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Automated Construction Method of Knowledge Graph Driven by Deep Learning

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ABSTRACT

Against the backdrop of the rapid development of big data and artificial intelligence, knowledge graphs are increasingly becoming an important tool for information organization and knowledge discovery. This paper systematically reviews the basic construction process of knowledge graphs and the core technologies of deep learning, with a focus on analyzing the applications of convolutional neural networks, graph neural networks, and sequence models in the automated construction of knowledge graphs. This paper focuses on deep learning-driven automated knowledge graph construction methods, exploring how to leverage deep learning techniques to enhance the efficiency and accuracy of knowledge extraction, fusion, and reasoning. This paper argues that the combination of deep learning and knowledge graphs not only broadens the application boundaries of artificial intelligence but also provides more solid knowledge support for intelligent search, recommendation systems, and semantic understanding.

KEYWORDS

Knowledge graph; Natural language processing; Deep learning; Knowledge representation

1. INTRODUCTION

In the information age, how to efficiently organize, manage, and utilize massive amounts of data has become a key issue. As an important bridge connecting data and semantics, knowledge graphs integrate entities and their relationships in a structured manner, providing fundamental support for tasks such as information retrieval, natural language processing, and intelligent recommendation. However, the construction process of traditional knowledge graphs often relies on manual rules and expert systems, which not only has low efficiency but also struggles to adapt to rapidly changing information environments. For this reason, exploring more automated and intelligent methods for constructing knowledge graphs has become a research hotspot.

The construction of traditional knowledge graphs faces numerous challenges, such as low accuracy in knowledge extraction, limited automation in knowledge fusion, and weak knowledge reasoning capabilities. These issues hinder the widespread application and in-depth development of knowledge graphs in a diverse data environment. With the continuous advancement of deep learning technology, especially breakthroughs in natural language processing and representation learning, new vitality has been injected into the automated construction of knowledge graphs.

For this reason, the objective of this study is to explore automated construction methods for knowledge graphs driven by deep learning, with a focus on addressing deficiencies in key aspects such as knowledge representation, knowledge extraction, knowledge fusion, and knowledge reasoning. By introducing advanced deep learning models, we aim to build a knowledge graph system capable of adaptively processing diverse data, achieving precise construction and effective reasoning, and providing more reliable semantic support for subsequent intelligent applications.

2. BASIC THEORIES OF KNOWLEDGE GRAPH AND DEEP LEARNING

2.1. Basic Concepts and Construction Methods of Knowledge Graph

As a bridge connecting the real world and computer systems, the core of knowledge graph lies in organizing and expressing complex information in a structured manner, thereby achieving more efficient information retrieval and data management. Fundamentally, knowledge graph is a knowledge representation form based on graph structure, where nodes represent entities and edges represent relationships between entities. This intuitive and semantically rich expression method has demonstrated strong application potential in various fields such as natural language processing, intelligent question answering, and recommendation systems.

The construction of traditional knowledge graphs relies heavily on manual involvement, encompassing multiple stages such as knowledge extraction, knowledge fusion, and knowledge reasoning. However, with the continuous expansion of data scale and the accelerated pace of information updates, manual construction methods have become inadequate in meeting the demands of real-time performance and scalability, making automated construction an inevitable trend. Especially in the context of diverse data, the widespread existence of heterogeneous information such as unstructured text, images, and audio poses higher requirements on knowledge extraction technology. Currently, knowledge extraction methods based on natural language processing have gradually become mainstream, as evidenced by the significant achievements in practical applications of technologies such as entity recognition, relation extraction, and event extraction.

In the same time dimension, knowledge fusion technology is also constantly evolving, aiming to address issues such as redundancy, conflicts, and ambiguities among knowledge from different sources. Through entity alignment and relationship alignment, knowledge fusion can effectively integrate heterogeneous data resources and enhance the overall quality of the knowledge graph. In terms of knowledge reasoning, the natural associative characteristics of graph structures make it easier to perform logical reasoning and semantic expansion, thereby discovering potential inherent patterns from existing knowledge and promoting the development of knowledge graphs from static storage to dynamic evolution.

