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Decision Briefing Generation on Meteorological Social Events

by Kaize Shi

Thesis submitted in fulfilment of the requirements for the degree of

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Certificate of Original Authorship

I, Kaize Shi, declare that this thesis is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the Faculty of Engineering and Information Technology at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

I certify that the work in this thesis has not previously been submitted for a degree nor has it been submitted as part of the requirements for a degree at any other academic institution except as fully acknowledged within the text. This thesis is the result of a Collaborative Doctoral Research Degree program with Beijing Institute of Technology. This research is supported by the Australian Government Research Training Program.

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Abstract

Meteorological disasters have the characteristics of suddenness, complexity, dynamics, and diversity, which have inflicted severe challenges on emergency decision support services in disaster environments. Nowadays, mobile internet technologies such as smartphones, social networks, wearable devices, and high-speed communication are widely used, making each user a ubiquitous social sensor integrating human and machine. Social sensors collect data from mobile devices worn or carried by humans, intuitively perceive the environmental conditions associated with a meteorological disaster through human senses, and have the advantages of comprehensive coverage, communication in real-time, and low cost.

Decision briefing is an effective support mode of emergency management services for sudden meteorological disasters, and it is also the primary way to deliver meteorological decision knowledge. This thesis focuses on the critical technologies for the automatic generation of meteorological event knowledge-enhanced decision briefing based on social sensor signals, providing meteorological decision support services focusing on accurate knowledge mining, efficient information integration, and formalized knowledge representation for decision-makers in the decision process of sudden meteorological disasters. The main research foci and innovations of this thesis are as follows:

1. Co-occurrence feature-based sudden meteorological event detection: Aiming at the low detection accuracy of meteorological events caused by limited coverage of physical sensor signal, poor timeliness, and lack of co-occurrence feature mining of meteorological events in previous research, **this thesis proposes a sentence-level feature-based meteorological event detection model**. The model is based on social sensor signals and introduces prior meteorological knowledge through the pre-trained language model in sentence vectorization. The wide-grained capsule network mines the attributes of the independent and co-occurrence features of meteorological events and then undertakes the real-time synchronous detection of multi-category co-occurrence meteorological events in a specific period. The proposed model achieves quantitative evaluation results of 0.941, 0.862, 0.738 and 0.795 on $Accuracy$, P_{micro}, R_{micro} and $F_{micro-1}$, respectively, which is significantly better than other baseline models.

2. Multiple knowledge-enhanced meteorological decision briefing generation: Aiming at the low decision efficiency caused by information complexity, high chaos, and a large amount of data in the sudden meteorological disaster environment, **this thesis proposes a multiple knowledge-enhanced summarization model**. The model comprises a cascade structure of a summary generation module and a multiple knowledge

enhancement module, which automatically generates meteorological decision briefing content by guiding the summary generation process with specific meteorological event and geographical location knowledge in the social sensor signal. The proposed model achieves 0.2025, 0.0807, and 0.1740 of the $ROUGE-1$, $ROUGE-2$, and $ROUGE-L$ in the content evaluation and 0.656 of F_1 score in the sentiment evaluation, significantly better than other baseline models.

3. Meteorological event knowledge-enhanced decision briefing optimization: Aiming at the weak decision support serviceability caused by the chaotic language style, colloquial text, and poor formatting of the social sensor signals-based meteorological briefing content, **this thesis proposes an event knowledge-enhanced briefing optimization module**. This module comprises a text form judgment model, a formalization words detection model, and an event knowledge guided text formalization model, which optimizes the transfer of the meteorological briefing content by calculating the text formalization judgment threshold, formalization word weight, and generates formalized words. The proposed model achieves quantitative evaluation results of 21.489 on the $BLEU$, which is significantly better than other baseline models.

In addition, this thesis reports on the construction of a prototype application of the meteorological decision briefing integrated with the above research foci, which showcases the use of social sensor signals to provide feedback on daily meteorological events, then provides decision support services based on meteorological decision briefing. This thesis presents interdisciplinary research on artificial intelligence, social computing, meteorological data mining, emergency management, and intelligent decision support services, which is a comprehensive analysis and extended application of interdisciplinary issues. This research has significant application value for improving the decision efficiency of meteorological departments and reducing the loss caused by sudden meteorological disasters.

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I am about to graduate from the University of Technology Sydney in this jacaranda blooming season, drawing an end to my twenty-two years of student career. During these years, I have been with good teachers, supported by parents and accompanied by friends. Now I would like to take this opportunity to express my gratitude.

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Thanks to the University of Technology Sydney. UTS provides a global platform, allowing me to exchange and study with top researchers from various cultural backgrounds worldwide, broadening my research and stimulating new research ideas.

The end of one story is the beginning of another. Each man is the architect of his fate. Think. Change. Do.

List of Publications

Related to the Thesis :

1. **Kaize Shi**, Xueping Peng, Hao Lu, Yifan Zhu, Zhendong Niu: Application of Social Sensors in Natural Disasters Emergency Management: A Review. IEEE Transactions on Computational Social Systems. 2022, doi: 10.1109/TCSS.2022.3211552.

2. **Kaize Shi**, Changjin Gong, Hao Lu, Yifan Zhu, Zhendong Niu: Wide-grained capsule network with sentence-level feature to detect meteorological event in social network. Future Generation Computer Systems. 102: 323-332 (2020)

3. **Kaize Shi**, Yusen Wang, Hao Lu, Yifan Zhu, Zhendong Niu: EKGTF: A knowledge-enhanced model for optimizing social network-based meteorological briefings. Information Processing & Management. 58(4): 102564 (2021)

4. **Kaize Shi**, Hao Lu, Yifan Zhu, Zhendong Niu: Automatic generation of meteorological briefing by event knowledge guided summarization model. Knowledge-Based Systems. 192: 105379 (2020)

5. **Kaize Shi**, Xueping Peng, Hao Lu, Yifan Zhu, Zhendong Niu: Automatic Generation of Meteorological Briefing by Multi Knowledge Enhanced Summarization Model. (Under review)

6. **Kaize Shi**, Xueping Peng, Hui He, Kun Yi, Zhendong Niu: Multi-KGS: A Multiple Knowledge Guided Summarization Model for Generating Social Network-based Meteorological Decision Report. (Under review)

Others :

8. Yifan Zhu, Qika Lin, Hao Lu, **Kaize Shi**, Donglei Liu, James Chambua, Shanshan Wan, Zhendong Niu. Recommending Learning Objects through Attentive Heterogeneous Graph Convolution and Operation-Aware Neural Network. IEEE Transactions on Knowledge and Data Engineering. (2021)

9. Qika Lin, Yifan Zhu, Hao Lu, **Kaize Shi**, Zhendong Niu: Improving University Faculty Evaluations via multi-view Knowledge Graph. Future Generation Computer Systems. 117: 181-192 (2021)

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11. Hao Lu, Yifan Zhu, Yong Yuan, Weichao Gong, Juanjuan Li, **Kaize Shi**, Yisheng Lv, Zhendong Niu, Fei-Yue Wang: Social Signal-Driven Knowledge Automation: A Focus on Social Transportation. IEEE Transactions on Computational Social Systems. 8(3): 737-753 (2021)

12. Yifan Zhu, Hao Lu, Ping Qiu, **Kaize Shi**, James Chambua, Zhendong Niu: Heterogeneous teaching evaluation network based offline course recommendation with graph learning and tensor factorization. Neurocomputing 415: 84-95 (2020)

13. Yusen Wang, **Kaize Shi**, Zhendong Niu: A Session-based Job Recommendation System Combining Area Knowledge and Interest Graph Neural Networks. SEKE 2020: 489-492

14. Yifan Zhu, Sifan Zhang, Yinan Li, Hao Lu, **Kaize Shi**, Zhendong Niu: Social weather: A review of crowdsourcing‚Äêassisted meteorological knowledge services through social cyberspace. Geoscience Data Journal 7 (1), 61-79 (2020)

15. Changjin Gong, **Kaize Shi**, Zhendong Niu: Hierarchical Text-Label Integrated Attention Network for Document Classification. HPCCT/BDAI 2019: 254-260

16. Yifan Zhu, James Chambua, Hao Lu, **Kaize Shi**, Zhendong Niu: An opinion based cross‚Äêregional meteorological event detection model. Weather 74 (2), 51-55 (2018)

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Chapter 1

Introduction

1.1 Background

Global warming has led to frequent meteorological disasters, resulting in huge losses to human production and life[66, 87, 264]. Climate change directly affects agriculture[213], natural resources[204], and the energy industry[82], also indirectly affects social activities such as public security[166] and the global economy[285]. The changes in the intensity and frequency of meteorological hazard factors and the complexity of disaster-bearing carriers make emergency management more complicated. Intelligent emergency decision-making becomes a priority for countries to deal with sudden meteorological disasters.

International organizations have introduced various measures to deal with sudden meteorological disasters. In 2011, the United Nations Intergovernmental Panel on Climate Change (IPCC) compiled the Special Report entitled "Managing Extreme Event and Disaster Risks and Improving Climate Change Adaptation Capacity,"[77] which recommended that governments develop meteorological disaster early warning systems and provide innovative insurance to promote infrastructure and expand social safety nets to cope with extreme climate change. In October 2020, the World Meteorological Organization (WMO) released the "State of Climate Services 2020 Report: Move from Early Warnings to Early Action"[324], pointing out that the number of meteorological disasters in the past 50 years has increased, the average death toll fell by a third, but disasters and economic losses rose sharply. Climate change is complex and severe.

Climate change has significantly increased the frequency, intensity and severity of extreme meteorological disasters, impacting environmentally vulnerable areas. The meteorological early warning system does not cover or protect all people worldwide. WMO recommends that countries strengthen their investment to fill the capacity application gap of the meteorological disaster decision support system and shift the emergency management of meteorological disasters to early warning-based decision-making. In February 2021, the International Telecommunication Union (ITU) established a Focus Group on AI for Natural Disaster Management (FG-AI4NDM) [122], to promote data collection and processing in natural disasters through artificial intelligence and then improve hazard modeling by extracting complex patterns from growing spatial data. The FG-AI4NDM focuses on the service capabilities of artificial intelligence technology in sociology and demography, providing decision support services with disaster-bearing carriers as the core in disaster environments.

In recent years, the increasingly apparent contradiction between meteorological emergency service capabilities and public requirements has brought new challenges to scientific decision-making, intelligent management, and optimal control. At this stage, the meteorological department mainly uses radar, satellite, and other physical sensors to sense extreme meteorological events, continuously exploring the application services of social sensors in meteorological disaster emergency management and further improving the organization of meteorological emergency management services. Social sensors are the medium for mapping physical space events to cyberspace, which can process and analyze social public opinion information in relation to users' requirements. From specific signal sources to establishing social sensors with specific functions, it is necessary to undertake search, selection, corpus adjustment and refinement, feature extraction and analysis, and sampling period determination. Therefore, a social sensor comprises the network signal source, user, corpus, and analysis model.

The social sensor-based decision briefing effectively improves the serviceability of meteorological emergency knowledge. Social sensor signals provide a richer data source for meteorological decision briefing, enabling the decision briefing content to describe the objective meteorological environment using individual subjective perceptions[26]. Previous decision briefings mostly rely on manual writing and generation, affecting real-time emergency decision-making. The development of artificial intelligence technology makes the efficient and automatic generation of decision briefings possible and provides development space to further improve its service capabilities in specific scenarios. The decision briefing can describe the specific events, public opinion trends, and hot topics.

Analyzing and summarizing the key points from the massive amount of information assists decision-makers in achieving an efficient decision-making process[171]. At present, automatic decision briefing generation has been applied to multiple domains[131], where domain knowledge drives professional services for decision briefings[237]. However, the briefing-based meteorological decision support services still have the following deficiencies:

- Less social signals: At this stage, decision briefings are mainly written and generated based on the signals from remote sensing, the Internet of Things, radar, and other physical sensors, ignoring social attributes such as public requirements, psychology, and public opinion in decision support services. Social sensor signals can introduce human perception into the decision support process by applying crowd-sourced intelligence to provide decision briefings with real-time and feature-rich data. Compared with physical sensors, the low cost and wide distribution of social sensors further broaden the data scope of various intelligent decision support applications.

- Lack of intelligence: The intelligence of the decision briefing is mainly manifested in the briefing content and generation process. Previous briefing content is primarily based on the physical sensors' quantitative data, lacking the individual opinion's qualitative description. Regarding decision briefing generation methods, previous decision briefings mostly rely on manual writing or extraction from fixed templates, which consumes many human resources, makes the content rigid, and lacks flexible natural language representation. The development of artificial intelligence models provides new technical support for intelligent decision briefing generation.

