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Construction Methods of Knowledge Graph and Domain-Specific LLM for Coal Mine Rockburst

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Методы построения графа знаний и предметно-ориентированной модели LLM для анализа горных ударов на угольных шахтах

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coal mine rockburst, knowledge graph, domain-specific large language model, causal reasoning, multi-source data fusion, knowledge governance, intelligent decision support.

Coal mine rockburst is a complex dynamic disaster induced by the accumulation and sudden release of energy during underground coal extraction. With the continuous increase in mining depth and intensity, both the frequency and severity of rockburst incidents have shown a significant upward trend, posing growing threats to mine safety, equipment integrity, and production continuity. Despite extensive research, the prevention and control of rockburst still face major challenges, including fragmented multi-source heterogeneous data, knowledge silos across systems, limited causal chain reasoning, and difficulties in timely and accurate decision-making. These issues hinder the comprehensive understanding of disaster mechanisms and reduce the effectiveness of prevention strategies. To address these limitations, this study proposes a systematic framework for constructing and enhancing a coal mine rockburst knowledge graph supported by a domain-specific large language model. The framework integrates multi-source data fusion, ontology-driven semantic modeling, and causal reasoning to establish a structured and machine-understandable representation of rockburst-related knowledge. Meanwhile, the domain-specific large language model is employed to improve knowledge extraction, enhance node semantics, support intelligent question answering, and enable dynamic updating of the knowledge graph. By combining the strengths of knowledge graphs and large language models, the proposed approach provides a unified platform for knowledge governance in the rockburst domain. It effectively improves the accessibility, interpretability, and analytical depth of rockburst-related knowledge, offering strong support for risk assessment, disaster prediction, and intelligent decision-making in coal mine safety management.

Ключевые слова:
горные удары на угольных шахтах, граф знаний, предметно-ориентированная большая языковая модель, причинно-следственная связь, слияние данных из нескольких источников, управление знаниями, интеллектуальная поддержка принятия решений.

Горные удары на угольных шахтах представляют собой сложную динамическую катастрофу, вызванную накоплением и внезапным высвобождением энергии во время подземной добычи угля. С непрерывным увеличением глубины и интенсивности добычи угля частота и тяжесть инцидентов, связанных с горными ударами, демонстрируют значительную тенденцию к росту, представляя растущую угрозу безопасности шахт, целостности оборудования и непрерывности добычи. Несмотря на обширные исследования, предотвращение и контроль горных ударов по-прежнему сталкиваются с серьезными проблемами, включая фрагментированные разнородные данные из множества источников, разрозненность знаний в различных системах, ограниченную причинно-следственную связь и трудности в своевременном и точном принятии решений. Эти проблемы препятствуют всестороннему пониманию механизмов катастрофы и снижают эффективность стратегий предотвращения. Для решения этих проблем в данном исследовании предлагается систематическая структура для построения и совершенствования графа знаний о горных ударах на угольных шахтах, поддерживаемого предметно-ориентированной большой языковой моделью. Предлагаемая структура объединяет слияние данных из нескольких источников, семантическое моделирование на основе онтологий и причинно-следственные рассуждения для создания структурированного и машиночитаемого представления знаний, связанных с горными ударами. Одновременно используется предметно-ориентированная LLM для улучшения извлечения знаний, повышения семантики узлов, поддержки интеллектуального ответа на вопросы и обеспечения динамического обновления графа знаний. Сочетая преимущества графов знаний и больших языковых моделей, предлагаемый подход обеспечивает единую платформу для управления знаниями в области горных ударов. Он эффективно повышает доступность, интерпретируемость и аналитическую глубину знаний, связанных с горными ударами, обеспечивая мощную поддержку оценки рисков, прогнозирования катастроф и принятия интеллектуальных решений в управлении безопасностью угольных шахт.

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Introduction

Coal mine rockburst is a highly destructive and complex dynamic disaster that occurs during the coal mining process. With the continuous increase in mining depth, both the frequency and severity of rockburst incidents have risen significantly, posing serious challenges to mine safety and production [1–4]. Rockburst disasters not only cause casualties and equipment damage but also result in enormous economic losses and social impacts [5–8]. Therefore, the accurate prediction and effective prevention of rockburst disasters have long been critical tasks in the field of coal mine safety production.

However, the prevention and control of coal mine rockburst currently face numerous challenges in knowledge governance [9–14], which severely restrict the accuracy of disaster prediction and the effectiveness of control measures. First, the prevention and control of rockburst involve multi-source heterogeneous data, including geological structure information, monitoring data, accident reports, policy documents, and expert experience. These data come from diverse sources, exist in various formats, and are scattered across different systems and platforms, forming “data silos” that lead to information fragmentation and hinder effective integration and sharing [15–19]. Such data fragmentation makes it difficult for technical personnel to comprehensively and accurately acquire and analyze relevant information, thereby affecting the overall assessment and prediction of rockburst disasters.

