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Risk Mitigation Strategy for Power Grid Construction Accidents Based on Knowledge Graph Representation Learning

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Abstract:

In order to solve the problems of lack of accident relation, unstable response results and insufficient diversity in power grid construction accident risk handling, a method of power grid construction accident risk handling based on knowledge graph representation learning was proposed. First of all, for enhancing the correlation between accidents, the power grid construction accident report was taken as the data source, and the information graph structure was constructed according to the accident elements and the relationship between the elements through knowledge graph technology. Secondly, for improving the retrieval speed and accuracy, Bert model and GraphSAGE model were used to complete the knowledge graph representation learning and the accident feature vector was obtained. Finally, for having more comprehensive knowledge coverage, the accident case database was established to compare and match the new accident knowledge map. The risk control and emergency treatment of power grid construction accidents we carried out. The results show that the method combined with GraphSAGE model has better processing effect on knowledge graph, the stability of output data is improved by 12.3%, and it can make rapid response, forming an efficient accident risk processing system. It is concluded that the designed method can significantly improve the efficiency of power grid construction accident handling, and provide reference and support for power grid construction accident risk handling.

Keywords: knowledge graph, representation learning, power grid construction accident, GraphSAGE model, construction safety management

INTRODUCTION

With the development of social economy, in response to the call for sustainable development, electricity has been put into a wider range of production and life applications as a clean energy [1]. At the same time, due to the increase in social power demand, the construction scale of power grid projects has gradually expanded, exposing more safety management problems in construction [2]. At present, a number of new systems and standards have been invested [3] to improve the quality of grid engineering. In addition, the application of computer-related technologies has made new breakthroughs in the control and treatment of accident risks in the construction process of power grid projects [4]. Among them, knowledge graph, as an emerging technology, has great room for development [5].

Prevention is an important policy for power safety production. Construction accidents can be controlled and predicted to a certain extent, so accident risk control and emergency treatment is one of the most important tasks in construction safety management [6]. From the perspective of construction safety management technology, there have been relatively mature research results in the field of construction in recent years. The application of BIM technology [7], sensor technology [8], computer vision [9] and other technologies has built a relatively sound construction safety management system, which can effectively reduce the probability of construction accidents. However, the core of the general construction safety management method is to focus on the construction content, including construction materials, construction procedures, etc., focusing on the risk control and treatment of on-site construction links [10]. It does not take into account the needs of power grid project operation and dispatching, as well as the complex relationships among them, and the obtained evaluation indicators are too diverse, so the extraction of core knowledge is insufficient. Therefore, in the process of power grid construction, it is more important to pay attention to the complex operation patterns of power grid projects and the needs of dispatching operators [11] to ensure the construction quality of power grid projects. Knowledge graph can effectively solve the problems existing in current research, reorganize and summarize complex knowledge and use a concise network structure to reflect, extract core knowledge, greatly improve the rate of information retrieval [12], and enhance the level of control and treatment of power grid engineering construction accident risk.

In 2012, Google officially proposed the “Knowledge Graph” project, and knowledge graph entered the public's vision for the first time as a specialized technology, providing a new solution for the safety management of power grids. Tan et al. [13] built a power grid customer service question and answer system that integrated domain characteristic knowledge graph, and realized the construction of the graph response system. Liu et al. [14] proposed a construction method of power grid equipment knowledge graph based on multi-source data fusion, and expounded the process of multi-source data integration graph, which improved the coverage of graph and broadened the application scenarios of knowledge graph. Sun et al. [15] proposed the knowledge graph construction and IoT (Internet of Things) optimization framework for power grid data knowledge extraction, reshaped the structure of power grid data management platform, and provided new ideas and research directions for power grid data under big data in the future. Lin et al. [16] applied knowledge graph to the processing of substation alarm information and made an attempt in the prediction and risk warning of power grid security. Xiao et al. [17] used knowledge graph technology to extract, express and manage power grid fault handling information, which contributed to the development of power grid intelligent decision-making. Yuan et al. [18] proposed an optimization management system for power grid dispatching operation based on knowledge graph, and demonstrated the effect of the system in power grid dispatching operation management, proving the application value of knowledge graph in the field of power grid management. In addition, many applied researches of knowledge graph have been carried out in power equipment health management, power grid engineering monitoring technology, etc., which promotes the development and innovation of knowledge graph technology in power grid engineering.