- Weak knowledge application: Applying professional knowledge in vertical domains an effective way to improve decision support service capabilities and meet the requirements of fine-grained decision-making. Multi-dimensional professional knowledge endows decision support services with knowledge-based kinetic energy. At this stage, the lack of a fine-grained analysis of professional knowledge leads to weak applicability of knowledge in the decision support service process, which limits the positive guiding role of professional knowledge in the decision-making process. The knowledge-enhanced model provides more effective abilities in guiding the decision support services.

The main reason for the aforementioned deficiencies is that the current intelligent decision support system's data source, service mode, and knowledge application ability are relatively weak. The wide application of mobile Internet technologies such as smartphones, mobile terminals, and wearable devices makes every individual a ubiquitous social sensor for human-machine integration, where the social network is the primary way for people to obtain and disseminate information. The social architecture brings rich data sensing nodes to the social network, making it the leading platform for social sensors. Based on the above characteristics, this thesis focuses on "**Decision Briefing Generation on Meteorological Social Events**", providing decision support services for decision makers based on meteorological social events, driven by meteorological knowledge and with a formalized language style. In particular:

1. Social sensors have high-efficiency situational awareness capabilities for natural systems and can detect and mine sudden meteorological events in real time. The social sensor is a vital data perception channel in sudden meteorological disasters. It can be realized from the meteorological disaster event[236], derived social impact[157], public sentiment[309], and other multi-dimensional monitoring perceptions of meteorological events. Focusing on the broad area of social sensor signal perception and the universality of public opinion situation feedback, it is of great significance to study the critical technologies for situational awareness and the detection of large-scale sudden meteorological events based on social sensor signals.

2. As an effective decision support service model, decision briefing has been widely used in intelligence mining, government services, etc. Artificial intelligence provides more diverse and flexible technical support for automatic decision briefing generation[79]. Focusing on the inefficient decision-making problem caused by the explosion of social sensor signals in sudden meteorological disasters, it is of great significance to study the critical technology of the automatic generation of decision briefings based on text summarization models, screen and describe the multiple knowledge, and provide efficient and real-time decision support services for decision-makers.

3. Language style transfer models have achieved remarkable results in many applications, including sentiment translation[160] and comment rewriting[143]. Social sensor signals are collected from a wide range of sources, where the regional and language habit differences between multi-source information will cause the same event to have multiple expression styles. Focusing on the decision-making interference caused by the complex expression of social sensor signals and the confusion of styles in sudden meteorological disasters, it is of great significance to study the knowledge-driven meteorological decision

briefing optimization method, providing decision-makers with a briefing with formalized content.

1.2 Research Proposal

In the mobile Internet era, various mobile applications represented by social networks are deeply integrated with public life. Massive user generated content (UGC) provides more diverse data feedback for social sensor-based meteorological disaster emergency management services and also improves the model's ability to mine and apply social sensor signals. Compared with physical sensors, human-centered social sensors have emotional and interactive attributes that integrate human intelligence, which is significant for emergency decision support services in sudden meteorological disasters. The diverse representation capabilities of social sensor signals also bring new opportunities for the research and applications of natural disaster emergency decision-making, including:

- Novel data-drive: Massive ubiquitous social sensor signals include knowledge elements such as meteorological environment situations, group behavior habits, group wishes, and group crowd-sourcing wisdom. Compared with physical sensor signals, social sensors are composed of interconnected people and mobile devices, which have the advantages of broader signal coverage, more robust situational description capabilities, and more fine-grained intelligent representation. More importantly, in the mobile Internet era, deploying social sensors will allocate the cost to individual users, and decision-making departments can realize meteorological environment perception based on social sensor signals at almost no cost. The social sensor signal can supplement, improve and verify the physical sensor signal, and provide more generous data support for the decision support service of the meteorological department.

- Novel modeling space: The introduction of social sensor signals solves the problems of modeling bias and service inefficiency caused by the lack of consideration of social characteristics in the previous meteorological decision support systems. Cyber-physical social systems (CPSS) introduce social signals based on the previous cyber-physical systems (CPS) and broadens the application space dimension. CPSS provides an overall development and extension space for complex social systems to realize parallel systems in which artificial and natural social systems co-evolve and promote each other. It also provides more fine-grained application services for situational awareness, information dissemination, and public opinion mining in sudden natural disasters.

- Novel knowledge service: Knowledge service is based on knowledge retrieval, organization, analysis, and reconstruction, which also integrates services into the problem-solving process according to user requirements and the application environment, thereby effectively providing innovative knowledge-based application support. The intelligent meteorological decision-making knowledge service in the CPSS space focuses on knowledge automation, aiming to provide intelligent decision support services guided by professional social signal-based knowledge in the meteorological domain. Realizing the mining, storage, organization, and analysis of professional knowledge in massive social signals can further improve the application service capability of professional meteorological knowledge, which is crucial to ensuring the effective operation of meteorological knowledge services.

- Novel decision model: The new decision model is based on the joint application of intelligent decision support services and artificial intelligence models, which focuses on describing the application of human intelligence in decision support services. Compared with previous decision models, intelligent decision models which integrate social signals consider the active role of individual and group intelligence in the decision-making process, and gradually transition from quantitative decisions based on physical sensors to multidimensional personalized decisions that integrate group characteristics and individual differences. The domain knowledge is used to guide the decision-making process to assist decision-makers in formulating more precise and diversified decision-making schemes.

The research of this thesis is driven by the social sensor signals, in CPSS space, guided by professional meteorological knowledge, and serviced by decision support briefings. The goal is to achieve the semantic abstraction and knowledge focus of decision-making from social sensor signals → information → knowledge → decision. By combining the meteorological decision-making task in a real scenario, the efficient transformation of social sensor signals and intelligent decision-making is completed (as shown in Fig.1.1). The whole process of intelligent decision support is guided by professional meteorological knowledge.

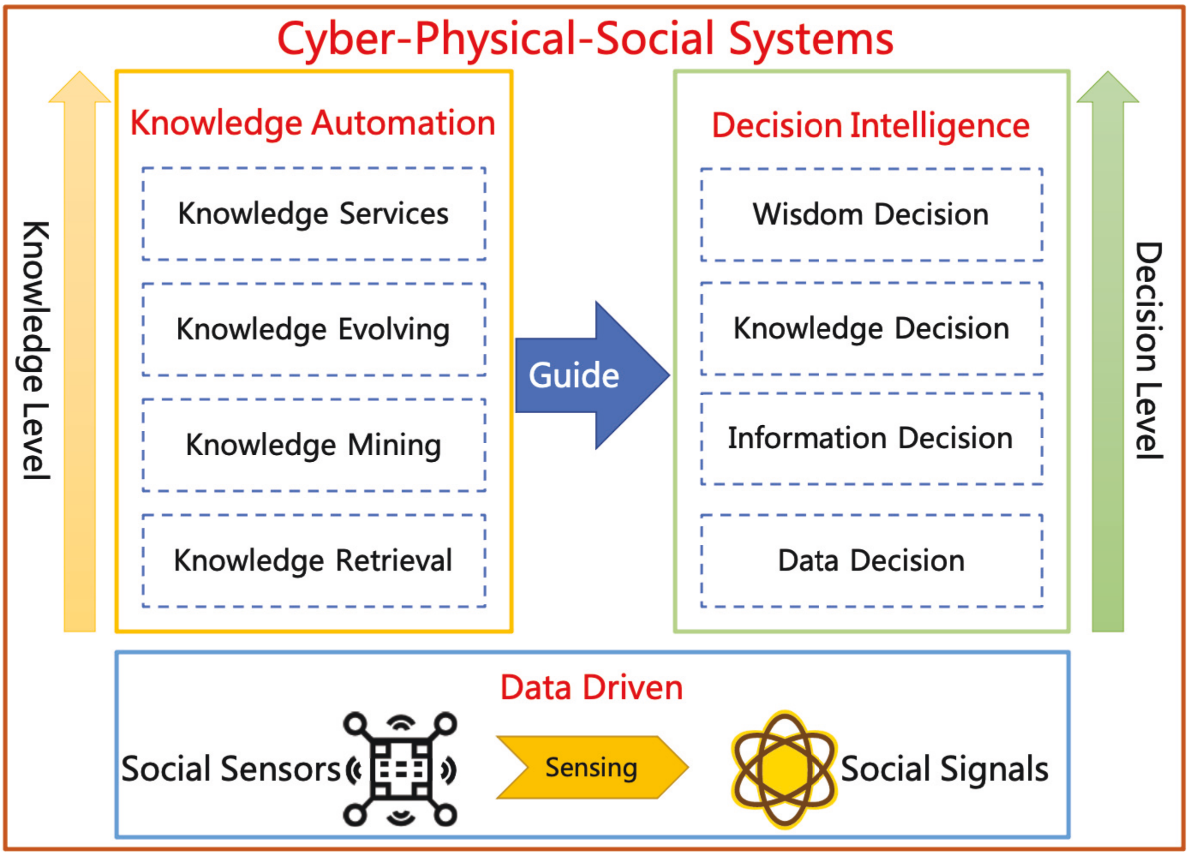

Figure 1.1: The relationship of research proposal.

1.3 Research Achievements

Based on the above research proposal, this thesis uses the meteorological social signals in Sina Weibo[1] as research data. Specifically, this research studies the aforementioned critical scientific issues, focusing on **co-occurrence feature-based sudden meteorological event detection**, **multiple knowledge-enhanced meteorological decision briefing generation**, and **meteorological event knowledge-enhanced decision briefing optimization**. By researching critical technologies for meteorological decision briefing generation that focus on wide-grained meteorological events, domain knowledge-driven services, and a formalized language style, the research provides intelligent, real-time, diverse, and efficient decision support services for meteorological decision-makers. The main innovations of this thesis are as follows:

1. Co-occurrence Feature-based Sudden Meteorological Event Detection

To address the low detection efficiency of mass meteorological events in sudden mete-

[1] https://en.wikipedia.org/wiki/Sina_Weibo

orological disasters, this thesis proposes a sentence-level feature-based meteorological event detection model to efficiently detect meteorological events in social sensor signals. The model uses a meteorological corpus to fine-tune the general BERT embedding to introduce prior meteorological knowledge. Considering the independent and co-occurrence features of meteorological events, the model is based on the fine-tuned BERT embedding and constructs a wide-grained capsule network with multi-level receptive fields to accurately detect multiple meteorological events. This research has been published in Future Generation Computer Systems (CORE A).

2. Multiple Knowledge-enhanced Meteorological Decision Briefing Generation

To address the weak application ability of information caused by the explosive growth of social sensor signals in sudden meteorological disasters, this thesis proposes a multiple knowledge-enhanced summarization model to generate content for meteorological decision briefing. The model takes the source Weibo posts, meteorological event knowledge, and geographic location knowledge as input, automatically generating the briefing content constrained by the specific knowledge. This briefing generation process achieves efficient knowledge mining for massive meteorological social sensor signals.

3. Meteorological Event Knowledge-enhanced Decision Briefing Optimization

To address the text style of the social sensor-based meteorological decision briefing which is poorly formalized, this thesis proposes a meteorological briefing formalization module. This module comprises the text form judgment model, formalization word detection model, and event knowledge-guided text formalization model. The text form judgment model is used to detect formal words and calculate the formal discrimination threshold; the formalization word detection model is used to calculate the formal weight of the input words; the event knowledge-guided text formalization model optimizes the input text and improves the efficiency of decision support by optimizing the service capability of the meteorological decision briefing content. This research has been published in Information Processing & Management (CORE A).

The logical relationship of the above innovations is shown in Fig.1.2. The sentence-level feature-based meteorological event detection model realizes the situational awareness and detection of sudden meteorological events. Then, the content of the decision briefing is automatically generated based on the multiple knowledge-enhanced summarization model. Finally, the meteorological briefing formalization module optimizes the generated briefing content.