Second, the mechanism of rockburst disasters is complex, involving the interaction of multiple factors such as geological conditions, mining technology, and mine pressure [20–24]. Constructing a complete causal chain of disaster formation is key to achieving accurate prediction and effective prevention. However, several difficulties remain in this regard. On one hand, due to data incompleteness and uncertainty, it is difficult to accurately characterize the causal relationships among various factors [25–27]. On the other hand, existing numerical simulation methods suffer from limitations in both timeliness and accuracy, making them inadequate for the rapid decision-making required in real production environments [28–30]. As a result, technical personnel often lack sufficient scientific basis when formulating prevention and control measures, leading to unsatisfactory outcomes.

In addition, the prevention and control of rockburst are also challenged by system and rule conflicts [31–33]. In actual production, coal mining enterprises must comply with multiple safety standards and operational regulations, which may be inconsistent or even contradictory. In the absence of a unified coordination mechanism, technical staff may experience confusion during implementation, increasing the risk of operational errors [34–37]. Meanwhile, with the rapid advancement of technology, new technical tools and management approaches continue to emerge. How to organically integrate these innovations with existing regulations has become an urgent problem to solve [38–41].

In summary, the knowledge governance challenges in the coal mine rockburst domain are primarily reflected in the following aspects:

– fragmented multi-source heterogeneous data leading to information isolation;

– difficulties in constructing disaster-causing causal chains affecting prediction accuracy;

– insufficient timeliness of numerical simulations constraining rapid decision-making;

– conflicts among systems and rules increasing management complexity.

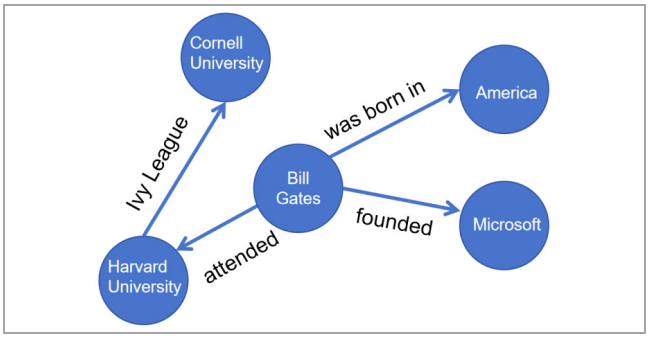


Fig. 1. A general knowledge graph

The root cause of these challenges lies in the explosive growth of knowledge complexity driven by technological development, coupled with the lack of efficient and systematic knowledge management approaches, which significantly reduce decision-making efficiency.

Therefore, there is an urgent need for a knowledge management tool capable of integrating multi-source data, supporting causal reasoning, and consolidating domain expertise to enhance the scientific and effective management of rockburst prevention and control. As an emerging structured semantic network technology, the knowledge graph (KG) possesses strong capabilities in knowledge representation and reasoning, providing new ideas and methods for addressing the above challenges. This paper will explore in detail the construction and application of a coal mine rockburst knowledge graph, aiming to provide robust knowledge support for coal mine safety management.

Domain-specific knowledge graphs for coal burst in mines

General knowledge graphs and domain-specific knowledge graphs for coal burst in mines. A general knowledge graph is a large-scale structured semantic network designed to represent real-world entities, concepts, and their interrelationships in the form of a graph [43]. By representing knowledge as a graph composed of nodes (entities or concepts) and edges (relationships), it effectively organizes and manages massive amounts of semantic information. The core of a general knowledge graph lies in its structured representation of knowledge, which enables computers to efficiently understand and process information. As shown in Fig. 1, the knowledge graph provides a structured representation of key information related to Bill Gates. They contain hundreds of millions or even billions of entities and relationships, providing users with rich and diverse knowledge retrieval services. These knowledge graphs cover a wide range of domains, from natural phenomena to social culture, from scientific principles to everyday knowledge, encompassing almost all aspects of human understanding. The construction of general knowledge graphs is usually based on open data. Structured knowledge triples (subject – predicate – object) are extracted from large volumes of text, web pages, and other data sources to build the knowledge network. For example, “Bill Gates, founded, Microsoft” is a typical example of a knowledge triple. Through this approach, general knowledge graphs can integrate fragmented pieces of information into an organic whole, offering users more accurate and comprehensive knowledge retrieval services.

