Construction of a Knowledge Graph for Conflict and Dispute Events Based on Multimodal Data

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Abstract. The research presented in this article focuses on the construction of a Knowledge Graph for contradictory dispute events, leveraging multimodal data. A Knowledge Graph is a structured knowledge base composed of entities and their interrelations, enriched with extensive semantic information and reasoning capabilities. This particular Knowledge Graph is built upon diverse modalities of data sources, including images, texts, and structured data, specifically tailored for the domain of contradictory disputes. The primary objective of the study is to scientifically manage such disputes by mining and analyzing the information embedded in the data. This approach facilitates intelligent detection, assessment, early warning, and personnel alerts for various types of contradictory dispute events. The research significantly contributes to the effective handling and resolution of conflicts in the public security domain, offering robust support through advanced data-driven insights.

Keywords-conflict and dispute; knowledge graph; multimodal data.

1 Introduction

The field of conflict resolution involves a large amount of multimodal data, including unstructured data such as text, images, videos, and audio, in addition to structured data [1]. This includes text data from sources such as 110 emergency call records, case files, and petition records. Currently, law enforcement agencies lack effective utilization of these unstructured data, relying on manual operations, and there is an urgent need to fully develop and extract semantic information from them. Furthermore, existing structured data is often treated as simple element lists without emphasis on relative relationships, lacking in-depth analysis and processing. During data retrieval, the matching is performed without understanding, resulting in low query efficiency.

To address these issues, this article combines the work of conflict resolution with the three-year plan for the technological development of policing. In response to the demand for analysis of massive conflict resolution data, the research develops multimodal data collection and processing technologies. It constructs a knowledge graph for conflict resolution events based on multimodal data, facilitating the transformation of data into knowledge. Subsequently, a set of applications related to conflict resolution is developed based on this knowledge graph, greatly enhancing the law enforcement's ability to discover and resolve conflicts.

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In the construction of the knowledge graph for conflict resolution events based on multimodal data, the article leverages the law enforcement big data platform to aggregate and process structured and unstructured data such as 110 emergency incidents, collaborative case handling, personnel labels, personnel files, key populations, phone numbers, and vehicles. This forms the data support for the knowledge graph. Using the data foundation, the graph is modeled, and knowledge is extracted from the basic data to form triple knowledge data involving entities and relationships. The knowledge is then fused around individuals and events to form the prototype of the knowledge graph. Based on this prototype, knowledge reasoning is applied, ultimately creating a comprehensive multimodal knowledge graph for conflict resolution that encompasses individuals, events, objects, organizations, time-space, virtual identities, and their relationships.

Building on the knowledge graph, the article develops a series of warning models, such as a domestic violence dispute risk scoring model and a family dispute risk scoring model. Furthermore, it constructs functionalities including dispute-related retrieval, dispute person profiles, dispute detection and warning, and dispute traceability analysis, empowering various business scenarios in the relevant field.

2 Knowledge graph construction

The concept of the Knowledge Graph [2] was initially introduced by Google in May 2012 with the aim of improving the quality of search results, enhancing the capabilities of search engines, and providing users with a better search experience. The Knowledge Graph is essentially a graph structure, where nodes represent entities, edges represent relationships between entities, and node properties correspond to entity attributes. Knowledge, being the advanced product of data, allows machines to move beyond statistics-driven data analysis, enabling them to develop cognitive abilities similar to humans. This facilitates not only machine "knowing" but also "understanding," surpassing the effectiveness ceiling of data-driven methods.

In recent years, significant progress has been made in the fields of Natural Language Processing (NLP) and Information Extraction (IE), providing valuable insights for the development of more intelligent and adaptive natural language processing systems. This paper conducts an in-depth review of several representative works to comprehensively understand the current trends and key technologies in these domains.

To begin with, our focus extends to the domain of open-source frameworks, where Bocklisch et al. [5] introduce Rasa, an open-source framework designed to facilitate the development of conversational agents and chatbots. This framework opens up possibilities for widespread collaboration and innovation. Following this, Kan et al. [6] propose a unified generative framework based on prompt learning, addressing diverse information extraction tasks through prompt-based approaches and demonstrating its effectiveness in extracting structured information from unstructured data.

In the realm of general information extraction, Liu et al. [7] introduce Rexuie, a recursive method with an explicit schema instructor to achieve universal information extraction. Additionally, Lu et al.[8] put forward UniEX, a unified information extraction framework based on a span-extractive perspective, emphasizing its effectiveness and efficiency in handling diverse information extraction tasks.

For few-shot learning, Lu et al. (2022) [9] design a Unified BERT model for natural language understanding with limited training data, overcoming challenges associated with using pre-trained models. Simultaneously, Yan et al. (2023) [10] propose UTC-IE, a unified token-pair classification architecture, showcasing its effectiveness across various natural language processing tasks.

In the domain of entity and relation extraction, Zheng et al. [11] introduce a novel tagging scheme to enhance the accuracy of joint extraction of entities and relations. Furthermore, Yin et al. (2020)devise an entity relation extraction method based on the fusion of multiple information and attention mechanisms, effectively capturing diverse information.Yin et al. (2020) demonstrate an enhanced method for entity relation extraction that leverages a fusion of multiple information sources and attention mechanisms to improve accuracy[12].