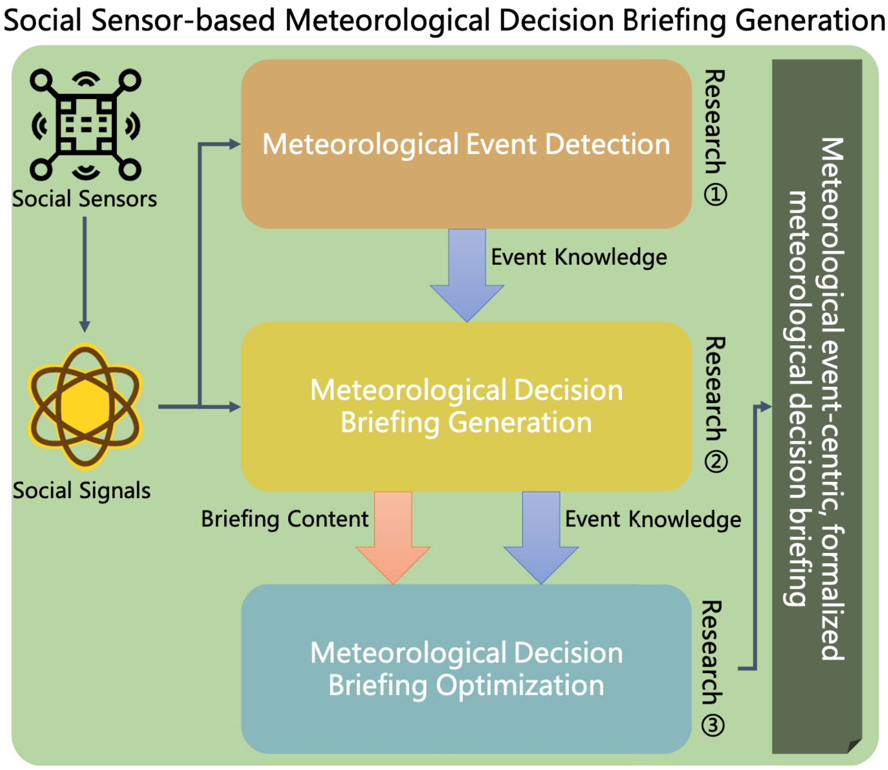

Figure 1.2: The logical relationship of the innovations

1.4 Thesis Organization

The organization of this thesis is shown in the Fig.1.3.

Chapter 1: Introduction. This chapter clarifies the novel requirements of social sensor signals for intelligent meteorological decision support services, condenses the scientific issues of social sensor-based meteorological decision intelligence, and clarifies the principles of this thesis. This chapter also formulates the research objective of guiding the intelligent decision-making process with professional meteorological knowledge and proposes innovative research to solve the critical scientific problems around the research objective. Finally, this chapter clarifies the organization of the thesis.

Chapter 2: Literature Review. This chapter reviews the social sensor-based natural disaster emergency management literature from three application functions: natural disaster situation awareness and event detection, disaster information dissemination and communication, disaster sentiment analysis and public opinion mining. Based on the application functions, this chapter summarizes and analyzes the research status, data application model, decision-making technology, and application service system of social sensors in natural disaster emergency management. This chapter clarifies the

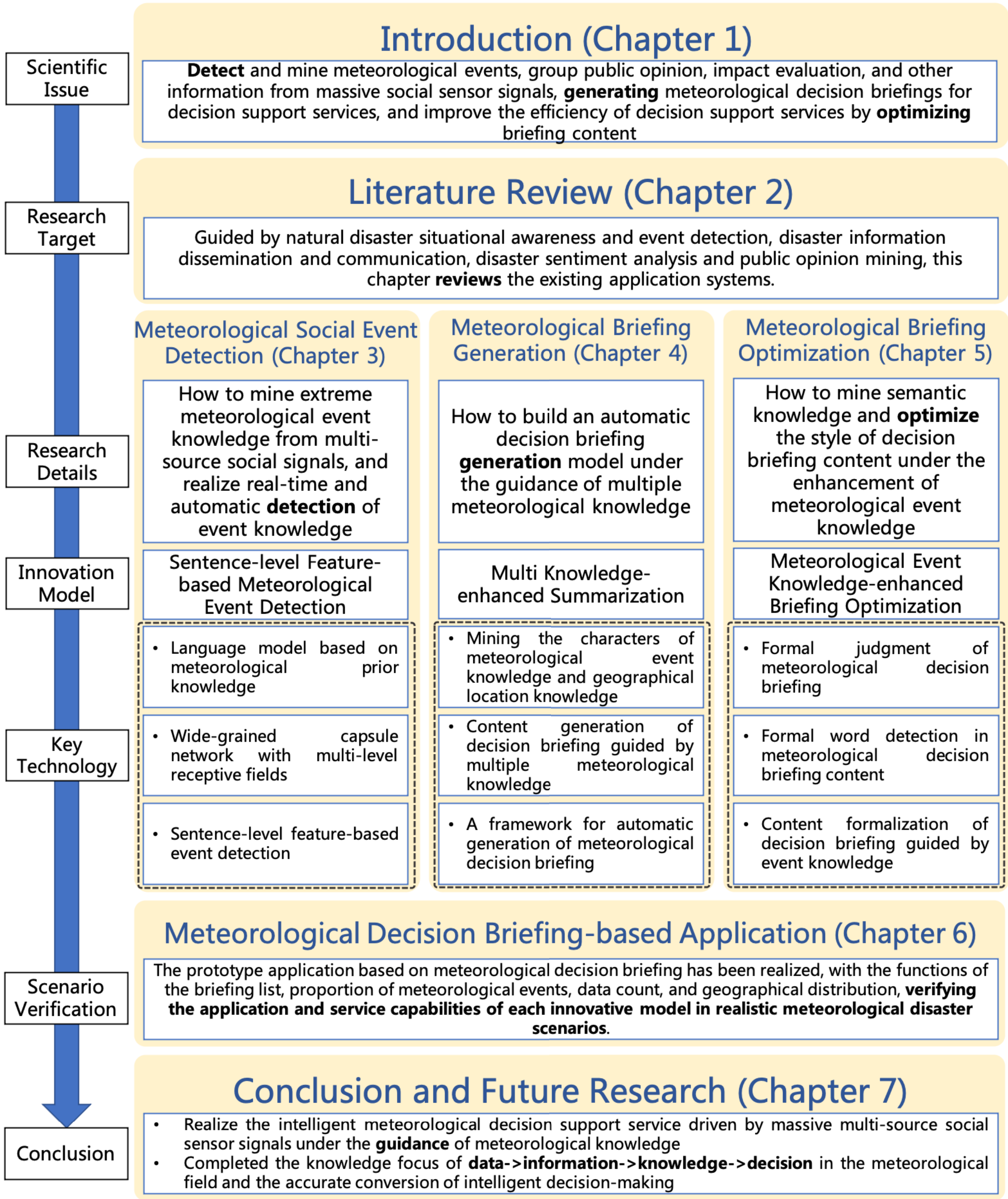

Figure 1.3: Thesis organization

application demand guidance, focusing on accurate knowledge mining, an intelligent decision-making mode, and efficient service capability for the follow-up research.

Chapter 3: Co-occurrence Feature-based Sudden Meteorological Event Detection. In view of the high cost, poor real-time response, low coverage, and other shortcomings of physical sensors, this chapter proposes a sentence-level feature-based meteorological event detection (SFMED) model. The model builds a knowledgeable language model by fine-tuning the general BERT model to introduce the meteorological domain's prior knowledge into the event detection process. By analyzing the co-occurrence features of meteorological events, a wide-grained capsule network with multi-level receptive fields is designed, which can accurately detect multiple meteorological events. Compared with other baseline models, the SFMED model achieves the best test results in terms of $Accuracy$, P_{micro}, R_{micro} and $F_{micro-1}$.

Chapter 4: Multiple Knowledge-enhanced Meteorological Decision Briefing Generation. To address the issues of manual dependence, rigid content, low flexibility, and other shortcomings of previous meteorological decision briefings, this chapter proposes a multiple knowledge-enhanced summarization (MKES) model. The MKES model comprises two modules: the summary generation module and the knowledge enhancement module. The knowledge enhancement module guides and constrains the summary generation process using meteorological event knowledge and geographical location knowledge, ensuring the generated summary focuses on describing the specific knowledge in the source text. Compared with the baseline models, the MKES model achieves the best results on the $ROUGE-1$, $ROUGE-2$, and $ROUGE-L$ in the content evaluation and F_1 score in the sentiment evaluation.

Chapter 5: Meteorological Event Knowledge-enhanced Decision Briefing Optimization. In view of the poor formalization of language style, colloquial, and other defects of the social sensor-based meteorological briefing, this chapter proposes an event knowledge-enhanced decision briefing optimization module, which consists of a text form judgment model, a formalization word detection model, and an event knowledge guided text formalization (EKGTF) model. The EKGTF model is a knowledge enhancement model that can formalize the language style of the decision briefing content while paying attention to the description of the core meteorological event knowledge in the source text. Compared with other baseline models, the EKGTF model achieves the best test results in $BLEU$.

Chapter 6: Meteorological Decision Briefing-based Application. This chapter reports on the design of a prototype application of meteorological decision briefing integrating the aforementioned innovative models by investigating the requirements of decision-makers for decision support services in real sudden meteorological disaster environments. Specifically, the application comprises four functional modules: briefing list, the proportion of meteorological events, data count, and geographic distribution. This chapter elaborates on the prototype application process and the functions of each module through specific meteorological disaster scenarios and illustrates the decision support service capabilities of the proposed innovative model in sudden meteorological disaster scenarios through cross-validation with meteorological events in the real world. This application has been applied to the Meteorological Public Opinion Mining Platform.

Chapter 7: Conclusion and Future Research. This chapter summarizes the research details and innovations of the thesis. It also clarifies the future tasks, including time series prediction of meteorological situations based on multi-modal social signals, multi-source extreme meteorological environment situational awareness technology integrating physical and social sensor signals, and real-time public opinion guidance intervention combined with the trend of sudden meteorological events. By further exploring the joint application of social sensor signals and artificial intelligence methods, decision-makers can improve emergency decision-making and responses to sudden meteorological disaster environments.

1.5 Conclusion

This chapter clarifies the research background of decision briefing generation on meteorological social events. It presents the shortcomings of the existing emergency decision support services in terms of social signal participation, the intelligence of decision support services, and knowledge application. This chapter details the research proposals of the critical technology for generating the meteorological social events-based decision briefing using social sensor signals as the driving force, the CPSS as the modeling space, and meteorological knowledge as the application guidance. The research in this thesis focuses on co-occurrence feature-based sudden meteorological event detection, multiple knowledge-enhanced meteorological decision briefing generation, and meteorological event knowledge-enhanced decision briefing optimization, which provides the decision-makers with intelligent emergency decision support services based on meteorological decision briefing. Finally, this chapter concludes with a summary of the relationship between innovation and thesis organization.

Chapter 2

Literature Review

Extreme meteorological events belong to the sudden natural disasters[1], which are serious social hazards and require emergency treatment[4, 66]. Sudden natural disasters are accompanied by social development and run through human history. The increasing global warming has led to the frequent occurrence of extreme meteorological environments, and natural disasters have become more serious[176, 257].

The continuous popularization of portable mobile devices and the application of high-speed communication technologies have brought new opportunities and challenges for natural disasters emergency management[2, 90, 193, 197]. The Internet provides a broad space for information about the development of sudden natural disasters, overcoming the limitations of traditional media. Most emergencies in the real world mapped by cyberspace are presented as events with complex multidimensional features, including personal opinions, sentiment, and wisdom. Such characteristics make the Internet a booster for emergent natural disasters, expand emergencies' spread and influence, and increase disasters' complexity.

Social networks are the main channel for developing and disseminating emergent natural disaster events in cyberspace[201]. Social network users combine their perception and wisdom to form ubiquitous social sensors based on social network platforms and data analysis methods. Social sensors can provide novel data-driven information for natural disasters emergency management and represent a vital data perception method of

[1]Sudden natural disasters include flood and drought disasters, meteorological disasters, earthquakes, geological and marine disasters, biological disasters, and wildfires. These events are defined by China's General Emergency Response Plan for National Public Emergencies.

crowdsourcing. This approach has the advantages of comprehensive coverage, real-time, high flexibility, diversified modes, and low cost. Realizing effective interventions based on social sensors for sudden natural disasters in the parallel space is of great significance for reducing economic losses and maintaining social stability. In addition, social sensors are based on a single user as the basic unit, making the social sensor a component in bidirectional communication. Such a characteristic gives the social sensor the ability to mine sentiment and fine-grained individual subjective features[281]. Furthermore, this characteristic meets the demand for precise emergency management application service in the natural disaster environment, which also provides the ability to address the complex changes of sudden natural disaster events[35].

Social sensors have multidimensional data perception capabilities and can realize feedback from the actual natural system's dimensions of time, space, content, and network[280]. Social sensors have multiple application functions in emergency management. Alexander et al.[8] divided the application of social sensors in emergency management into seven categories: listening to public views, monitoring the situation, extending emergency response management, crowdsourcing and collaborative development, building social cohesion, promoting disaster philanthropy, and academic research. Zhang et al.[312] streamlined the main functions of social sensors in emergency management into three categories: efficiently obtaining information on disaster situations, supporting self-organized peer-to-peer assistance activities, and enabling disaster management agencies to hear from the public. Jung et al.[112] divided the information dissemination function of social sensors in emergency management, including interpersonal communication with others, local government information release channels, mass information dissemination media, information sharing and collection, and information communication between different channels. This chapter comprehensively analyze and summarize the existing research and divide the application functions of the social sensors in natural disaster emergency management into three categories:

- Natural disaster situation awareness and event detection: focusing on the early warning, monitoring, and intervention of sudden natural disaster events.
- Disaster information dissemination and communication: social sensor-based information transmission and public communication in sudden natural disaster.
- Disaster sentiment analysis and public opinion mining: perception and mining of public sentiment and opinion in sudden natural disaster.