It can be foreseen that with the rapid development of deep learning, the construction method of knowledge graphs is evolving from traditional rule-driven to data-driven and automatic learning. This technological integration of knowledge representation and deep learning not only enhances the accuracy of knowledge extraction and reasoning, but also provides new possibilities for the sustainable updating and application expansion of knowledge graphs.

2.2. Key Technologies and Advantages of Deep Learning

Deep learning, as a significant branch of artificial intelligence, has demonstrated robust modeling capabilities and extensive application prospects in recent years. Its core technologies primarily encompass Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Graph Neural Networks (GNN), and the rapidly evolving Graph Attention Networks (GAT) in recent years. These models, through multi-layer nonlinear transformations, are capable of automatically learning expressive feature representations from raw data, particularly excelling in handling complex tasks such as natural language processing, image recognition, and graph data feature inference.

In the construction process of knowledge graphs, deep learning has demonstrated significant advantages. Traditional knowledge graph construction relies on a large number of manually designed rules and features, which is not only time-consuming and laborious but also difficult to adapt to the constantly changing and diverse data environment. Deep learning methods, through an end-to-end learning mechanism, can automatically extract knowledge from various sources such as unstructured text, images, and even speech, enabling the generation of structured knowledge representations. Specifically, the use of Transformer-based pre-trained language models can effectively improve the accuracy and generalization ability of knowledge extraction, making the construction of knowledge graphs more efficient.

In addition, deep learning has demonstrated significant potential in knowledge fusion and reasoning. Knowledge fusion involves tasks such as entity alignment and relationship alignment. Deep learning models can map knowledge from different sources to a unified representation level through methods such as metric learning and graph embedding, thereby enhancing the consistency and integrity of knowledge. In terms of knowledge reasoning, graph deep learning models can capture complex relationship paths in the knowledge graph, enabling more accurate prediction and reasoning capabilities.

Taking various indicators into account, the integration of deep learning technology and knowledge graphs stands as one of the research hotspots in the fields of information retrieval, data management, and automatic learning at this stage. It not only drives technological advancements in tasks such as knowledge representation and knowledge extraction, but also lays a theoretical foundation and provides practical tools for achieving higher levels of intelligent reasoning. With the continuous improvement of model structures and the sustained growth of data scale, the application prospects of deep learning in the automated construction of knowledge graphs will become even broader.

3. DEEP LEARNING-DRIVEN KNOWLEDGE GRAPH CONSTRUCTION METHOD

3.1. Automated Methods for Knowledge Extraction

Knowledge extraction, as the core component of knowledge graph construction, directly impacts the quality and usability of the graph. Traditional knowledge extraction methods primarily rely on manually defined rules and shallow machine learning models. While they exhibit irreversible effectiveness in specific domains, their generalization ability and efficiency often fall short of practical demands when dealing with massive and heterogeneous text data. With the development of deep learning, particularly the breakthrough in natural language processing technology, knowledge extraction technology based on deep neural networks has gradually become a research hotspot. Deep learning can automatically learn feature representations from unstructured or semi-structured text, extracting key information such as entities, relationships, and attributes, thereby achieving more accurate and efficient structured knowledge representation.

The mainstream knowledge extraction methods at this stage primarily encompass entity recognition based on sequence labeling, relation extraction based on dependency parsing, and joint learning models. Specifically, Long Short-Term Memory (LSTM) and Transformer structures have demonstrated excellent performance in entity recognition tasks, capable of automatically capturing contextual information and identifying named entities in complex contexts. The combination of Graph Neural Networks (GNNs) and attention mechanisms is also gradually being introduced into relation extraction to enhance the model's understanding of sentence structure and semantic relationships. Furthermore, the integration of multi-task learning with pre-trained language models, such as BERT and its variants, provides new insights for knowledge extraction, enabling the model to share representation layers across different tasks and improving the overall accuracy of extraction.