Moreover, research on knowledge graph construction has gained considerable attention. Yu et al.[13] provide a summary of knowledge extraction technologies oriented towards knowledge graph construction, emphasizing their significance in building and enhancing knowledge graphs. Lastly, Al-Moslmi et al.[14] offer a comprehensive review of named entity extraction for knowledge graphs, covering the latest technologies and challenges faced.

In conclusion, these studies collectively contribute to the ongoing development of NLP and IE, laying a solid foundation for the construction of more intelligent and adaptive natural language processing systems.

2.1 Data support

In recent years, law enforcement agencies have accumulated massive, heterogeneous, and dynamic data in their big data initiatives. However, there is a lack of effective ways to express, organize, and manage this data, leading to a medium-level informatization trap and hindering the progression towards intelligent law enforcement. Introducing the Knowledge Graph into the field of law enforcement not only consolidates and integrates fragmented information accumulated over the years but also aligns with the practical situation of law enforcement agencies, which primarily focus on relationships between individuals.

The theme map of social contradictions and disputes is based on a knowledge graph, combined with domain themes for the organization and representation of knowledge within the domain. Through the algorithms of the knowledge graph, the goal is to explore the latent semantic relationships and feature patterns of knowledge in the field of social contradictions and disputes. It focuses specifically on constructing two types of theme maps: one for the content themes of conflict and dispute information and another for event themes [15]. The research directions for the theme map of social contradictions and disputes are as follows:

Content Theme Map of Social Contradictions and Disputes,

Utilize topic mining and identification models to classify themes related to social contradictions and disputes on social media platforms. Construct a social contradiction and dispute theme map with core elements such as theme categories and user relationships [16]. Investigate the features and correlations of content related to social contradictions and disputes by detecting overlapping semantic communities and influential members within the theme map [17].

Event-Centric Knowledge Graph of Social Contradictions and Disputes:Focus on modeling, extracting, and detecting events related to social contradictions and disputes. Employ methods for automatically constructing a knowledge graph centered around events, extracting knowledge from data sources such as news articles to enhance users' interpretation of conflict events [18]. Use knowledge graph models to decompose conflict events, represent temporal relationships, and build an automated system for a knowledge graph of social contradiction and dispute events [19].

Learning Topic Labels for Contradiction and Dispute Events,Learn topic labels for events related to social contradictions and disputes. Use semantic features of text and intrinsic event relationships to improve the accuracy of event detection, making key information related to conflict events more easily identifiable [20].

Addressing the issue of diverse sources of conflict resolution data, the research explores multimodal data collection and aggregation technologies. Leveraging the law enforcement big data center, the study efficiently aggregates both structured and unstructured data related to conflict resolution from internal and external sources, forming the data support for the knowledge graph of conflict resolution events. This includes:

Internal proprietary resources: 110 emergency incident data, confidence data for phone numbers, data on individuals with specific types of previous convictions, collaborative case data, courier data, hotel accommodation data, household registration data, and ride-hailing accommodation data, among others. All of these data are Chinese text data.

Civil affairs marriage data.

Litigation data such as court acceptance and filing.

Mental health patient data from health commissions.

Special care population data from political and legal affairs committees.

Social security data from the human resources and social security bureau.

Provident fund data from the provident fund management center.

Data from the 12345 mayor's hotline.

Petition data.

Sensitive item online purchase data from internet platforms, and so on.

2.2 Graph construction

Structured conflict resolution data needs to undergo transformation into knowledge. Constructing a knowledge graph of conflict resolution is the optimal implementation for building a conflict knowledge base. It truly achieves the integration and correlation of a diverse conflict knowledge base and diverse conflict resolution data in both physical storage and logical relationships. The use of a graph structure, most in line with human thought patterns, is crucial for the unified management of data and knowledge. Based on the aggregated, processed conflict resolution data (including structured and unstructured text data) from internal and external law enforcement sources, the construction of a multimodal knowledge graph for conflict resolution events involves six steps: ontology design, data preprocessing, knowledge extraction, knowledge fusion, knowledge reasoning, and graph knowledge mapping storage [3].

2.3 Ontology design

Research on foreign domain ontology construction: Chi et al. developed a foundational domain ontology for supporting information retrieval tasks based on a continuously expanding collection of reference literature [21]. Beirade et al. constructed an ontology for the Quran based on semantic relationships between terms, aiming to extend the semantic retrieval of Quranic texts [22]. Italian archival professionals utilized the EAC-CPF ontology based on archival record standards to achieve retrieval and utilization of European archival linked data.

Navarro et al. proposed an ontology framework to model relationships between Android applications and system elements, employing machine learning to analyze the resulting complex network for the analysis and identification of malicious software [23]. Yang built a logistics financial risk ontology model, incorporating association inference rules and the Apriori algorithm into a knowledge ontology database for self-learning and support correction [24].

Moran et al. used machine learning algorithms and a web ontology to generate traceable, interoperable, and observation-based classification outputs for multi-source classification of nature reserves [25]. The International Council on Archives (ICA) introduced the OWL ontology RIC-O, offering a universal vocabulary and formal rules for creating RDF datasets that describe any type of archival record resource consistently. It supports publishing RDF datasets as linked data, using SPARQL queries, and employing ontological logic for inference [26].

