connection similarity between the paths from users to items for recommendation by constructing a user item graph and using the connection relationships of the entities in the graph. The main challenges of this approach are how to design reasonable paths and how to model the connection relationships between entities.

Some recommendation methods treat the knowledge graph as a heterogeneous information network and then use the meta-structure in the graph to directly compute the connected similarity of paths to make recommendations. Similarity based on meta-structure can be used as a constraint for user and item representation, and also for predicting user interest in similar users or similar items in the interaction history.

Sun et al. proposed a recurrent knowledge graph embedding method, RKGE, which automatically mines the path relationships between users and items through recurrent neural networks without the need to manually define meta-structures. Recurrent neural networks are able to model sequences of different lengths and learn not only entity semantics but also the entire path sequence, thus providing a unified learning approach for the representation of entities and entity relationships.

4.1.3. Propagation-based recommendation methods

To make full use of the information in the knowledge graph for better recommendation, the propagation-based recommendation approach integrates the semantic representation of entities and relations as well as the connectivity information. The propagation-based recommendation approach is based on the idea of embedding propagation, which aggregates embeddings of multi-hop neighbor nodes in the knowledge graph to deepen entity representations. Then, a rich representation of users and items is obtained, and user preferences are predicted.

4.1.4. Summary

The embedding-based approach uses knowledge graph embeddings to learn the knowledge graph to obtain embeddings of entities and relationships, and further integrates them into the recommendation model. However, the semantic associations between entities are ignored in this approach. The path-based approach mines path connection similarity using user item graphs to mine path connection relationships either through predefined meta-structures or automatically. Path-based approaches can also provide users with interpretation of results. In addition, sparse dataset scenarios may not provide enough paths to mine connection relationships. The propagation-based approach achieves both the exploitation of the connection relations for paths in the knowledge graph structure and learning the feature representations of entities and relations through the idea of embedding to fully utilize the information from both sides. In addition, propagation-based recommendation methods have the ability to explain the recommendation process. Table 1 briefly illustrates the advantages and disadvantages of the three types of approaches.

Table 1 Comparison of three types of methods

Type	Advantage	Disadvantage
Embedded-based approach	Simple and flexible	The semantic relationship and interpretability between entities are negl ected
Path-based approach	Good interpretability	It has requirements for path selection and is not suitable for sparse data set scenarios
Communication-based approach	Make full use of knowledge Map information	Limit the spread due to computational costs

4.2. Knowledge Graphs Address Two Common Drawbacks of Recommender Systems Data Sparsity

4.2.1. Knowledge Graphs to Address Data Sparsity in Recommender Systems

Accuracy, as the primary issue of recommendation system, is related to the user's viscosity to the system and is crucial to improve the overall economic value. According to research, the accuracy of current recommendation systems is around 72%, and there is room for further improvement in the accuracy of recommendation systems. in addition to incorporating auxiliary information into recommendation systems based on user portraits, item attributes, and out-of-context information, knowledge graphs, as auxiliary information with more semantic information, can be incorporated into recommendation systems to better alleviate data sparsity and improve accuracy. proposed by Zhang, the CKE model, using the TransR method to process the structural information of the knowledge graph to obtain the structured information vectors of entities, and combine the obtained text information vectors and view information vectors to form the potential representation of items. the DKN model proposed by Wang, using the TransD method to learn the entity vectors in the knowledge graph, and learn the contextual entity vectors of the one-hop range of entities and stitching vectors in different spaces using multiple channels, solving three major challenges in news recommendation.The MKR model proposed by Wang uses a multi-task learning framework to alternate the recommendation system with a knowledge graph feature learning task for optimal training, and uses knowledge graph embedding to assist the recommendation task, making the recommendation more flexible and adaptable.The KGCN model proposed by Wang, is an end-to-end convolutional network that treats items as the center of the knowledge graph domain, thus fusing domain information and mitigating the effects of data sparsity.