To sum up, the application of knowledge graph-based security management in power grid construction is in its infancy. The construction environment of power grid is complex, the data processed are rich in types and have obvious professional characteristics. The current knowledge graph research mostly focuses on the functional field of power grid engineering, and there is a lack of research on the risk treatment of construction accidents, the exploration of the relationship between accidents is not deep enough, the processing results fluctuate greatly, and a stable system for timely response to construction accidents has not been formed. Therefore, in view of the special operation form and existing defects of power grid construction, an accident risk handling method combining knowledge graph representation learning is proposed. Firstly, entity elements such as construction time and construction location are extracted from the accident investigation report, and knowledge map is constructed according to triplet relationship, and the visualization of knowledge map is realized through neo4j. Secondly, the graph neural network model is used to complete the representation learning of the accident knowledge map, and a new vector representation after dimensionality reduction and simplification is obtained. Finally, the similarity calculation is used to compare the accident case base with the target knowledge graph, and the risk treatment methods such as on-site response scheme and personnel scheduling measures for the accident cases with the highest matching degree are obtained to deal with the risk of on-site power grid construction accidents.

CONSTRUCTION OF POWER GRID CONSTRUCTION ACCIDENT KNOWLEDGE GRAPH

Knowledge graph is essentially a semantic network, usually composed of nodes and edges, the basic unit is “entity-relation-entity” triplet, the core elements are entity, relationship and attribute. Entities and their attributes exist in the form of nodes, while relationships and their attributes exist in the form of directed edges [19]. The construction of power grid construction accident knowledge map includes the basic links of knowledge modeling, knowledge extraction and knowledge storage visualization.

Data Processing

This paper takes power grid safety accidents as the research object, and the accident data are mainly from the accident investigation reports provided by the power grid. The data form is mainly text data, with large volume and complex content, so it is necessary to filter and process the data.

In this paper, BIO annotation method is adopted, and each element in the text sequence corresponds to B, I or O respectively. B represents the beginning of the entity, I represents the middle or end of the entity, and O represents the non-physical part. According to the characteristics of power grid construction accidents, the effective contents of accidents are divided into time, place, people, construction tasks, construction objects, accident causes, accident results, etc. Then, using the BIO annotation tool to annotate the text according to task requirements and data set characteristics.

Knowledge Modeling

The ontology of knowledge graph is a formal specification for describing entities, which is usually used to define the attributes and relationships of entities. According to the analysis results of the power grid construction accident reports, the seven-step ontology construction method is adopted to represent the concept and relationship between the accident process and the accident cause, which is used as the mode layer of the power grid construction accident knowledge graph.

According to the description habit of construction accident, the definition of accident knowledge graph ontology is divided into three concepts: accident name and attribute, accident content and accident handling method. The name and attributes of the accident are further subdivided into time, place, contractor, etc. The contents of the accident are subdivided into personnel involved, construction equipment, construction tasks, task objects, etc. Accident handling methods are divided into on-site first aid measures, personnel deployment, punishment measures, etc. Then the four relationships between the concepts are further established, as shown in Figure 1. The relationship between the accident name and attribute and the accident content is defined by ‘hasObject’. The relationship between the accident content and the included accident element is defined by ‘hasElement’. The relationship between the accident element and the cause of the accident is defined by ‘hasReason’. The relationship between the accident content or the cause of the accident and the solution is expressed through ‘hasSolution’.

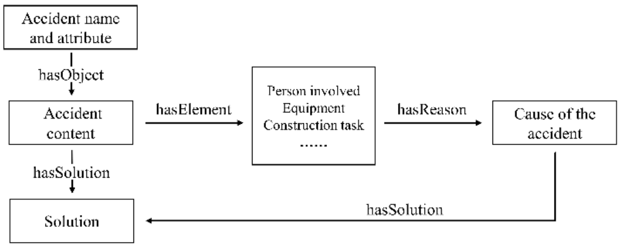


Figure 1. The definition of Power grid construction accident knowledge graph ontology

Knowledge Extraction

Aiming at the problems such as large number of entities and complex semantics in the power grid construction process, this paper selects the deep learning method based on BiLSTM-CRF model [20] to realize knowledge extraction.

The BiLSTM (Bidirectional Long Short-Term Memory) framework, depicted in Figure 2, consists of two layers of LSTM (Long Short-Term Memory) units arranged in a reverse order. Both LSTM layers are linked to the output layer, and the final output is determined by both the forward and backward RNNs (Recurrent Neural Network).