Ontology is an abstract model that describes the objective world [4] and formally defines concepts and their interrelationships within the knowledge graph. The knowledge graph consists of entities, relationships between entities, and entity attributes, with the basic structure being a triple <entity, relationship, entity>. The complex interconnected network of basic structures forms the knowledge graph. Correspondingly, ontology design comprises entity design, relationship design, and attribute design, ultimately forming the model layer of the knowledge graph.

Regarding entity design, six major entity categories were designed for the multimodal knowledge graph of conflict resolution events, namely individuals, events, objects, organizations, virtual identities, and space-time. The specific design is outlined, derived from the aggregation and analysis of data from sources such as law enforcement networks, government networks, the internet, and industry-specific networks, covering data related to natural person social activities, online activities, financial activities, and more.

In terms of relationship design, by analyzing attribute connections, space-time connections, semantic connections, and feature connections between entities, a total of 53 categories of mutual relationships, including person-person, person-event, event-event, person-object, and others, were designed for the multimodal knowledge graph of conflict resolution events. Ultimately, this resulted in a comprehensive interconnected network composed of individuals, events, space-time, objects, and organizations.

In terms of attribute design, entities were supplemented and enriched by introducing five categories of conflict resolution attributes: basic attributes, social attributes, economic attributes, behavioral attributes, and risk attributes. In addition to the primary attribute serving as the unique identifier of identity, a total of 83 attribute types were designed.

2.4 Data preprocessing

In the construction process of the multimodal knowledge graph for conflict resolution events, four types of data commonly used in law enforcement work are primarily utilized: structured data, text data, image data, and audio data. Structured data undergoes integration, aggregation, governance, and verification through the law enforcement big data platform, forming resource and thematic libraries, which are then mounted in a globally unified data resource catalog. Unstructured data includes text data, image data, and audio data. For text data, natural language understanding (NLU) and natural language generation (NLG) [27] are employed for standardization, expansion, error correction, translation, and other preprocessing steps. Image and audio data are primarily transformed into text data using OCR and ASR technologies based on Transformer [28], followed by further processing.

2.5 Knowledge extraction

Knowledge extraction [29] includes named entity recognition, relationship extraction, event extraction, and attribute extraction. To build the graph, it is essential to extract entity, relationship, and attribute information from multimodal data in both structured and unstructured formats. For structured data, a direct mapping-based extraction method is employed, where a single field serves as an entity or attribute, and fields in the same row are related to each other. For text data, entities, relationships, and attributes need to be extracted from the text, converting unstructured or semi-structured data into structured triplets.

This work adopts the UIE model [30] as the knowledge extraction model, which is a method for joint entity-relation (or attribute) extraction. It utilizes a Structural Schema Instructor (SSI) based on the schema plus input sentence method to automatically generate Structural Extraction Language (SEL). This approach fully leverages the interaction information and dependency relationships between entities and relations (or attributes) in the text. It unifies the extraction of entities, relations, and attributes in a single model, as illustrated in figure 1:

SSL serves as a prompt to guide the model in performing a specific information extraction task.

Results of different information extraction tasks can be represented as a specific SEL.

The model inputs SSL + Text and generates SLE, using a Seq2Seq sentence generation model for training.

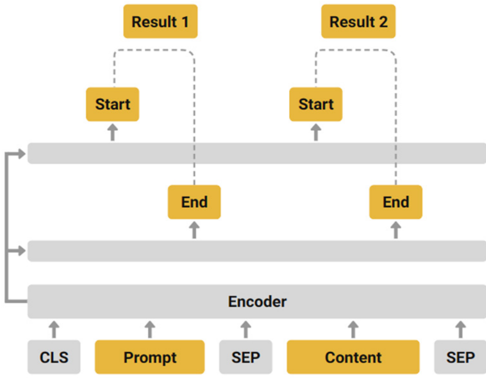

Figure 1. UIE Knowledge Extraction Model Technical Roadmap.

2.5.1 SSI(Structural Schema Instructor)

In the UIE model, SSI refers to the model's interaction with predefined schemas at the sentence level. SSI enhances the UIE model's ability to accurately extract key information from text, improving accuracy and efficiency. SSI involves adjusting the model architecture, such as introducing special attention mechanisms or graph networks, to consider predefined schemas while processing each sentence. SSI allows the UIE model to adapt its extraction strategies flexibly for various information extraction tasks. SSI improves model performance in tasks like named entity recognition and relation extraction.

To sum up, SSI enhances the UIE model's accuracy and adaptability in information extraction by improving the interaction between the model and predefined schemas.

2.5.2 SEL(Structured Extraction Language)

The label representation of the information extraction task is varied, some are represented by SBME, and some are directly represented by the start and end position. In this paper, for unified modeling, different IE(information extraction) task labels need to be encoded into a unified form. Therefore, a structured extraction language (SEL) is proposed,as illustrated in figure 2.

The IE structure can actually be reduced to two atomic operations:

Spotting: refers to the pieces of information that locate the target in a sentence, such as an entity or trigger word in an event.