However, although general knowledge graphs possess strong capabilities in knowledge representation and reasoning, their limitations become increasingly evident when applied to specific domains such as coal mine rockburst.

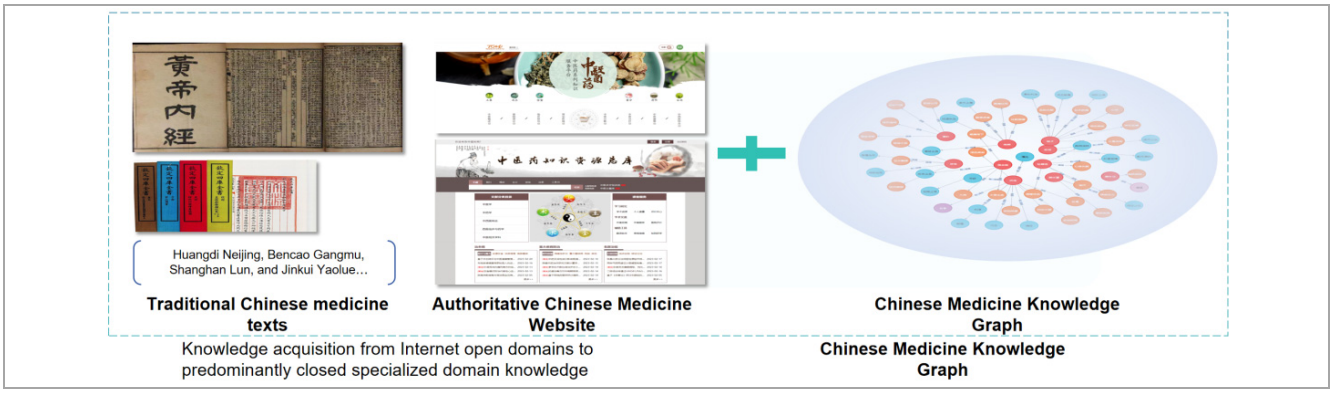


Fig. 2. A Domain-specific knowledge graphs

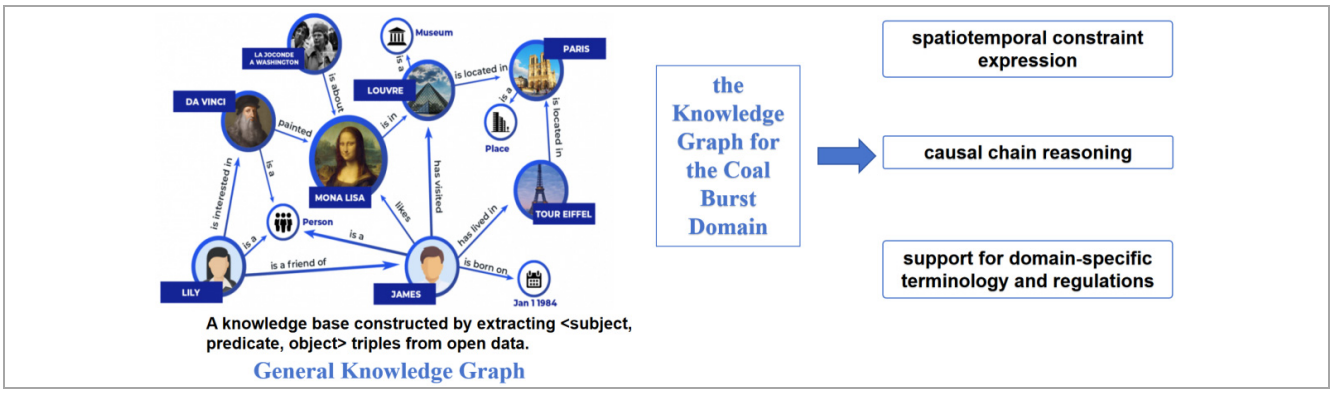


Fig. 3. The transition from general to domain knowledge graphs

While general knowledge graphs cover a wide range of knowledge areas, they often lack sufficient depth and domain expertise, making it difficult to meet the needs of professional users for complex knowledge queries and reasoning [43; 44]. For instance, in the field of coal mine rockburst, a general knowledge graph may fail to accurately represent the spatiotemporal constraints of geological structures, the causal chains of rockburst formation, and specialized prevention and control technologies. To overcome these limitations, domain knowledge graphs have emerged. As illustrated in Fig. 2 [45], a domain knowledge graph focuses on a specific field by integrating domain-specific concepts, entities, relationships, and related semantic information to form a structured knowledge network. It provides professional users with more precise and in-depth knowledge retrieval and reasoning services, thereby addressing the complex knowledge demands within a specialized domain.