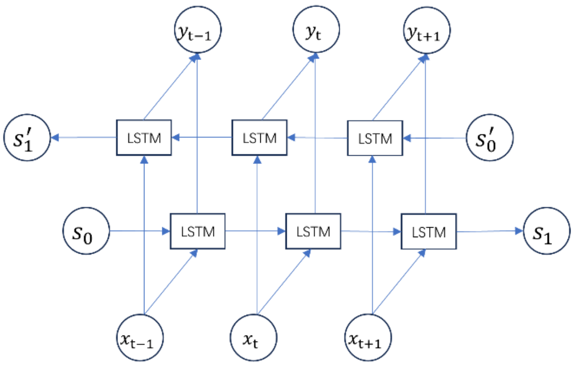


Figure 2. Basic framework of BiLSTM model

The text data of power grid construction accidents are long and complicated, so it is necessary to pay attention to the interaction between degree words and negative words when dividing them at a more detailed level. Therefore, by using BiLSTM model, the input sequence can be processed forward and backward to get the output result, which can better obtain the context features and capture the bidirectional semantic dependency.

The BiLSTM model takes the label with the highest score as the output result, but it does not take into account the relationship between words, so the output label lacks logic. The CRF (Conditional Random Field) is a decision model, which can add some constraints to reduce the invalid prediction label sequence. Therefore, the CRF model can effectively consider the constraint relationship between labels, further improve the accuracy of entity recognition, and ensure the effectiveness of predictive labels.

In knowledge extraction, BiLSTM is used to extract the feature of sentences, and CRF is used to learn the context of labels. Entities, entity relationships, and entity attributes are extracted, as shown in Table 1.

Table 1. results of knowledge extraction

Name	Extract Content
Entity	accident time, accident place, occurrence stage, personnel involved, accident cause, etc.
Entity relationship	accident-type, accident-object, accident-cause, etc.
Entity attribute	accident name, accident participants, etc.

Knowledge Storage Visualization

After entity extraction, the obtained triple data of entities and relations are stored in the structured file using python language. Then neo4j is used to import nodes and relationships to achieve mapping and generate a visual graph, as shown in Figure 3.

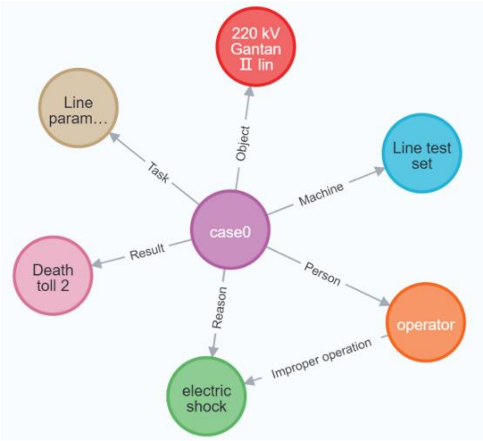


Figure 3. Schematic diagram of the visual knowledge graph

RISK TREATMENT METHOD OF POWER GRID CONSTRUCTION ACCIDENTS

The characteristics of power grid construction accidents are different from other accidents. The current methods of handling construction accidents lack the consideration of the relationship and connection between the accident elements, and there is no complete feedback system, which cannot make a quick response to the on-site accident handling. In order to solve the existing problems, this paper proposes to establish the case database of power grid construction accidents, and introduce the combination of graph neural network model and knowledge graph representation learning to build the power grid construction accident risk processing system. This system not only comprehensively considers the relationship between accident factors and factors to provide a reference scheme for on-site decision-making of construction accidents, but also realizes keyword matching through knowledge graph representation learning to provide rapid response support, improve the efficiency of construction accident risk treatment, and reduce the adverse impact of construction accidents. The technical route of this method is shown in Figure 4.

