Journal of Artificial Intelligence Practice (2023)
Clausius Scientific Press, Canada

DOI: 10.23977/jaip.2023.060810
ISSN 2371-8412 Vol. 6 Num. 8

The current research status of knowledge graph in bridge and its application prospects

Yitong Bai

Chongqing Jiaotong University, Chongqing, 400074, China
632201151203@mails.cqjtu.edu.cn

Keywords: Artificial Intelligence, Knowledge Graph, Bridge Engineering, Inference Prediction, Data Management

Abstract: In the context of the big data era, bridge data shows exponential growth, and there are characteristics such as temporal order and multi-source heterogeneity, how to use artificial intelligence (AI) to effectively manage and utilize these data has become a research hotspot in the field. This paper reviews the current research status of knowledge graph in the bridge field and its application prospects, mainly including the following aspects: 1) bridge knowledge graph construction. 2) bridge field data management, analysis and prediction. 3) knowledge graph in the bridge field application cases and challenges. 4) knowledge graph in the bridge field. The aim is to provide comprehensive analysis and guidance for future data research and application in the bridge field.

1. Introduction

Knowledge Graph describes concepts and phenomena in the real world through elements such as entities, attributes and relationships [1]. Its core goal is to transform unstructured data into structured knowledge and knowledge interconnection, allowing computers to better understand and process complex relationships, making information easier to understand and search, and thus supporting its application in multiple domains [2]. As shown in Figure 1: the form of knowledge graph is constantly updated with the development of big data technology and artificial intelligence [3]. The concept of knowledge graph in the modern sense was first proposed by Google in 2012, which marks a new stage of knowledge graph.

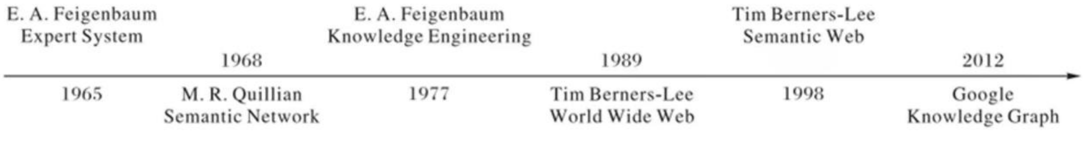

Figure 1: Evolution of knowledge graph.

As an important part of transportation infrastructure, bridges bear the important function of connecting population and resources in different areas and promoting social and economic development. With the continuous development of bridge engineering, the data in this field is characterized by uneven quality and strong temporal sequence[4]. With the continuous growth of the data scale, the traditional data storage methods can no longer meet the huge data storage and usage needs before introducing new technologies, and bring great challenges to the correlation analysis of data. Using AI technology to realize the management and application of bridge data has become an urgent need and future development trend in the field of bridge engineering [5].

Applying knowledge graphs to the bridge field can effectively address its existing challenges, mainly in the following aspects[2]: improving design efficiency, realizing efficient data management, and achieving intelligent decision-making.

2. Bridge Knowledge Graph Construction

2.1. Data Acquisition Introduction

The construction of bridge knowledge graph requires a large amount of data acquisition, and currently there are two main sources of available data: one is the non-public or semi-public internal database in the bridge field; the other is the publicly available data on the Internet, which is usually dispersed in web pages. Classified by the type of data acquisition, the data can be divided into unstructured, semi-structured and structured data [6].

In domain knowledge graph construction, it is common to use a mixture of top-down and bottom-up approaches [7]. For unstructured data manual annotation is used to store them in the entity repository. For semi-structured data, semi-supervised or unsupervised learning is performed using AI techniques such as neural networks. For structured data, it is directly correlated. After acquiring the above three kinds of data, it is also necessary to use methods such as outlier detection and missing value processing to clean and integrate the acquired data to ensure the consistency and accuracy of the data, so as to prepare high-quality basic data for the next knowledge graph construction.

2.2. Knowledge Extraction

Knowledge extraction refers to the extraction of structured information from texts of different structures and sources. Knowledge extraction in the bridge domain mainly includes bridge entity extraction, bridge relationship and attribute extraction.