Associating Associating: indicates a relationship between two different pieces of information. For example, the relationship between entity pairs or the role of events.

It can be seen that SEL has the following advantages:

Different IE structures are unified encoding, so different IE tasks can be modeled as the same text-to-structure generation process.

All the extracted results of a sentence can be expressed as the same structure effectively, and joint extraction can be carried out naturally;

The generated output structure is very compact, which greatly reduces the complexity of decoding.

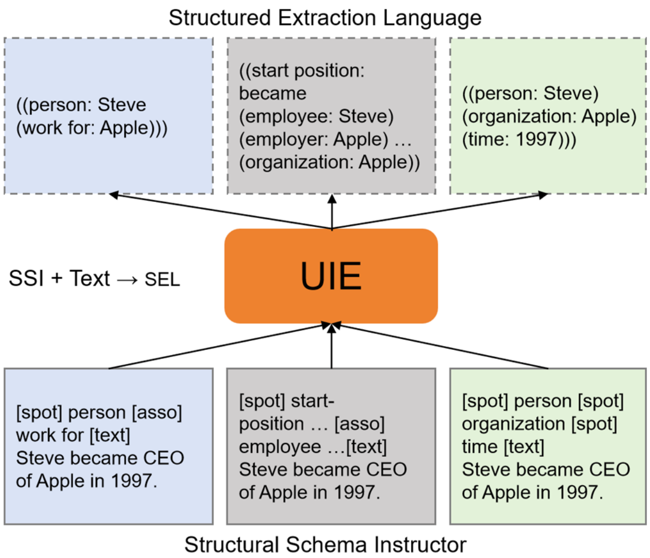

Figure 2. SEL frame diagram.

2.5.3 UIE(Universal Information Extraction)

Given the extraction type S of structured pattern and the sequence X of text, SEL structured information can be generated by UIE model. To wit:

$$y = \mathrm{UIE}(s \oplus x) \tag{1}$$

The specific input can be expressed as:

$$\begin{aligned} s \oplus x = \; & [s_1, s_2, \ldots, s_{|s|}, x_1, x_2, \ldots, x_{|x|}] \\ = \; & [[\text{ spot }], \ldots [\text{ spot }] \ldots, \\ & [\text{ asso }], \ldots, [\text{ asso }] \ldots, \\ & [\text{ text }], x_1, x_2, \ldots, x_{|x|}] \end{aligned} \tag{2}$$

The UIE model is essentially a standard Transformer, including Encoder and Decoder.Firstly, the SSI information and the sentence are concatenated and encoded by encoder, as follows:

$$H = \mathrm{Encoder}\left(s_1, \ldots, s_{|s|}, x_1, \ldots, x_{|x|}\right) \tag{3}$$

Where $s_1, \ldots, s_{|s|}$is the message and $x_1, \ldots, x_{|x|}$ is the sentence. Then, the extracted information is decoded by autoregressive method. As follows:

$$y_i, h_i^d = \mathrm{Decoder}\left([H; h_1^d, \ldots, h_{i-1}^d]\right) \tag{4}$$

First, define $D_{pair} = (x, y)$. for x, input: [spot] person [asso] work for [text]Steve became CEO of Apple in 1997. For y, input :(person: Steve(work for: Apple)). It can be found that in the process of generation, person and work for are sure to appear in the output. These two things are what we've defined as spotting and associating. The author found that if you add a loss to the generated token, it will be better to determine whether the current token is spotting or associating. The positive samples here are spotting or assocating, and the negative samples are random tokens. The losses are as follows:

$$\mathcal{L}_{\text{Pair}} = \sum_{(x,y)\in\mathcal{D}_{\text{pair}}} -\log\ p(y \mid x, s_{\text{meta}}; \theta_e, \theta_d) \tag{5}$$

Define an autoregressive loss:

$$\mathcal{L}_{\text{Record}} = \sum_{y\in\mathcal{D}_{\text{record}}} -\log\ p(y_i \mid y_{<i}; \theta_d) \tag{6}$$

In order to improve the semantic representation of UIE, the MLM task is also added. The losses are as follows:

$$\mathcal{L}_{\text{Text}} = \sum_{x\in\mathcal{D}_{\text{text}}} -\log\ p(x'' \mid x'; \theta_e, \theta_d) \tag{7}$$

Finally, these three kinds of losses are added together to carry out large-scale pre-training:

$$\mathcal{L} = \mathcal{L}_{\text{Pair}} + \mathcal{L}_{\text{Record}} + \mathcal{L}_{\text{Text}} \tag{8}$$

2.6 Knowledge fusion

Knowledge Fusion refers to the integration of descriptive information about the same entity or concept from multiple data sources, enabling the heterogeneous integration and disambiguation of knowledge from different sources under a unified standard[35].When constructing a knowledge graph for conflict and dispute events based on multimodal data, we encounter diverse and heterogeneous data sources varying in quality. This leads to a situation where seemingly different pieces of extracted knowledge might actually be different representations of the same knowledge. For instance, "Zhang San's spouse" and "Zhang San's wife" refer to the same entity. Therefore, it is necessary to merge and unify these different representations and granularities of contradictory and dispute knowledge, forming a richer, more accurate, and complete knowledge graph. Knowledge fusion, also known as entity alignment, involves integrating descriptions of the same real-world entity from different data sources into a single entity[31]. This process eliminates the redundancy caused by data heterogeneity, thereby improving the data quality of the knowledge graph and laying the foundation for knowledge sharing and semantic interoperability.

