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A review of similar entity search research based on knowledge graph

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Abstract
In the era of big data, how to help users accurately filter out effective information from a large amount of digital information is the current challenge facing search engines. Knowledge graph has richer semantic information and can effectively conduct more accurate object-level search, and it is a major change to apply knowledge graph to search engine. In this paper, we summarize the classification of similar entity measurement algorithms based on knowledge graphs, review the development history of similar entity measurement algorithms under different algorithm classifications, introduce typical algorithms and prospect the future development.

Keywords: knowledge graph, entity search, similarity

Introduction

Knowledge graph is currently a popular research area, and it is essentially a semantic network. For a knowledge base that includes a large number of entities, we need to pay attention to the information about the association between entities. In addition to the information about the entities themselves, one of the problems faced is: given two entities, how to determine whether they are similar to each other and how much they are similar to each other. Similar entity search based on knowledge graph mainly uses the structured features of knowledge graph and the semantic information of entities, which can help users to retrieve and discover the relevant entities of interest. Realizing complex correlation queries with the rich information contained in knowledge graphs improves the search accuracy rate. Research on knowledge graphs has made great progress in recent years, and review studies on knowledge graphs have been published one after another, which include studies on knowledge extraction, knowledge representation, and knowledge inference, as well as a review of knowledge graph construction and knowledge fusion problems [1]. However, there is still a lack of literature that systematically compares the research progress of knowledge graphs in the direction of similar entity search. For this reason, this paper composes the literature related to similar entity search of knowledge graph, and describes the research progress of the key technologies used in similar entity search of knowledge graph; then, it describes the grounded application of similar entity search of knowledge graph in vertical industries; finally, it discusses the development trend and many challenges of similar entity search based on knowledge graph.

Knowledge graph-based similar entity metrics

Knowledge Graph Overview

Knowledge graphs aim to describe various concepts, entities, and the relationships between them. Entities are concrete things that exist in the objective world and are distinguishable, such as London is the capital of England, Hamburg, etc. A concept usually reflects a set of kinds of entities or types of objects, such as people, animals, etc. Attributes are the characteristics and parameters that an entity has, and different attributes correspond to different edges. Relationships are the edges that connect different entities and describe the objective association between entities [2]. Simulated the knowledge base of human linguistic behavior by constructing complex elemental network associations, and discovered knowledge related to nodes by using marked directed graphs with attributes and semantic relations between things [3]. Defined the knowledge representation model as semantic network and considered it as a preliminary exploration of semantic analysis methods. Google firstly proposed the concept of knowledge graph [4], and applied knowledge graph as technical support for search engines. At present, the technologies related to large scale knowledge graph have been widely used in the fields of intelligent search, intelligent Q&A, and so on. Both semantic networks and knowledge graphs use the form of graphs for knowledge representation. However, in the semantic network, nodes represent objects and concepts, edges represent relationships between nodes, and the values of nodes and edges can be defined by users, which makes it difficult for multi-source data fusion; while in the knowledge graph, nodes represent entities or attribute values, and edges represent relationships or attributes, which represent the attributes of things and semantic relationships between things explicitly and use the form of triples to portray. For this reason, the construction of knowledge graphs is more standardized, the structure is simple and intuitive, the use is flexible, and the quality of data is guaranteed.

Domain ontology is an important step in forming a knowledge graph, and it is also the foundation and skeleton of the knowledge graph. The ontologies include concepts, attributes, and relationships between concepts, which can describe the knowledge structure. A domain ontology is a collection of terms describing a domain that constrains and manages the knowledge graph at the schema level. The ontology base can be seen as a template for a structured knowledge base, which is reflected in the schema layer, and the logical architecture of the knowledge graph contains a schema layer and a data layer [5]. The data layer is the basis of the knowledge graph, which is the enrichment and expansion of the ontology base at the entity level under the specification and constraint of the schema layer. Among the existing research results, relying on the existing mature ontology libraries, similar entity search based on knowledge graph is more deeply researched and practiced in several fields.