For the bridge entity extraction technique, some researchers have proposed a deep learning-based bridge named entity recognition method. For example, in 2021, Li Lian et al [8] proposed a method based on Transformer-B modeling the word and phrase embedding of bridge text using Transformer encoder to capture the word nesting features, then further extracting the direction sensitivity features by using BiLSTM network, and finally, using CRF model for sequence annotation to achieve the recognition of bridge named entities; Liu et al [9] proposed an information extraction method based on ontology and semi-supervised conditional random field, which utilizes a small amount of labeled data for information extraction and improves the performance of bridge entity extraction by further learning a large amount of unlabeled data to adapt to unknown entities.

The bridge relationship extraction technique refers to extracting the semantic relationships between bridge entities from the bridge text, such as the compositional relationship of the structure, the relationship of the effect of diseases on the bridge, etc., and using these relationships to link the entities together. In the construction of knowledge graph, the links between attribute values and attributes or attributes and entities can also be regarded as a kind of relationship, so that the attribute extraction problem can be transformed into a relationship extraction problem to be solved [10]. Currently, the mainstream solution in this field is to integrate relationship extraction with deep learning, and many models have been born in this cross-cutting field, such as the method using BiLSTM-ED proposed by Zheng [11] and others, the recursive neural network method proposed by Chen [12] and others, and the multi-entity relationship extraction technique based on improved kernel function and CNN proposed by Gao Dan [13] and others. Returning to the bridge domain, the difficulties of relationship extraction mainly include the diverse and complex types of relationships in the bridge text and the variable expressions. Based on these problems, Li Tong [14] proposed a relationship extraction method based on the Lattice-LSTM-Softmax model for the bridge detection domain, which integrates the word-level features and the character features, improves the inaccuracy of the entity delineation, and increases the accuracy of relationship extraction in bridge inspection domain.

2.3. Knowledge Fusion

Through the above knowledge extraction, we obtain a large amount of structured data, but due to the different forms of data, the problem of knowledge hybridization from different data sources often occurs, which needs to be processed by knowledge fusion and disambiguation. For the knowledge fusion technique, Zeng et al [15] proposed a multi-feature fusion-based homonymous expert disambiguation method, using the nearest neighbor propagation clustering algorithm to construct a multi-feature fusion representation model, which is effective for the problem of homonymous disambiguation; Li et al [16] proposed an LSTM-based method to automatically learn global discriminative representation features of various coreferences, which effectively solves the phenomenon of word polysemy.

2.4. Application of knowledge

The knowledge graph constructed through the above steps can basically meet the needs of practical engineering, and its applications are mainly focused on the following aspects:

(1) Semantic search [17]: through the semantic understanding of user query and query matching of knowledge graph, to realize high accuracy and high-quality search results, and improve the search efficiency and user experience.

(2) Knowledge Q&A [18]: converts natural language questions into structured queries, utilizes entities and relationships in the knowledge graph for reasoning, achieves a more intelligent and interpretable Q&A system, and supports multiple rounds of interaction and contextual understanding.

Mining potential problems and needs using entities and relationships in the knowledge graph to achieve a more personalized and diverse recommender system with rules at its core, providing comprehensive and multidimensional support and services for recommendation and decision-making with improved interpretability and trustworthiness.

(3) Recommendation and Decision Making [19]: mining potential problems and needs using entities and relationships in the knowledge graph to achieve a more personalized and diverse recommender system with rules at its core, providing comprehensive and multidimensional support and services for recommendation and decision-making with improved interpretability and trustworthiness.

3. Data management, analysis and forecasting in the field of bridges

3.1 Traditional data processing methods

In terms of data acquisition and storage. The design, construction, operation and maintenance of bridges generate a large amount of data, and Table 1 shows several public datasets in this field. Traditional methods usually use a database to store data, but the current database in the field of bridges is basically in the hands of the constructor, each project has its own independent database, there is a serious information silo phenomenon, and there is a lack of publicly accessible and quality-controlled large data sets. The diversity of data sources and the non-uniform format make their integration and management very difficult.

Table 1: Publicly available datasets in the bridge domain

Dataset name	Data format	Data size
YOLO Bridge Crack Detection Dataset	jpeg,json	2836 files
Bridge Cracking Data Set	jpg	500 files
Pavement disease dataset of cross-river bridges	jpg ,json	1718 files
Road crack data set	jpg ,json ,png	20751 files

In terms of data processing, traditional methods are mainly based on statistical analysis to explore the relationship between data, such as statistical pattern recognition [20], Bayesian modeling [21], and gray correlation methods [22]. These statistical methods are effective for some simple problems, but their expressive and analytical abilities are slightly insufficient for the increasingly complex bridge structure and variable external environment, and they are less efficient when dealing with large-scale data and multidimensional data, and it is difficult to excavate the deeper features and laws of the data. Therefore, it is necessary to research and develop new bridge data processing methods to improve the value and application of bridge data.