The construction of a domain knowledge graph typically involves an in-depth analysis of the domain's knowledge system to identify its core concepts, entities, and relationships. It also requires collecting multi-source data from the domain, including literature, reports, databases, and expert experience, and integrating them into the graph. By extracting structured knowledge triples from the integrated data and building the ontology model of the domain knowledge graph, the system can deliver more intelligent and context-aware knowledge services. For example, in the coal mine rockburst domain, a domain knowledge graph can utilize causal chain reasoning to construct a complete disaster-causing causal chain, revealing the causal relationships among various factors and providing a scientific foundation for disaster prediction and prevention.

The transition from general knowledge graphs to domain knowledge graphs represents an inevitable trend in the application of knowledge graph technology to specific domains. By incorporating spatiotemporal constraint representation, causal chain reasoning, and support for domain-specific terminology and standards, domain knowledge graphs can better meet the complex knowledge demands within specialized fields, as shown in Fig. 3. In the field of coal mine rockburst, the spatiotemporal constraint representation capability enables accurate description of the contextual background of rockburst events, providing more precise temporal and spatial information to support disaster prediction and prevention. The causal chain reasoning capability allows the construction of complete disaster-causing causal chains, revealing the causal relationships among various influencing factors. Meanwhile, the ability to support professional terminology and standards ensures the accurate expression and understanding of specialized concepts and regulations, offering more precise knowledge services for domain experts. These capabilities make domain knowledge graphs highly valuable in the prevention and control of coal mine rockburst. They can provide strong technical and analytical support for engineers, managers, and researchers in coal mining enterprises, enhancing the scientific basis and efficiency of safety management and decision-making.

The technical core of the knowledge graph for the coal burst domain. In the process of constructing a knowledge graph for the coal mine rockburst domain, its core technical framework must focus on addressing three key challenges: spatiotemporal constraints, cross-modal fusion, and domain-specific interpretability, as shown in Fig. 4. These technical components together form the fundamental architecture of the knowledge graph, enabling the effective integration of multi-source data, supporting complex reasoning, and providing precise knowledge services tailored to the professional domain.

First, the knowledge graph for coal mine rockburst must effectively represent spatiotemporal constraints, as

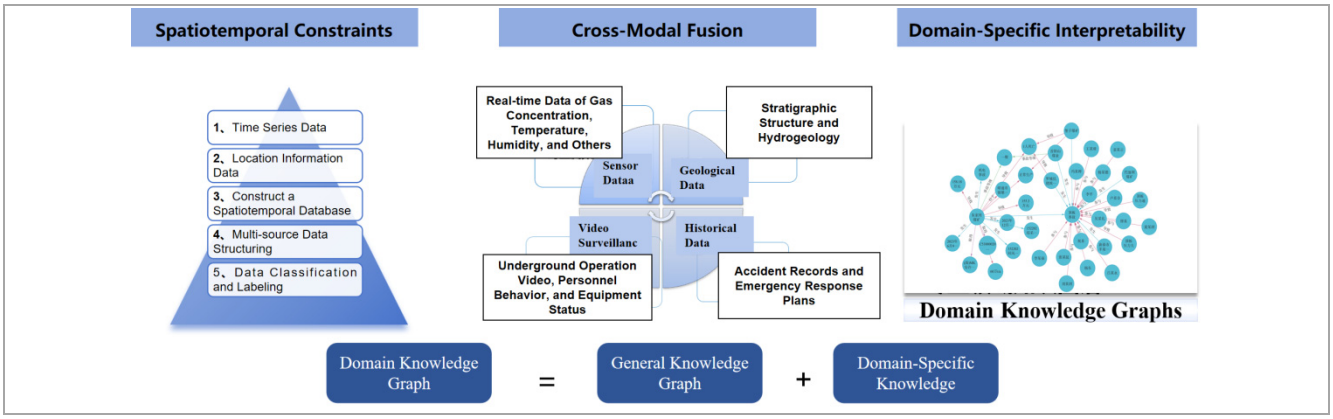


Fig. 4. The technical core of the knowledge graph for the coal burst domain

rockburst events are influenced by geological conditions, mining activities, and dynamic temporal–spatial factors. Second, it should possess cross-modal fusion capability to integrate multi-source heterogeneous data – such as geological reports, monitoring records, and expert knowledge – providing a more comprehensive understanding of event mechanisms. Finally, professional interpretability is essential; by constructing a domain-specific ontology that defines key concepts, entities, and relationships, the knowledge graph can accurately represent causal links (e.g., between coal seam compression and rockburst) and support reliable reasoning for prediction and prevention.

