International Journal of Knowledge and Systems Science
Volume 14 • Issue 1

Banking System Incidents Analysis Using Knowledge Graph

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ABSTRACT

Risk incidents in the banks' systems have caused significant social impacts and economic losses. This study proposes a risk incident knowledge modeling and analysis approach based on the knowledge graphs to realize the effective integration and continuous accumulation of incident knowledge. The authors are the first to analyze the advantages of knowledge graphs in risk incident knowledge integration for the bank's core system. Moreover, they study and compare the related field's state-of-the-art models (including CRF, BiLSTM, BiLSTM-CRF, BERT-BiLSTM-CRF). This paper proposes an improved Bert-BiLSTM-CRF model to perform entity recognition which replaces "individual word mask and training" with "full word mask and training" targeted to solve the problem of low accuracy in the extraction of incident text entities in the banking system. Experiments on 1000 banking system incident material show that the improved Bert-BiLSTM-CRF model outperforms the state-of-the-art models based on the comparison of recall (R), precision (P), and F1-measure, with a 2%-9% improvement in the F1-measure.

KEYWORDS

Banking System, Incident Analysis, Knowledge Graph, Knowledge Management, Name Entity Recognition

INTRODUCTION

Banks' financial transactions, which involve the operation of client funds, contribute significantly to the growth of the national economy. As a result, banks have stringent requirements for the timeliness and consistency of transactions and data, which must be accurate, secure, usable, and traceable (Krause & Giansante, 2018). In the banking IT system, the construction of the core banking system accounts for the most significant and complex overall expenditure. High-tech projects require considerable capital and continuous human resource investment and involve the cooperation or coordination of the related systems of the entire bank (Q. Zhao et al., 2020). Although both the technology and management of the core banking system have advanced significantly after decades of experience, risk incidents still occur occasionally. According to the report from the China Banking Regulatory Commission, risk incident information and investigation reports released by various local supervisory and management departments, as well as news reports from mainstream media and other sources, data of risk incidents

DOI: 10.4018/IJKSS.325794
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that occurred in the bank's core system from 2021 to 2022 (cc, 2022; China, 2022; Cngold, 2022; Jingwei, 2022; NTES, 2022; Finance, 2022; Jiemian, 2022; JRQ, 2022; Zaobao, 2022) were collected. These are shown in Table 1, indicating that both influence and economic losses are on the rise. The situation regarding risk management in the development of the core banking system is still severe. Core banking system incidents have significant economic and social impacts but provide valuable experience for implementing subsequent bank projects. By analyzing incidents related to the core banking system, we can better understand the causes of these incidents, providing valuable insights for incident prevention.

In recent years, relevant research on the knowledge graph (KG) has become very popular. Scholars have applied knowledge graph technology to study risk identification and analysis of incidents in various fields. Liu et al. proposed a new knowledge graph–based approach to explore railway operational incidents, which helped in developing targeted preventive measures and identifying the latent features of the corresponding railway operational incidents (J. Liu et al., 2021). Pedro et al. proposed a novel information-sharing system using linked data, ontologies, and KG technologies, facilitating a new "open" information-sharing paradigm with data-driven applications in construction safety management (Pedro et al., 2022). Fang et al. integrated computer vision algorithms to develop a KG that can automatically and accurately identify and successfully detect hazards in varying contexts from images (Fang et al., 2020). Shin et al. proposed an AI-based analysis system, the Symptom-Based Expert for Advanced Response to Chemical Hazards, which enables the analysis of real-time field data, transforming it into insights and actions for emergency response (Shin et al., 2022). Zheng et al. implemented a KG to bridge the information gap between decentralized databases, demonstrating its efficiency in named entity recognition in the chemical industry (Zheng et al., 2021). Liu et al. learned from historical reports to build a connected network of hazards and incidents, forming a KG, and applied it to railway hazard identification and risk assessment (Liu & Yang, 2022). By realizing the visualization and quantitative description of the potential relationship, this approach helps formulate railway risk preventive measures.

Table 1. Bank core system incidents in 2021 to 2022

No.	Time	Bank Name	System Incident Description	Impact Level
1	11/05/2022	China Merchants Bank	Online banking, ATM, and credit card does not work	High
2	13/06/2022	ICBC	Bank branches are unable to handle business	High
3	18/06/2022	DBS Bank	Many user transactions are double charged	Moderate
4	23/11/2021	DBS Bank	Can't log in to the mobile app and digital bank website	High
5	05/06/2022	HSBC	App and website cannot handle financial services	High
6	01/03/2021	Mizuho Bank	3,000 ATMs in Japan were temporarily shut down	Moderate
7	25/04/2022	Maybank	App and web version completely disabled	High
8	01/07/2021	Bank of Ningxia	The interruption of deposits and withdrawals for 37 hours	High
9	26/03/2022	Japanese bank	ATM and online banking system failures	High
10	28/02/2021	Mizuho Bank	ATM temporarily unavailable due to system failures	High

Zhou et al. present a novel open-domain conversation generation model to demonstrate how large-scale commonsense knowledge can facilitate language understanding and generation (Zhou et al., 2018). Trisedya et al. propose the learning of embeddings that can capture the similarity between entities in different knowledge graphs (Trisedya et al., 2019). In order to still enjoy the benefit brought by the graph structure while preventing dilution of knowledge from distant nodes, Kampffmeyer et al. proposed a Dense Graph Propagation (DGP) module with carefully designed direct links among distant nodes (Kampffmeyer et al., 2019). Shang et al. proposed a novel end-to-end Structure-Aware Convolutional Network that combines benefits (Shang et al., 2019). Wang et al. proposed Knowledge-Aware Graph Neural Networks with Label Smoothness Regularization (KGNN-LS) to provide better recommendations (H. Wang et al., 2019). Yao et al. proposed the use of pre-trained language models for knowledge graph completion (Yao et al., 2019). X. Chen et al. reviewed the basic concepts and definitions of knowledge reasoning and the methods for reasoning over knowledge graphs (X. Chen et al., 2020). Ji et al. summarized recent breakthroughs and perspective directions to facilitate future research (Ji et al., 2021). Hogan et al. provided a comprehensive introduction to knowledge graphs, which have recently garnered significant attention from both industry and academia in scenarios that require exploiting diverse, dynamic, large-scale collections of data (Hogan et al., 2021). In their survey, Ji et al. (2021) provided a comprehensive review of knowledge graphs, covering research topics about 1) knowledge graph representation learning, 2) knowledge acquisition and completion, 3) temporal knowledge graphs, and 4) knowledge-aware applications. They summarized recent breakthroughs and proposed directions to facilitate future research. Ji et al. proposed a full-view categorization and new taxonomies on these topics (Ji et al., 2021).

According to the characteristic features of incidents in various fields, the aforementioned articles compare and optimize the current mainstream knowledge graph methods. The proposed approach is more suitable for incident identification and protection in these various fields. It is evident that banking system incidents are not included in the current research field. Obviously, studies in the field of banking system incidents are still rare. Therefore, this paper will compare the latest method according to the characteristic features of banking system incidents and propose the most suitable knowledge graph method for banking system incidents. As the basic units of KG, named entity recognition (NER) and linking are the core technologies of KG construction. Knowledge is usually dynamically incremental due to the complexity, openness, diversity, and large scale of human knowledge. Entity recognition technology can detect new entities in the text and add them to the existing knowledge base; in contrast, entity-linking technology can discover new knowledge about specific entities in a targeted manner.