3.2 Knowledge graph-based data association

Data association using knowledge graph can effectively solve the problems arising from traditional data processing methods [23]. The data integration, analysis and prediction of knowledge graph provides more in-depth and comprehensive application support for bridge engineering. It can effectively integrate information from different data sources, including structural design, construction monitoring and maintenance records, to form an integrated data structure. By modeling the relationships between entities, the complex knowledge system in bridge engineering can be expressed more accurately, providing stronger support for deeper data analysis. Knowledge graph correlation data also helps to discover the potential laws and patterns hidden behind the data, providing a more intelligent means of data management and analysis in the bridge field.

4. Application cases and challenges of knowledge graph in bridge field

4.1 Application Cases

Currently, knowledge graph has been widely used in various aspects of bridges, and this section mainly focuses on the following three aspects to provide an overview.

In bridge construction, Zhu Jun et al [24] proposed a 3D visualization method for bridge construction based on knowledge graph, which solves the problems of poor standardization and low cognitive efficiency of the bridge construction process, and provides visual guidance for the subsequent bridge construction process.

In the area of bridge maintenance and inspection, Yang Xiaoxia et al [25] completed the construction of bridge inspection knowledge graph using OWL ontology modeling language, Lattice-LSTM and Neo4j graph database, and solved the problem of insufficient data extraction and fusion in the bridge inspection report. Yang et al [26] proposed a knowledge graph question and answer by utilizing BERT and a novel hierarchical cross-attention mechanism Li et al. [27] proposed a new model called bridge structure and health monitoring ontology by utilizing the advantages of semantic web technology, which solves the serious "data silo" problem in traditional SHM solutions.

In bridge construction, Fang et al [28] combined computer vision algorithms with ontology models to develop a knowledge graph that can automatically and accurately identify hazards and recognize safety regulations in real time, and successfully detect the presence of physical hazards from different engineering environments. Ma et al [29] proposed a method for recommending bridge construction schemes considering carbon emission constraints based on knowledge graph and similarity computation, which successfully supports the decision-making of low-carbon construction schemes for bridges. At present, the research of knowledge graph in bridge field is in the beginning stage, and there are still a lot of prospects and possibilities of application.

4.2 Issues and Challenges

The main challenges in bridge knowledge graph applications are the heterogeneity and standard differences between different data sources. The data in the bridge domain come from different devices, monitoring systems, engineering literature, etc., which may have differences in format, units, accuracy, and credibility, and the existing means to cope with these challenges still have some problems [30]. Secondly, the current knowledge graph construction still cannot be fully automated, which requires the knowledge graph builder to fully understand the huge and complex cross-domain knowledge including the structural design, material properties, and construction process of bridge engineering. Finally, existing knowledge graphs in the bridge domain are mostly integrated with existing data and standards, and there are deficiencies in the acquisition of real-time and expert knowledge.

5. Future application prospect of knowledge graph in bridge field

With the continuous progress of AI technology and the increasing development of bridge engineering, the application of knowledge graph in the field of bridges will enter a broader and deeper development stage. In the future, the development of knowledge graph in the bridge field will show the following trends:

(1) Cross-domain multimodal knowledge integration: the bridge field spans a wide range of data, involving civil engineering, material science, geology and other subject areas; structural data, material data, environmental data and other multimodal data. The future knowledge map will better integrate these cross-field and multi-modal knowledge, making the data management of bridge engineering more comprehensive and precise, and constructing a more comprehensive bridge engineering knowledge map to provide prediction and guidance for subsequent engineering decisions.

(2) Application oriented to the whole life cycle: at present, the bridge domain knowledge map constructed by scholars basically focuses on only one phase of bridge engineering, and the future knowledge map will run through the whole life cycle of bridge engineering, including design, construction, monitoring, maintenance, updating and other phases, in order to realize a more comprehensive and integrated engineering management.

(3) Complementary diagram and model: Knowledge map and big language model are both means used to represent and process knowledge. Knowledge graph stores rich objective knowledge and can be constantly updated, and the big language model has strong generalizability and semantic analysis ability, both have their own strengths and weaknesses, complement each other, the depth of their combination can provide a more perfect knowledge processing method for artificial intelligence, and it will also become the future direction of research in this field [31].