By addressing the three core challenges – spatiotemporal constraints, cross-modal fusion, and professional interpretability – the knowledge graph for coal mine rockburst can effectively integrate multi-source data, support complex causal reasoning, and provide precise knowledge services for the domain. These technical foundations not only enhance the applicability of knowledge graphs in the field of coal mine rockburst but also establish a solid technological basis for rockburst prediction, prevention, and decision support.

The four core functions of the knowledge graph in the coal burst domain. The construction of a knowledge graph for the coal mine rockburst domain is not merely aimed at storing and displaying knowledge; more importantly, it leverages its structured and semantic characteristics to provide comprehensive support for coal mine safety production. Specifically, the knowledge graph plays a crucial role in four key aspects: knowledge integration, causal reasoning, knowledge accumulation, and decision support.

First, the knowledge graph demonstrates strong advantages in knowledge integration. The prevention and control of coal mine rockburst involve multi-source heterogeneous data – such as geological structures, monitoring data, accident reports, policies, and expert knowledge – that are often fragmented across systems. By integrating these data into a unified framework, the knowledge graph enables interconnection and interoperability. For instance, combining geological exploration data with real-time monitoring information allows for a more comprehensive understanding of geological conditions and more accurate rockburst risk assessment. This integration enhances data usability and provides a solid foundation for analysis and decision-making.

Second, the knowledge graph exhibits powerful causal reasoning capabilities. Rockburst formation involves complex interactions among geological, mechanical, and operational factors. By establishing a structured semantic network, the knowledge graph can clearly represent causal chains, such as between coal seam compression and roof fracture, thus enabling prediction of rockburst probability and impact. This reasoning ability deepens understanding of disaster mechanisms and supports the formulation of effective prevention and control strategies.

Furthermore, the knowledge graph contributes to knowledge accumulation in the coal mine rockburst domain. Domain knowledge includes not only scientific findings and technical standards but also practical experience that is often difficult to inherit or share. By formalizing and storing such knowledge – such as expert experience and accident case analyses – the knowledge graph preserves valuable insights and facilitates learning for new professionals. This promotes continual knowledge inheritance and reduces the risk of expertise loss.

Finally, the knowledge graph offers significant potential for decision support. Managers in coal mining enterprises must make timely and informed decisions in complex environments. By providing comprehensive and structured knowledge on geological conditions, monitoring data, and control technologies, the knowledge graph assists in developing more scientific and targeted prevention strategies. This enhances decision accuracy and reliability while effectively reducing management risks.

Construction and enhancement of knowledge graph and large language model for coal mine rockburst

Technical roadmap for the coal burst knowledge graph. The construction of a knowledge graph for coal mine rock bursts is a systematic engineering process involving the collection, processing, and integration of multi-source data, as well as the extraction, modeling, and application of knowledge. This process requires the comprehensive use of multiple technical approaches to ensure the accuracy and practicality of the resulting knowledge graph. As shown in Fig. 5, the core of the technical route lies in efficiently extracting valuable knowledge from massive, heterogeneous data sources and organizing it into a structured knowledge network.

The construction of a coal mine rock burst knowledge graph consists of four key stages: data acquisition, information extraction, knowledge integration, and knowledge storage.

In the data acquisition stage, it is necessary to comprehensively collect multi-source data such as geological exploration reports, real-time monitoring data from equipment, accident case records, policy documents, and expert experience. These data must then undergo preliminary screening and cleaning to ensure reliability and usability.

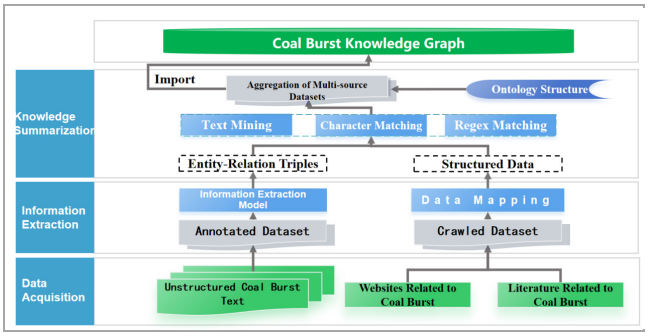


Fig. 5. Technical roadmap for the coal burst knowledge graph

Data Type	Quantity	Source
Mine Coal Burst Reports	138 Mine Coal Burst Reports	Coal Burst Research Institute
Q&A Data	1,135 Mining-related Q&A Data Entries	Internet
Mine Legal and Regulatory Document Retrieval Block	12,437 Legal and Regulatory Document Blocks	Government Public Data
Terminology Explanations of Coal Mine Rockburst	371 Terminology Explanations of Coal Mine Rockburst	Mining Industry

Fig. 6. Data of the coal burst knowledge graph

In the information extraction stage, natural language processing (NLP) and machine learning techniques are employed to convert unstructured or semi-structured data into structured knowledge units. For example, key information about accident occurrences can be extracted from incident reports, while critical features can be mined from monitoring data.