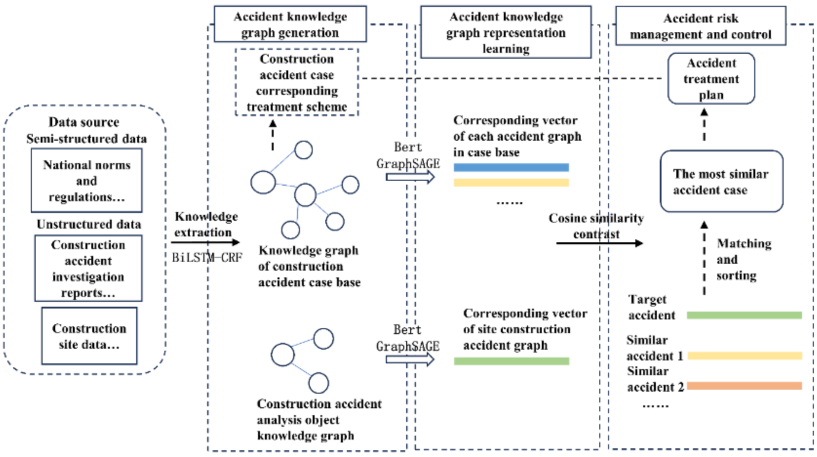


Figure 4. The technical roadmap of power grid construction accident risk treatment method

Accident Knowledge Graph Generation

According to the accident records of power grid construction, the text of each accident is annotated with BIO tags. By extracting entities and relationships with BiLSTM-CRF model, triples consisting of entities and relationships are obtained. All the obtained triples are imported into Neo4j, completing the construction of knowledge graph. Thus, the knowledge graph of power grid construction accident case library and the knowledge graph of construction accident analysis object are generated.

Accident Knowledge Graph Representation Learning

After the construction accident knowledge graph has been built, in order to improve the efficiency and accuracy of accident comparison, this paper has proposed the knowledge graph representation learning for construction accident knowledge graph. The construction accident knowledge graph reflects the relationships between accident elements and utilizes the characteristics of nodes and edges in graph structures to speed up the search rate. After the similarity comparison and matching based on the representation learning, the accuracy of the results will be improved.

Bert model representation learning

Bert is a bidirectional pre-trained language model based on Transformer, which excels at capturing contextual semantics. When combined with the knowledge graph, it can effectively highlight important information and improve recognition results [21].

Bert model is used to mark the entity and relationship of the accident knowledge graph, and obtain the corresponding tokens. Put them into the sequence, obtain the corresponding position information through location coding, and generate the vector representation corresponding to the accident knowledge graph, as shown in Figure 5. Each node of the knowledge graph will get the corresponding 768 dimensional vector after processing, and each knowledge graph contains multiple nodes, so several 768 dimensional vectors will be obtained.

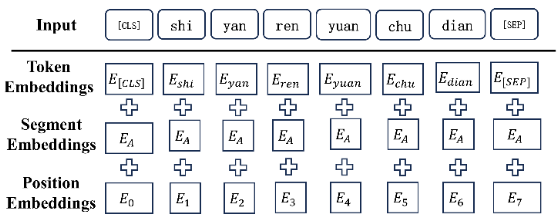


Figure 5. Schematic illustration of Bert model representation learning

GraphSAGE model representation learning

The GraphSAGE model is a representation learning method for graph nodes, which is consistent with the graph structure of knowledge graph, with nodes corresponding to entities and relationships corresponding to edges. Compared with other GNN (Graph Neural Network) methods, it has obvious improvement, and the sampling method is optimized from full graph sampling to node-centered neighbor sampling, which can greatly improve the efficiency of the model. At the same time, there are different options for neighbor aggregation, and multi-dimensional vectors can be selected according to the specific situation to achieve dimensionality reduction. The GraphSAGE model is mainly divided into two stages of sampling and aggregation [22], as shown in Figure 6. The main process is divided into three steps:

1. *Neighbor sampling:* k represents the retrieval depth from the target node. The central node of each accident knowledge graph is the target node, and the surrounding nodes connected with the target node through the edge are the neighbor nodes.

2. *Neighbor aggregation:* Aggregation starts from the nodes sampled by K-order neighbors. The embedding information of the target node mapping is obtained by aggregating k edges for k times.

3. *Node update:* Use the aggregated information to update the parameters.