NER starts from its early stage, mainly based on dictionary and rules methods. These rely on manual rule templates constructed by linguists, are prone to errors, and cannot be transplanted between different domains. Therefore, this approach cannot process complicated or unstructured data and can only handle simple text data. This approach was followed mainly by statistical, machine learning–based methods, including the hidden Markov model (HMM), the maximum entropy model (MEM), the support vector machine (SVM), and the conditional random fields (CRF). NER is regarded as a sequence annotation problem in machine-based learning, using large-scale corpora to learn annotation models. However, these methods still require a lot of human participation in feature extraction and rely heavily on the corpus, so the identification effect is unsatisfactory.

Deep learning has recently been applied to the Chinese-named entity recognition research. The deep learning–based method avoids the tedious manual feature extraction by acquiring the features and distributed representations of the data, and it has a good generalization ability. The first use of neural networks applied to named entity studies was made by Hammerton. They used a unidirectional long- and short-term memory (LSTM) network, which had good sequence modeling ability, so LSTM-CRF became the infrastructure of entity recognition (Hammerton, 2003); later, Collobert et al. first used convolutional neural network (CNN) and CRF to study named entity recognition in CoNLL-2003 (Pinheiro & Collobert, 2014); Guillaume et al. proposed a neural network model that combined Bidirectional Long Short-Term Memory (BiLSTM) with CRF, and this bidirectional structure can be obtained using this model (Lample et al., 2016). The following sequence information has been widely used in named entity recognition, and the BiLSTM-CRF model, tested on the 2003 corpus, achieved a relatively high F1 value of 90.90%; Huang et al. integrated manually designed spelling features based on the BiLSTM-CRF model, achieving an F1 value of 88.83% on the CoNLL-2003 corpus (Huang et al., 2015); Chiu and Nichols added a CNN processing layer on the front end of the LSTM model and reached 91.26% F1 value on the CoNLL-2003 corpus (Chiu & Nichols, 2016); in the field of chemistry, Luo et al. adopted the BiLSTM-CRF model based on an attention mechanism, achieving an F1 value of 91.14% on the BioCreative IV Set (Luo et al., 2018); Wu et al. proposed joint segmentation and CNN-BiLSTM-CRF model training to enhance the entity recognition boundary of the Chinese NER model, and introduced a method of generate samples from the existing marker data to further improve the entity recognition performance of the entity (Wu et al., 2019); Dong et al. proposed that the Radical-BiLSTM-CRF model use bidirectional LSTM to extract the characteristics of the root sequence and then with word direction the input of the model (Dong et al., 2016); the Lattice LSTM model proposed by Zhang and Yang (2018), which explicitly uses word and word sequence information to avoid word error transmission, achieved a high F1 value of 93.18% in MSRA corpus; W. Liu et al. proposed the WC-LSTM model, added word information to the beginning or end of the whole character, enhanced semantic information, and achieved a 93.74% F1 value in MSRA corpus (W. Liu et al., 2019). However, there is a problem with the above methods: these methods cannot represent polysemy because they mainly focus on the feature extraction of words, characters, or features between words and ignore the context or semantics of the word context, which extracts only a static word vector without contextual context information, resulting in the decline of actual recognition ability. To solve this problem, Google team Devlin et al. proposed a bidirectional encoder representation from transform (BERT) (Devlin et al., 2018). The language preprocessing model is to characterize the word vector. As an advanced pretrained word vector model, BERT further enhances the word vector module and type generalization ability; fully describes the character level, word level, sentence level, and even sentences; and better characterizes the syntactic and semantic information in different contexts. Fabio et al. applied the BERT-CRF model to Portuguese NER, achieving the best F1 value on HAREMI (Souza et al., 2019); Straková et al. applied the BERT preprocessing model to entity recognition and achieved quite desirable results on CoNLL-2002 Dutch, Spanish, and CoNLL2003 English (Straková et al., 2019).

Zhao et al. proposed a concept-enhanced named entity recognition model (CNER), in which features from three different granularities (i.e., concept, word, and character) are combined for bio-NER. Most conventional NER approaches are heavily dependent on feature engineering, and such sentence level–based methods suffer from the tagging inconsistency problem (Q. Zhao et al., 2020). Based on the above observations, Qiu et al. proposed a neural network approach; namely, attention-based bidirectional long short-term memory with a conditional random field layer (Att-BiLSTM-CRF), for named entity recognition to extract information entities describing geoscience information from geoscience reports (Qiu et al., 2019). Wigington et al. showed that CTC is not suitable for multi-label tasks and presented a novel Multi-Label Connectionist Temporal Classification (MCTC) loss function for multi-label, sequence-to-sequence classification (Wigington et al., 2019). Muhammad et al. examined the impact of the conditional random field and the structured support vector machine in the task of Arabic NER (Muhammad et al., 2020). Asgari-Chenaghlu et al. proposed two novel deep learning approaches utilizing multimodal deep learning and Transformers (Asgari-Chenaghlu et al., 2020). S. Chen et al. presented an effective solution to providing a meaningful and easy-to-use feature extractor for named entity recognition tasks: fine-tuning the pre-trained language model. The first is to translate speech into text, such as the audible voice and concept (human speech), and the second is to define only sound, such as animal sound, car, etc. There is no algorithm that is specifically designed for this field (S. Chen et al., 2021); instead, techniques such as N-grams and neural networks are used to explain and treat this type (Younis et al., 2021). Wang et al. continued to train the pre-trained BERT model using unlabeled texts related to the domain of test identification, so as to inject domain knowledge into the pre-trained BERT model and realize the domain adaptation (B. Wang et al., 2022). Bilal et al. proposed a consolidated framework for Twitter mining that aims to uncover the deficiency of the current state-of-the-art approaches to topic distillation and domain discovery. This is due to the shortage of both clinical repositories and clinicians to conduct data annotation. The ontology-based approach has been presented as a means of extracting the semantics of textual data (Abu-Salih, 2021). Bilal al. proposed capturing domain knowledge in ontologies which are then used to enrich the semantics of data with specific semantics conceptual representation of entities (Abu-Salih et al., 2018). Bilal al. found that, in the healthcare domain, there are a lack of detailed clinical entities and relations (Wongthongtham & Salih, 2018).

This literature review focuses on the application of knowledge graphs and research methods for named entity recognition. Based on these goals, the review identifies two gaps in current research: 1) a lack of research on applying knowledge graphs to incidents in the banking system, including a detailed analysis of the characteristics of this domain and how they can be integrated with knowledge graphs; and 2) issues with the accuracy of named entity recognition models when applied to incidents in the banking system. Therefore, this paper aims to address these two gaps by conducting research and finding solutions.

The BERT model adopts the occlusion language model (masked language model, MLM) and next sentence prediction (NSP) technology to adjust the model parameters gradually so that the text semantic representation output by the model can describe the essence of the language (Ji et al., 2021). Although MLM and NSP can learn and output the word vector containing contextual information in the traditional BERT model, it still has some drawbacks. The MLM task is trained by a word granularity mask, which is not conducive to learning the complete word meaning representation. The improved BERT-BiLSTM-CRF model proposed in this paper makes up for this shortcoming.