Next, during the knowledge integration stage, an ontology model of the knowledge graph is constructed to integrate the extracted structured knowledge. Domain-specific concepts, entities, relationships, and their semantic constraints are defined to form a complete knowledge network, while knowledge redundancy and conflicts are resolved.

Finally, in the knowledge storage stage, the integrated knowledge is imported into a graph database to form a complete knowledge graph, enabling users to perform rapid querying and analysis. This also facilitates visualization and intelligent reasoning, while supporting dynamic updates to reflect changes and new insights in coal mine operations in a timely manner.

Through this technical route, the coal mine rock burst knowledge graph can effectively integrate multi-source data, support complex causal reasoning, and provide precise knowledge support for coal mine safety management. This process not only involves data collection and processing but also encompasses knowledge extraction, modeling, and application, making it a multidisciplinary and comprehensive engineering task. By constructing the knowledge graph, coal mining enterprises' technical managers and researchers can access a comprehensive and accurate knowledge platform that helps them better understand and respond to the complex dynamic disaster of rock bursts.

Ontology design for the coal burst knowledge graph. Ontology design is a core component in constructing the knowledge graph for coal mine rock burst management. It defines the concepts, entities, relationships, and semantic constraints within the domain. Through the ontology model, dispersed knowledge units can be integrated into a structured knowledge network, providing a solid foundation for the construction and application of the knowledge graph.

When designing the ontology, it is first necessary to identify the core concepts and entities of the domain based on the expertise and research findings of field specialists. These core concepts and entities serve as the cornerstone of the knowledge graph, encompassing all aspects related to rock burst phenomena during coal mining operations.

Data of the coal burst knowledge graph. In the construction of the coal mine rockburst knowledge graph, data collection and organization are fundamental steps of critical importance. The quality and completeness of the data directly affect the accuracy and practical value of the knowledge graph. As shown in Fig. 6, relevant literature, expert knowledge, existing databases, and terminology sets related to coal mine rockbursts were collected from the internet and previously available data sources. After data cleaning and organization, a total of 138 rockburst-prone mines, 1.135 coal mine domain question–answer pairs, 12.437 policy documents, and 371 technical manuals were effectively integrated.

The multi-source data – including rockburst reports, Q&A records, policy documents, and technical manuals – provide abundant resources for knowledge graph construction. Rockburst reports contain detailed records of geological structures, mining processes, monitoring data, and specific rockburst events; Q&A data reflect the practical problems encountered by technicians and their solutions; policy documents outline technical standards, operational procedures, and safety management requirements for rockburst prevention and control; and technical manuals encapsulate rich practical experience and technical summaries. Together, these data encompass professional knowledge, technical expertise, regulatory policies, and operational norms.

By collecting and organizing such diverse data sources, a comprehensive and accurate knowledge foundation can be established for constructing the coal mine rockburst knowledge graph. This data not only enriches the content of the knowledge graph but also provides a holistic knowledge platform for technical managers and researchers in coal mining enterprises, helping them better understand and address the complex dynamic hazard of rockbursts.

Entity extraction for knowledge graph. In the construction of the coal mine rockburst knowledge graph, entity extraction serves as a key step in transforming unstructured textual data into structured knowledge. Online platforms contain vast amounts of unprocessed text data – such as accident reports, geological exploration documents, and policy papers – which embed valuable knowledge about rockburst phenomena. As shown in Fig. 7 [47], the objective is to automatically extract rockburst-related entities and relationships from these documents to enrich the content of the knowledge graph.

To achieve automatic extraction of entities and relations related to coal mine rockbursts from web-based textual data, a high-quality annotated dataset must first be established, consisting of texts paired with expert-labeled entities. Domain experts are essential in this stage to ensure labeling accuracy and consistency. Next, an appropriate pretrained model (such as BERT or RoBERTa) is selected and fine-tuned for the entity extraction task specific to the coal mine rockburst domain. The fine-tuning process involves adjusting model parameters and optimizing the objective function to enhance the model's comprehension of domain-specific language and its capability to recognize entities accurately. Once the model is trained, it can be applied to new textual data (such as recent accident reports or monitoring data) to automatically identify entities and convert them into structured knowledge units (for example, knowledge

triples), which are directly imported into the knowledge graph. This not only enriches the graph's content but also supports downstream applications.