(a) Situational Awareness (b) Information Dissemination (c) Sentiment Expression

Figure 2.1: Three typical social sensor signals on Sina Weibo during the rainstorm in Henan, China, in July 2021.

The Fig.2.1 shows the typical social sensor signals of the above three application functions in Sina Weibo during the rainstorm in Henan, China, in July 2021[2].

The data flow of the social sensor in natural disaster emergency management applications can be divided into five stages: social sensors, sudden natural disasters, datasets, technical methods, and application system. The framework is shown in Fig.2.2. Social sensors rely on Sina Weibo, Twitter, Facebook, Instagram, and other social media plat-

[2] https://en.wikipedia.org/wiki/2021_Henan_floods

forms to realize the perception of social signals in sudden natural disasters. The datasets classify and integrate social sensor signals according to task requirements. The technical method is used to design the model for feature analysis. Finally, a social sensor-based application system with diversified service capabilities based on the above application functions are constructed. The three social sensor's application functions provide requirement guidance for the entire application process of data flow, encouraging application systems to conduct fine-grained analysis and application of data, models, and knowledge according to task requirements.

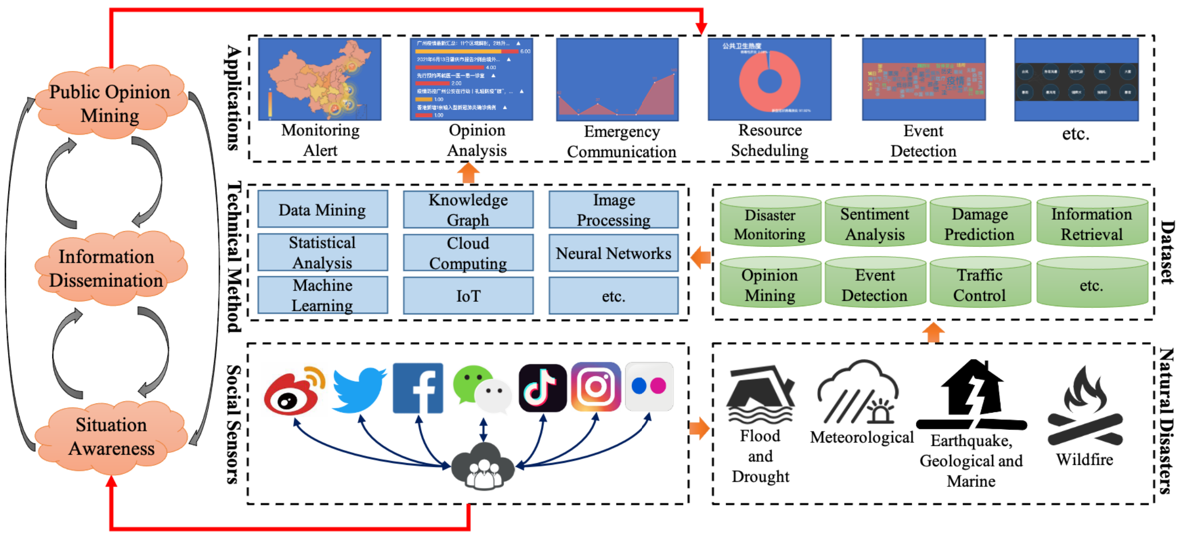

Figure 2.2: The social sensor-based emergency management framework for sudden natural disasters.

This chapter analyzes the research status, data, technical methods, and application systems of social sensors in emergent natural disasters following the framework shown in Fig.2.2. The remainder of this chapter is organized as follows. Section 2.1 analyzes the social sensors' development background, research significance, and research status from the above three application functions. Section 2.2 investigates application data, including data modalities and datasets. Section 2.3 analyzes the mainstream technical methods of the social sensor-based applications. Section 2.4 discusses the current social sensor-based natural disaster emergency management systems according to the above application functions. The conclusion of this chapter are discussed in section 2.5.

2.1 Research Status

Social sensors integrate network signal sources, users, corpora, and analysis models and use the physical space method to mine social signals in cyberspace, realizing the processing and analysis of information in natural environments[271]. To advance from a specific signal source to a social sensor with specific functions, it must go through the search, selection, corpus optimization, feature extraction, and sampling period determination.

Goodchild[86] proposed volunteered geographic information (VGI) in 2007, which refers to using each user as a geographic information sensor based on an Internet platform to realize geographic information collection, processing, management, and maintenance. Early VGI research focused on analyzing and applying GPS and other physical sensor data. With the development of social sensor perception, current research of VGI has gradually focused on applying social knowledge[258].

Sudden natural disasters are highly destructive and can cause damage to disaster-bearing carriers from multiple dimensions. Social sensors have complex situational awareness capabilities, including the unified perception of text, image, audio, video, and other multimodal data. The user entity is taken as the standard alignment unit, which reduces the potential information loss of traditional methods in the data fusion alignment process. Researchers use this advantage to achieve situational awareness and event detection for sudden natural disasters and to build social sensor-based natural disaster early warning and monitoring systems[7, 111, 225].

Social sensors construct stable and highly concurrent social sensor networks based on their large user base. The distributed network structure makes up for the defects of physical sensors in a natural disaster environment, such as accessible communication damage, small information radiation range, and communication chain clog. Social sensors rely on social network platforms and are easier to operate than specialized physical sensor equipment. This characteristic gives social sensors efficient bidirectional communication capabilities, which significantly improves the communication efficiency of the disaster rescue process[242]. These advantages also make social sensors a mainstream channel for disseminating and communicating emergency information in sudden natural disasters, providing a new approach to emergency resource dispatching[229].

Most natural disasters in actual natural systems produce public opinion crises in ideal artificial systems, and the social sensor is one of the most effective means of individual sentiment analysis and public opinion mining. The effective mining of hazardous public opinion in the natural disaster environment can prevent the propagation of negative rumors and help maintain the security and stability of the natural system.

Table 2.1 lists the research content related to natural disaster situation awareness and event detection (SA), disaster information dissemination and communication (ID), and disaster sentiment analysis and public opinion mining (PM) functions of the social sensor in natural disaster emergency management scenarios, including flood and drought disasters, meteorological disasters, earthquakes, geological and marine disasters, and wildfires. Fig.2.3 summarizes the research elements of each function of social sensors. Among them, the SA function realizes the analysis of disasters' direct influence. The research includes multisource sensors and multimodal data fusion, perception of spatiotemporal characteristics of disasters, detection of the impact on public resources, and emergency rescue parallel deduction. The ID function analyzes natural disasters' process influence, including information broadcasting, information credibility review and supervision. The PM function is used to analyze natural disasters' social influence, including sentiment analysis and intervention, derived social public opinion mining and guidance. The research elements will eventually promote the application of social sensor-based knowledge automation for natural disasters emergency management, intelligent decision support, and parallel system deduction. The follow-up research in this section will detail the research status of social sensors in various natural disaster emergency management scenarios according to different application functions.

2.1.1 Natural Disaster Situation Awareness and Event Detection

Social sensors' natural disaster situation awareness and event detection function depends on their advantages of wide distribution, real-time, flexibility, and low deployment cost and is the most widely used function in natural disaster emergency management[88, 243]. The social sensor is important for constructing the natural disaster knowledge management system as a practical data perception approach for knowledge sharing, reuse, and decision making in natural disaster environments[305]. During the 2011 earthquake in Japan, Twitter-based social sensors were used in large-scale emergency management services for earthquake and tsunami disasters. This disaster scenario verified the situational awareness ability of the social sensor in natural disasters[50].

The primary application of natural disaster situational awareness is to detect disaster events. Meteorological disaster characterized by suddenness, uneven spatiotemporal

Table 2.1: Research on the application of social sensors in the natural disasters emergency management.

Nature disasters	Function	Literature	Research details
Flood and drought	SA	[17, 19, 76, 102, 154, 199, 222]	Situation awareness of flood trends, flood eyewitness retrieval
	ID	[52, 89, 114, 187, 214, 247, 303]	Flood communication link restoration, overall coordination of rescue resources, intervention of key nodes in flood information dissemination
	PM	[91, 306]	Relevance mining of flood impact on traffic, flood public sentiment mining
Meteorol -ogical	SA	[103, 141, 147, 148, 156, 222, 236–238, 265, 266]	Meteorological event detection, meteorological-traffic impact situation awareness
	ID	[20, 42, 44, 96, 116, 207, 219, 221, 239, 251]	Meteorological disaster risk exchange, key node intervention in the dissemination of meteorological information
	PM	[164, 329]	Visual mapping of public opinion on meteorological disasters, guidance of public opinion on meteorological disasters
Earthquake, geology and marine	SA	[55, 60, 203, 217, 222, 242, 278, 290, 296]	Earthquake information retrieval, outbreak detection, derivative disaster detection, impact assessment, damage detection
	ID	[40, 45, 49, 53, 69, 123, 178, 240, 263, 288]	Earthquake and tsunami disaster information dissemination, risk information exchange, intervention in key nodes of earthquake information dissemination
	PM	[9, 80, 158, 299]	Mining of public sentiment trends in earthquake
Wildfire	SA	[83, 108, 170, 212, 243, 310]	Wildfire detection, human and vehicle hazard warning, personnel migration and evacuation simulation planning
	ID	[1]	Wildfire dynamic broadcast
	PM	[70, 150]	Analysis of the difference of emotional characteristics of multi-category users, mining of trends in public opinion

distribution, complex frequency, and prominent mass occurrence are common natural disasters. Liu et al.[147] detected rainstorm events based on Sina Weibo data and

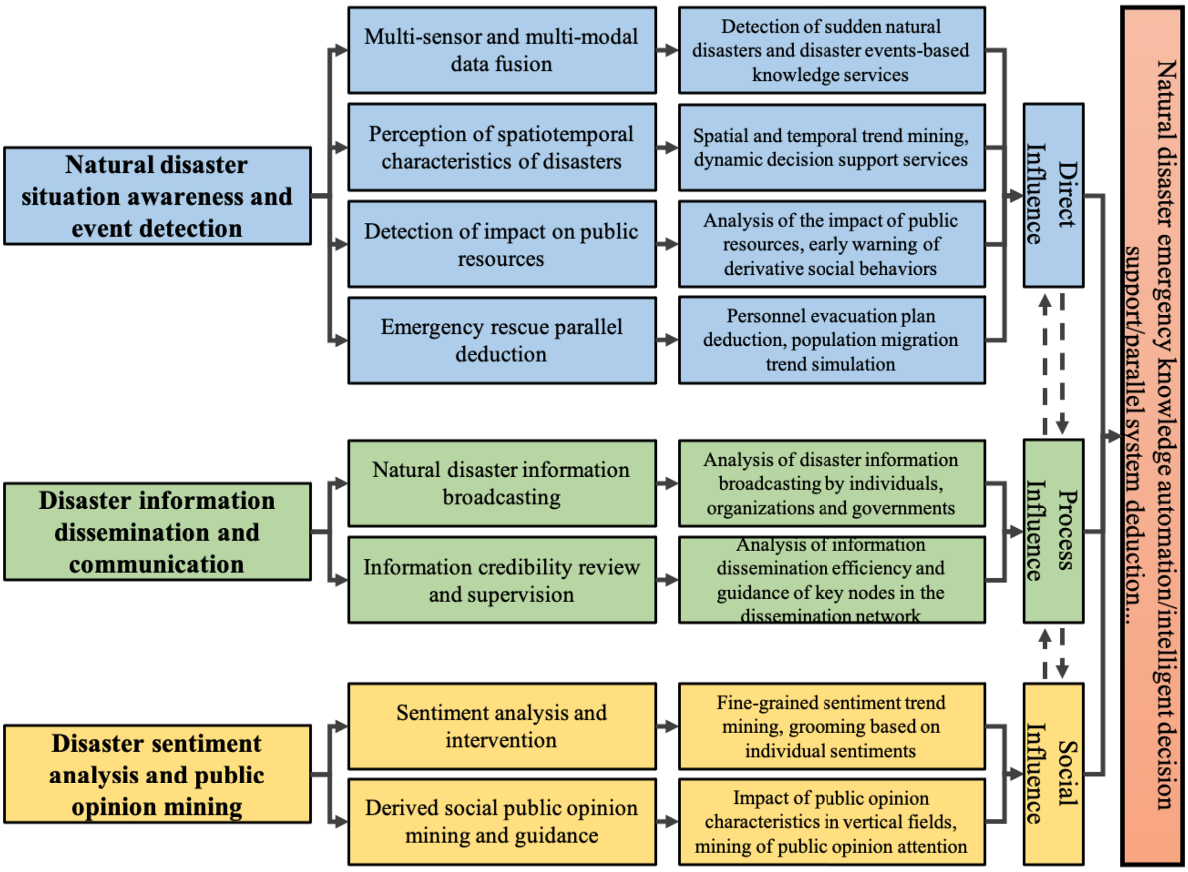

Figure 2.3: Basic research elements of social sensors-based natural disaster emergency management.

verified the feasibility of convolutional neural networks in applying rainstorm event detection based on social signals. Shi et al.[236] realized the real-time simultaneous detection of multicategory meteorological events based on Sina Weibo data by mining the co-occurrence relations between meteorological events. They also designed a method for generating meteorological briefings guided by meteorological events knowledge to provide decision support services for the meteorological department[237, 238]. In terms of earthquake perception, Yang et al.[296] built a social sensor that senses changes in the earthquake situation by designing a social media information retrieval framework and applying sensor planning services. They used 2013 Ya'an earthquake information from Sina Weibo as an example to test the service capabilities of the proposed method in earthquake emergency management tasks. Maldonado et al.[170] used the NLTK word frequency analysis tool to realize automatic detection of four natural disasters, such as wildfires, by analyzing the trend of wildfire-related keyword frequency changes. Social sensors can also perceive images. Compared with text, images provide more intuitive feedback on the situation of natural disasters. Hyvarin et al.[103] used images posted on Flickr to detect hail events. By comparing the results of physical sensor-based situational awareness, they verified the effectiveness of social sensors' feedback on extreme weather events. They suggested that social sensors be used as a public service data source to achieve the auxiliary perception of hail events.

