Proceedings of the 2nd International Conference on Machine Learning and Automation
DOI: 10.54254/2755-2721/106/20241287

Application of Artificial Intelligence Methods in Knowledge Graphs

Sijiu Yu

Chongqing University, No.174 Shazhengjie, Shapingba, Chongqing, China

1806473827@qq.com

Abstract. This paper mainly explores the application of artificial intelligence (AI) technologies in knowledge graphs (KGs), focusing on how natural language processing (NLP), machine learning, and deep learning methods can achieve the automated construction of KGs. First, the paper introduces the basic concepts of KGs and the limitations of traditional construction methods. Then, it analyzes recent technological advancements in knowledge graph construction, data fusion, and reasoning, with particular emphasis on the application of graph convolutional neural networks (GCNs) in handling multi-relational data. Finally, the practical applications of KGs in business analytics, healthcare information systems, and recommendation systems are discussed, demonstrating their broad potential in data management and reasoning.

Keywords: Knowledge graph, Graph convolutional neural networks, Artificial intelligence.

1. Introduction

With the advent of the era of big data, enterprises and research institutions are facing exponential growth in the amount of data. Efficiently managing and utilizing massive data has become a key issue driving technological progress and business innovation. KGs, a technology that enables the semantic integration and representation of knowledge, have gradually become an important research tool and a hotspot in business analytics. KGs were first proposed by Google in 2012 with the goal of improving the search engine's comprehension and response capabilities by constructing a graph of entities and their relationships. In the construction of KGs, traditional methods primarily rely on manual work, which not only requires a large amount of repetitive, non-meaningful labor but also struggles to quickly process vast amounts of data in today's big data environment. With the development of AI technologies, the integration of intelligent methods, such as NLP and machine learning, into the construction of KGs has become a growing trend.

2. Literature Review

In recent years, research on KGs has mainly focused on the following areas:

The first aspect is Knowledge Graph Construction. Researchers have used NLP, machine learning, and deep learning methods to automate knowledge extraction and relationship discovery. Overall, Ji et al.[1] collected and reviewed methods for representing and acquiring KGs, as well as their applications in various fields, discussing in-depth the techniques for constructing KGs and emphasizing the importance of automated and intelligent construction. In terms of specific methods, Miwa, M. et al.[2] adopted a joint extraction method using a bidirectional Long Short-Term Memory (LSTM) and tree-

DOI: 10.54254/2755-2721/106/20241287

structured LSTM models to process text sequences and dependency tree structures for entity and relationship extraction. The experimental results showed that the joint extraction method significantly improved precision and recall compared to traditional cascade methods. Lin, Y. et al.[3] enhanced relationship extraction by using instance-level selective attention mechanisms and convolutional neural networks (CNNs), achieving more accurate relationship extraction from noisy data.

The second aspect focuses on knowledge graph fusion. Overall, Shvaiko et al.[4] reviewed the current state and challenges in the field of ontology matching. They introduced various matching methods, providing a detailed analysis of the advantages and disadvantages of existing techniques, such as string matching, linguistic methods, structural matching, and semantic matching. They pointed out the need to improve the automation level of the matching process in the future, while allowing user intervention and adjustment to handle the heterogeneity between different ontologies. In terms of specific methods, Dong et al.[5] proposed a probabilistic knowledge fusion method aimed at large-scale web information integration. Through probabilistic models, they integrated information from multiple data sources to construct a large-scale knowledge graph. Machine learning and statistical methods were then used to fuse information from different sources, addressing issues such as data redundancy and conflicts, significantly improving the accuracy and coverage of the knowledge graph. The paper discussed integrating information from different data sources but may not delve deeply into handling noisy or low-quality data.