Publicly annotated datasets are scarce in the field of banking system incidents, and related research is still in its nascent stages. At present, the following two points need improvement: (1) The current KG method research does not include banking system incidents. (2) It is found that although these models are based on deep learning, the input word vectors are static word vectors, which cannot fully characterize the characteristics of word vectors in different contexts, thus affecting the accuracy of named entity extraction. This paper proposes the improved BERT-BiLSTM-CRF model as a means to improve the NER effect in comparison to state-of-the-art models (including CRF, BiLSTM, BiLSTM-CRF, and BERT-BiLSTM-CRF), and introduces the concept of intelligent knowledge support to incident risk management in the banking system for the first time.

This study first suggests a banking system incident knowledge modeling method based on a KG, which can effectively integrate and continuously accumulate banking system incident knowledge. Visual analysis can provide knowledge support for risk management of the banking system. The novel contributions of this paper are summarized as follows:

1. A knowledge-based incident knowledge modeling method for the banking system is proposed, which is for the first time applied to banking system incidents and can effectively integrate and continuously accumulate knowledge.
2. We propose an improved BERT-BiLSTM-CRF model for named entity recognition, which replaces “Individual word mask and training” with “Full word mask and training,” targeted to solve the problem of low accuracy in the extraction of incident text entities in the banking system.
3. This paper has completed the process of data cleaning, knowledge extraction, knowledge storage, and knowledge application for the existing bank incident data and built a banking system event analysis system based on knowledge graph.
4. Aiming at the problem of incident risk management in the banking system, we put forward the concept of intelligent knowledge support for the first time.

KNOWLEDGE GRAPH AND ITS APPLICATION VALUE

Knowledge Graph

A knowledge graph (KG) is a structured, semantic knowledge base that uses a network structure to describe concepts, entities, and their interrelationships in the real world. It is one of the critical methods of knowledge organization and representation in the significant data era. Its basic units are the “entity-relation-entity” triplets and related attribute-value pairs. Machine understanding and interpretation are facilitated by predefining entities, relationship types, and attributes.

According to different application fields, KGs can be divided into general and domain KGs. Domain KGs are typically oriented towards specific industries and require a high level of knowledge, depth, and accuracy (So, 2023). The KG of the bank core’s systemic risk incident, constructed in this study, is a typical domain KG with clear concepts and relationship patterns (H. Zhao et al., 2020).

ADVANTAGES OF A KNOWLEDGE GRAPH IN THE BANKING SYSTEM’S INCIDENT KNOWLEDGE INTEGRATION

Using a KG to integrate incident knowledge into banking systems offers the following advantages:

1. It can realize the continuous accumulation of incident knowledge in the banking system. The KG uses a semantic network to represent knowledge, which is more flexible and extensible. The knowledge extracted from various incident data sources can be quickly integrated into the existing KG to realize the continuous accumulation of incident knowledge in the banking system.
2. The critical knowledge elements required for risk management can be selectively extracted. Unstructured incident data, described in natural language, are random and diverse, which is not conducive to knowledge reuse. The critical incident data, extracted after structuring and normalizing, are stored in the knowledge map. The required key knowledge elements can be selectively extracted despite specific risk management needs.
3. It can integrate the semantic information of the banking system incident data. The entities and relationships of the KG have clear semantic connotations owing to the pre-definition of the concepts and relationship patterns involved in the domain. The application scope of knowledge is also reflected using the associated project context information.
4. It can integrate and expand the banking system incident knowledge. The key knowledge elements extracted from incident data collected can be effectively integrated through various relationships, thereby increasing the scope of domain knowledge.
5. It can provide the foundation for intelligent applications and the visual display of knowledge. KGs enable semantic query, accurate knowledge retrieval, and visual display.

CONSTRUCTION OF KNOWLEDGE GRAPH OF BANKING SYSTEM

Domain Knowledge Graph Construction Process

A domain knowledge graph (KG) is a knowledge base for a specific domain. Building a domain KG should be driven by the industry’s needs and should follow the principle of “starting from demand and ultimately applying.” The KG life cycle can be divided into the following stages: determine knowledge requirements ® knowledge modeling ® knowledge acquisition ® knowledge storage ® knowledge management ® knowledge application.

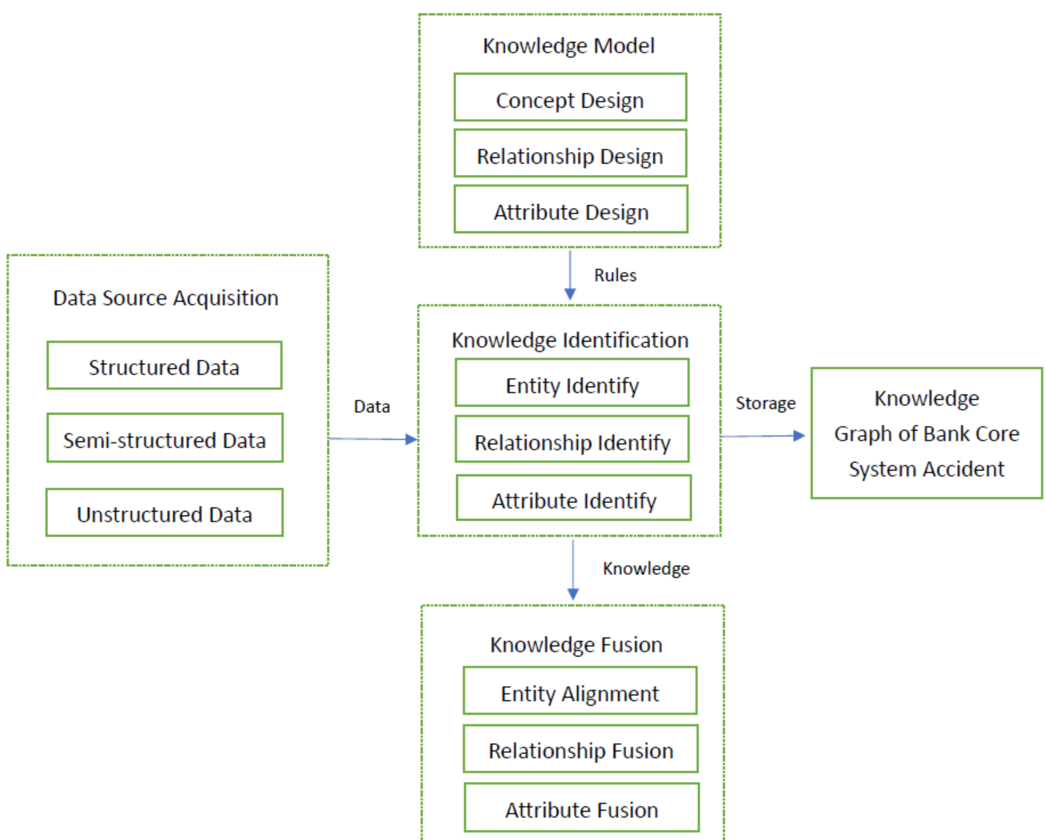
New requirements are imposed in the knowledge application process, promoting an iterative KG improvement and evolution process (Dutta et al., 2022). The construction process of KG includes knowledge modeling, acquisition, and storage. Knowledge modeling must determine the types of entities and relationships in the knowledge network through conceptual and relationship schema design. Knowledge acquisition refers to the extraction of knowledge elements from various data sources, while knowledge storage refers to storing acquired knowledge in a specific physical structure (ur Rehman, 2021).