Natural disaster environment situational awareness also includes finding help seekers in disasters. Singh et al.[242] proposed a Markov model-based algorithm to identify helpers in disaster environments by mining the tweets of victims during an earthquake. Rudra et al.[222] constructed a tweet-based word graph and realized the automatic summary generation of missing, trapped, and injured people's tweets in floods, typhoons, and earthquakes. Giannakeris et al.[83] proposed a framework for a new type of human-vehicle hazard warning system in a fire environment based on image data from Flickr that realizes the detection, evaluation, and early warning of the safety levels of people and vehicles in a fire.

2.1.1.1 Multi-sensor and Multi-modal Data Fusion

The fusion of social and physical sensor data provides a comprehensive and credible data application method for natural disaster situation awareness and event detection. Rashid et al.[212] proposed CompDrone, a wildfire monitoring framework integrating social sensors and drone data. They first perceived the area where the wildfire occurs through social sensor signals and then used the physical sensors on a drone to locate the specific location of the wildfire. This method overcomes the disadvantages of the limited deployment area of physical sensors and the weak reliability of social sensor signals. Wang et al. [278] used a spatial logical growth model to describe the impact of earthquake shock intensity on residents and combined this model with population data sensed by physical sensors to estimate the area affected by an earthquake.

Social sensors can realize the unified real-time perception of multimodal data, including text, images, and videos, realizing the prediction, monitoring, and analysis of natural disasters[10]. The multimodal data fusion model gives social sensors the ability to analyze natural disaster events from multiple perspectives. Compared with single-modal data, multimodal data provide more comprehensive feedback on natural disaster events, and decision-makers can build more complete disaster emergency strategies[174, 184, 208]. As the most intuitive terminal sensor in situational awareness, humans can break the data barriers between various departments. Feng et al.[76]

realized the retrieval of witnesses by fusing the text and image social signals posted by users during a flood. They used clustering algorithms to map events and witnesses to the map, improving the efficiency of information feedback during disasters. Huang et al.[102] proposed a flood situational awareness method based on text and images on Twitter. They used a convolutional neural network (CNN) to classify Houston flood images and used keyword sensitivity tests to optimize the classification results of CNN, which overcame the non-timeliness, spatial isolation, and other limitations of physical sensors.

2.1.1.2 Perception of Spatiotemporal Characteristics of Disasters

Social sensors can be used to perceive spatiotemporal characteristics. Analyzing spatiotemporal characteristics such as early warning of natural disasters and disaster loss assessment is essential for social sensors in natural disaster situation awareness[121, 233]. Earthquakes and floods have a wide range and long duration of damage, which are the main application scenarios for spatiotemporal characteristics perception. Crooks et al.[60] analyzed the spatiotemporal characteristics of Twitter activities after an earthquake on the east coast of the United States. They found that Twitter can represent a mixed-signal fused with traditional physical sensor systems to identify the location of a specific earthquake event and its affected area. Poblete et al.[203] proposed an online method for extracting discrete-time signals from Twitter and detecting the outbreak of abnormal events, which can realize the detection and tracking of earthquakes on a global scale. Anam et al.[17] used a wavelet analysis model to perceive the development trend of mountain torrents based on tweets. They proposed a dynamic emergency resource response plan based on the trend of situations. Pereira et al.[199] used social sensors to perceive flood images and realized the assessment of the severity of flood development.

Most natural disasters result in complex secondary disasters. For example, earthquakes result in secondary disasters such as wildfire, floods, tsunamis, mudslides, and accident damage. These disasters are no less destructive than the earthquake itself. Realizing the perception and mining of secondary disasters is also an essential application of social sensors in the perception of natural disasters' spatiotemporal characteristics. Wu et al.[290] proposed a natural disaster-derived event discovery model based on social sensor signals, detecting secondary earthquake disasters through online sub-event retrieval and discovery.

Maps are the most intuitive mapping scheme for perceiving the spatiotemporal characteristics of natural disasters[234]. Based on the text classification model, Arapostathis et al.[19] used social sensors to perceive flood trends and corresponding government behavior in Greece and drew situation feedback. Resch et al.[217] proposed a spatiotemporal heat analysis method combined with semantic information extraction. They realized earthquake tracking and damage detection based on social sensors through location mapping.

2.1.1.3 Detection of Impact on Public Resources

Natural disasters have the most noticeable impact on transportation, medical, and other public resources. Compared with physical sensors, social sensors can break down data barriers between various departments and provide feedback about natural disasters and public social resources through users' intuitive perception. Lopez-fuentes et al.[154] used metadata and image data from social sensors to monitor the conditions of emergency supplies delivery road during floods. Lin et al.[141] used Twitter data to detect the impact of meteorological disasters on the traffic situation. They proved that weather variable feedback from Twitter data could improve the model's accuracy by designing a regression model that predicts the impact of weather on highway speeds. Compared with fixed physical sensors, the flexibility of social sensors gives them the ability to sense traffic flow dynamically. Tse et al. [266] found that human outdoor activities can be used as a medium to convey the impact of weather on traffic congestion. Lu et al.[156] used social sensors to mine the correlation between urban spatiotemporal and meteorological characteristics, realizing early spatiotemporal warning of traffic conditions using Qingdao as a case study. Furthermore, Hattori et al.[92] verified that social sensor signals could be used to mine the correlation between Japanese weather, earthquakes, and flu.

2.1.1.4 Emergency Rescue Parallel Deduction

Social sensors can support disaster response deduction based on parallel systems. Existing research focuses on the simulation and analysis of population evacuation planning in wildfires. Yue et al.[310] proposed a geotagged sensitive wildfire risk assessment scheme based on social sensors by taking wildfire risk as a function of wildfire hazard and socioecological vulnerability. The results show a significant linear correlation between wildfire risk level and population density, and a large number of vulnerable people may increase the probability of wildfire risk. This research proves the excellent application potential of geotagged social sensor data in disaster risk analysis. Jia et al.[108] proposed the Facebook Disaster Maps (FBDM) platform, which uses Facebook data to analyze population migration trends during wildfires. They used the Mann-Kendall test to analyze the differences in population migration trends in different regions and found that people evacuated faster in densely populated and fire-prone areas. This platform can provide population evacuation planning assistance for natural systems via an ideal artificial system. In addition, the study of Buylova et al.[38] verified that social sensors could be used as an essential way to evaluate evacuation intention and other human decision-making processes during earthquake and tsunami disasters.

2.1.2 Disaster Information Dissemination and Communication

The destructive power of natural disasters can severely damage communication infrastructure, and the rapid increase in communication data within a short period will cause blockage of traditional communication links. These deficiencies will affect the timeliness of rescue and early warning services that rely on communication. Social sensors have the advantage of information amplification due to strong concurrency, information traceability, and colossal number of users and are widely used in risk information communication, emergency resource scheduling, information self-correction, disaster concern assessment, and communication link reconstruction[28, 69, 89, 187, 214, 219, 240, 253, 303].

In a natural disaster environment, social sensor-based information dissemination is dependent on bidirectional communication characteristics[288], manifested as feedback and demand information exchange in the natural disaster development stage. Users can meet their information acquisition needs through social network community consultation[114, 247, 263]. Cho et al.[53] studied social sensor application during the 2011 earthquake in Japan and verified that crisis communication on Twitter during the disaster was dominated by peer-to-peer communication. They also called on the government to actively use social media to guide the disaster information communication process. Pourebrahim et al.[207] noted that governments should use social media to establish bidirectional communication channels between rescuers and victims to formulate more granular rescue plans.

2.1.2.1 Natural Disaster Information Broadcasting

Social sensors have considerable advantages in information dissemination, quickly realizing low-cost and wide-coverage information broadcasting[20]. Multicategory users, including natural disaster observers and science enthusiasts, transmit natural disaster information promptly through social networks, which overcomes the poor timeliness of physical sensors in disseminating natural disaster information[44, 239]. Dong et al.[69] proved that the number of followers of social media users is the most critical factor affecting the efficiency of information dissemination, thus illustrating the advantages of high-influence users in disaster information broadcasting. Chatfield et al.[45] verified the critical role of social sensors in disseminating disaster information in the 2012 Indonesian tsunami. They found that warning tweets posted by the government could be retweeted in a short period, thereby reaching a large number of users. This result verifies the positive impact of social sensors on improving the efficiency of information dissemination in natural disaster emergency management services. Abedin et al.[1] analyzed Twitter usage during Australian forest fires and found that emergency organizations and individual users tend to distribute fire dynamics through social network broadcasts.

Information dissemination based on social sensors has drawbacks. For example, the efficiency of natural disaster information dissemination is significantly reduced in underdeveloped and low-Internet-penetration areas. In some countries with multilingual environments, language isolation also weakens the efficiency of information dissemination[40, 123].

2.1.2.2 Information Credibility Review and Supervision

Users do not need a cumbersome review process to post information on social media, so social sensors have high information dissemination efficiency. However, the external environment will interfere with disseminating data that lacks review. Mersham[178] reported that although the government is concerned about sharing natural disaster warning information through social sensors, they are still gradually occupying a vital position in emergency management services. This trend also requires management agencies to strengthen the credibility review of social sensor-based information. The objectivity of social sensor data to natural disaster event feedback is affected by external factors such as event characteristics and short-term sociopolitical background[221, 251], which further requires the media to ensure accuracy when disseminating disaster information[96]. Decision makers should correctly guide public opinion trends, encourage citizens to participate in emergency management activities in social networks, and improve the service capabilities of social sensors in emergency management by expanding information dissemination links[42].

Social sensor's different user carriers have diverse information dissemination influence weights, among which critical node users have a dominant position in information dissemination. This feature emphasizes that high-influence users such as opinion leaders and Internet celebrities should actively disseminate disaster information[116]. For example, news organizations and Internet celebrities play a leading role in disseminating information about earthquakes or floods. Therefore, the effective intervention of key nodes in the social sensor-based information dissemination link is of great significance to improve the efficiency of information dissemination and positively guide the trend of public opinion[49, 52].

2.1.3 Disaster Sentiment Analysis and Public Opinion Mining

The natural disaster response process is divided into pre-disaster early warning, disaster response, and post-disaster recovery, and public sentiment also undergoes phase changes. Social sensors are an effective way to mine fine-grained individual sentiment and coarse-grained public opinion changes[329]. Yang et al.[299] took the 2013 Ya'an earthquake in China as an example and used deep learning models to extract public sentiment information from social sensor signals to analyze the disaster. They explored the law of public sentiment changes in the disaster environment to optimize the formulation of disaster reduction strategies by fusing earthquake information, population density distribution, and other geographic data.

The social sensor-based information in a natural disaster environment has significant regional characteristics. Hot topics in disaster-affected areas tended to be related to disasters, but in non-disaster-affected areas, there is no significant change. The sentiment, experience, group interaction, and other multidimensional characteristics affect individual behavior in disaster environments. The use of social sensors to achieve fine-grained mining of individual sentiment information is helpful to formulate personalized and accurate rescue decision strategies[80]. Alfarrarjeh et al.[9] proposed a social sensor-based individual sentiment analysis framework that analyzes user sentiment expressed by text and images in the earthquake environment by combining geographical location features to conduct sentiment relief and spiritual rescue.