The third aspect focuses on knowledge graph reasoning. In general, Wang et al.[6] reviewed knowledge graph embedding techniques and their applications. Knowledge graph embedding involves mapping entities and relationships from the knowledge graph into low-dimensional vector spaces for efficient processing in various machine learning tasks. They analyzed the application of knowledge graph embeddings in NLP, recommendation systems, and question-answering systems, highlighting the potential of graph neural networks in reasoning. In terms of specific methods, Michael Schlichtkrull et al.[7] proposed an extended Graph Convolutional Network (GCN) model called R-GCN, designed to handle graph data with multiple types of relationships. R-GCN introduces relationship-specific convolution operations based on standard GCNs, enabling the independent modeling of different relationship types, capturing more fine-grained relational information. The study found that R-GCNs can effectively capture the interactions between different types of relationships, providing stronger representational and reasoning capabilities.

The fourth aspect is the application of KGs. KGs have been applied in various specific fields. For example, in the field of weaponry and equipment, Yang Liping et al.[8] employed dictionary embeddings and integrated multiple deep learning models to improve the effectiveness of equipment entity recognition. Additionally, they designed a relationship extraction model based on RNPA (ResNet-PCNN-ATT) to reduce noise errors caused by incorrect annotations during the extraction task. Visualization of the graph construction demonstrated good results; however, due to the limited availability of relevant datasets, the performance on large datasets remains unknown. In the healthcare sector, Zhao Dandan et al.[9] applied a hybrid neural network approach using pre-trained models to address unstructured medical texts with high entity density and lengthy sentence structures. By integrating entity marking features with global semantic features and using a classifier for extraction, they concluded that a multi-feature fusion approach can enhance entity-relation extraction. However, due to issues such as imbalanced data distribution and the similarity in semantics between Interaction and Effect types, the overall recall and precision of the model were not high.

3. Research on Knowledge Graph Technology Based on

Currently, the research on introducing AI into KGs is flourishing, focusing primarily on enhancing the representational, reasoning, and updating capabilities of KGs. GCNs are one of the mainstream methods being researched, alongside other applications of deep neural networks and reinforcement learning.

DOI: 10.54254/2755-2721/106/20241287

3.1. Knowledge Graph Technology Based on Graph Convolutional Networks

GCNs are a deep learning model specifically designed to handle graph-structured data. By performing convolution operations on graph nodes, GCNs can effectively capture the relationships and features between nodes and their neighbors, demonstrating excellent performance when processing complex graph data. The application of GCNs in KGs primarily includes the following three aspects:

3.1.1. Representation of Entities and Relationships. GCNs apply convolution operations on graph structures, allowing them to capture local structural information of nodes and the complex interactions between nodes. GCNs can utilize the topological structure of the graph and the features of nodes to learn richer representations of entities and relationships.

Thomas N. Kipf et al.[10] proposed the foundational model of GCNs, demonstrating how local graph structures can be utilized for semi-supervised learning, significantly improving the performance of node classification tasks. This laid the groundwork for the application of graph convolution techniques in KGs. GCNs have shown their efficiency and superiority in handling graph-structured data, particularly in the context of sparse data. Following this, Michael Schlichtkrull et al.[11] introduced the Relational Graph Convolutional Network (R-GCN), which is specifically designed to handle multi-relational data in KGs. By introducing relationship-specific convolution operations, R-GCN is capable of processing different types of relationships, thereby enhancing the representation of both entities and relationships. William L. Hamilton et al. [12] proposed an inductive learning method that enables efficient node representation learning on large-scale graph data. Through the sampling of neighboring nodes and the aggregation of their features, GraphSAGE can learn node embeddings without requiring full graph information, making it particularly useful for handling dynamic KGs. Xu et al.[13] also proposed the Relational Graph Attention Network (RGAT), which combines graph attention mechanisms with relational embeddings to learn the representation of nodes and edges in knowledge graphs. RGAT introduces attention weights for different types of relationships, enabling more precise modeling of complex relationships. RGAT has demonstrated its advantages in tasks such as entity linking and relationship prediction in KGs, especially in handling graph data with highly complex relationships.

3.1.2. Multi-hop Reasoning and Complex Queries. Reasoning tasks in KGs often involve multi-hop relationships, and traditional methods have performed poorly in handling multi-hop reasoning and complex queries, as they struggle to efficiently traverse multiple nodes for inference. Methods based on GCNs, however, gradually aggregate neighboring node information through multiple convolutional layers, effectively handling multi-hop reasoning tasks by capturing relationship chains that span multiple nodes, thereby enhancing reasoning capabilities.