Through these steps, rockburst-related entities and relationships can be automatically extracted from large-scale textual data, providing abundant knowledge resources for constructing the coal mine rockburst knowledge graph. This process significantly improves the efficiency of knowledge graph construction and offers crucial technical support for rockburst prediction, prevention, and management in coal mining operations.

Construction of the coal burst knowledge graph. The construction of a knowledge graph for coal mine rockburst is a key process for integrating multi-source data and achieving efficient knowledge management and application. By organizing the extracted entities and relationships into a structured knowledge network, the knowledge graph provides strong support for the prediction, prevention, and management of coal mine rockbursts. As shown in Fig. 8, this process involves several essential steps, including ontology design, knowledge fusion, and graph construction and validation.

Graph construction and validation are crucial to ensuring the quality and usability of the knowledge graph. By importing the fused knowledge into a graph database, a complete coal mine rockburst knowledge graph is established. The graph database efficiently stores and queries graph-structured data, supporting complex causal reasoning and knowledge retrieval. To verify the accuracy and practicality of the knowledge graph, its performance was tested through real-world cases in rockburst risk assessment and prevention strategy recommendation. For instance, technical personnel can use the knowledge graph to quickly identify the rockburst risk level of a specific coal mine and obtain corresponding prevention and control recommendations. Validation results demonstrate that the knowledge graph provides precise knowledge support for coal mine safety management.

Intelligent question answering and LLM-driven knowledge graph enhancement. In the field of coal mine rockburst, the ultimate goal of constructing a knowledge graph is to enable an intelligent question-answering (QA) system that supports rapid and accurate information retrieval and decision-making. To achieve this, we developed an intelligent QA system based on a domain-specific large language model (LLM). This system leverages the knowledge graph for information extraction and semantic understanding, thereby providing precise and context-aware answers.

1. Implementation of intelligent question answering. As shown in Fig. 9, using the developed domain-specific LLM, intelligent QA is performed for queries related to coal mine rockburst. The system analyzes the user's question, automatically queries the knowledge graph, retrieves relevant information, and generates accurate responses. This process not only improves the efficiency of information retrieval but also enhances the accuracy and reliability of the QA system. For example, users can inquire about specific coal mine safety regulations or rockburst prevention measures, and the system can quickly extract relevant information from the knowledge graph to provide detailed and precise answers.

2. Knowledge graph-enhanced document retrieval. The knowledge graph plays a crucial role in improving document retrieval efficiency and accuracy. By utilizing the constructed rockburst knowledge graph, users can quickly query relevant information and achieve efficient knowledge access. The structured nature of the knowledge graph enables more precise and context-aware document searches, allowing users to locate the required documents

