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Research on Application of Knowledge Graph in the Field of Emergency Supplies

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Abstract

Knowledge graph describes the complex relationship between entities in the real world in a structured form, which is the underlying support of artificial intelligence. The application of knowledge graph technology in emergency supplies and related emergency fields can get rapid response when emergencies occur. The knowledge graph is formed after the emergency plan and other information are processed, and the order of entity association is the corresponding processing team and necessary materials for emergencies. Knowledge graph in the field of emergency supplies has the following characteristics: extracting complex and diverse knowledge information, high expert participation, fine knowledge granularity, and high knowledge quality requirements, which is of great value to the research of knowledge graph in the field.

Keywords

Knowledge Graph; Emergency; Field of Emergency Supplies.

1. Introduction

Emergency supplies refer to the necessary material support in the whole process of emergency response to public emergencies such as serious natural disasters, accident disasters, public health incidents and social security incidents. The construction of emergency supplies and emergency resources management platform and the improvement of emergency management informatization level can effectively improve the ability to deal with major emergencies, play an important role in ensuring the safety of people's lives and property, and effectively and orderly carry out emergency work, which is of great significance for promoting the modernization of national emergency management system and capacity.

Relying on industry data and in-depth learning technology, knowledge graph has been widely used in many industrial core scenarios, which has led to the demand for knowledge graph construction. The construction technology of knowledge graph mainly includes data acquisition, data extraction, knowledge representation, entity alignment, knowledge reasoning and other steps. It is an important task to extract the semantic relationship between entities in the text. The result of extraction will directly affect the construction of knowledge graph and the effect of subsequent reasoning process. However, the knowledge extraction method for the emergency domain is still blank at present, and it is very important to select a suitable method for the extraction extended to a specific domain. Knowledge graph inference refers to the computational process of inferring new relationships and acquiring new knowledge by using existing relationships or facts in the graph, which plays an important role in various tasks such as knowledge graph completion, graph quality optimization, enhanced question answering and assisted semantic understanding.

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As an important branch of knowledge engineering, knowledge graph has gradually become the core driving force and important field of the development of artificial intelligence. This paper compares and analyzes the construction technology of knowledge graph, discusses the research methods of knowledge graph to make up for the defects of deep learning, and gives the research difficulties and potential ideas. From the current research progress, we can see that deep learning has become the mainstream method for knowledge graph construction, and has achieved good results.

2. Knowledge Graph

The concept of knowledge graph was proposed by Google in 2012 to improve the search engine. Knowledge graph is a typical multilateral relationship graph, which is composed of nodes (entities) and edges (relationships between entities). It is essentially a semantic network, which is used to reveal the connections between everything. The construction process of knowledge graph is shown in Fig.1.