Michihiro Yasunaga et al.[14] proposed the QA-GNN (Question Answering with Graph Neural Networks) model, which combines pre-trained language models with graph neural networks to perform graph reasoning on KGs. By integrating the semantic understanding of the language model, the model generates accurate answers. Later, Sun et al.[15] proposed the GRAFT-Net (Graph Retrieval and Fusion Network) model, which integrates knowledge bases and textual data. GRAFT-Net excels in open-domain question answering tasks, particularly when dealing with complex queries that involve incomplete knowledge bases and large-scale text data. Although graph neural networks perform well on graph-structured data, they are highly sensitive to small-scale adversarial perturbations, which necessitates further exploration of the robustness of graph learning models. Zang et al.[16] proposed a general adversarial attack method called "Anchor Nodes." Experiments showed that even a small number of adversarial nodes could significantly degrade the performance of graph learning models, demonstrating the effectiveness and broad applicability of these attack methods.

3.1.3. Knowledge Graph Completion and Link Prediction. Knowledge graphs often contain a large amount of missing information and unconnected nodes. Traditional methods for graph completion and link prediction are inefficient when dealing with large-scale data. GCNs, by aggregating local neighborhood information of nodes, can better predict missing links and, through multi-layer convolution operations, process more extensive neighborhood information, thereby improving the accuracy of link prediction.

Berg et al.[17] proposed the GC-MC (Graph Convolutional Matrix Completion) model, which applies graph convolutional networks to matrix completion tasks, specifically for link prediction in KGs. The model learns latent representations of entities by applying convolutional operations on the graph structure, allowing for the prediction of missing links. GC-MC performs excellently in knowledge graph completion and recommendation system tasks, demonstrating the powerful ability of GCNs to handle sparse matrices and link prediction tasks. Additionally, Wang et al.[18] proposed the NGCF (Neural Graph Collaborative Filtering) model, which utilizes graph neural networks to perform convolutional operations on user-item bipartite graphs to capture complex interactions between users and items. Although primarily applied to recommendation systems, the model's method is also applicable to knowledge graph completion and link prediction tasks. Finally, from the systematic summary by Nickel, Maximilian et al.[19], which covers relational machine learning, including the application of GCNs in KGs, we can see that the introduction of AI methods has effectively solved problems in knowledge graph technology, such as reasoning path search, graph completion, entity linking, and relationship extraction.

3.2. Knowledge Graph Technology Based on Other Methods

In addition to the currently mainstream GCNs, the introduction of other AI methods, such as deep neural networks (DNNs) and reinforcement learning (RL), has also driven the rapid development of knowledge graph technology.

Deep neural networks, by increasing the number of hidden layers and using relational embedding models, can effectively predict and complete missing entity-relation pairs. For instance, Tim Dettmers et al.[20] proposed a relational embedding model based on CNNs, which uses convolutional operations to capture the complex relational structures between entities, thereby improving the model's expressive power. Similarly, Sun et al.[21] introduced the RotatE model, which represents relationships between entities in a complex vector space through rotational operations. This model excels in handling symmetric, inverse, and composite relationships and has shown outstanding performance in link prediction tasks within KGs.

Inference or path search in KGs typically relies on predefined rules or statistical models, but these methods struggle to handle complex reasoning paths and long-distance relationships. Zhang et al.[22] proposed a reinforcement learning-based path search model that can find optimal paths within knowledge graphs to answer complex natural language questions. Additionally, Lin et al.[23] introduced a model that combines reinforcement learning's reward mechanisms for multi-hop reasoning, solving the issue of completing missing triples in KGs, reducing the exploration of redundant paths, and improving the precision and efficiency of knowledge graph completion.

4. Application Value and Advantages of Knowledge Graphs

Knowledge graphs build complex semantic networks, transforming massive amounts of unstructured data into structured knowledge to solve real-world problems across different fields.