Similar Entity Search

An entity represents the specific semantic meaning of an object in the real world, and it is the most basic element in the knowledge graph. There are certain relationships among entities, whose basic forms mainly include (entity1-relationship-entity2) and (entity-attribute-attribute value), etc. If entities are represented as v, similar entity search based on knowledge graph can be used $\{G, q, R(q, v_i)\}$ to carry out the representation, where G is the knowledge graph, which consists of a large number of entities and the relationships between them; q is denoted as the user's query request, $R(q, v_i)$ which is used to measure the relevance or similarity between the user's query and the entities v_i in the dataset, and to ranking the scoring results. The process of implementing similar entity search based on knowledge graph is shown in Fig. 1, and the core part of entity search system is how to interact the user's query input with the knowledge graph. First, the system is required to transform the natural language retrieval object entered by the user into a query entity. Subsequently, the entity search system will identify the semantic entities in the retrieval formula and perform query expansion and inference on the structural relationships between the entities. Finally, the system ranks the results of query processing in terms of relevance and provides the results that best meet the user's needs to the user. In the process of executing the query, the system also needs to construct corresponding storage methods and indexes because the query processing is affected by different matching strategies and to improve the efficiency of retrieval. The specific process is shown in Figure 1.

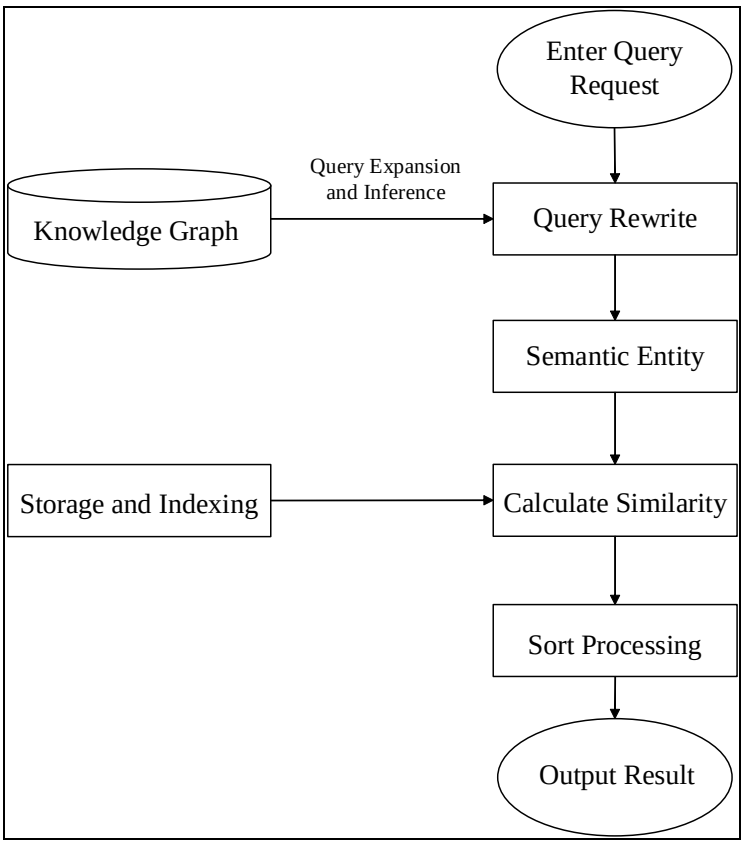

Fig 1: Flowchart of similar entity search in knowledge graph

Semantic-based similar entity search

The methods for computing text similarity for semantic information of entities are currently divided into two main directions: statistical-based approach and semantic analysis-based approach [6]. The similarity calculation based on statistical methods usually adopts the vector space model [6] for text representation, which represents the text as a collection of feature words, takes these feature words as the most basic elements, then counts the

word frequencies in the text to get the feature words, and represents the similarity of the text by calculating the similarity on the vector space of feature words. Using the VSM model, the key is to calculate the word weights, which are usually calculated using the TFIDF [6] vector. The VSM model uses the statistical properties of the feature words in the text and can represent the text effectively. However, the resulting feature vectors are high dimensional and have high sparsity, which affects the effectiveness of the computation.

A semantic-based analysis method is proposed to improve the limitations of VSM. Semantic analysis refers to the semantic relationship between words and considers the similarity of words [7]. Proposed a method to calculate word similarity based on word-semantic network edges by analyzing the node density, depth and linking relationships [7]. There is also a method based on the semantic lexicon WordNet [8-11], in which a collection of synonyms is used as the base construction unit. The words in the set of synonyms represent similar meanings and in some cases these words can be interchanged with each other. In addition, there is another document topic generation model, LDA model [12], which can mine the deep semantic information in the text, although it is also a statistical-based approach, but it can effectively reduce the dimensionality and improve efficiency.