This study first conducts knowledge modeling by designing domain concepts, relationships, and attributes and then identifies entities, relationships, and attributes from different data sources to obtain knowledge. Finally, the knowledge is acquired and stored in the knowledge base, thereby creating the banking system's incident domain knowledge. The process is illustrated in Figure 1. The process can be briefly summarized as follows: firstly, the rules of the model are established, including the design of concepts, relationships, and attributes. Next, data from different sources are obtained. Knowledge identification is then carried out, and the results are stored in a knowledge graph. Finally, knowledge fusion is performed, which involves the fusion of entities, relationships, and attributes.

Concept and Relational Schema Design

A concept represents an abstraction of a class of entities within a specific domain, with each type of entity potentially having different attributes. Conceptual design involves defining the concepts and attributes within a domain, based on its knowledge requirements. A relationship signifies the connection between two entities. For a specific domain, there may be different relationships between different types of entities. This study employs the entity relationship diagram (ERD) method, used in traditional database design, to analyze real-world concepts and their relationships (Cagiltay et al.,

Figure 1. Construction process of a knowledge graph of bank system incidents



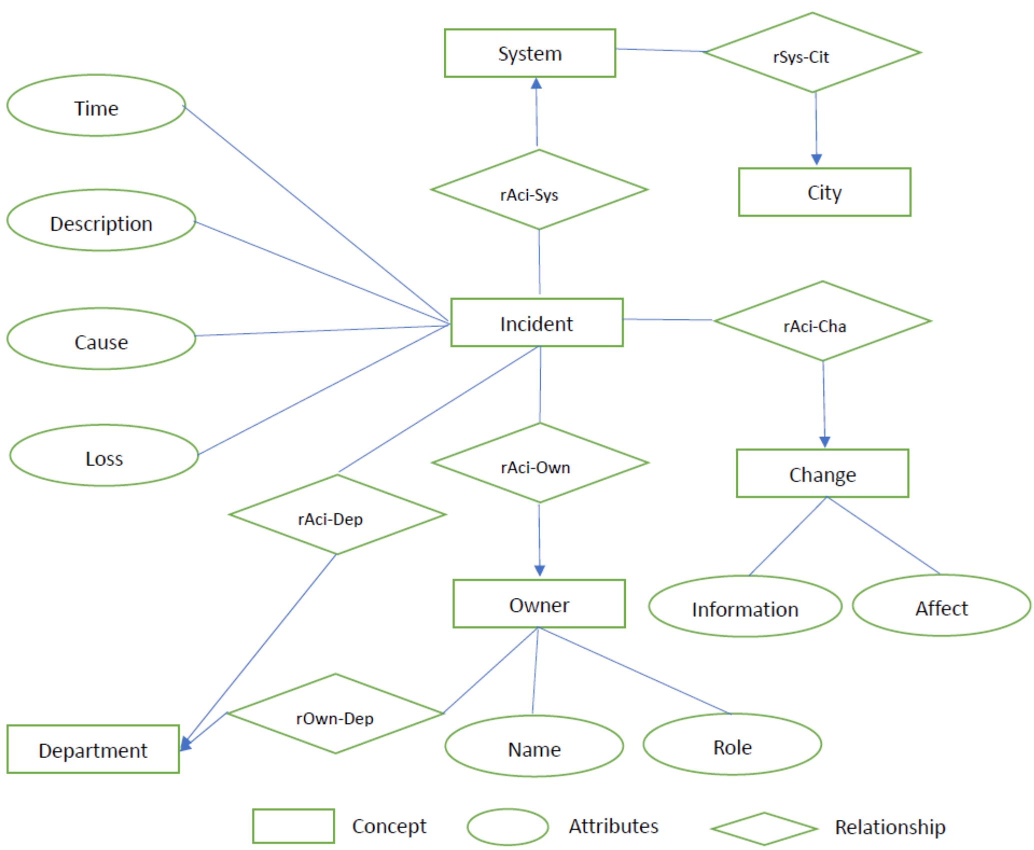
2013). Arrows are used to indicate the direction of a relationship. The critical knowledge elements—comprising the domain's concepts, connections, and attributes—are extracted by analyzing existing incident case data. This is represented in the improved ERD, as shown in Figure 2. In the context of an incident, there are four different attributes and four direct relationships, encompassing system, change, owner, and department. Based on this relationship diagram, it becomes convenient to proceed with the analysis and construction of a knowledge graph.

Extraction of Key Knowledge Elements of Banking System Incidents

The key knowledge elements of banking system incidents include entity objects, attributes, and relationships between entities, as defined in the aforementioned conceptual and relational model design. Key knowledge elements such as system name, implementation task, technical method, incident module, reason, number of affected customers, and loss amount must be identified for each incident in a banking system, using the incident description text. With the help of natural language processing–based technologies, the automatic extraction of knowledge can be realized, which is beneficial for the continuous accumulation of incident knowledge in the banking system. The main methods include rule and dictionary-based methods, statistics-based methods, deep learning–based methods, and combinations of these methods (Zhu et al., 2022).

Key knowledge elements such as incident keywords, date of occurrence, loss amount, and incident reason are extracted from the collected and sorted bank system incident data. This relevant knowledge

Figure 2. Concept-relation-attribute diagram of banking system incidents



is then expanded based on the construction and operation of the bank's core system (Čeović et al., 2022). Additionally, significant amounts of attribute data are contained within various entities and relationships. This knowledge forms the basis for subsequent incident analysis (Dhanda, 2022).

Let's take an example of a banking system incident that is described as follows: On April 1, 2022, a customer received a double transfer amount due to a system error. After investigation, it was found that the settlement system bug had caused a double deposit and affected amounts close to HKD (Hong Kong Dollar) 100 million. David and Stephen, the system owners from the settlement and internet financial department, cooperated with the IT department to quickly perform an investigation and remediation. They discovered that the cause of the incident was the system upgrade conducted in March 2022. Based on the above description, the identified entities, relationships, and attributes are presented in Table 2.

Data Sources and Knowledge Acquisition in the Field of Banking System Incidents

Sources of knowledge in the banking system domain include various types of structured, semi-structured, and unstructured data.

1. Structured data is information stored in a relational or object-oriented database. As the industry has become more digital, most data related to banking system incidents are stored in relational databases such as Oracle, MySQL, and DB2. Relational databases employ a classic relational model, usually stored in two-dimensional tables, which are intuitive and easy to understand. When constructing a KG in banking system incidents, this study uses structured data as the basis and then expands on other data.
2. Data from various industry websites is semi-structured, often specialized, and typically exhibits better data consistency and integrity. The information is described as belonging to a specific field. Owing to the semi-structured nature of website content, it is usually only necessary to