4.1. Knowledge Management Field

The construction and maintenance of KGs depend on a large amount of structured data. However, in practical applications, data is often incomplete or sparse. For example, financial institutions frequently handle complex financial data and risk assessment relationships, involving a large amount of cross-departmental and cross-domain data associations. The RotH (Rotation in Hyperbolic Space) model can help systems precisely model these complex relationships in high-dimensional spaces, thereby improving the ability for data analysis and risk assessment. Additionally, in supply chain management, businesses must deal with the complex relationships among suppliers, products, logistics, and customers, which involve a vast amount of sparse data and intricate relationship networks, such as product-delivery person and customer-address relationships. The SimplE (Simple Embedding) model, as a bilinear factorization method, can handle multi-relational and sparse data in knowledge graphs. By using bidirectional embeddings to enhance the representation of relationships, SimplE simplifies the model structure and improves computational efficiency.

4.2. Recommendation System Domain

In recommendation systems, KGs face challenges such as data updates and cold-start issues, making it difficult for the system to provide accurate recommendations when there is insufficient user interaction information. For example, Spotify's music recommendation system and LinkedIn need to frequently update user preference data, analyze users' career histories, skill descriptions, and job requirements, and map them to standardized career and skill categories. In this context, William L. Hamilton et al.[24] proposed the GraphSAGE (Graph Sample and AggregatE) model. By sampling neighboring nodes and aggregating their features, the model dynamically updates node embeddings without needing access to full graph information, making it particularly suitable for handling large-scale dynamic graphs.

4.3. Search Engine Domain

In the search engine domain, KGs face challenges such as keyword matching and inaccuracies in handling ambiguous and polysemous queries. To address the issue of capturing special relationships in search engines, the QA-GNN model can be introduced. This model, which combines pre-trained language models with graph neural networks, is designed for natural language question-answering tasks, helping search engines better understand and predict complex user behaviors and product relationships. To improve the accuracy of search and recommendation results, the R-GCN model, proposed by Michael Schlichtkrull et al. in 2018, can be applied. By introducing unique convolutional operations for different types of relationships, R-GCN enhances the representation and modeling of multi-relational data, addressing the limitations of search engines in handling complex queries involving multiple relationships.

5. Conclusion

This paper discusses the significance and advantages of AI technologies in the construction, reasoning, and application of KGs. By incorporating advanced technologies such as deep learning, reinforcement learning, and graph convolutional networks, the efficiency of knowledge graph construction, reasoning capabilities, and application outcomes have been significantly improved. Through practical application cases, the paper showcases the broad application prospects and immense commercial value of KGs in fields such as search engine optimization, personalized recommendations, and career matching. In the future, as AI technologies continue to develop, knowledge graphs will play an increasingly important role in data mining and business analytics, driving intelligent transformation and innovation across various industries.

References

[1] Ji, S., Pan, S., Cambria, E., Marttinen, P., & Yu, P. S. (2022). A Survey on Knowledge Graphs: Representation, Acquisition, and Applications. IEEE Transactions on Neural Networks and Learning Systems, 33(2), 494-514.

[2] Miwa, M., & Bansal, M. (2016). End-to-End Relation Extraction using LSTMs on Sequences and Tree Structures. Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), 54(1), 1105–1116.

[3] Lin, Y., Shen, S., Liu, Z., Luan, H., & Sun, M. (2016). Neural Relation Extraction with Selective Attention over Instances. Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), 54(1), 2124–2133.

[4] Shvaiko, P., & Euzenat, J. (2013). Ontology Matching: State of the Art and Future Challenges. IEEE Transactions on Knowledge and Data Engineering, 25(1), 158-176.