2.1.3.1 Sentiment Analysis and Intervention

The lack of official information in natural disasters can trigger negative sentiment and public opinion. Effectively guaranteeing the openness and transparency of information can prevent the appearance of damaging and extreme public opinion. This requires governments and other decision-making departments to use social sensors to realize real-time monitoring of public sentiment in natural disasters, relieve public tensions through official media accounts, and strengthen investment in social media sentiment intervention during disaster recovery[150, 306]. The research of Ma et al.[164] proved that official media can effectively guide public sentiment and relieve tension during meteorological disasters, thereby promoting disaster prevention, reduction, and recovery. In April 2019, a wildfire broke out in Liangshan, China, which caused the deaths of 27 firefighters and 4 local officials. This incident caused a heated discussion on Sina Weibo. Liu et al.[150] used this case as the background and analyzed public opinion information. They found that women are more inclined to share information and express their sentiment through social networks, and users in coastal areas are more active on social networks than are those in western China. They also noted that the government should actively use social sensors to achieve interactive communication with the public to avoid negative public opinion.

2.1.3.2 Derived Social Public Opinion Mining and Guidance

Public opinion information in natural disasters is not limited to the natural disaster itself. Disaster response policies, rescue plans, and the secondary social impact of disasters on transportation, medical treatment, economics, and other vertical domains can stimulate public opinion[157]. Du et al.[70] compared the information of official news and Twitter during the California fire season in 2018. They found that both platforms paid more attention to the disaster, while Twitter users focused on rescue information. The information in official news was universal, authoritative, and susceptible to political influence.

2.2 Data

Social network platforms such as Twitter, Facebook, Weibo, and Instagram are the primary data sources of social sensors in natural disaster emergency management. As shown in Fig.2.4, the data processing can be divided into data acquisition and generation, data processing and analysis, and data application and display.

The current data acquisition and generation processes rely on official APIs, crawlers, and manual collection methods. For example, Twitter has developed the Twitter API[3], a data interface that provides data support for research. The parallel system is designed to build a unified system composed of the natural actual system and corresponding

[3] `https://developer.twitter.com/en/docs/twitter-api`

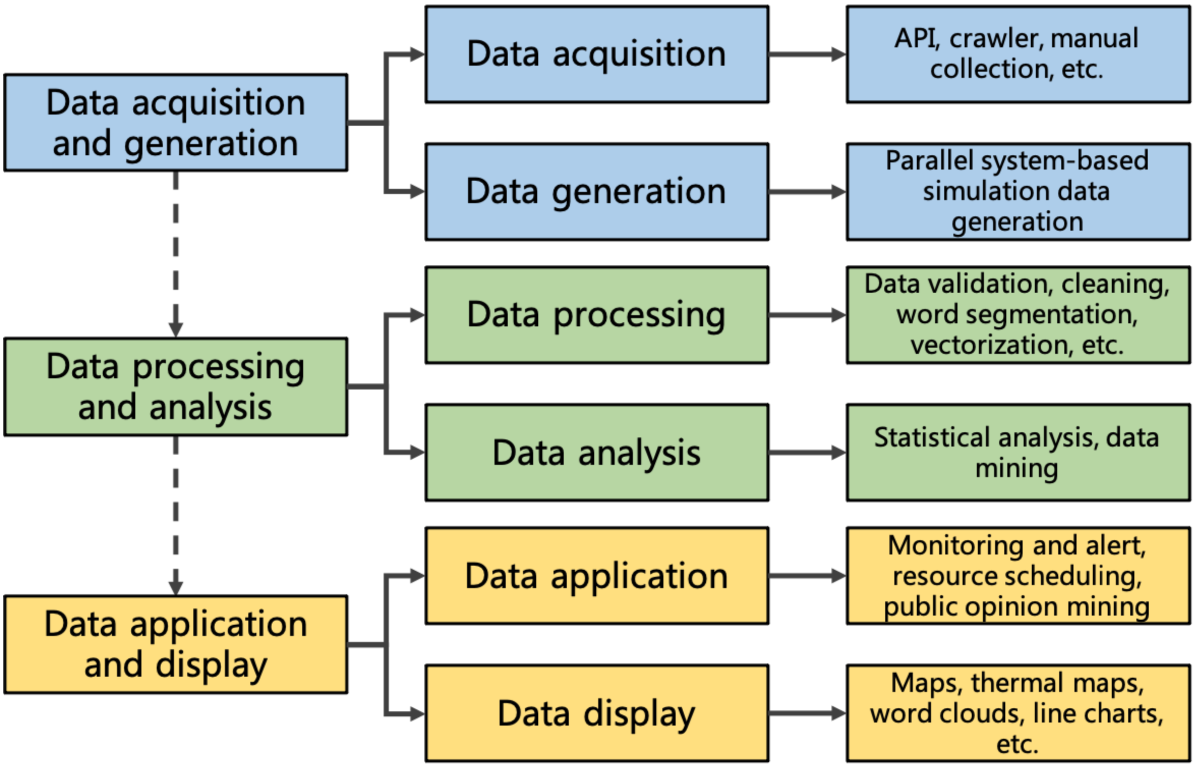

Figure 2.4: Data processing flow for the social sensor-based natural disasters emergency management.

ideal artificial system, making simulated data generation a widely used data acquisition method[75, 277]. An ideal artificial system can accurately simulate the actual natural system. At this stage, parallel systems have mature applications in intelligent transportation[135, 136, 157, 179, 180, 255, 272, 273, 328], education[256], control[284], and disaster emergency management[71, 322], and the social signal is an essential data source in ideal artificial systems.

Data processing and analysis realize the preprocessing of original data and the construction of a knowledge application analysis model. Social signals contain more noisy data than do physical signals, so preprocessing steps, such as data verification and cleaning, are particularly important to improve the service capabilities of downstream tasks. Data verification focuses on credibility evaluation and rumor filtering to avoid social panic caused by misinformation in a disaster environment[254, 276]. The data cleaning process can filter noise information, including garbled characters and Emoji, through regular expressions and other methods. Text vectorization is the input basis of downstream models. Models such as BERT[67] and Word2vec[181] are also used to vectorize words and sentences in the data preprocessing stage. The data analysis stage can be divided into statistical analysis and intelligent analysis with data mining methods, which will be discussed in detail in the next section.

Data application and display rely on data visualization platforms. The visualization display method can reveal the changing laws of the data and display the knowledge concretely as the sublimation of the key characteristics of the data. Fan graphs, line graphs, and other graphs can visually display the results of statistical data analysis, while region maps and heat maps are often used as the display carrier of data mining results. Apache ECharts[4] and D3.js[5] are commonly used data visualization components.

2.2.1 Data Modality

At present, the data modalities provided by social sensors include text, image, audio, and video[10]. Table 2.2 lists the knowledge features reflected by different modality data in natural disaster emergency management.

Table 2.2: Knowledge features of natural disasters reflected by multi-modal data.

Modality	Knowledge features	Literature
Text	Time, GPS location, User information, Number of retweet and follower, Address description, Event description, Contact information, Sentiment, etc.	[1, 9, 17, 19, 20, 28, 40, 42, 44, 45, 49, 51–53, 55, 56, 58, 60, 69, 70, 76, 80, 88, 89, 91, 92, 95, 96, 102, 104, 108, 114, 116, 120, 121, 123, 147, 148, 150, 154, 156, 158, 164, 169, 170, 175, 177, 178, 183, 187, 194–196, 203, 207, 212, 214, 217, 219, 221–223, 229, 233, 236–240, 242, 246, 247, 251, 263, 265–267, 274, 288, 290, 296, 299, 303–306, 310, 329]
Image	Target, Situation, Messages, etc.	[6, 7, 33, 34, 76, 83, 102, 103, 111, 154, 183, 184, 189, 199, 225, 282, 283]
Audio	Voice communication, Data enhancement, etc.	[208, 261]
Video	Scene situation, Video communication, Dynamic monitoring, etc.	[152, 208, 261]

Table 2.2 indicates that the current applications of social sensors in natural disaster emergency management focus on text and image data. Text is the most widely used

[4]https://echarts.apache.org/en/index.html
[5]https://d3js.org/

data modality because of its diverse and flexible knowledge representation capabilities. The rise of various short video social applications has made video data increasingly mainstream in recent years. This trend gives video data the potential to become the mainstream application data modality in social sensor-based natural disaster emergency management research.

2.2.2 Dataset

Data sharing platforms such as Kaggle[6] and CrisisLex[7] have provided research datasets for social sensor-based natural disaster emergency management. This section divides the data modality by text, image, and video and summarize the existing mainstream datasets, as shown in Table 2.3.

2.3 Technical Method

According to the differences between the features considered by technical methods in the social sensor-based natural disaster emergency management applications, this section divides the methods into statistical analysis and data mining. The division is shown in Table 2.4.

The statistical analysis method mainly uses the statistical quantitative analysis model to analyze the social signals' correlation and spatiotemporal distribution. The data mining methods include machine learning or deep learning models to achieve the fine-grained mining of the social signals' features.

2.3.1 Statistical Analysis

Statistical analysis is a simple and efficient technical method that can be used with charts to realize visual display and data analysis. Statistical methods such as the Pearson correlation and Granger causality test focus on application scenarios such as correlation analysis[49, 52, 92, 229, 265, 266]. Methods such as Mann-Kendall focus on the application scenarios of spatiotemporal distribution statistics[17, 108, 148, 203, 247].

[6] https://www.kaggle.com/

[7] http://www.crisislex.org/data-collections.html

Table 2.3: The dataset of the social sensor-based natural disaster emergency.

Modal	Dataset	Time	Source	Description
Text	Natural Hazards Twitter Dataset[177]	2020	Twitter	Natural disaster sentiment analysis
	Disaster Communal[223]	2018	Twitter	Disaster communal tweets
	CrisisLexT26[196]	2015	Twitter	Natural disaster crisis event
	Sandy Hurricane GeoT1[274]	2015	Twitter	Hurricane Sandy geotagged tweets
	SoSItalyT4[58]	2015	Twitter	Italian flood and earthquake
	Chile Earthquake T1[56]	2015	Twitter	Chilean earthquake tweets
	ClimateCovE350[194]	2015	Twitter	Meteorological event tweets
	CrisisLexT6[195]	2014	Twitter	Meteorological crisis event
	Event Detection corpus[175]	2013	Twitter	Natural disaster event
	JOPLIN[104]	2013	Twitter	Tornado tweets
Image	xBD[282]	2020	Flickr, Twitter	Currently the largest natural disaster image dataset
	Incidents Dataset[283]	2020	Flickr, Twitter	Natural disaster and traffic accident event
	AIDR-DT[7]	2020	Twitter	Natural disaster classification
	AIDR-Info[7]	2020	Twitter	Natural disaster image validity judgment
	FCSM[34]	2018	Twitter	Flood image classification
	CrisisMMD[6]	2018	Twitter	Natural disaster tweets and image
	DMD[184]	2018	Instagram	Natural disaster damage identification
	DAD[189]	2017	Twitter	Earthquake, typhoon and hurricane disaster image
	DIRSM[33]	2017	Twitter	Natural disaster image retrieval
Video	Disaster Video Dataset[208]	2019	YouTube	Hurricane damage assessment
	Flood Video Dataset[152]	2018	YouTube	Flood situation assessment video

2.3.2 Data Mining

Data mining methods focus on analyzing complex features to meet the requirements of various scenarios. For example, researchers have realized the detection of natural disasters such as earthquakes, rainstorms, and floods through the decision tree and

Table 2.4: Technical methods of social sensors in the application of natural disaster emergency management.