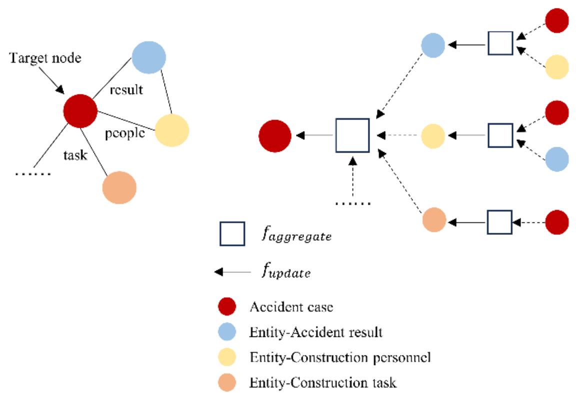


Figure 6. Schematic diagram of the GraphSAGE model

The knowledge graph learned by Bert representation is very large, and the process of similarity calculation is complicated and slow if multi-dimensional vectors are used directly. Therefore, it is required to combine the GraphSAGE model to further simplify the knowledge graph after representation learning. The vector matrix obtained after processing by Bert model can be input into the GraphSAGE model as the feature matrix, and a new vector representation is generated through node aggregation. The output first-order matrix is the accident feature vector corresponding to the accident knowledge graph.

Accident Risk Management and Control

Similarity calculation

After obtaining the representation learning result of knowledge graph of power grid construction accident case base, it is used as reference object for similarity comparison. When a new construction accident occurs, through the same processing process, a new accident feature vector can be obtained as the analysis object. Cosine similarity method is used to calculate the similarity, and the calculation formula is as follows:

$$\cos(A,B)=\frac{\sum_{i=1}^{n}a_i b_i}{\sqrt{\sum_{i=1}^{n}a_i^2}\times\sqrt{\sum_{i=1}^{n}b_i^2}} \tag{1}$$

In formula (1), A or B represents the accident feature vector, a_i or b_i represents the corresponding isotropic value, n represents vector dimension value.

Contrast and matching

The cosine similarity between the analysis object and the reference object is compared one by one. When the cosine value exceeds 0.9, the two objects are considered to be similar; in other cases, they are considered to be dissimilar. Sort by the cosine value, and a higher cosine value means a higher similarity. The output of the most similar accident cases corresponding to the treatment method, as the reference solution for the new accident, for the construction site to provide timely first aid measure and personnel deployment planning, as far as possible to reduce the adverse impact of accident.

CASE VERIFICATION

Construction of Accident Knowledge Graph

In this paper, an electric shock accident was selected as the analysis object for empirical analysis. The general situation of the accident was:

At 8 p.m. on May 20, a company in the 220 kV Gantan II line parameters test process, operators in the removal of the test device end of the test lead, line induction led to electric shock test personnel, 2 people died after ineffective rescue, constituting a general personal accident.

According to the accident description, information such as the accident occurrence stage, casualties, and economic losses were extracted and stored as csv files. And the csv files were imported into neo4j to establish entities and their attributes, thus completing the construction of the accident knowledge graph.

Results Of Risk Treatment of Power Grid Construction Accidents

Accident knowledge graph case base generation

In this paper, the accident investigation reports provided by the power grid were used as the data source, and 133 pieces of accident text information were obtained totally. After the data were preprocessed and 16 pieces of invalid information such as too few words and incomplete content were removed, 117 pieces of accident texts were collected as data sets. BiLSTM-CRF model was used to complete the knowledge extraction task for the annotated construction accident data. A total of 1053 entities and 819 relationships were extracted, and the entity concepts and relations obtained were imported into neo4j to build the power grid construction accident knowledge graph case database. The partial diagram is shown in Figure 7.