Structure-based similar entity search

The structure-based similar entity metric mainly uses the connection relationship between entities in the knowledge graph to calculate the node similarity. It mainly includes random walk method and meta-path method. Random walk similarity metrics are universal, but the random walk paths cannot satisfy the good properties such as symmetry. The representative methods are ECTD [13] and PCRW [14]. Random walk based method occupied the mainstream before the meta-path was proposed, for example, ECTD [13] applied it to movie recommendation task while proposing similarity metric. In the field of information retrieval, the PCRW - model to measure the similarity of entities in a directed graph constructed from scientific literature metadata. Later, OptRank [15] constructed a random walk transfer probability matrix using heterogeneous information. After the meta-path approach was proposed, the random walk approach is still used by many applications because of its advantages such as no need to design meta-paths manually. For example, HeteRS [16] represents the heterogeneous information network as multiple transformation matrices, given the query nodes, the results are obtained using multivariate Markov chain solutions.

The meta-path approach treats the knowledge graph as a heterogeneous information network (HIN), and then constructs matching computations based on path rules between nodes. Since different meta-paths contain different semantics, different meta-paths connecting two objects may lead to different similarities. PathSim [17] evaluates the similarity of objects of the same type based on symmetric paths. RelSim [18] measures the similarity between relational instances in a HIN based on the relational similarity of meta-paths. HeteSim [19] measures the relevance of any object pair under any meta-path. AvgSim [20] overcomes the high computational and memory requirements problems of HeteSim. W-PathSim algorithm [21], which improves PathSim by applying the LDA (Latent Dirichl*et al*location) topic model to generate weighted attributes of object links. The meta-path similarity metric requires manual design of meta-paths in practical applications, and the difference in the dependence of different graph structures on meta-paths also leads to compromise in practical applications.

Graph-based representation learning similar entity search

Network representation learning [22], also known as network embedding, aims to learn low-dimensional vector representations of network nodes from the latent space, and network embedding has been successfully applied to many data mining tasks in structural feature extraction. In recent years, a large number of network representation learning algorithms have been proposed by researchers to solve network analysis tasks. These algorithms can be generally classified into three categories: matrix factorization based models, probabilistic models, and deep learning based models. Matrix decomposition-based methods including GraRep [23], HOPE [24] and M-NMF [25] generate network embeddings by decomposing the adjacency matrix of the network. Probability-based models include DeepWalk [26], LINE [27], node2vec [28] and HSRL [29], the Deepwalk algorithm is based on the idea of Word2vec [30], which treats nodes as words and random walking sequences as sentences, combined with the Skip-Gram neural language model to learn the network representation. LINE is applicable to large networks, which maps the nodes in a large network into a space of a specific dimension according to the closeness of the relationship. Node2vec is an extension of DeepWalk, which combines both breadth-first and depth-first graph search algorithms for node neighborhood exploration, add p and q two parameters to control random walk to avoid repeatedly passing through certain nodes.

With the development of graph neural network (GNN) [31], GNN-based deep network embedding algorithms have received attention from researchers, a representative class of methods includes autoencoder-based network embedding models, including SDNE [32], R-GCN [33], and DGE [34], etc. These models reconstruct the original topology of the network by autoencoder to achieve the representation learning of low-dimensional network embedding. The P-GNN (position-aware graph neural networks) model [35], increases the model's ability to learn the global structure of nodes by learning a node-position-aware embedding method.

The above network representation learning methods ignore the heterogeneity in the network, and the data of knowledge graphs are all belong to heterogeneous information networks (HINs), therefore, in recent years, network embedding algorithms based on HINs have also received increasing attention from researchers , and these methods assume that the network of nodes and edges are multi-typed relationships and design different algorithms to cope with the heterogeneity of the network, among which meta-path [17] based approaches are used

to extract different semantic relationships between different types of nodes in heterogeneous networks by designing different meta-paths, where HIN2Vec [36] predicts different types of meta-paths between network nodes based on Deep Walk, while representation learning of meta-paths and nodes. Metapath2vec [37] is by changing the random walk over different types of meta-paths. While in the deep learning-based approach, HEER [38] achieves heterogeneous network representation learning by learning the representation of different types of edges and the metric of network heterogeneity, and HGT [39] achieves heterogeneous network representation learning on the basis of meta-relationship extraction based on the introduction of an attention mechanism that depends on node type and edge type. Although existing network representation learning algorithms have achieved some success in similar entity search, but these algorithms ignore the higher-order semantic relationships among node objects in heterogeneous information networks.