In this work, we employ a method based on equivalent relation reasoning, utilizing the edges in the linked data for equivalent reasoning. The equivalent parts of heterogeneous ontologies can directly substitute for each other. These equivalencies include those based on personal identifiers like ID numbers, phone numbers, and vehicle plate numbers, as well as those based on semantics and logic. For example, in dispute events lacking direct information like ID numbers or phone numbers, person information descriptions are aligned with a central person database. This fusion is achieved based on familial lineages and marital relationships. If "Zhang San's father" is implicated in a case, we use Zhang San's ID number or phone number to find his father's ID number and then merge his father with the case based on the ID number.

2.6.1 Knowledge reasoning

Knowledge extraction algorithms may fail to recognize certain relationships or attributes, and as knowledge information is continually updated, the knowledge graph itself inherently possesses a certain level of incompleteness. To ensure the accuracy and completeness of knowledge information, it is essential to continually update and refine the knowledge graph through knowledge reasoning techniques. Knowledge reasoning aids in relation prediction and completion, uncovering new knowledge and enriching the knowledge graph[32]. By utilizing a combination of rule-based reasoning and graph neural network-based reasoning methods, it is possible to automatically infer latent relationships between entities in complex, high-dimensional domain knowledge graph data, supporting predictive completion and associative recommendations.

In this work, we employ knowledge reasoning based on rules, link prediction, and graph classification algorithms. This reasoning capability encompasses relation and attribute reasoning, deeply mining graph information to complete various entities, relationships, and attributes in the domain knowledge graph, including people, events, objects, places, and organizations[33]. It also involves extracting and correcting ambiguous or erroneous information, thereby forming a broader, more in-depth, and precise knowledge structure. For relation reasoning, this includes relationships between people, people and organizations, people and objects, people and places, organizations and places, people and events, organizations and events, events and places. For example, in people-to-people relationship reasoning, if A is B's mother and B is C's mother, it is inferred that C is A's grandmother. In people-to-organization relationship reasoning, if A is employed at XX Technology Co., Ltd. and B is A's colleague, then B is inferred to be an employee of XX Technology Co., Ltd. In terms of attribute reasoning, updates include the existing attributes of people, events, objects, organizations, and places, such as personal information, organizational unit information, vehicle information, and location information. For instance, in updating personal information, if Zhang San (ID 0000) currently resides at Block 10, Unit 202, A Community, XX District, XX City (updated in 2022), and is found in an event to be residing at Block 20, Unit 1204, B Community, XX District, XX City (updated in 2023), this updates the attribute information of the individual.

2.6.2 Knowledge graph storage

In this work, we utilize NebulaGraph, a graph database, for storing the knowledge graph, as referenced in [34]. Compared to traditional relational data storage methods, NebulaGraph significantly enhances query efficiency. It supports a flexible design for graph-based storage, capable of handling ultra-large graphs with trillions of edges and billions of nodes while maintaining millisecond-level query latency. This capability is particularly effective in supporting the massive graph data storage requirements in the public security domain.

For data mapping and graph ingestion, we employ the NebulaExchange tool. After transforming data into a multifaceted conflict and dispute knowledge graph, we establish, store, and manage the field mapping relationships between the thematic and subject databases and the graph database knowledge model (including entity types, labels, events, and relationships). Based on these mapping relationships, executable data graphing tasks are constructed. Through task execution and management, the data graphing storage operations are completed, enabling the grounding of the knowledge graph in the graph database storage.

3 Experimental settings

Based on police information and case information, this work aims to extract important entity and relationship information from unstructured and semi-structured texts such as brief facts, alarm content and police dispatch content. This kind of information may be the key node of the atlas, supplementing and perfecting the content of the knowledge atlas, and playing an important role in practical applications such as case combination, research and judgment analysis, and early warning analysis. In this extraction, it is necessary to understand different semantic descriptions and extract key information, including conflict and dispute event behavior + six elements (person, time, place, cause, process, and result). According to the actual business requirements of data mining extraction, the extraction effect accuracy requirements of related extraction labels are given. Most entity extraction accuracy requirements of 85% or above, relationship extraction accuracy requirements of 80%.

3.1 Data acquisition and cleaning

The business data is sorted out, the non-standard text such as white space characters in the data is removed, duplicate data is deleted, and all kinds of conflict and dispute data samples are shown in Table 1. In this chapter, 80% of the conflict-dispute corpus is selected as the training set, 20% is the test set, and different conflict-dispute corpus sizes are used as inputs for performance evaluation and comparative experiments.

Table 1 The number of data samples of various types of conflicts and disputes.