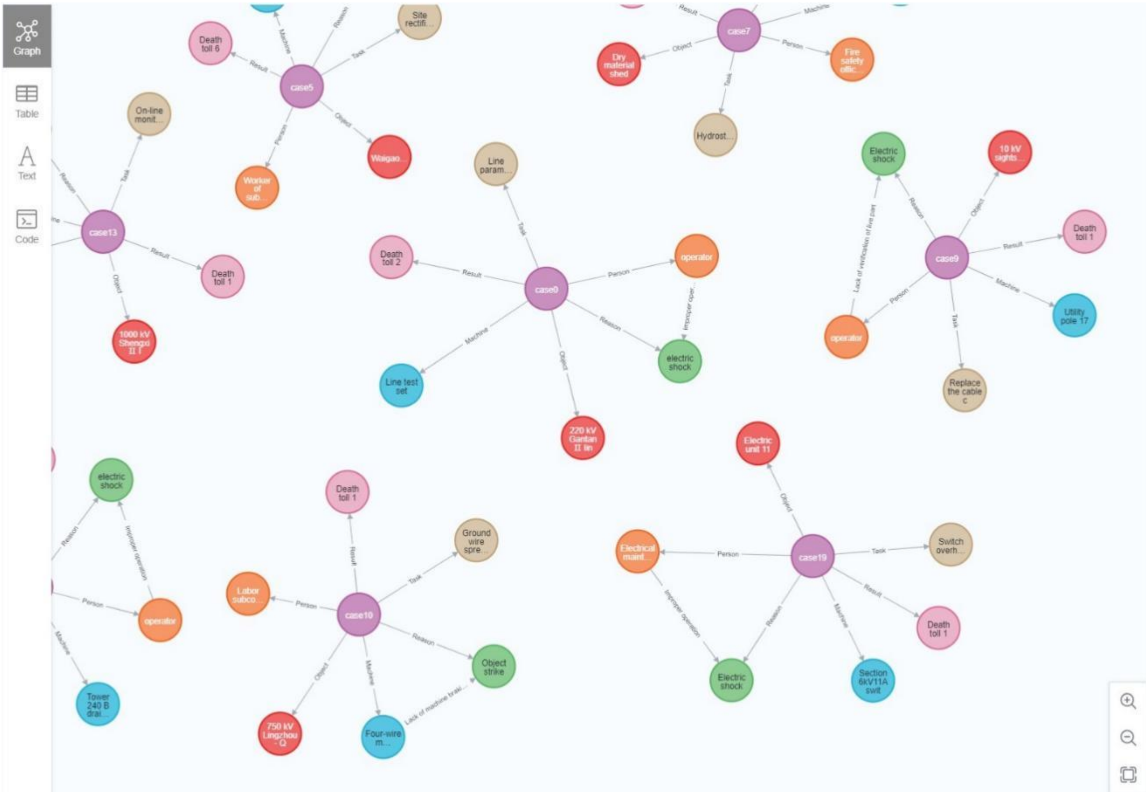


Figure 7. Partial diagram of case base of knowledge map of power grid construction accident

Representation learning for accident knowledge graph

According to the knowledge graph representation learning method, Bert model and GraphSAGE model were selected to realize vector processing of the accident knowledge graph. The example is shown in Table 2. It can be seen that the knowledge graph was processed into a sixth-order matrix by Bert model, corresponding to six sets of 768 dimensional vectors. Further processing by GraphSAGE model, the sixth-order matrix was transformed into a first-order matrix, corresponding to a group of 768 dimensional vectors. The calculation content was greatly reduced, and the matching rate was significantly improved. The maximum and minimum values of the two groups of representation learning results were compared respectively, and the difference was less than 10%, indicating that the accuracy of the representation learning of the accident knowledge graph was guaranteed. After the eigenvector representation of the accident was obtained, the similarity degree between the accident and the analysis object can be compared by calculating the vector value.

Table 2. Example of accident knowledge graph representation learning

Case 0	Bert model representation learning results	GraphSAGE model representation learning results
Array	[0:6]	[0:1]
Max	10.132445	10.155026
Min	-14.7260065	-13.313152
Shape	(6,768)	(1,768)
Size	4608	768

Results of accident risk management and control

The accident feature vectors obtained after representation learning were used to calculate the similarity, and the cosine similarity value was taken as the measurement standard to rank the accident cases in the case database from high to low. The results are shown in Table 3.

Table 3. Matching scores of power grid accident case base

Accident number	Feature class	Vector representation	Similarity score	Ranking
Case 0	Target feature	*[0.6939,-0.1924,-0.5342…]*	—	—
Case 19	Similar feature	*[0.6598,-0.2090,-0.5528…]*	0.96046	1
Case 9	Similar feature	*[0.6429,-0.1256,-0.3907…]*	0.95424	2
Case 8	Similar feature	*[0.6319,-0.1099,-0.3578…]*	0.94194	3