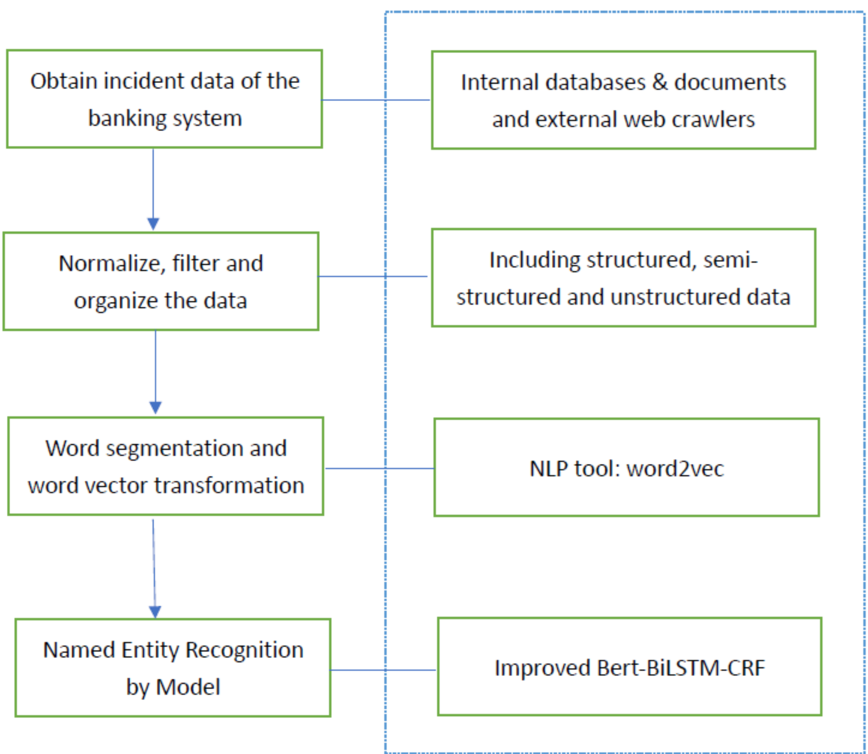
Table 2. The key knowledge elements of the banking system incident

Type	Name	Example Data
Entity	Incident	Double deposit
	System	Settlement system
	Owner	David & Stephen
	Department	Settlement & Internet Financial
	Change	Monthly upgrade of 03/2022
Relationship	rAci-Sys	Double deposit, r, Settlement system
	rAci-Own	Double deposit, r, David & Stephen
	rOwn-Dep	David & Stephen, r, Settlement & Internet Financial
	rAci-Dep	Double deposit, r, Settlement & Internet Financial
	rAci-Cha	Double deposit, r, Monthly upgrade of 03/2022
	rSys-Cit	Settlement system, r, HongKong
Attribute	Time	01/04/2022
	Description	Customer receives double transfer amount
	Reason	Settlement system bug
	Loss	HKD 100 million

parse it according to its structure when extracting knowledge from particular tags. For example, corresponding semantic tags can be extracted when acquiring industry data using web crawlers.
3. Sources such as manuals, standards, norms related to banking system incidents, internet pages, open-linked data, open knowledge bases, online encyclopedias, and specific structured data fields in databases contain a substantial amount of textual data. Extracting knowledge from text is challenging due to its unstructured nature. The automatic identification and extraction of domain knowledge can be realized using natural language processing–related technologies.

The first step in learning, using unstructured text data as an example, is identifying entities in the text (Yu et al., 2005). Common entity recognition techniques include methods based on dictionaries and rules, statistical machines, and deep learning. Dictionary- and rule-based methods require establishing a naming dictionary and rule templates to obtain entity names that are appropriate for knowledge extraction from text, given its distinct natural language expression characteristics. Machine learning–based methods must perform statistical analysis on the text corpus for knowledge acquisition and select feature sets that can effectively reflect entity characteristics, such as word, context, dictionary, part-of-speech, stop word, core word, and semantic features. The entity recognition model is obtained through training, and this method has a strong dependence on the corpus. Deep learning–based approaches possess powerful sequence modeling capabilities, effectively capture context information, and are able to fit into neural networks non-linearly. Given that neural networks often utilize vectors as inputs, this method involves word vector conversion. This study provided a better model for entity recognition based on improved BERT-BiLSTM-CRF. The process is shown in Figure 3. To summarize the process briefly: different types of data, both internal and external

Figure 3. Named entity recognition process based on improved BERT-BiLSTM-CRF model



to banking incidents, are classified and filtered. Word segmentation and vector transformation are performed using the NLP tool, word2vec. Finally, the improved BERT-BiLSTM-CRF model is used for entity recognition.

Improved BERT-BiLSTM-CRF Model

Several state-of-the-art models, including CRF, BiLSTM, BiLSTM-CRF, and BERT-BiLSTM-CRF, are compared. Even though these models are based on deep learning, it is observed that the input word vectors are static and do not fully capture the properties of word vectors in different contexts, which can impact the accuracy of named entity extraction. Therefore, this paper proposes an improved BERT-BiLSTM-CRF model for entity recognition.

In the traditional BERT model, although the MLM task can learn and output word vectors containing contextual information, there are still some drawbacks. The MLM task is trained with word-level masks, which isn't conducive for learning a comprehensive word representation. Therefore, this paper attempts to use a whole-word mask for training and adjusts the training ratio, as depicted in Table 3. It can be seen from the table that the whole word mask method replaces a complete word with a MASK label instead of a word, which is more in line with the Chinese word formation method and helps to improve the effect of the pre-training task.

In the original sentences, words that were erased were replaced by a special symbol, [Mask], in 80% of instances, replaced with a random word in 10% of instances, and left unchanged in the remaining 10%. The main reason for this is that the [Mask] token will not appear in the sentence in the subsequent fine-tuning task, and another advantage of this is that when predicting a word, the model does not know whether the word in the corresponding position is correct or not (10% probability), which forces the model to rely more on contextual information to predict vocabulary, and gives the model a certain error correction ability.

To enhance the training effect, this paper attempts to increase the training ratio of [Mask] from 80% to 90%, while reducing [Random] and [Unchanged] from 10% to 5% each. After comparison with the original model, it's found that the adjusted ratio and "full word mask and training" are more suitable for recognizing entity names in banking system incident texts, leading to improved recognition effectiveness.

Table 3. The Example of new method (adjust training ratio and full word mask and training)

Original Masked Language Model	Improved Masked Language Model
A special symbol [Mask] used to replace words in 80% of cases	A special symbol [Mask] used to replace words in 90% of cases
A random word used to replace words in 10% of cases	A random word used to replace words in 5% of cases
The original words remained unchanged in the remaining 10% of cases	The original words remained unchanged in the remaining 5% of cases
Individual word mask and training	Full word mask and training
Example: 银行因存储磁盘[Mask]读写严重延时[Random],造成生产数据库[Mask]损坏,导致存取款[Mask]、网银等业务中断[Unchanged]37个多小时。	Example: 银行因存储磁盘[Mask]读写严重延时[Random],造成生产数据库[Mask]损坏,导致存取款[Mask]、网银等业务中断[Unchanged]37个多小时。
Translation: Due to the serious delay in reading and writing of storage disks, the production database was damaged, resulting in the interruption of deposits and withdrawals, online banking, and other services for more than 37 hours.	Translation: Due to the serious delay in reading and writing of storage disks, the production database was damaged, resulting in the interruption of deposits and withdrawals, online banking, and other services for more than 37 hours.

EXPERIMENTAL VALIDATION

Experimental Dataset

Over the past three years, more than a thousand banking system incidents have been compiled for this study. As indicated in Table 4, the dataset consists of a total of 5,051 entities, with the experimental corpus comprising approximately 60,000 words. Sample data can be viewed in Table 2, while the relationships between incidents and other concepts or attributes are illustrated in Figure 2. Table 4 presents a statistical summary derived from the analysis, showing key entities and their counts across different categories. This data will be utilized for named entity recognition and the construction of the knowledge graph.