6. Summary

The bridge domain knowledge graph aims to associate the large amount of information accumulated in the bridge industry with knowledge, and to semantically analyze and visualize the stored information through knowledge application, so as to provide guidance and prediction for later bridge construction and so on. This paper summarizes the bridge knowledge graph construction technology from four aspects: data acquisition and processing, knowledge extraction, knowledge fusion, and knowledge application; secondly, it compares the knowledge graph data association with the traditional data processing methods; then it outlines the specific applications of bridge knowledge graph in construction, building, maintenance, and inspection, etc., and points out the problems existing in this field; finally, it provides an overview of the cross-domain multimodal knowledge graph in bridge knowledge graph. Finally, the future development of bridge knowledge mapping in the direction of cross-domain multimodal knowledge integration, full life cycle application and map-mode complementation is prospected. It is hoped that this paper can provide reference and inspiration for the research and application of knowledge graph in the field of bridge engineering.

References

[1] Huang Hengqi, Yu Juan, Liao Xiao, Xi Yunjiang. (2019) Review on Knowledge Graphs. Computer Systems & Applications, 28(6), 1-12.

[2] Guan SP, Jin XL, Jia YT, Wang YZ, Cheng XQ. (2018) Knowledge Reasoning Over Knowledge Graph: A Survey. Ruan Jian Xue Bao/Journal of Software. 29(10), 2966-2994. http://www.jos.org.cn/1000-9825/5551.htm

[3] Tian Ling, Zhang Jinchuan, Zhang Jinhao, Zhou Wangtao, Zhou Xue. (2021) Knowledge graph survey: representation, construction, reasoning and knowledge hypergraph theory. Journal of Computer Applications, 41(08), 2161-2186.

[4] Xiao Yaqi. (2021) Research on Retrieval and Analysis of MEP Information in Facility Management Based on Domain Ontology. M.S. thesis, Tsinghua University, Beijing.

[5] Jianxi Yang, Fangyue Xiang, Ren Li, Luyi Zhang, Xiaoxia Yang, Shixin Jiang, Hongyi Zhang, Di Wang, Xinlong Liu. (2022) Intelligent bridge management via big data knowledge engineering, Automation in Construction, Volume 135.

[6] W. Lv, Z. Liao, S. Liu and Y. Zhang. (2021) Meim: a multi-source software knowledge entity extraction integration model. Computers, Materials & Continua, vol. 66, no.1, 1027–1042.

[7] Fu Leijie, Cao Yan, Bai Yu, Leng Jiewu. (2021) Development status and prospect of vertical domain knowledge graph in China. 38(11), 3201-3214.

[8] Li Ren, Li Tong, Yang Jianxi, Mo Tianjin, Jiang Shixin, Li Dong. (2021) Bridge Inspection Named Entity Recognition Based on Transformer-BiLSTM-CRF. Journal of Chinese Information Processing, 35(4), 83-91.

[9] Kaijian Liu, Nora El-Gohary. (2017) Ontology-based semi-supervised conditional random fields for automated information extraction from bridge inspection reports. Automation in Construction, 81, 313-327.

[10] Qiu Ling, Zhang Ansi, Li Shaobo, Zhang Yizong, Shen Mingming, Zhou Peng. (2022) Survey on buildings knowledge graphs for aerospace manufacturing. Application Research of Computers, 39(04), 968-977.

[11] Suncong Zheng, Yuexing Hao, Dongyuan Lu, Hongyun Bao, Jiaming Xu, Hongwei Hao, Bo Xu. (2017) Joint entity and relation extraction based on a hybrid neural network. Neurocomputing, 257, 59-66.

[12] Chen Lin, Timothy Miller, Dmitriy Dligach, Hadi Amiri, Steven Bethard, Guergana Savova. (2018). Self-training improves Recurrent Neural Networks performance for Temporal Relation Extraction. In Proceedings of the Ninth International Workshop on Health Text Mining and Information Analysis, Brussels, 165–176.

[13] Gao Dan, Peng Dunlu, Liu Cong. Entity Relation Extraction Based on CNN in Large-scale Text Data. (2018) Journal of Chinese Computer Systems, 39(05), 1021-1026.

[14] Li Tong. (2022) Research on Key Technologies of Bridge Inspection Text Information Extraction Based on Deep Neural Networks. M.S. thesis, Chongqing Jiaotong University, Chongqing.