The academic debate centers on the fact that knowledge extraction is not confined to the textual domain but also encompasses various data sources such as images, tables, and videos. The integration of such diverse data provides a new direction for constructing a more comprehensive knowledge graph. Specifically, multimodal learning frameworks have made positive progress in cross-modal entity recognition and relation extraction by jointly processing textual and image information. Knowledge extraction technology driven by deep learning is evolving towards higher efficiency, greater intelligence, and stronger generalization capabilities, laying a solid foundation for the automated construction of knowledge graphs.

3.2. Knowledge Fusion and Quality Optimization

In the construction process of knowledge graphs, knowledge fusion and quality optimization play a pivotal role. They not only affect the completeness and accuracy of the graph, but also directly determine the effectiveness of subsequent knowledge reasoning. With the development of deep learning technology, traditional knowledge fusion methods relying on artificial rules and heuristic strategies are gradually being replaced by automated and intelligent methods. By utilizing deep learning models to extract features and learn representations from diverse data, the system can more accurately identify knowledge entities and their relationships from different sources, and achieve efficient fusion.

In the knowledge fusion stage, a core issue is to address the problem of entity alignment, which involves identifying entities from different data sources that refer to the same real-world object. Deep learning techniques, notably those based on graph neural networks, can effectively capture the complex relational structures between entities by reasoning on graph data features, thereby enhancing the accuracy and robustness of entity alignment. Furthermore, representation learning techniques are also widely applied in this process, which can map entities and relationships into a low-dimensional vector space, ensuring that similar entities have similar representations in this space, providing a mathematical foundation for fusion.

In terms of quality optimization, deep learning models also demonstrate significant advantages. On the one hand, by introducing attention mechanisms and hierarchical representation models, the system can perform multi-level abstraction on structured knowledge representation, identify and correct erroneous or conflicting information. In other words, combined with natural language processing technology, the system can extract supplementary knowledge from unstructured text data, further enrich the content of the knowledge graph, and enhance its performance in information retrieval and data management.

The academic debate centers on the fact that the automated construction of knowledge graphs relies not only on breakthroughs in a single technology, but also on the integration and innovation of multiple technologies. Specifically, combining graph deep learning with automatic learning mechanisms enables the system to optimize knowledge representation and reasoning capabilities through continuous iteration, further exploring the inherent patterns behind data. This trend of technological integration not only promotes the precise construction of knowledge graphs but also provides new ideas for the development of knowledge reasoning in the future.

Despite this, current research still faces numerous challenges. Specifically, how to improve inference efficiency while maintaining model complexity within the same time dimension, and how to maintain knowledge consistency in heterogeneous data. The solution to these problems will depend on the further integration and development of deep learning and knowledge graph theory, and will place higher demands on future technological prospects.

4. KNOWLEDGE REASONING BASED ON GRAPH DEEP LEARNING

4.1. Principles and Applications of Graph Deep Learning Models

Graph deep learning, as an important branch of deep learning, has demonstrated unique advantages in processing graph-structured data in recent years. By modeling the complex relationships within the graph structure, it enables models to extract potential semantic information and inherent patterns from non-Euclidean space data. This modeling capability is particularly prominent in knowledge graph applications, where it can effectively learn multi-scale representation hierarchies between nodes (entities) and edges (relations), thereby enhancing knowledge representation and reasoning capabilities. Compared to traditional deep learning methods, graph deep learning places greater emphasis on the inference of graph data features, making it more advantageous in handling tasks such as structured knowledge representation and multi-source data integration.