The NER Model Evaluation Index

In the field of NER, precision P, recall R, and F1-measure are generally recognized to evaluate the performance of models. Each evaluation index is calculated as follows:

$$P = \left(\frac{a}{B}\right) \times 100\%$$

$$R = \left(\frac{a}{A}\right) \times 100\%$$

$$F1 = \left(\frac{2PR}{P+R}\right) \times 100\%$$

where a is the number of correctly identified entities, A is the total number of entities, and B is the number of identified entities. Precision P was used to assess the accuracy of the model extraction of entities, and the recall R was used to assess the comprehensiveness of the model extraction of entities. When the two metrics are inconsistent, the two harmonic mean, $F1$ is further used to evaluate the effect of the model on identifying entities.

Model Building and Parameter Setting

The NER model is constructed using TensorFlow, a model-building tool. TensorFlow is a framework developed by the Google AI team for various deep learning algorithms. Table 5 displays the results achieved under various combinations of parameters, with Group 1 being identified as the best.

Table 4. The entities of the experimental corpus

Entity Category	Quantity	Key Related Entities	Number of Related Entities
Incident	925	Reason, Loss	4
System	63	Owner, Department	2
Owner	29	System, Change	2
Department	11	System, Change	2
Change	329	System, Time	3
Time	972	Incident, Change	2
Description	1,000	Incident, Change	2
Reason	817	Time, Incident	3
Loss	905	Time, Incident	3

Table 5. The experimental results under different combinations of parameters

Parameter	Value (Group 1)	Value (Group 2)	Value (Group 3)
seq_length	128	64	180
batch_size	24	12	36
epoch	15	10	20
learning_rate	0.00002	0.00002	0.00002
dropout	0.5	0.5	0.5
Result	**Value (Group 1)**	**Value (Group 2)**	**Value (Group 3)**
P	96.75%	94.68%	93.71%
R	85.72%	82.39%	84.52%
F1	90.90%	88.11%	88.88%

Reasonable Division of the Experimental Corpus

In addition to the 8:1:1 ratio, the experimental corpus is also divided into training, validation, and test sets in a 6:2:2 ratio to examine the effects of different proportions. For the set of 1,000 incident materials, comparative experiments were conducted using the improved BERT-BiLSTM-CRF model, with results presented in Table 6. As can be seen from the table, the P, R, and F1-measure obtained by using the 6:2:2 ratio are significantly lower than the results obtained by using the 8:1:1 ratio, indicating that it is reasonable to divide the experimental corpus according to the 8:1:1 ratio.

Comparative Analysis of the Overall Model Identification Effect

Five different experiment sets were conducted to compare the overall entity identification effectiveness of various NER models. Considering the cases of the 1,000 incidents mentioned above and dividing the experimental corpus into the training, validation, and test set in an 8:1:1 scale, the experimental results are shown in Table 7.

Table 6. The experimental results under different experimental corpus division ratios

Different Experimental Corpus Division Ratios	P(Total)	R(Total)	F1(Total)
6:2:2	92.49%	84.15%	88.12%
8:1:1	96.75%	85.72%	90.90%

Table 7. The comparison of different named entity recognition models

Model	Disadvantage	P	R	F1	Number of Entities Identified
CRF	Rely on corpus and features; slow convergence	83.16%	81.29%	82.21%	4106
BiLSTM	Parameter tuning is complicated; easy to overfit	82.15%	80.17%	81.15%	4049
BiLSTM-CRF	Poor short word recognition; complex parameter tuning	88.28%	81.55%	84.78%	4119
BERT-BiLSTM- CRF	Not conducive to learning a complete word representation	95.59%	82.36%	88.48%	4160
Improved BERT-BiLSTM- CRF	Relies on extensive text training and validation	96.75%	85.72%	90.90%	4330

As can be seen from Table 7, F1 of the BiLSTM-CRF model is 3.63% higher than F1 of the BiLSTM model, indicating that the CRF model improves the overall recognition effect after considering the constraint relationship between word labels. After adopting the BERT-BiLSTM-CRF model, F1 is enhanced by another 3.7%, indicating that the dynamic word vectors containing contextual semantic information obtained by the BERT model greatly improved overall recognition ability. After combining the improved BERT model, the F1 of the improved BERT-BiLSTM-CRF model proposed in this paper is 2.42% higher than the F1 of the BERT-BiLSTM-CRF model, which shows that training by changing "Individual word mask and training" to "Full word mask and training" can promote better understanding of the semantic information of the text, thereby further improving the overall recognition ability of the model.

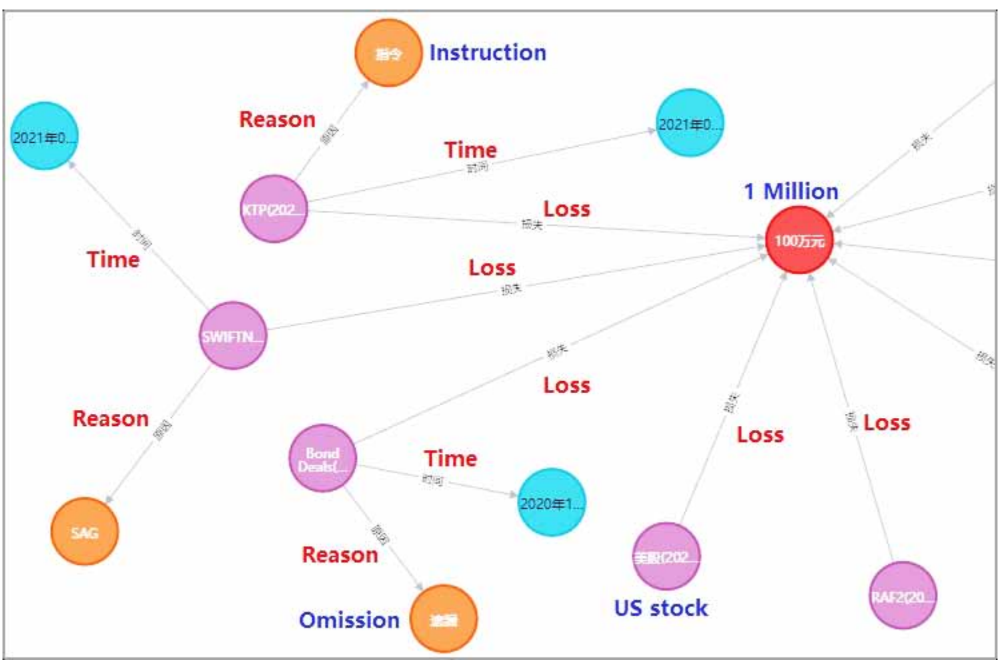
Knowledge Storage Based on Neo4j Graph Database

Knowledge extracted through various methods is stored in a specific physical structure. Currently, KG storage methods mainly adopt a traditional relational database, RDF (request definition file) triple, and graph database. Among these, the "graph" data structure is an ideal management tool for KGs, as it can efficiently handle the operations of various complex relationships and is utilized for graph database storage (Junsang et al., 2023).

According to the graph database management system (DB-Engines Ranking of Graph DBMS), Neo4j is the most popular graph database software developed by the Neo4j Company. It stores graph structure data with nodes and relationships as objects. This study uses Neo4j tags to store the knowledge related to banking system incidents and to identify entities and relationship types related to these incidents.