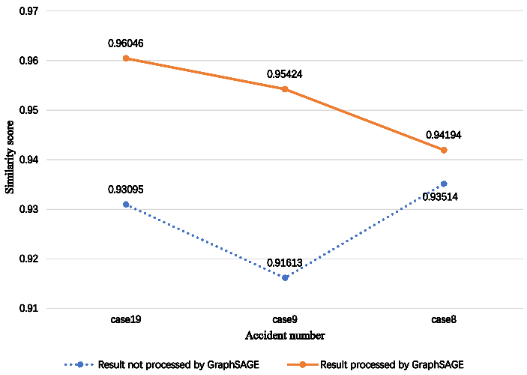
Querying the case base according to the results in the table 3, case19 was an electric shock accident for electrical maintenance, the number of casualties was 2; case9 was an electric shock accident for outdoor pole climbing operation , the number of casualties was 1;case8 was an electric shock accident for power tower rectification operation , the number of casualties was 1.The obtained accident cases and analysis object were basically the same in terms of accident type and cause, but there were differences in construction task, operation object, casualty, etc., and different similarity rankings were got from these differences. The most similar accident case and analysis object were both electric shock in line operation, and the number of casualties was the same. This was the distinguishing factor that set it apart from other similar accidents. Therefore, it could be proved that the graph matching result after representation learning was in accordance with the real scene. Simultaneously, to demonstrate the advantage of the GraphSAGE model in processing knowledge graph, unprocessed vectors were designated as controls, and the comparison results of similarity scores between the two are presented in Figure 8.

Based on the similarity score data, the calculation according to the variance formula:

$$S^2 = \frac{\sum_{i=1}^{N}(X_i - \bar{X})^2}{N} \tag{2}$$

In formula (2), S^2 represents the variance, X_i represents each sample value, $\bar{X}$ represents sample mean, N represents sample size.

The variance of accident feature vector similarity score data not processed by GraphSAGE model was $6.65076*10^{-5}$, the variance of accident feature vector similarity score data processed by GraphSAGE model was $5.92188*10^{-5}$. Comparative experiment showed that the GraphSAGE model had its superiority and necessity in the representation learning of knowledge graph. The stability of the response results obtained by the GraphSAGE model was improved by 12.3%.



Figrue 8. The impact of the GraphSAGE model on experimental outcomes

Finally, according to the analysis results, the accident case with the highest similarity to the analysis object was obtained from the accident database, and its accident reports and data was consulted as reference, as shown in Table 4. New treatment decisions were extracted and suggestions were provided for subsequent construction arrangements, personnel deployment and punishment measures.

Table 4. Part of similar accident handling plan

Accident number	Similarity score ranking	Preliminary treatment plan
Case 19	1	1. Organize, study and strictly implement electric power safety working procedures and work ticket system. 2. Carry out hazard identification and strictly implement on-site safety measures. 3. Staff members are strictly prohibited from expanding their work content without authorization. If you need to change the security measures, you must fill in a new work ticket and go through the work permit formalities again. 4. The person in charge of the work should always be at the work site, carefully monitor the safety of the staff, and correct unsafe behaviors in time. 5. Strictly implement daily safety disclosure, and prevent safety disclosure from becoming mere formality. 6. Check the “five prevention” device of the electrical equipment to ensure that the electrical anti-error lock is in good condition. 7. All units of unit maintenance, technical transformation, construction and other work should strictly implement safety measures, and strengthen on-site safety supervision. 8. The maintenance, technical reform, construction and other work of all units will be suspended for one day from now on, and the study and safety inspection will be carried out seriously.

CONCLUSION

This paper proposes a knowledge graph-based risk treatment method for power grid construction accidents, constructively establishes a construction accident case database, makes up for the lack of comprehensive coverage of accident treatment, and helps to promote the standardization of power grid construction accident treatment. Meanwhile, the knowledge graph is used to associate the accident elements and the relationships between them, and the Bert model and GraphSAGE model are combined to complete the graph representation learning. A clear infographic structure is established to realize the visualization of risk treatment, and a complete emergency treatment system for power grid construction accidents is formed. In addition, the results of the controlled experiment showed that the GraphSAGE model achieved better performance in the representation learning of the knowledge graph. The data processed by the GraphSAGE model had stronger stability and smaller numerical deviation, and the accuracy of the matching result was increased by 12.3%. However, there is still room for improvement in the method of event representation. For knowledge graph, although triples are selected as event representation methods in the process of knowledge extraction to retain information such as the binary-complement structure, there is still inevitable data loss, and the construction of ontology also has certain deficiencies in the depth and scale of information. When it is applied to complex construction scenes in the future, it is necessary to construct a more perfect ontology network to realize the expression of accident information. In general, the construction of power grid construction accident case database provides reliable data support for subsequent accident analysis and traceability. In the future, the universality of this method can be gradually expanded, accident early warning can be combined with on-site data, and the safety management system of power grid construction can be further improved.

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