Category of dispute	Subclass of dispute	Training set	Test set	Sum total
conflict and dispute	Family marriage emotional disputes	89679	22420	112099
	Neighborhood dispute	53151	13288	66439
	Life dispute	143764	35941	179705
	Noise dispute	133430	33358	166788
	Economic dispute	224030	56007	280037
	Consumption dispute	218322	54580	272902
	Labor dispute	94741	23685	118426
	Medical dispute	5781	1445	7226
	Education dispute	2082	521	2603
	Real estate dispute	1607	402	2009
	Disputes over land expropriation and demolition	5707	1427	7134
	Property ownership dispute	3602	900	4502
	Traffic dispute	44090	11023	55113
	Work dispute	15819	3955	19774

3.2 Chema design

Based on the business scenarios and characteristics of disputes, we designed a schema for dispute events. Taking traffic disputes as an example, the schema is illustrated in figure 3:

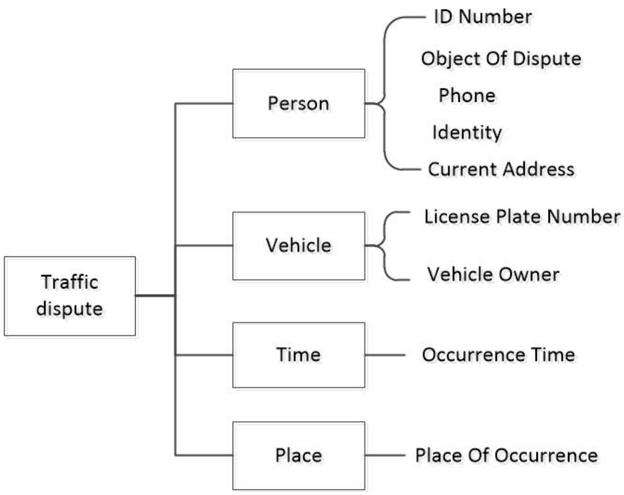

Figure 3. Schema of Dispute Events (Taking Traffic Disputes as an Example) .

3.3 Data annotation

In alignment with the predefined schema, labels are meticulously crafted and applied to business texts using the doccano labeling platform for data annotation purposes. To ensure a comprehensive representation, each label category is applied to approximately 100-150 sample data instances. Throughout the annotation process, it is imperative to intermittently conduct random quality inspections of the labels to ensure consistency and accuracy in the annotation. This approach facilitates a rigorous and systematic examination of the annotation quality, reinforcing the reliability of the data labeling process.

3.3.1 Training and evaluation of uie model

The marked data is processed to form a training set and sent into the UIE model for automatic training. In the training process, the model is optimized. The main tasks are as follows:

3.3.2 Boundary data inspection

The test set is used to conduct boundary check on the trained UIE model, that is, the UIE model is used to predict the data of the test set. The training set with a confidence level above 0.85 is directly verified, and the data with a confidence level below 0.5 is screened out and re-labeled for training.

3.3.3 Boundary data training

Put the re-labeled boundary data into the optimized UIE model and continue training until the model fits the boundary data.

3.3.4 Model optimization

In this work, the model stored in the original pytorch format is converted to ONNX format to improve the inference speed and compatibility of the model. The ONNX Runtime is a high-performance inference engine for deploying ONNX models to production environments, supporting both DNN and traditional ML models, and integrating with accelerators on different hardware.

3.3.5 Model evaluation indicators

Three basic evaluation indexes were used in the field of entity relationship extraction: Precision (P), Recall (R) and F1 Mesure. The accuracy rate refers to the proportion of the number of correctly identified information in the total number of identified information. Recall rate refers to the proportion of correctly identified information to the total number of existing information; The F1 score is a harmonic average of accuracy and recall. The calculation formula for each indicator is as follows:

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP+FP}} \tag{9}$$

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP+FN}} \tag{10}$$

$$\mathrm{F1} = 2 * \frac{\mathrm{Precision} * \mathrm{Recall}}{\mathrm{Precision+Recall}} \tag{11}$$

TP represents true cases (that is, the number of information extracted correctly), FP represents false positive cases (that is, the number of information extracted incorrectly), and FN represents false negative cases (that is, the number of information that exists but is not extracted).

3.3.6 Experimental results and evaluation

In this chapter, the performance of the optimized UIE model is evaluated and compared on the test set, and the extraction effect of the model is evaluated from the entity relation attribute, the overall sample extraction effect and the classification sample extraction effect dimension.

We selected several different Chinese pre-trained language models, including: MacBERT and UIE-BASE, and used the grid search method to tune the hyperparameters that affect the results of the training model, and found several optimal hyperparameters.

We will verify the quality of the multi-modal knowledge graph we constructed from the following different dimensions: first, compare the performance of the two models from the overall level, including the different entities involved in conflict and dispute scenarios and the relationships between these entities.

Table 2 offers an in-depth comparison of the MacBERT and UIE-BASE models, focusing on their performance across different learning rates, specifically 1e-5 and 5e-5. The analysis reveals a consistent pattern: under the same learning rate conditions, the UIE-BASE model outperforms MacBERT in terms of extraction capabilities. This superiority is particularly pronounced at a learning rate of 1e-5, where the UIE-BASE model reaches its peak performance, evidenced by an outstanding F1 score of 85.3%. This finding highlights the efficiency and effectiveness of the UIE-BASE model in processing data at optimized learning rates.