The Neo4j graph database provides a Cypher tool to operate graph data, use the Load comma separated value (CSV) command to complete a batch import of banking system incident data, and initially establish a banking system's incident KG. Figure 4 shows the nodes corresponding to the same entities in a unified style. The figure shows that the purple circles represent incidents, each of which corresponds to a reason, time, and loss. As the loss associated with each of these incidents is

Figure 4. Sample knowledge graph of bank system incidents



the same amount of 1 million (as indicated by the red circle), they are connected to one another. This graph facilitates the analysis of incidents that share common characteristics.

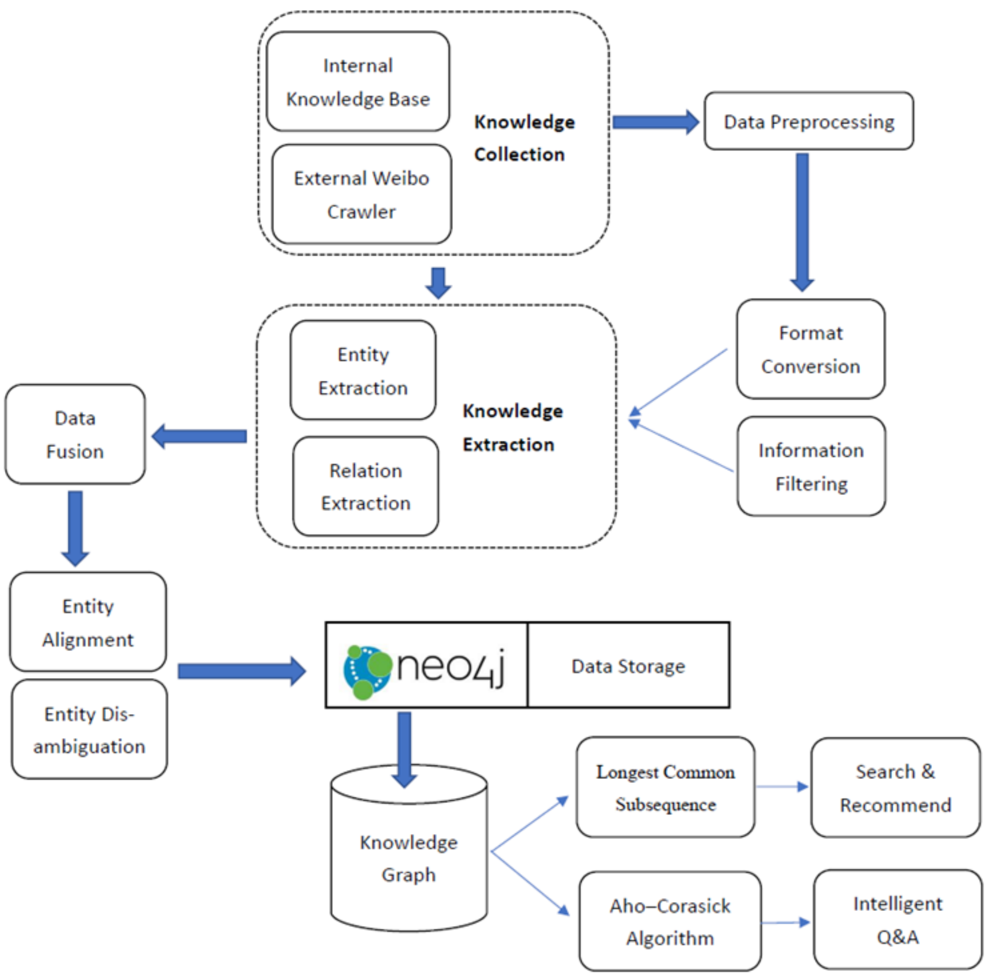
Incident Analysis of Banking Systems Based on Knowledge Graph

Based on the established knowledge graph (KG) of the banking system's incidents, the Cypher tool provided by Neo4j allows us to quickly gather relevant knowledge, enabling multi-dimensional and multi-level incident statistical analysis. Figure 5 illustrates the process of incident analysis based on the banking system's KG.

The process involves several steps, starting with the collection of both internal and external knowledge. Then, the data is processed, formatted, and filtered for relevant information. The next step is the extraction of knowledge, followed by data fusion, alignment of entities, and disambiguation. The process culminates in the creation of a knowledge graph using the Neo4j tool. Finally, the specified algorithms are used for search recommendations and intelligent question-answering.

The KG of the banking system's incidents can offer comprehensive data support for specific analysis tasks like incident classification and query, statistical analysis, and correlation analysis,

Figure 5. The incident analysis process of banking systems based on KG



thereby enabling multi-dimensional and multi-level incident analysis. The analysis results can be visually displayed.

Association Path Analysis

Within the same KG, a path is established through one or more relationships between entities. Based on the association path, various semantic searches and intelligent question-answers can be realized, and a visual interpretation path can be provided (Sukviboon & Yenradee, 2023). For instance, as shown in Figure 6, searching for the "account opening" incident returns all related information, including different time points of the incident, reasons for each event, and incurred losses, thereby demonstrating potential correlations. The association path facilitates the rapid identification of reason and losses of future incidents, thereby enabling expedited response measures to be taken, ultimately reducing the impact of accidents and mitigating loss for the bank.

Intelligent Enquiry

In the traditional keyword-based standard normative article retrieval method, relevant articles can only be retrieved when the search term appears in the article. However, due to the diversity of natural language expressions, the recall and precision rates of this method are low (Xia et al., 2011). Additionally, the lack of links between normative clauses limits the search results. An intelligent inquiry, based on the KG, can procure more accurate knowledge content by understanding the semantics of the search information, and can broaden the scope of search results when combined with the interconnections within the knowledge (Callaghan, 2017). Based on the traditional search, intelligent search first performs semantic analysis on user search requests, maps them to entities or KG attributes, and then returns structured knowledge to users according to the KG's semantic network. The basic process is shown in Figure 7. The process comprises four steps, with each step corresponding to the use of a tool on the right-hand side. The entire process is briefly outlined as follows: firstly, input the search keywords, then perform entity recognition based on the trained model. Next, use

Figure 6. Sample visual display of association path analysis results for "account opening"