Technology		Application	Literature
Statistical	Correlation statistics	Statistics on the correlation between tweets and natural disasters, and statistics on the correlation between natural disasters and derivative events	[49, 52, 92, 229, 265]
	Spatiotemporal distribution statistics	Natural disaster abnormal signal detection and population migration trend analysis	[17, 108, 148, 203, 247]
Data mining	Support vector machine	Natural disasters and disaster victims detection, resource scheduling, disaster spatiotemporal information mining	[19, 270, 303]
	Decision tree	Disaster event and derivative event detection, disaster degree assessment	[20, 24, 55, 91, 156, 214]
	Naive bayes	Natural disaster detection	[182]
	Markov model	Victim detection	[242]
	Topic model	Natural disaster subject clustering, natural disaster-derived event detection	[51, 91, 120, 217, 266]
	Convolutional neural network	Victim detection, natural disaster-derived event detection, natural disaster situation assessment, sentiment analysis	[76, 102, 111, 147, 154, 169, 183, 199, 236, 246, 299]
	Recurrent neural network	Natural disaster knowledge service, natural disaster prediction	[95, 237, 304, 311]
	Regression model	Data correlation mining, media and disaster impact assessment	[49, 219, 267, 278]
	Sentiment dictionary	Sentiment classification and sentiment trend mining	[164]
	Event extraction	Natural disaster-derived event detection	[290]

other models[19, 24, 55, 95, 102, 111, 147, 154, 156, 169, 182, 183, 214, 236, 246, 270, 304]; use the support vector machine and convolutional neural network to classify and detect the situation of disaster-bearing carriers[76, 199, 242, 303]. The topic model and the sequence model are used to analyze spatiotemporal trends, such as the situation, rescue process, and public opinion[51, 217, 278, 311]. In addition, the flexibility of topic models also makes them commonly used in disaster sentiment analysis[91, 266] and alert release[120]. Moreover, regression models are also widely applied for releasing alerts[219, 267].

With the continuous upgrading of data, models, and computing power, the technical methods of social sensor-based emergency management applications have gradually shown the following evolution trends:

(1) Development from single-model-based analysis to multiple-model-based analysis. Multimodel joint analysis improves the application efficiency of the social sensor signal's knowledge features. Hernandez et al.[95] realized named entity recognition of the victims' location in an earthquake by combining the Bi-LSTM model and CRF model and realized the mapping of regions, victims, and shelters through kernel density estimation. The development of multitask learning illustrates the positive role of individual models in mutually reinforcing each other in joint model architectures. Shi et al.[237] enhanced the model to generate briefing content containing core meteorological disaster event knowledge through the event knowledge guidance module, which improves the efficiency of decision support services.

(2) Development from a general model to a knowledgeable model with domain features. Pretraining models is an effective way to introduce domain prior knowledge. This approach has shown remarkable ability in natural language processing, computer vision, and other tasks. Shi et al.[236–238] used a meteorological corpus to fine-tune the general BERT model to introduce meteorological domain prior knowledge for downstream tasks. The experimental results prove that the knowledgeable language model can significantly improve overall performance compared with the general language model.

(3) Development from primary natural disaster-based analysis to consider disasters and the corresponding social impacts. The social impact of primary disasters attracts much public attention, including urban traffic, communications, and psychology. When analyzing the trend of the spatiotemporal process of primary disasters, the potential social impacts generated at different stages should also be considered. Lopez et al.[154] used convolutional neural networks to analyze the trafficability of urban roads in heavy rain. Raza et al.[214] achieved restoration of the communication capability in a disaster area according to the severity of the flood through the XGBoost-based model.

2.4 Application System

On the basis of the application system requirements in disaster scenarios, this section classifies the current reported social sensor-based natural disaster emergency management systems into three categories, namely, early warning and monitoring system, resource scheduling system, and public opinion mining system, which, respectively, rely on the application functions of natural disaster situation awareness and event detection, disaster information dissemination and communication, and disaster sentiment analysis and public opinion mining. Social sensor-based application systems and the corresponding descriptions are shown in Table 2.5. This section further abstracts the specific functions of the application systems into five categories: Event Description (ED): detect and describe natural disaster events based on words, sentences, and other expressions; Location Mapping (LM): mine and map location information; Hotspot Analysis (HA): analyze and describe the hot spots of public concern; Trend Analysis (TA): statistics or forecast data trends; Alert Release (AR): realize early warning and forecast of disaster information. LM and HA are the basic functions that are the focus of most current application systems. With the development of artificial intelligence models such as time series prediction[3], the application systems should pay more attention to integrating the TA and AR functions to predict natural disaster situations and public opinion trends; thus, early response plans and warnings can be prepared to reduce losses.

2.4.1 Early Warning and Monitoring System

Social sensor-based natural disaster early warning and monitoring systems are used to detect natural disaster events, release early warnings, and monitor situations. Early warning and monitoring services based on social sensors are presented in an independent system or as a vital component of the disaster early warning system[37, 59]. Some general frameworks can adjust data sources according to the scenario requirements to enhance the system's application service capabilities in specific natural disasters[203].

The dynamic planning of natural disaster reduction decision making is essential for reducing disaster losses. A lack of social sensor-based intelligent disaster reduction decision-making applications remains. Social sensors can realize dynamic perception of the disaster environment and monitor the subjective views of the victims during the rescue process. From the victims' perspective, the dynamic disaster reduction decision-making process combines the characteristics of the situation and rescue operations, which provides a reference for decision makers to formulate more reasonable and targeted early

Table 2.5: The social sensor-based application systems in natural disaster emergency management. In the "open source" column, ✓ represents a publicly accessible system; × represents a private or commercial system.

Application systems	Literature	Description	Open source	System function
Early warning and monitoring	[59]	GeoSocial Gauge: Social geographic knowledge generation system	×	ED, LM, HA
	[203]	BurstDetector: Sudden disaster detection system	✓	ED, LM
	[209]	Emergency Situation Awareness (ESA) system	✓	ED, LM, HA, TR, AR
	[23]	EARS: earthquake alert and report system	×	ED, LM, HA, TR, AR
	[24]	Emergency detection decision support system	×	ED, TR
	[88]	TED: Twitter earthquake detector	×	ED, LM, HA, TR, AR
	[20]	Meteorological disaster alert system	×	TR, AR
	[214]	Flood-affected area marking system	×	LM
	[123]	TWRsms: Tsunami warning and response social media system	✓	ED, LM, TR, AR
	[37]	The European crisis warning system, which has been integrated into Alert4All.	✓	ED, LM, HA, TR, AR
	[243]	Wildfire detection and management general platform	×	ED
	[30]	FFireDt: Fast-fire detection architecture	×	ED
	[170]	Natural disaster monitoring system	×	ED, HA
	[259]	Fire detection visualization system	×	ED, LM
	[83]	PVD: Human and vehicle hazard assessment and early warning system	✓	ED, AR
	[212]	CompDrone: Wildfire monitoring framework	×	ED
	[293]	Disaster response and community service system	×	ED, LM, HA, TR
	[182]	Fire information monitoring system	×	ED
	[242]	Flood tweets priority classification system	×	ED, LM
	[278]	Earthquake-affected area assessment framework	×	ED, LM, HA, TR
	[22]	Edge computing framework of fire detection	×	ED
	[76]	Map-based flood monitoring framework	×	ED, LM, TR
	[120]	Japan Typhoon Warning System	×	ED, HA, TR, AR
Resource scheduling	[296]	SMIR: Disaster information retrieval framework	×	ED, LM
	[260]	OCULUS Fire: Disaster control command system	×	ED, LM
	[46]	Disaster warning information broadcasting system	×	ED, LM
	[215]	Disastrous information retrieval system	×	ED
Opinion mining	[223]	Disaster communal and anticommunal tweets mining system	✓	HA
	[9]	Disaster sentiment analysis framework	×	HA
	[236, 237]	Meteorological public opinion monitoring system	×	ED, LM, HA, TR

warning plans.

2.4.2 Resource Scheduling System

Social sensor-based natural disaster resource scheduling systems are used to realize natural disaster response resources' command and scheduling, information broadcasting, and disaster information retrieval[215, 260, 296]. The disaster response resources also include volunteers and private rescue teams, and social sensors are an effective means to discover such social resources.

Reasonable resource scheduling is essential for efficient rescue in natural disaster environments. There remains a lack of specialized resource scheduling applications based on social sensor signals. Zhengzhou's provincial capital city attributes make it the city most affected by Henan's heavy rains in 2021. With the intervention of rescue groups, Zhengzhou was gradually saturated with rescue resources, while Xinxiang and other cities suffering from the same severe disaster but with relatively low visibility still lack rescue resources. Thus, the intelligent dispatch and overall allocation of rescue resources in a disaster environment are conducive to reducing overall losses, and social sensors are the main channel for sensing the supply and demand of rescue resources.

2.4.3 Public Opinion Mining System

The social sensor-based natural disaster public opinion mining system is used to perceive individual sentiment trends in the disaster environment and to monitor public opinion changes[9, 236, 237]. Few dedicated independent systems for analyzing the trends of public sentiment exist. Most are integrated as sentiment analysis components in the public opinion mining system to realize the comprehensive mining of public opinion information, including opinion heat, hot events, and public sentiment.

Timely intervention to address negative public opinion is essential for maintaining social stability in a natural disaster environment, but there remains a lack of comprehensive social sensor-based intelligent public opinion guidance applications. Most official media refute rumor information via their social network accounts manually. This method has a lag and cannot stifle rumors in their early stages to narrow the scope of influence. Social sensors can accurately detect rumors, and intelligent application models such as text generation provide the possibility for rumor-driven automatic public opinion guidance information generation.

2.5 Conclusion

This chapter summarizes the research status, data application mode, decision-making technology, and application service system of social sensors in the sudden natural disasters emergency management application from the functions of natural disaster situation awareness and event detection, disaster information dissemination and communication, and disaster sentiment analysis and public opinion mining. The research of this chapter clarifies the significance of the follow-up innovation model. This research has been published in IEEE Transactions on Computational Social Systems.

CHAPTER 3

CO-OCCURRENCE FEATURE-BASED SUDDEN METEOROLOGICAL EVENT DETECTION

3.1 Introduction

Meteorological social event detection refers to using social sensors to realize situational awareness of meteorological events. Traditional meteorological event detection mostly relies on signals from physical sensors, including radar, satellite, and remote sensing equipment[168, 218]. However, deploying physical sensors often requires many resources, and most physical sensors have limited coverage and poor flexibility. In contrast, social sensors enable real-time, multi-angle, comprehensive feedback on events happening in real space[27, 39, 124–126, 139, 155, 227].

There are generally co-occurrence features among meteorological events, such as the occurrence of gale often before the heavy rain and blizzards accompanied by road icing. Focusing on these features, this chapter proposes the **S**entence-level **F**eature-based **M**eteorological **E**vent **D**etection (SFMED) model to detect 14 types of meteorological events[1] in Sina Weibo. The structure design of the SFMED model contains two modules: a fine-tuned BERT model with meteorological knowledge and a wide-grained capsule network with multi-level receptive fields, which considers the co-occurrence feature based

[1]The events include Typhoon, Rainstorm, Blizzard, Cold wave, Gale, Sandstorm, High temperature, Drought, Thunder, Hail, Frost, Fog, Haze, and Icing. These events are defined by China Meteorological Administration (CMA) and also used as a national standard (General Administration of Quality Supervision, Inspection and Quarantine of the People's Republic of China & Standardisation Administration of the People's Republic of China, 2011).

on the sentence-level meteorological event features. The meteorological event detection process is shown in Fig. 3.1. The SFMED model has been applied to the Meteorological Public Opinion Mining Platform. It visually displays the daily meteorological events so that the decision-makers can know the national meteorological dynamics on that day.

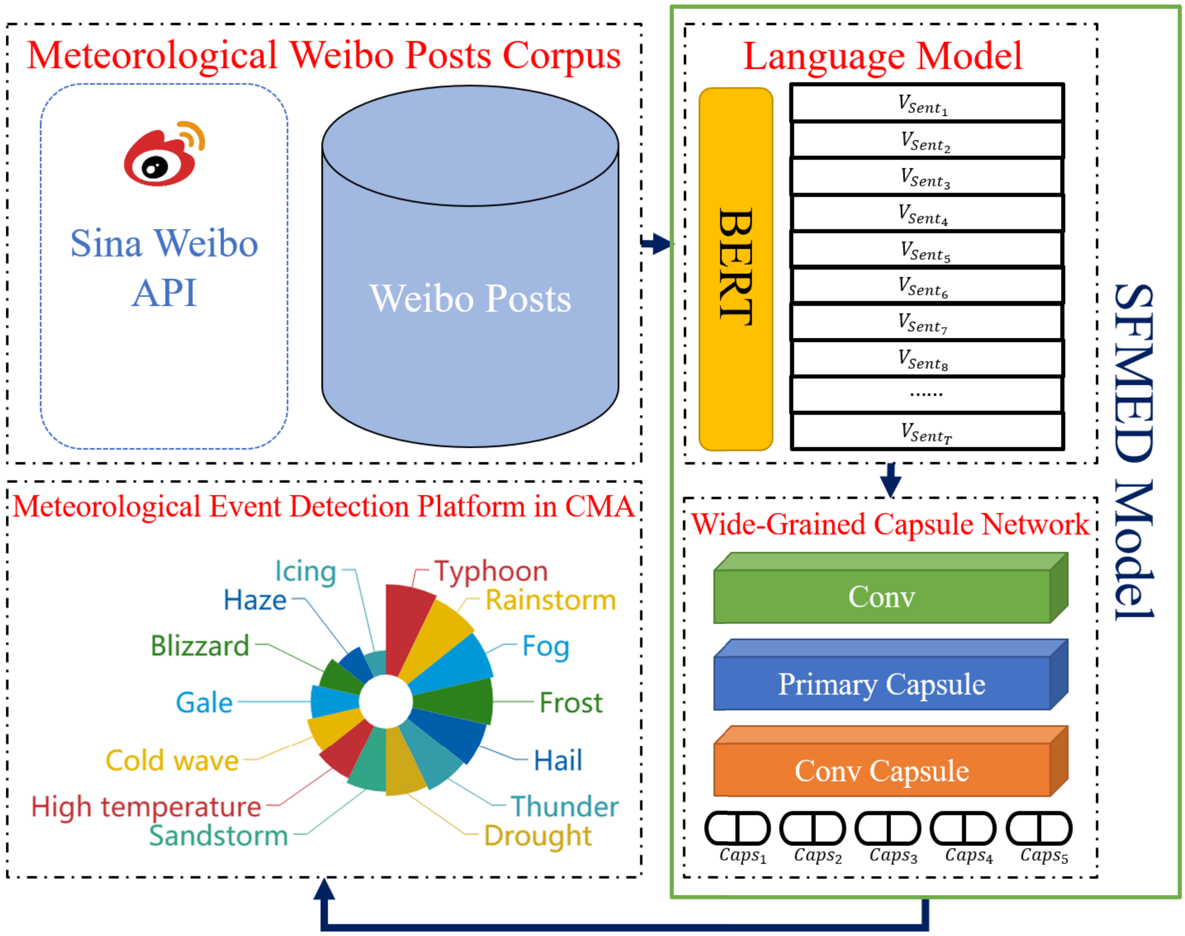

Figure 3.1: Illustration of the proposed meteorological event detection process.