[5] Dong, X. L., Gabrilovich, E., Heitz, G., Horn, W., Murphy, K., Sun, S., & Zhang, W. (2014). Knowledge Vault: A Web-Scale Approach to Probabilistic Knowledge Fusion. Proceedings

of the 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 20(1), 601–610.
[6] Wang, Q., Mao, Z., Wang, B., & Guo, L. (2017). Knowledge Graph Embedding: A Survey of Approaches and Applications. IEEE Transactions on Knowledge and Data Engineering, 29(12), 2724-2743.
[7] Schlichtkrull, M., Kipf, T. N., Bloem, P., van den Berg, R., Titov, I., & Welling, M. (2018). Modeling Relational Data with Graph Convolutional Networks. The Semantic Web: 15th International Conference, ESWC 2018, Heraklion, Crete, Greece, June 3–7, 2018, Proceedings, 10843, 593-607.
[8] Yang, L., Wu, F., Zhang, X., et al. (2020). A study on knowledge graph construction for early warning equipment based on deep learning. Systems Engineering and Electronics (volume and issue pending confirmation).
[9] Zhao, D., et al. (2020). Medical entity relationship extraction based on pre-trained models and hybrid neural networks. Journal of Software (volume and issue pending confirmation).
[10] Kipf, T. N., & Welling, M. (2017). Semi-Supervised Classification with Graph Convolutional Networks. Proceedings of the International Conference on Learning Representations (ICLR).
[11] Schlichtkrull, M., Kipf, T. N., Bloem, P., van den Berg, R., Titov, I., & Welling, M. (2018). Modeling Relational Data with Graph Convolutional Networks. The Semantic Web: 15th International Conference, ESWC 2018, Heraklion, Crete, Greece, June 3–7, 2018, Proceedings, 10843, 593-607.
[12] Hamilton, W. L., Ying, R., & Leskovec, J. (2017). Inductive Representation Learning on Large Graphs. Proceedings of the 31st International Conference on Neural Information Processing Systems (NeurIPS), 1024-1034.
[13] Busbridge, D., Sherburn, D., Cavallo, P., & Hammerla, N. Y. (2019). Relational Graph Attention Networks. Proceedings of the International Conference on Learning Representations (ICLR).
[14] Yasunaga, M., Ren, H., Bosselut, A., Liang, P., & Leskovec, J. (2021). QA-GNN: Reasoning with Language Models and Knowledge Graphs for Question Answering. Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL-HLT), 535-546.
[15] Sun, H., Dhingra, B., Zaheer, M., Mazaitis, K., Salakhutdinov, R., & Cohen, W. (2018). Open Domain Question Answering Using Early Fusion of Knowledge Bases and Text. Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing (EMNLP), 4231-4242.
[16] Zang, X., Xie, Y., Chen, J., & Yuan, B. (2021). Graph Universal Adversarial Attacks: A Few Bad Actors Ruin Graph Learning Models. Proceedings of the Thirtieth International Joint Conference on Artificial Intelligence (IJCAI-21), 3328-3334.
[17] Berg, R. v. d., Kipf, T. N., & Welling, M. (2017). Graph Convolutional Matrix Completion. Proceedings of the 31st International Conference on Neural Information Processing Systems (NeurIPS 2017), 3954-3964.
[18] Wang, X., He, X., Wang, M., Feng, F., & Chua, T. S. (2019). Neural Graph Collaborative Filtering. Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR '19), 165-174.
[19] Nickel, M., Murphy, K., Tresp, V., & Gabrilovich, E. (2016). A Review of Relational Machine Learning for Knowledge Graphs. Proceedings of the IEEE, 104(1), 11-33.
[20] Dettmers, T., Minervini, P., Stenetorp, P., & Riedel, S. (2018). Convolutional 2D Knowledge Graph Embeddings. Proceedings of the Thirty-Second AAAI Conference on Artificial Intelligence, 32(1), 1811-1818.
[21] Sun, Z., Deng, Z., Nie, J., & Tang, J. (2019). RotatE: Knowledge Graph Embedding by Relational Rotation in Complex Space. Proceedings of the 7th International Conference on Learning Representations (ICLR).

[22] Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL-HLT), 4171-4186.
[23] Lin, X. V., Socher, R., & Xiong, C. (2018). Multi-Hop Knowledge Graph Reasoning with Reward Shaping. Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing (EMNLP), 3243-3253.
[24] Hamilton, W. L., Ying, R., & Leskovec, J. (2017). Inductive Representation Learning on Large Graphs. Advances in Neural Information Processing Systems (NeurIPS), 1024-1034.