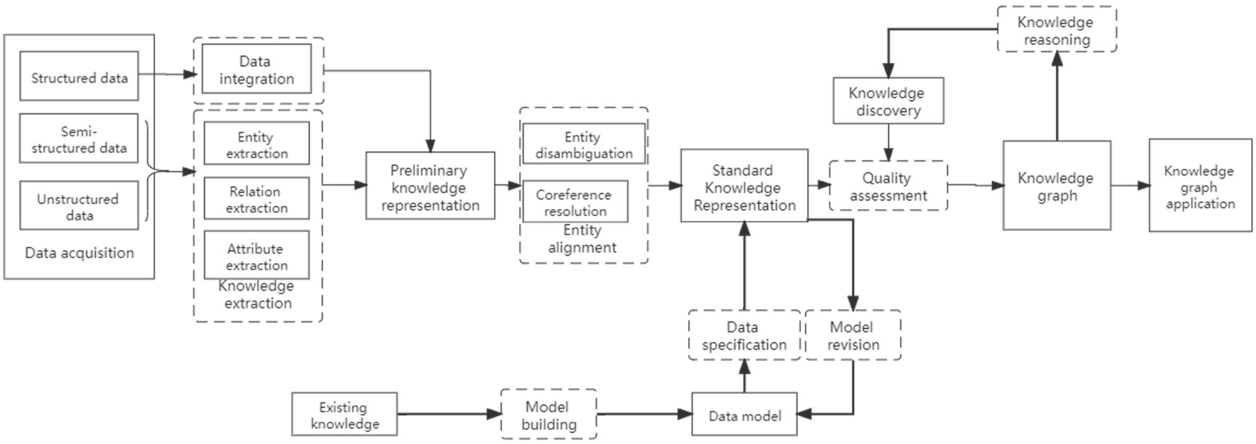

Fig. 1 Construction process of knowledge graph

Knowledge graph aims to extract concepts, entities and relationships from various types of complex data, which are the relationship between things. Computable model. Knowledge graph can be divided into general knowledge graph and domain knowledge graph according to the coverage of knowledge and different fields. With the continuous development of science and technology, knowledge graph is widely used in the field of NLP, such as semantic search[1], intelligent question answering[2], assistant decision-making[3] and other fields. Knowledge graph has become an important driving force and core field for the development of artificial intelligence.

The early knowledge base is usually constructed manually by experts in related fields, which has high accuracy and utilization value, but it has some limitations, such as complex construction process, requiring the participation of domain experts, high resource consumption and small coverage. Typical early knowledge bases include WordNet[4], ConceptNet [5], etc. WordNet is a dictionary knowledge base developed by the Cognitive Science Laboratory of Princeton University since 1985, which is mainly used for word sense disambiguation. WordNet mainly defines the semantic relationship between nouns, verbs, adjectives and adverbs. For example, in the hyponymy between nouns, "Canine" is the hypernym of "Dog". WordNet contains more than 150,000 words and 200,000 semantic relations. ConceptNet is a common sense knowledge base, which originated from the OMCS (Open Mind Common Sense) project created by MIT Media Lab in 1999. ConceptNet uses an informal, natural language-like description that focuses on the relationships between words. ConceptNet is composed of relational knowledge in the form of triples, which contains nearly 28 million relational descriptions.

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3. Entity Relation Extraction

Generally speaking, the source of data can be divided into three types of formats: structured data, semi-structured data and unstructured data. The acquisition methods of structured data include D2R technology and linked data acquisition graph graph method. Semi-structured data acquisition: wrapper technology, information extraction from semi-structured text. This article focuses on the third category: unstructured data. Unstructured data mainly refers to data models that are not predefined, incomplete or irregular, such as HTML, Word documents, PDF files, and so on. The structure of unstructured document is complex, but the amount of information is rich, and it plays an important role in obtaining information. In the field of emergency response, the complete data of emergency supplies, the description of emergencies including emergency supplies, and the overview of historical emergency events are all composed of unstructured data. Because it contains a lot of value and occupies most of the data sources, obtaining the effective content of unstructured data has become a problem that needs to be solved. In this paper, the model of entity relation extraction in emergency domain is mainly composed of four parts: data acquisition, data preprocessing, sequence labeling and joint extraction of entity relations.

Early joint extraction models are usually based on structured chemical methods with artificially constructed features. Bekoulis et al. [6] pointed out that there are some problems in the current entity relation extraction task, such as the performance of the model is heavily dependent on the performance of the NLP tool and there is entity relation overlap. In this paper, the relation extraction task is regarded as a multi-head selection problem to solve the problem of relation overlap. Li et al. [7] treat the task of entity relation extraction as a multi-round question and answer problem, which can well capture the hierarchical dependence of labels. In 2020, Xiao et al. [8] designed a chapter-level joint learning model Ch-MEL, which uses BI-LSTM and self-attention mechanism to enhance the learning representation, and combines joint decoding with parameter sharing. Wang et al. [9] proposed the TPLinker method to reduce the joint extraction to the label pair connection problem, and introduced a new handshake labeling scheme to align the boundary labels of entity pairs under each relationship type, showing advanced performance in overlapping and multi-relationship extraction. Wang et al. [10] proposed a new paradigm of union method defined in a unified label space, which regards entities as an undirected self-loop relationship, and introduces a two-dimensional table to represent all entities and relationships completely. Yan et al. [11] proposed a new coding paradigm-joint coding, and based on this paradigm, designed a partition filtering encoder adapted to multi-task learning, which can encode the task characteristics of NER and RE at the same time to ensure fully balanced interaction between tasks, and effectively avoid the shortcomings caused by sequence coding and parallel coding.