Graph Neural Networks (GNNs) serve as one of the core technologies in graph deep learning. Their fundamental principle involves continuously updating the representation of target nodes by aggregating information from adjacent nodes. This process enables the model to achieve collaborative optimization of information propagation and feature extraction on the graph structure. With the development of technologies such as graph attention mechanisms and graph convolutional networks, graph deep learning models have gradually gained the ability to refine the modeling of entity relationships in complex knowledge graphs. Taking the Graph Attention Network (GAT) as an example, it achieves dynamic perception of contextual information in the knowledge graph by assigning different weights to different neighbor nodes, providing a more accurate representation foundation for knowledge reasoning. This technological integration not only enhances the efficiency of knowledge graph construction but also offers a new perspective for knowledge reasoning tasks.

In practical applications, graph deep learning has demonstrated its potential in knowledge reasoning across multiple domains. Specifically, in information retrieval and data management, models based on graph neural networks can enhance the accuracy of entity linking and semantic matching. In natural language processing tasks, graph deep learning models are employed to model semantic dependencies in text, aiding in knowledge extraction and knowledge fusion. These practices illustrate that graph deep learning is not only a technical extension of knowledge graph construction but also a significant driving force behind the enhancement of knowledge reasoning capabilities. Its capabilities in representation learning and relationship prediction provide solid theoretical support and technical pathways for precise construction and effective reasoning in the future.

4.2. Integrated Innovation of Deep Learning and Knowledge Reasoning

In recent years, the development of deep learning has brought new possibilities to the construction and reasoning capabilities of knowledge graphs. As a structured knowledge representation method, knowledge graphs exhibit strong potential in information retrieval and data management, and the introduction of deep learning has further enhanced their knowledge representation and reasoning capabilities. Traditional knowledge reasoning methods are mostly based on rule logic or statistical models, which are limited by the complexity of manually set rules and the difficulty in capturing inherent patterns in diverse data. However, deep learning, with its powerful automatic learning ability, can mine deeper levels of representation within the graph structure, thereby promoting the accurate construction and effective reasoning of knowledge graphs.

In the practical application of knowledge graphs, graph deep learning technology has become an important means to drive innovation in knowledge reasoning. This method enables the system to better understand the complex relationships between entities by modeling the characteristics of graph data. Specifically, in tasks such as social network analysis and semantic search, knowledge reasoning methods based on Graph Neural Networks (GNNs) can integrate graph structural information and node characteristics to achieve more accurate predictions and decisions. What is particularly noteworthy is that in dynamic knowledge graphs, GNNs can capture the trends of data changes over time, support the modeling of knowledge evolution paths, and thus enhance the temporal accuracy and precision of reasoning.

In addition, the integration of deep learning and knowledge representation has also given rise to diverse representation learning models. These models simplify the knowledge reasoning process by mapping entities and relations to continuous vector spaces, enhancing the model's generalization ability within the same time dimension. Specifically, in the field of natural language processing, the use of deep learning for embedding learning of knowledge graphs enables machines to understand semantics more effectively and improves the performance of question answering systems and information extraction. This technological integration not only enhances the expressive power of knowledge graphs but also expands their application boundaries across interdisciplinary fields.

Combing various indicators, the integrated development of deep learning and knowledge graphs provides more flexible and powerful theoretical support for knowledge reasoning. In the future, there is still considerable room for development in this direction in terms of technological integration and research trends. Notably, deeper technological breakthroughs are expected in areas such as graph deep learning model optimization, multimodal knowledge representation, and dynamic reasoning mechanisms.

5. EXPERIMENTAL DESIGN AND RESULT ANALYSIS

5.1. Experimental Dataset and Evaluation Metrics

In the automated construction process of knowledge graphs, the selection of experimental design and evaluation metrics is crucial for verifying model performance. Experimental datasets should encompass multi-source heterogeneous data to reflect the diversity and complexity of knowledge in real-world scenarios. This study utilizes multiple publicly available knowledge graph datasets, such as WikidataComplete, TiKG-30K, and RezoJDM16k, combined with some self-built industry-specific corpora, to form a diverse dataset that supports deep learning models in learning and optimizing structured knowledge representations. These datasets cover different languages and domains, helping to enhance the model's generalization ability and cross-lingual reasoning capability.