Table 3 offers a detailed examination of the UIE model's capabilities in extracting entities and delineating the relationships between them within dispute scenarios. Upon meticulous inspection of the table, one can observe that the majority of entity extractions have surpassed the noteworthy benchmark of 85% for acceptance, reflecting the model's remarkable precision.

Furthermore, the table reveals that the relationship extraction component has consistently achieved an acceptance index exceeding 80%, further underscoring the model's proficiency in capturing these crucial connections within the data.

Table 2 Comparison of extraction performance between uie model and macbert model.

Model	Hyperparameter	Learning_rate	Evaluation Indicators		
			Precision(%)	Recall(%)	F1 Score(%)
MacBERT	batch_size=16 epochs=30 warmup_rate=0.01 weight_decay=0.01	1e-5	89.66	83.07	86.24
		5e-5	85.40	82.35	83.85
UIE-BASE		1e-5	93.18	88.23	90.64
		5e-5	86.27	84.36	85.30

Table 3 Extraction effect of uie model on main entity relationship.

Category	**Evaluation Indicators**		
	Precision(%)	Recall(%)	F1 Score(%)
Person who called the police	95.52	89.51	92.42
Person who received the call	95.00	92.23	93.59
ID Number	91.53	92.65	92.09
Phone	94.24	80.00	86.54
Address	86.84	70.21	77.64
Organization	100.00	70.12	82.44
X's household registration	100.00	100.00	100.00
X's current address	96.67	93.55	95.08
Dispute object of X	92.78	78.95	85.31
Children of X	100.00	75.00	85.71
Spouse of X	80.24	73.52	76.73

Table 4 provides a detailed overview of the performance of the User Intent Extraction (UIE) model in identifying various types of disputes. The effectiveness of the model is not uniform across different dispute categories; it demonstrates superior performance in some areas while falling short in others. This variation in effectiveness can be attributed to the model's handling of smaller and more intricate data sets associated with certain types of disputes. Such data sets pose challenges in context comprehension and extraction efficiency, leading to inconsistent outcomes. The observed performance disparities underscore the necessity for ongoing enhancements in the UIE model, particularly in its ability to process and accurately interpret a wide range of complex and diverse dispute types. This improvement is crucial for ensuring the model's reliability and applicability in various real-world scenarios where understanding the nuances of different disputes is essential.

Table 4 Extraction effect of each dispute type.

Category of dispute	Subclass of dispute	Evaluation Indicators		
		Precision(%)	Recall(%)	F1 Score(%)
conflict and dispute	Family marriage emotional disputes	84.79	82.14	83.44
	Neighborhood dispute	90.46	88.47	89.45
	Life dispute	92.33	85.16	88.60
	Noise dispute	82.39	80.21	81.29
	Economic dispute	94.38	85.35	89.64
	Consumption dispute	90.70	88.70	89.69
	Labor dispute	66.63	94.21	78.06

	Medical dispute	62.45	50.13	55.62
	Education dispute	31.37	19.36	23.94
	Real estate dispute	97.04	53.72	69.16
	Disputes over land expropriation and demolition	56.15	43.13	48.79
	Property ownership dispute	99.40	96.49	97.92
	Traffic dispute	91.82	84.21	87.85
	Work dispute	97.15	86.17	91.33
	Total	93.18	88.23	90.64

Figure 4 shows the extraction performance of the UIE-BASE model and the MacBERT model respectively at different learning rates. It can be seen from the figure that the UIE-BASE model with a learning rate of 1e-5 has the highest accuracy and recall rate. Figure 5 shows the values of each evaluation indicator by the UIE model for different entity relationships.

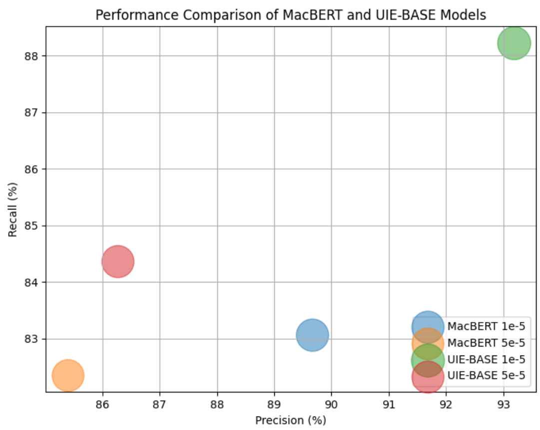

Figure 4. Performance Comparison of MacBERT and UIE-BASE Models.

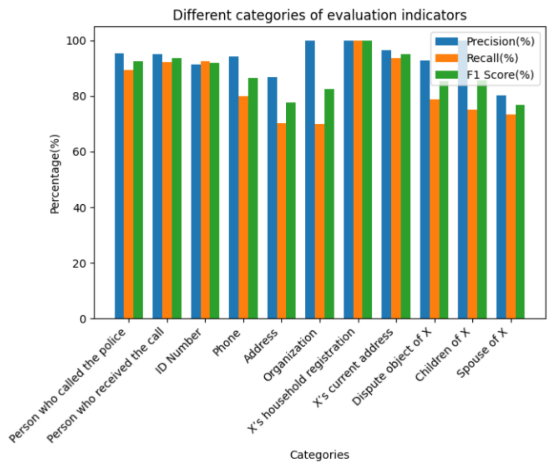

Figure 5. Bar chart of the results of UIE model in the extraction of entity relations in conflicts and disputes.