[15] Zeng Jianrong, Zhang Yangsen, Wang Siyuan, Huang Gaijuan, Cui Jia, Ma Huan. (2020) Acta Scientiarum Naturalium Universitatis Pekinensis, 56(04), 607-613.

[16] Chen Li, Zhiqiang Rao, Qinghua Zheng, Xiangrong Zhang. (2018) A set of domain rules and a deep network for protein coreference resolution. Database, Volume 2018, 65.

[17] Gao Long, Zhang Hanchu, Yang Liang. (2018) Intelligent Information Search Technology Based on Knowledge Graph and Semantic Computin. Information studies: Theory & Application, 41(07), 42-47.

[18] Wang Zhiyue, Yu Qing, Wang Nan, Wang Yaoguo. (2020) Survey of Intelligent Question Answering Research Based on Knowledge Graph. Computer Engineering and Applications, 56(23), 1-11.

[19] Chang Liang, Zhang Weitao, Gu Tianlong, Sun Wenping, (2019) Bin Chenzhong. Review of recommendation systems based on knowledge graph. CAAI Transactions on Intelligent Systems, 14(02), 207-216.

[20] Farrar C R, Worden K. (2007) An introduction to structural health monitoring. Philosophical Transactions of the Royal Society A: Mathematical. Physical and Engineering Sciences, 365(1851), 303-315.

[21] Okasha N M, Frangopol D M. (2012) Integration of structural health monitoring in a system performance based life-cycle bridge management framework. Structure and Infrastructure Engineering, 8(11), 999-1016.

[22] Zhang Litao. (2022) Sensors Fault Diagnosis of Large Bridge Structural Health Monitoring Systems. Modern

Transportation Technology, 8(4), 36-39.
[23] Gao Jinsong, Zhang Qiang, Li Shuaike. (2022) Construction of Knowledge Graph and Linked Data Storage of Movable Cultural Relics-Taking Hubei Provincial Museum as an Example. Journal of Modern Information, 42(04), 88-98.
[24] Zhu Jun, Lai Jianbo, Xie Yakun, Chen Peijing, Sun Wenjin. (2023) Knowledge-guided Spatiotemporal Narrative 3D Visualization Method for the Bridge Construction Process. Geomatics and Information Science of Wuhan University. DOI:10.13203/J.whugis20230239.
[25] Yang Xiaoxia, Yang Jianxi, LI Ren, Luo Mengting, Jiang Shixin, Wang Guiping, Yang Yifan. (2022) Knowledge graph construction and knowledge question answering method for bridge inspection domain. Journal of Computer Applications, 42(S1), 28-36.
[26] Yang, J, Yang, X, Li, R, Luo, M, Jiang, S, Zhang, Y, & Wang, D. (2023). BERT and hierarchical cross attention-based question answering over bridge inspection knowledge graph. Expert Systems with Applications, 233.
[27] Li, R, Mo, T, Yang, J, Jiang, S, Li, T, & Liu, Y. (2021) Ontologies-Based Domain Knowledge Modeling and Heterogeneous Sensor Data Integration for Bridge Health Monitoring Systems. IEEE Transactions on Industrial Informatics, 17(1), 321–332. https://doi.org/10.1109/TII.2020.2967561
[28] Fang, W, Ma, L, Love, P. E. D, Luo, H, Ding, L, & Zhou, A. (2020). Knowledge graph for identifying hazards on construction sites: Integrating computer vision with ontology. Automation in Construction, 119. https://doi.org/10.1016/j.autcon.2020.103310
[29] Ma, Z, Zhang, S, Jia, H, Liu, K, Xie, X, Qu, Y. (2023) A Knowledge Graph-Based Approach to Recommending Low-Carbon Construction Schemes of Bridges. Buildings, 13, 1352. https://doi.org/10.3390/buildings13051352
[30] Cao Qian, Zhao Yiming (2015) Technical realization process of knowledge graph and related applications, 38(12), 127-132. DOI:10.16353/j.cnki.1000-7490.2015.12.026.
[31] Shirui Pan, Linhao Luo, Yufei Wang, Chen Chen, Jiapu Wang, Xindong Wu. (2023) Unifying Large Language Models and Knowledge Graphs: A Roadmap. Journal of Latex Class Files, 14, 8. arXiv:2306.08302, 2023.