Similarity search based on other models

Unlike general ordinary networks, knowledge graphs have additional non-relational information, including node attribute information, node type information, and node description information. Reasonable fusing this information can improve the accuracy of similar entity search. However, few algorithms consider the cross-correlation between the two models information of network structure and node attributes. [40] Proposed the ASNE model, in which the final node embedding is represented by fusing the learned structure-based node embedding with the attribute-based node embedding to achieve the interactive learning of structure and attribute information. [41] Proposed the BiANE model for node embedding learning of bipartite attributed network, which designs a new attribute-structure correlation loss function for joint learning of attributes and structures.

Entities have hierarchical type information and concise descriptions of entities, which are not well represented by any existing methods. Therefore, [42] proposes the DKRL (description-embodied knowledge representation learning) model based on the characteristics of entity descriptions. The algorithm idea is to combine the continuous bag-of-words (CDOW) model and the convolutional neural networks (CNN) model to represent the semantic information. The limitation of this model is that it only considers the entity descriptions used for representation learning, and does not consider the textual information of various relationships or entity types. To address this problem, GAKE (graph aware knowledge embedding) model [43] was proposed. [44] Combines knowledge mapping and logic rules, i.e., the KALE (knowledge and logic embedding) model, which is centered on representing and modeling triples and logic rules in a unified framework.

Application of similar entity search

Knowledge graphs for similar entity search are commonly used in search engines, in addition to the common areas of intelligent recommendation and medicine. [45] Proposed explicit semantic ranking with knowledge graph embedding to help academic search better understand the meaning of query concepts. The application scenarios of similar entity search based on knowledge graphs have evolved from simply constructing knowledge graphs for retrieval initially to integrating mining inference for platform-level applications later, and the domain has been expanded from the mature biomedical field to include the integration with new technologies [46]. Smart recommendation is one of the popular areas of knowledge graph applications, which can provide the most appropriate recommendations to users [47]. Smart recommendations in e-commerce are most commonly used. If a user wants to query information about a product, he or she needs to input keywords, and the knowledge graph based intelligent recommendation will output product-related information to the user. When a user finishes purchasing a product, the intelligent recommendation can also determine the user's purchasing needs and shopping scenarios through the knowledge graph and provide the user with information about other complementary products. Graph Search, a new product based on knowledge graph published by Facebook. It uses knowledge graph to connect important elements in social networks, to form a huge social relationship graph, helping users to quickly and accurately identify closely related people.

Future Work

We propose future work based on existing problems with similar entities search in knowledge graphs as follows:

(1) Interpretability. Interpretability refers to the ability of the system to give a reasonable interpretation of the obtained search results. It is particularly important in entity expansion and entity recommendation. The interpretation of search results is to explain to the user the evidence of the answer provided by the system, and most of the existing knowledge graph based similar entity search techniques are based on the semantics and structure of entities. However, this approach does not consider the problem of missing knowledge. The existence of knowledge deficiencies in the knowledge graph makes it challenging to interpret the search results. To solve this problem, it is necessary to consider how to set up a timeline to address the change of relationships between entities over time [48] and how to interpret entities that do not have direct relationships.

(2) Integration of diverse data sources. Similar entity search is inseparable from rich data sources. Compared with the structured features of the knowledge graph, unstructured data such as text, video, and image are much larger than the structured data sets. By fusing the structured knowledge graph with unstructured data, new entities and new relationships can be added to the knowledge graph from unstructured data. Compared with structured data, unstructured data is richer in entities and relationships. For this reason, mining based on unstructured data can extend the emerging entity relationships into the knowledge graph and improve the effectiveness of queries. Some studies have started to explore the integration of the two [49], but this research is

still in its infancy and lacks a general model. Currently, the development of neural network algorithms has made it possible to represent different types of data (e.g., text, image, video, etc.) in a unified space, and it is worthwhile to explore the use of neural networks to construct relationships between entities from unstructured data.

Summary

As a structured and semantic expression of knowledge, the powerful semantic processing and interconnected organization capabilities of knowledge graphs provide the basis for intelligent information applications. As the main way of search engine, entity search based on knowledge graph has played an important role in intelligent search, intelligent Q&A, personalized recommendation, etc. It also shows good application prospects in education and research, medical treatment, biomedical treatment, and some industries that need to conduct big data analysis. This paper details the definition, implementation process, enumerate research papers, summarizes the application scenarios and future development directions of entity search. Due to the multidisciplinary nature of knowledge graphs, the integration of research on knowledge base construction, natural language understanding, machine learning, and data mining is needed to jointly promote the research and development of this field.

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