4.2.2. Knowledge Graph Solution for Recommender System Interpretability

Since recommendation systems are generally "black-boxed", i.e., it is not known how the recommendation system captures the user's interest and the user does not understand the meaning of the items recommended by the system, interpretable recommendations have gradually become a hot research topic in order to make the recommendations more humanized in addition to personalization. Explainable recommendations not only enhance user trust and acceptance, but also provide users with an opportunity to preferentially select items to improve user satisfaction. Because the semantic path of the graph has logical reasoning, research scholars, enhance the satisfaction and trust of recommendation systems by incorporating knowledge graphs into recommendations and using the path between users and candidate items as an explanation for the items recommended to users.Cao proposed the KTUP model, which models the reasons for users' preference for an item, to enhance the recommendation results by combining the recommendation task with knowledge complementation accuracy and interpretability. the EIUM algorithm proposed by Huang, called interpretable interaction-driven user algorithm, provides an interpretability of sequential recommendations by predicting the items that users may prefer based on their historical behavior sequences. a joint learning framework for rule-based recommendations proposed by Ma uses the weight of rule learning as the interpretation of recommendation results.

5. Challenges and Research Trends of Recommender Systems

Recommendation systems aim to help users discover recommendation items that match their preferences from a large number of recommendation objects. In this paper, we analyze four different types of recommendation systems, including content-based recommendation techniques, collaborative filtering-based recommendation techniques, hybrid recommendation techniques, and deep learning-based recommendation systems. Although these recommendation techniques have achieved satisfactory recommendation results, they still face the following challenges, and future research can be attempted in these areas:

1) Recommend items for users through dynamic information.

The knowledge graph contains rich information on user behavior and item characteristics, but implicit and noisy preference signals are prevalent in users' long-term historical behavior, which undoubtedly reduces the effectiveness of modeling users' real interests. And in scenarios similar to news requiring timeliness, users' interest preferences are easily shifted. Therefore, capturing users' dynamic preferences during development and predicting their behavioral intentions can better improve user experience compared with traditional static recommendations.

2) The security of the recommendation system needs to be improved.

Large-scale online websites have attracted a huge number of users, especially the development of social networking websites, and the precise recommendation of items of interest for users has become one of the means to attract users to each website, and only the mining of multidimensional (characteristic) information of users can make it easier to find the recommended objects that match their preferences. In fact, users do not want their other personal privacy to be disclosed when they expect recommendation systems to recommend items of interest, and current research has scrambled users' information through data distortion and data obfuscation algorithms. Although this data scrambling can protect users' privacy, it can also lead to inaccurate extracted user information, which greatly reduces the accuracy of recommendations. Therefore, the next research can focus on a method that can protect users' privacy and improve the accuracy of recommendations at the same time.

3) Lack of methods to extract user preference features.

The current recommendation system relies more on the user's rating or feedback of the recommended item, and ignores the features of the user and the recommended item itself, and the current research lacks appropriate modeling methods to extract the features, linear and nonlinear relationships between the user and the recommended item in a multidimensional way. Therefore, the next research needs to introduce more diverse ways to extract the features of users and recommendation objects.

4) Multimodal knowledge graph recommendation

Multimodal knowledge graphs introduce entities or entity attributes of different modalities based on traditional knowledge graphs, and also bring semantic associations between different modalities. Multimodal knowledge graphs that introduce textual or visual data can provide more auxiliary information, thus solving the data sparsity and cold-start problems.The multimodal knowledge-aware reinforcement learning network MKRLN proposed by Tao et al. correlates recommendations and explanations by providing actual paths in multimodal knowledge graphs. The method generates path representations by combining structural and visual information of entities, but existing methods mostly model and learn textual and visual modalities separately, and it is still challenging to integrate multimodal information and entity information directly together as new entities into recommendations.

6. Conclusion

This paper presents a review based on the introduction of recommendation systems, knowledge graphs, and details the recommendation algorithms based on knowledge graphs in solving the common problems of recommendation systems, i.e., data sparsity and interpretability aspects. Mitigating data sparsity can further improve the accuracy of recommendation systems, make users trust more in the system's ability to capture interest, and provide an explanation for recommendation results that can enhance the transparency of recommendation systems and improve user trust. With scholars' in-depth research on knowledge representation of knowledge graphs, knowledge inference, potential research directions in this field are prospected in the hope of promoting the development of this field.

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