4 Knowledge graph application

4.1 Knowledge graph management center

The template is designed so that author affiliations are not repeated each time for multiple authors of the same affiliation. Please keep your affiliations as succinct as possible (for example, do not differentiate among departments of the same organization). This template was designed for two affiliations.

The knowledge graph management platform is utilized for comprehensive analysis of multifaceted conflict and dispute events, providing a foundation for tracing the causes of such disputes and facilitating their resolution. Specific applications include holographic archives, portrait analysis, graph factory, behavioral trajectories, relationship analysis, and associated dispute resolution. The holographic archives and portrait analysis enable the display of all information related to conflicts and disputes for multiple types of entities, such as people, events, locations, objects, and organizations. This comprehensive understanding of the background and current status of these entities supports risk assessment, resolution of conflicts and disputes, and the identification of risk events.

4.2 Intelligent question answering

Faced with the increasing complexity of dispute cases, traditional search results struggle to convey complex information. In the context of limited resources for law enforcement personnel, there is a growing demand for intelligent question-answering systems. In this work, we implement the RASA intelligent question-answering framework. Built upon a knowledge graph of conflict and dispute events based on multimodal data, the system, upon receiving input about a dispute event, automatically analyzes the case details. It then provides relevant mediation approaches and displays related similar cases and reference regulations. This assists users in effectively resolving conflicts and disputes from both legal and practical perspectives.

4.3 Plan recommendation

To achieve intelligent interaction with users, enhance the user experience, and reduce the difficulty of acquiring knowledge in the field of conflict and dispute, this work focuses on semantic parsing of user queries. Utilizing algorithms such as knowledge graphs and large models, the system generates graph representations, knowledge cards, charts, or textual answers, and recommends relevant laws, regulations, and similar cases. In this project, the recommendation of contingency plans is based on collaborative filtering methods, including event-based and contingency-plan-based collaborative filtering. The former assumes that events have similar handling methods and recommends contingency plans by analyzing the similarity between events. The latter assumes that contingency plans have similar characteristics and provides recommendations by analyzing the similarities among the plans.

4.4 Conflict monitoring and early warning

In the face of many problems such as new conflicts and disputes that may involve key personnel, complex types of conflicts and disputes, and limited personnel for disposal and resolution, it is inevitable that more intelligent technical means will be needed to conduct accurate early warning research and judgment on the multi-channel conflicts and disputes that have been gathered, and simultaneously give relevant police types, reduce the "people's transfer of punishment and punishment to life", and improve the capacity of the public security system to handle and resolve conflicts and disputes. The conflict and dispute monitoring and early warning in this work includes risk personnel early warning, risk event early warning and risk area early warning. Early warning of risk personnel by collecting the analysis of mental illness status, personal education, family status, police, gambling and key people and other information, build a point early warning system, can monitor family disputes, economic disputes, emotional disputes and other conflicts and disputes. The early warning of risk events is based on the frequency of "different colleagues" reflecting the demands, and meets the requirements of behavior, sensitive words, sources, types, number of people and other indicators to assign a comprehensive score, then judge whether it is a risk event, early warning of possible stakeholder events, and give a risk event level. The risk area early warning is based on the location of conflicts and disputes, the unified address database is matched and analyzed, and the areas with frequent conflicts and disputes are classified as "risk areas", and the clustering algorithm is used to give more accurate risk areas. In urban areas, the community is the unit, and in rural areas, the village is the unit, and the regional early warning layer is constructed to directly reflect the types and trends of conflicts and disputes in the communities (villages) with the highest number of conflicts and disputes in the city, and accurately depict the risks of social conflicts and disputes in the city.

4.5 Dispute file

Dispute files include event files and personnel files. The event file contains the basic information of the event, the event label, the event comprehensive evaluation, the event cause analysis, the relevant personnel information, the event graph, the early warning information and the research and judgment results, etc. The event graph displays all the entities related to the event, and the research and judgment results are realized through text input to the large model technology. Personnel files include personnel basic information, personnel labels, personnel comprehensive evaluation, visual statistics of related disputes, early warning information, related historical disputes, personnel maps, behavior tracks, relationship analysis, etc. Personnel related disputes collect all personnel dispute data through identity card number, mobile phone number, relationship and so on, and display the map visually.

5 Conclusions

This paper has deeply explored the causes and evolution laws of conflicts and disputes, has broken through new theories, new products, and new methods, and has gathered massive multi-modal data on the basis of public security big data work. It has also built a knowledge map of conflicts and disputes. It has created a solution for integrated analysis and early warning research and judgment of conflicts and disputes with key technologies such as intelligent search and answer, intelligent data analysis, and intelligent early warning research and judgment. In the next step, on the basis of the existing work, we will further improve the construction of the knowledge graph of conflicts and disputes, enhance the algorithm capability of the knowledge graph, better support the actual discovery and resolution of conflicts and disputes, and finally achieve the overall goal of building a safe China.

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