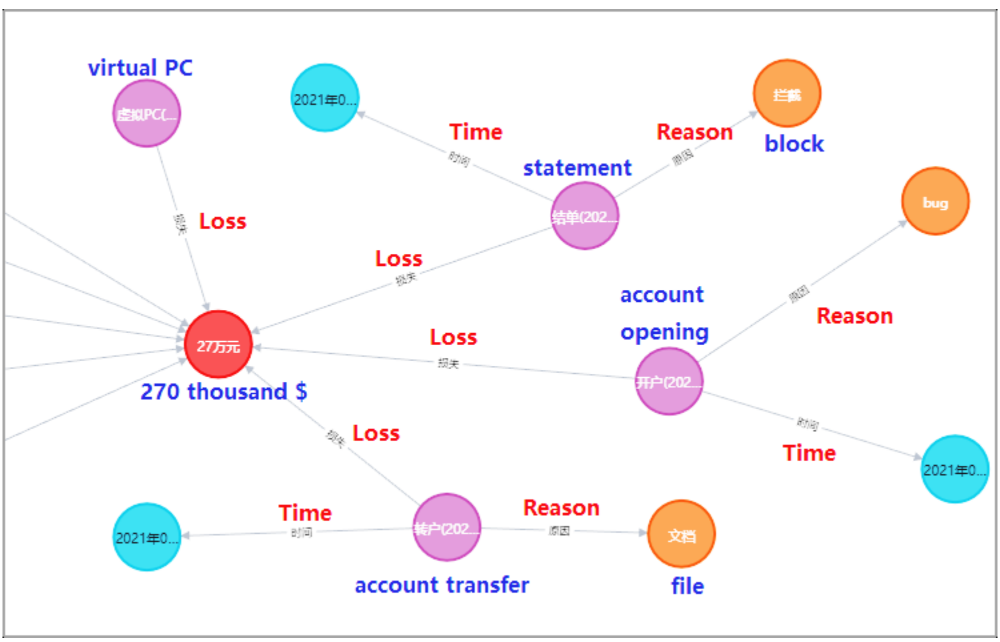
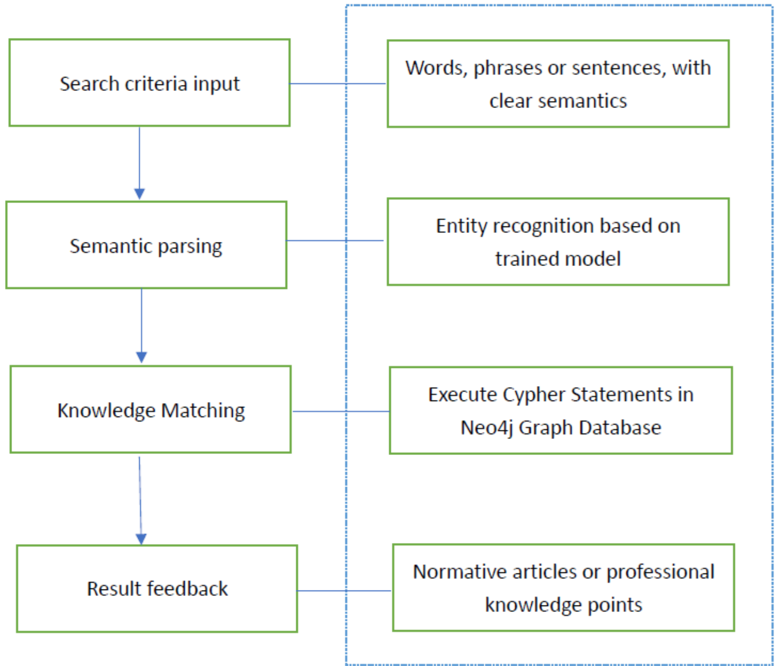


Figure 7. The basic process of intelligent search



the Cyber tool to perform knowledge matching on the Neo4j graph database. Finally, provide result feedback based on professional knowledge points.

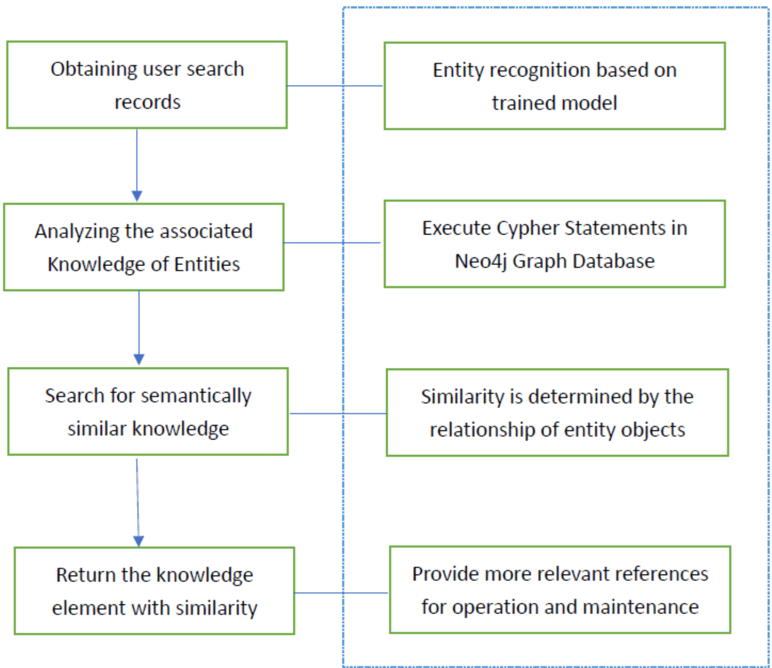
Knowledge Recommendation

Users control the knowledge acquisition process, primarily through knowledge retrieval, and actively provide knowledge requirements via an interactive interface. However, with the sharp increase in industry knowledge, users may not know the knowledge they lack. Knowledge recommendation is another significant method of knowledge acquisition. It is dominated by computers, automatically acquires user behavior characteristics, focuses on analyzing the core knowledge elements contained in the normative knowledge concerned, and actively provides a list of potentially interesting knowledge. The basic process is shown in Figure 8. The process can be briefly outlined as follows: firstly, obtain the user's search history based on the trained model. Next, use cyber tools to search for related knowledge entities on the Neo4j graph database. Similarity analysis is based on the degree of association between entities. Finally, make knowledgeable recommendations based on the results of the similarity analysis.

CONCLUSION

In the field of banking system incidents, publicly annotated datasets are lacking, and related research is still in its infancy. Although KG technology has been applied in the fields of incidents in different industries such as subways, coal mines, and construction, it has not yet included the field of incidents in the banking system. This paper is the first to apply KG technology to banking system incidents, compiling over 1,000 banking system incident materials to form an experimental corpus. To address

Figure 8. The basic process of knowledge recommendation



the issue where static word vectors fail to fully capture the characteristics of word vectors in varying contexts, this paper proposes the improved BERT-BiLSTM-CRF model, which yielded precision (P), recall (R), and F1-measure results of 96.75%, 85.72%, and 90.90% in experiments, respectively. This represents a 2% to 9% improvement over state-of-the-art models such as CRF, BiLSTM, BiLSTM-CRF, and BERT-BiLSTM-CRF. In addition, the concept of intelligent knowledge support is proposed in this paper for the first time based on the problem of incident risk management in the banking system, and related artificial intelligence technologies such as KGs are introduced. Then, a theoretical model of intelligent knowledge support based on KGs is constructed.

However, the experimental corpus used in this paper does not fully encompass the range of bank risk incidents, highlighting the need to expand the number of experimental corpora; moreover, incident knowledge has not been closely combined with rules, regulations, and maintenance manuals. Future studies on knowledge reasoning and incident text specification must be conducted to maximize the value of incident KGs.

ABBREVIATIONS

1. **KG:** Knowledge Graph
2. **NER:** Named Entity Recognition
3. **HMM:** Hidden Markov Model
4. **MEM:** Maximum Entropy Model
5. **SVM:** Support Vector Machine
6. **CRF:** Conditional Random Fields
7. **LSTM:** Long and Short-Term Memory Network

8. **BiLSTM:** Bidirectional Long Short-Term Memory
9. **BERT:** Bidirectional Encoder Representation from Transform
10. **MLM:** Masked Language Model
11. **NSP:** Next Sentence Prediction
12. **ERD:** Entity Relationship Diagram
13. **RDF:** Request Definition File
14. **CSV:** Comma Separated Value

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