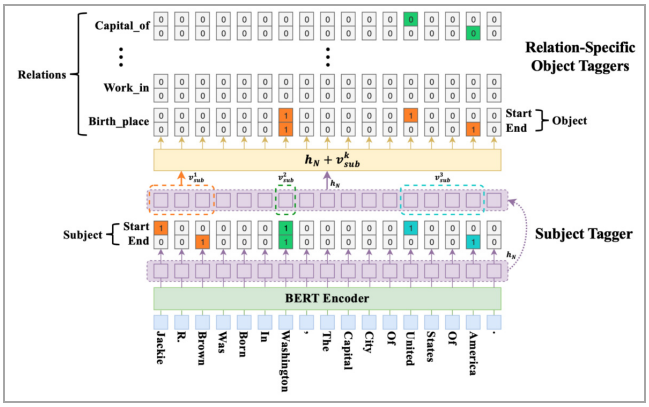


Fig. 7. Entity extraction based on BERT

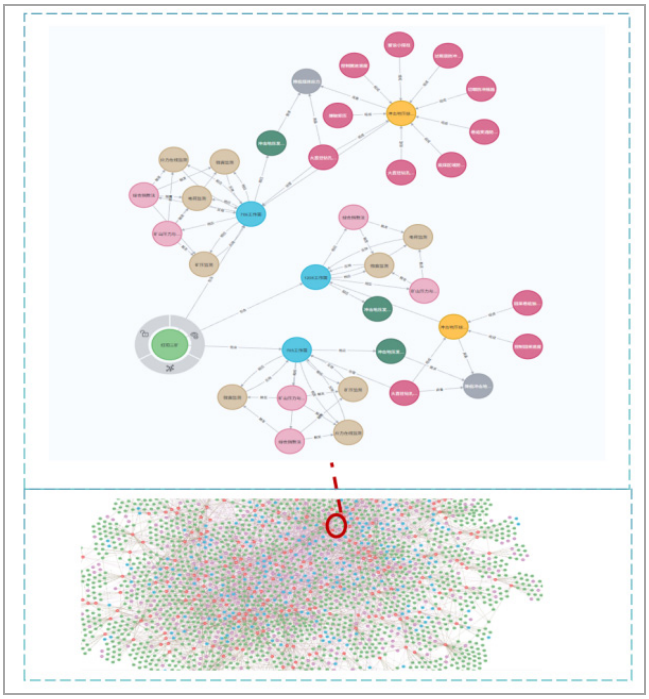


Fig. 8. Construction of the coal burst knowledge graph



Fig. 9. Domain-specific question answering

or information fragments through entities, relationships, and other graph elements. As shown in Fig. 10, technical personnel can query the knowledge graph to obtain the rockburst risk level of a specific coal mine, along with corresponding prevention measures and recommendations. This allows them to rapidly locate related policy documents, research reports, or case studies.

3. LLM-driven knowledge graph enhancement. To further enhance the practical value of the knowledge graph, we employ LLMs to summarize and enrich the node information within the graph, as illustrated in Fig. 11.

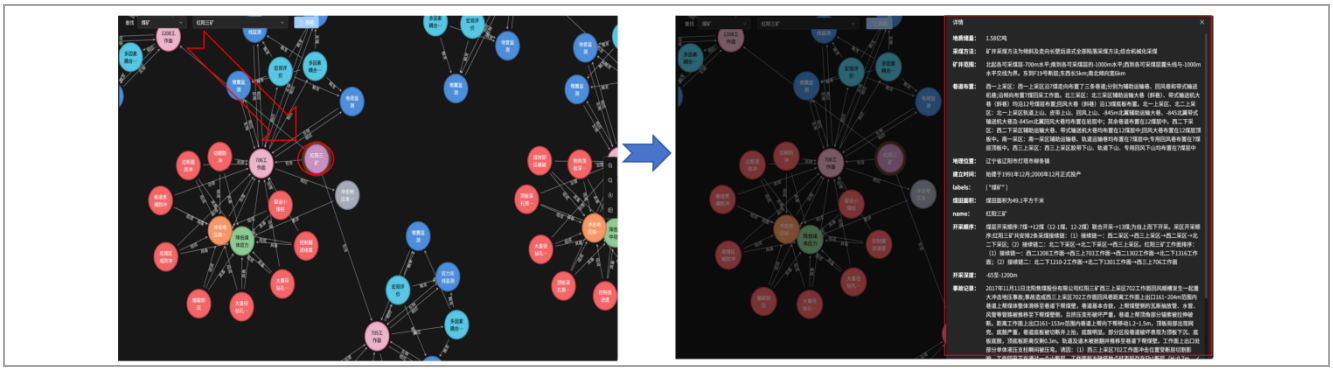


Fig. 10. Knowledge graph query



Fig. 11. The large model summarizes the information of each node

The superior semantic understanding and reasoning capabilities of LLMs enable a deeper comprehension of node content, thereby improving the overall quality and usability of the knowledge graph. In practical applications, LLMs can summarize node information, extract key insights, and generate more comprehensive and detailed descriptions. For instance, regarding rockburst prevention technologies in coal mines, LLMs can not only provide basic technical descriptions but also generate application cases, performance evaluations, and optimization suggestions based on related knowledge.

In addition, LLMs can support the dynamic updating of the knowledge graph. As coal mine safety practices continue to evolve, new knowledge and experiences need to be promptly integrated into the graph. By analyzing the latest literature, reports, and expert opinions, LLMs can identify and extract new knowledge units and incorporate them into the knowledge graph. This dynamic updating capability ensures that the knowledge graph consistently reflects the most recent advancements and best practices in the field.

Through intelligent question answering, knowledge graph-assisted document retrieval, and LLM-driven knowledge graph enhancement, we have developed a powerful knowledge management and decision-support tool for the field of coal mine rockburst prevention. This system not only improves the efficiency of knowledge graph construction and application but also provides technical managers and researchers in coal mining enterprises with a comprehensive and accurate knowledge platform, helping them better understand and address the complex dynamic disaster of rockburst.

Conclusion

This study addresses the challenges of knowledge governance in the field of coal mine rockburst by proposing a knowledge graph construction and enhancement framework that integrates multi-source data, causal reasoning mechanisms, and the semantic enhancement capabilities of LLMs. By systematically integrating geological exploration reports, monitoring data, policy documents, and expert experience, the constructed knowledge graph not only improves the accessibility and analyzability of rockburst-related data but also significantly enhances decision-making efficiency and accuracy through intelligent question answering and document retrieval functions.

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