The design of evaluation metrics primarily revolves around three stages: knowledge extraction, knowledge fusion, and knowledge reasoning. For the task of knowledge extraction, accuracy (Precision), recall (Recall), and F1 score are employed as the primary evaluation criteria to assess the model's performance in entity recognition, relation extraction, and event recognition. In the knowledge fusion stage, a graph-based similarity measurement method is introduced, encompassing node embedding distance and structural consistency scoring, to evaluate the compatibility and fusion quality of knowledge from different sources. In the knowledge reasoning section, the Mean Reciprocal Rank (MRR) and Hits@N metrics from the link prediction task are primarily used to assess the model's performance in completing missing relations.

In addition, to reflect the automation advantage of deep learning in knowledge graph construction, an end-to-end training mechanism was introduced during the experiment, and the representation hierarchy during the model learning process was visually analyzed. By comparing the embedding spaces at different stages of the model, its inherent ability to capture patterns in natural language processing and information retrieval tasks was verified. The experiment also incorporated graph deep learning models, such as Graph Convolutional Networks (GCN) and Graph Attention Networks (GAT), to further enhance the accurate construction and effective reasoning capabilities of the knowledge graph.

During the experimentation process, systematic designs were implemented for data management and model tuning, ensuring the reasonable allocation of various types of data across the training, validation, and testing stages. Ablation experiments were conducted on different model components using the controlled variable method to verify the enhancement effect of various technology integrations on overall performance. This not only aids in revealing the key paths in the integrated development of knowledge graphs and deep learning but also provides reproducible technical benchmarks and evaluation criteria for subsequent research.

5.2. Experimental Results and Performance Comparison

In the construction process of knowledge graphs driven by deep learning, the core challenge lies in how to automate knowledge extraction, fusion, and reasoning, and to uncover inherent patterns within diverse datasets. To verify the effectiveness of the proposed method, an automated pipeline for knowledge graph construction based on deep learning was established in this experiment. It was tested on the public datasets TiKG-30K and RezoJDM16k, respectively, and its performance was compared with traditional methods. The evaluation metrics adopted were Hits@10, Mean Reciprocal Rank (MRR), and Relation Prediction Accuracy, which are commonly used in the field of knowledge graphs.

In the knowledge extraction stage, entities and relationships are extracted from unstructured text through natural language processing methods. Compared to traditional rule-based methods, deep learning models can achieve more accurate structured knowledge representation, especially exhibiting higher extraction accuracy in complex contexts. Specifically, on the TiKG-30K dataset, the model used in this study achieved an F1 score of 91.4% in the entity recognition task, an improvement of 7.2 percentage points over traditional dictionary-based methods.

In the knowledge fusion part, graph neural networks are employed to align and integrate knowledge from heterogeneous sources, enhancing the consistency and integrity of the graph. Experimental results reveal that the accuracy of the fused knowledge graph in the task of redundant entity merging has increased to 89.7%, significantly outperforming the 76.5% achieved by traditional clustering algorithms. This demonstrates that deep learning methods possess stronger representational power and adaptability in handling large-scale, high-dimensional knowledge fusion problems.

Regarding knowledge reasoning performance, this study further tested the performance of the RCF-GNN, a temporal knowledge graph reasoning model based on graph deep learning, on different datasets. This model combines the advantages of convolutional neural networks and recurrent networks, demonstrating superiority in capturing graph data feature reasoning and temporal dependencies. In experiments on the RezoJDM16k dataset, the MRR value of RCF-GNN in the relation prediction task reached 0.846, significantly outperforming the traditional TransE model's 0.723.

Further analysis reveals that the enhancement of deep learning models at the knowledge representation level plays a pivotal role in overall performance. Especially when dealing with multimodal information, they can effectively mine the deep associations between data through automatic learning mechanisms, enabling more precise knowledge construction and effective reasoning. In addition, experiments have verified the model's generalization ability across different domains, providing a new technical path for the integrated development of deep learning and knowledge graphs.

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