4. Knowledge Reasoning

Because of the wide range of knowledge sources, after knowledge extraction, these knowledge presents the characteristics of decentralization, heterogeneity and autonomy, as well as redundancy, noise, uncertainty and incompleteness. Only cleaning data can not solve the above problems, so knowledge fusion is needed. Entity alignment is the most important part of multi-source knowledge fusion. Entity alignment aims to determine whether two or more entities from different information sources point to the same object in the real world. If multiple entities represent the same object, it is necessary to construct alignment relationships for the entities, and focus and fuse the relationships associated with the entities. For example, "water level observation instrument" and "pressure water level gauge" have the same number of 2160201 in the emergency supplies dictionary, so if these two entity nouns appear at the same time, they need to be aligned.

In recent years, the knowledge graph describing common sense and facts has become a widely used knowledge representation method in academia and industry, and the graph neural network has also shown excellent performance in information dissemination and relational induction bias in large-scale data. Xu et al. [12] proposed a graph neural network for large-scale knowledge graph reasoning tasks,

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which contains two modules following the architecture of message passing neural network[13], one for global information dissemination and the other for local information dissemination. Zhang et al. [14] proposed a graph neural network named ExpressGNN for probabilistic logic reasoning, which introduces Markov logic network into the framework of graph neural network, thus combining logic rules and probabilistic graphical models with graph neural networks. Lin et al. [15] proposed a graph-based relational reasoning model KagNet (Knowledge- aware graph Network), which uses GCN (Graph Convolutional Network) to update the entity representation in the knowledge graph. We use the Graph Convolutional Network (LSTM) to score the candidate paths and select the best one.

5. Visualization of Knowledge Graph

Graph database is a very typical non-relational database for the description of non-relational database, which can well support a series of operations such as query, deletion, addition and update of graph database. Compared with the traditional relational database, its query speed is faster, its operation is simpler, and it can provide richer relationship presentation forms. Neo4j database is a kind of graph database and a branch of NOSQL. Compared with other branches of NOSQL, Neo4j database is suitable for native expression of graph structure data. The design motivation of Neo4j is to describe the relationship between entities better and more efficiently. Traditional relational database pays more attention to describing the internal attributes of entities, and the relationship between entities is realized by foreign keys, so the join operation is usually needed to solve the relationship, and the join operation is usually time-consuming. Faced with the high demand for relationships in many applications such as social networks, relational databases have no advantage. Generally speaking, the structure stored in the graph database is the same as the structure of the graph in the data structure, which is composed of vertices and edges. As the main representative of graph database, Neo4j has two operation modes: service mode, which provides REST interface to the outside, and embedded mode, in which data is stored locally in the form of files and can be directly operated on local files.

The KGQA method based on semantic parsing regards the problem to be solved as a semantic parsing problem, that is, the natural language problem is transformed into a semantic representation and then graphped into a logical form. It can be seen as a weighted ranking problem of candidate answers, or a binary classification task. KGQA based on information retrieval is usually based on entity linking technology, which links the central entity to the knowledge graph to find related entities to get the candidate set, and then gets the best answer by sorting or scoring. The performance test of the system will take the accuracy of the results and the retrieval speed as the evaluation criteria.

6. Conclusion

On the basis of efficient storage of emergency supplies, considering the needs of different scenarios, there is no precedent at home and abroad to improve the management of emergency supplies by using knowledge graph technology. It provides theoretical support for the study of emergency resource optimization classification method and metadata specification, emergency and emergency resource association matching technology, and emergency resource dynamic management database construction, and improves the efficiency of emergency resource query and dispatch allocation. Emergency resource is an important part of emergency rescue capability assessment. When an emergency occurs, a large number of people, equipment and supplies are needed. In the absence of a rapid response mechanism, even well-trained emergency rescue teams will not be able to mitigate emergencies. The level of information technology in the field of emergency management is gradually improving, but the opacity of emergency resource data leads to low resource problems such as few samples and small samples, so this topic plays an important role in emergency resource scheduling and other work, and has practical value. In other knowledge graph classification, it will also have better reusability, minimum delay and maximum utility.

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