The contributions of this chapter can be summarized as follows:

- The BERT model with meteorological knowledge is fine-tuned to transform the source Weibo posts into sentence-level vectors. Such vectors are more suitable for the meteorological event detection task because of their significant meteorological features.

- The wide-grained capsule network is proposed. The model applies the multi-level receptive field that can capture the features of meteorological events from multiple angles and considers the correlation among meteorological events.

- The **S**entence-level **F**eature-based **M**eteorological **E**vent **D**etection (SFMED) model is constructed. The Meteorological Public Opinion Mining Platform applies the SFMED model to provide online services that detect, mine, and display daily meteorological events from the perspective of the social network. The platform can provide decision support services for meteorological decision-makers.

The remainder of this chapter is organized as follows. The related work on event detection in social networks are given in section 3.2. The details of the SFMED model are illustrated in section 3.3. Section 3.4 introduces the experimental process, including the dataset and implementation details. The results and analysis are in section 3.5. The conclusion of this chapter is discussed in section 3.6.

3.2 Related Work

There is some research about social network event detection in the specific domain, such as transportation event detection[62, 155, 323], public health event detection[31, 61, 64, 115], and geological disaster detection[13, 226, 227]. Social network event detection techniques are divided into unsupervised and supervised models[21]. Unsupervised models mainly include the cluster-based model, topic-based model, etc. Supervised models often treat the event detection task as a classification task, including models based on machine learning and deep neural networks.

Unsupervised models are often used in non-specific event detection tasks. Sankaranarayanan et al.[228] detected news events from tweets via the online leader-follower clustering algorithm. Sayyadi et al.[230] applied a graph cluster-based model that can build a network by keywords based on their co-occurrence in documents. This network can be used to find the related articles of keywords and also can be used to analyze events and track stories in social streams. Phuvipadawat et al.[202] utilized a clustering algorithm with a specific threshold to detect breaking news on Twitter. Long et al.[153] proposed a unified workflow of event detection on microblog data. They presented a cluster-based method to detect events based on the selected topic words. Weng et al.[286] implemented the EDCoW model, which can detect and filter the noise information in specific events. Huang et al.[101] proposed a generic news detection strategy based on hierarchical clustering and named entities, which identify event topics in the news by considering the features evolution of data. Unankard et al.[268] proposed a cluster-based location-sensitive hotspot event detection model, which is used to detect emerging events on Twitter. Lu et al.[159] implement a visual analytics framework that clusters the event from multiple media. Nguyen et al.[188] proposed a real-time model to identify and detect the events on Twitter at the early stage by density-based spatial clustering. Zhou et al.[325] detected the event from Twitter by using an unsupervised Bayesian model. Castellanos et al.[43] applied the formal concept analysis, enabling the better organization of the data and stability, thus better detecting the event topic on Twitter.

Supervised models are often used to detect specific events. Popescu et al.[205] detected the controversial events on Twitter by the gradient boosted decision tree. Becker et al.[29] obtained the text features through the clustering algorithm and differentiated real-world event and non-event clusters through the support vector machine. Taking each Twitter user as a sensor, Sakaki et al.[227] proposed an algorithm for monitoring tweets and detecting target events based on the support vector machine. They set up an earthquake reporting system in Japan, which can detect the 93% of earthquakes with the seismic intensity scale of three or more reported by the Japan Meteorological Agency (JMA). Shao et al.[232] proposed the DMGraphScan framework to implement domain-specific event detection and forecastings, such as detecting the outbreak of flu and haze. Since the deep neural network is good at learning event features adaptively, it has been widely used in social network event detection in recent years. Chen et al.[48] implemented a dynamic multi-pooling convolutional neural network. This method gives a new word vector representation model to acquire the sentence-level features without using complex NLP tools. Moreover, they designed a dynamic multi-pooling layer that returns essential information in each part of the sentence based on event triggers. Popescu et al.[206] detected events in multilingual environments such as English, Chinese, and Spanish by applying Bi-LSTM and CNN model. Nguyen et al.[190] proposed a joint framework that utilizes the bidirectional recurrent neural networks. This framework introduces the memory matrix, which improves the performance when extracting the events from the sentence with multiple events. Lee et al.[129] implemented a CNN-based model for adverse drug event detection in tweets. Zhang et al.[318] used the deep belief network and long short-term memory network to detect traffic accidents from social media. The practicability of the model is proved by comparing the accident-related tweets with the traffic accident log and abnormal traffic data.

Sabour et al.[224] proposed the capsule network. Compared to the traditional convolutional neural network, the capsule network is good at distinguishing objects by learning their attributes. Zhao et al.[321] pioneered the application of capsule networks to text classification tasks. The experiments based on benchmarks show the advantage of this structure. This chapter proposes the wide-grained capsule network as the event detection network of the SFMED model, which is used to realize the detection of meteorological events in Sina Weibo posts. The capsule network-based structure is good at distinguishing meteorological events based on attributes, which can consider the co-occurrence feature within meteorological events and is suitable for application scenarios.

BERT is a language model proposed by Google[68]. Since its inception, it has achieved remarkable results in multiple NLP tasks, such as question answering[5], information retrieval[300], and text summarization[149]. BERT is introduced to specific domains to enhance its applicability by learning knowledge with domain features[165]. Alsentzer et al.[12] and Huang et al.[98] applied the BERT model to the clinical domain. Their research proved that the BERT model with clinical knowledge has significant advantages in clinical NLP tasks. Lee et al.[128] proposed the BioBERT model with biomedical knowledge, which has been proven to be more suitable in biomedical NLP tasks, including named entity recognition, relation extraction, and question answering. SciBERT[191] is proposed for the scientific domain, which is pre-trained on a large corpus of scientific publications. It achieves new state-of-the-art results on scientific NLP tasks such as sequence tagging, sentence classification, and dependency parsing. The above studies prove that the BERT model with domain knowledge is more applicable in specific domains. This chapter fine-tunes the BERT model with knowledge of the meteorological domain. Such a fine-tuned BERT model is more sensitive to specific meteorological events.

3.3 Methods

Most of the above studies are applied to detect events in specific domains. By contrast, the events in the meteorological domain are correlated. For this reason, this section proposes the SFMED model, which detects meteorological events more efficiently by mining the co-occurrence feature. The SFMED model is divided into two modules: the fine-tuned BERT as the language model and the wide-grained capsule network as the event detection network. The structure of the SFMED model is shown in Fig. 3.2. The fine-tuned BERT model transforms each Weibo post into a sentence vector. The wide-grained capsule network learns the corresponding attributes of different meteorological events through the sentence vectors and classifies different meteorological events. The rest of this section elaborates on each module in detail.

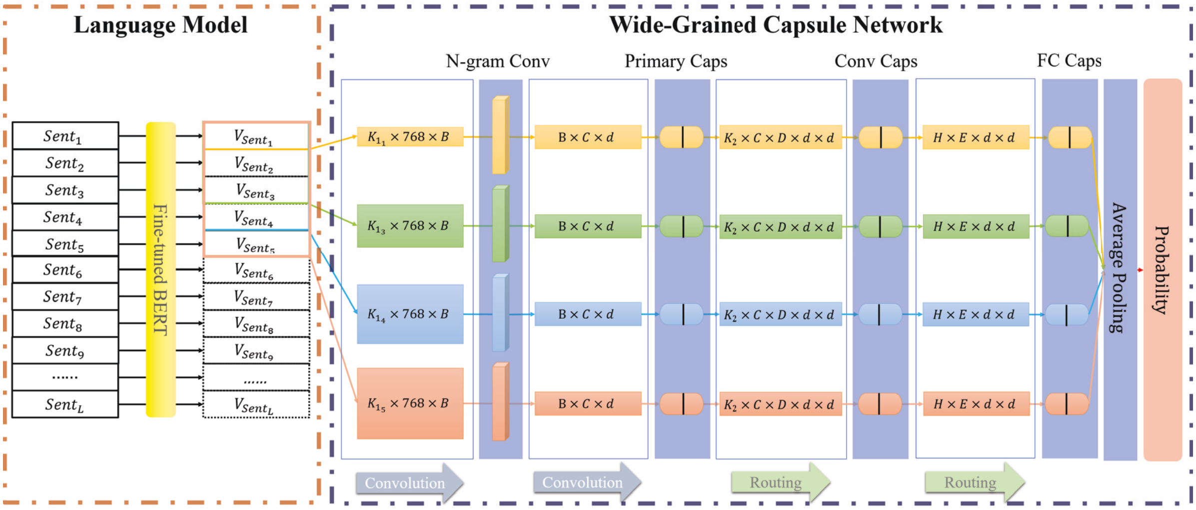

Figure 3.2: The structure of the sentence-level feature-based meteorological event detection model.

3.3.1 Language Model

The experiment fine-tunes the pre-trained "BERT-Base, Chinese"[2] model by using the meteorological Weibo posts. Such a fine-tuned BERT model learns the knowledge of the meteorological domain, and the vectors transformed by it are more suitable for the meteorological event detection task. Let $\mathbf{V}_{sent_\beta} \in \mathbb{R}^{1\times 768}$ ($\beta \in [1, L]$) represents the sentence vector transformed by the fine-tuned BERT model, where L is the number of Weibo posts.

3.3.2 Wide-grained Capsule Network

The experiment implements a wide-grained capsule network with the multi-level receptive field of size $\{1,3,4,5\}$. Currently, most CNN-based text classification researches adopt a multi-level receptive field[145, 321]. The receptive field with size 1 is a unique network structure often used to change the dimension of feature maps in image classification[94] and for full connection in machine translation[269]. This structure differs from word vectors when using sentence vectors as network input. Specifically, the model is good at learning the features of a single Weibo post with the receptive field of size 1. When the receptive field is greater than 1, it is good at learning various expressions of the same event or co-occurrence feature among different events. This section implements

[2]https://storage.googleapis.com/bert_models/2018_11_03/chinese_L-12_H-768_A-12.zip

the wide-grained capsule network with the multi-level receptive field, which can learn more comprehensive and valuable text features.

The structure of the wide-grained capsule network consists of 5 layers: N-gram convolutional layer, primary capsule layer, convolutional capsule layer, fully connected capsule layer, and capsule average pooling layer. The following sections will detail each layer of the wide-grained capsule network.

3.3.2.1 N-gram Convolutional Layer

The N-gram convolutional layer is a standard convolutional layer that extracts event features from multiple text representations. Let $\mathbf{W}^n \in \mathbb{R}^{K_{1_a} \times 768}$ be the N-gram convolution filter for the convolution operation, where $\mathbf{K}_{1_a}$ is the a-gram size ($a \in \{1,3,4,5\}$) while sliding over $\mathbf{V}_{sent}$. $\mathbf{W}^n$ convolves with the sentence-windows $\mathbf{V}_{sent_{\beta:\beta+K_{1_a}-1}}$ to produce a column feature map $\mathbf{m}^n \in \mathbb{R}^{L-K_{1_a}+1}$, each element produced by $\mathbf{W}^n$ can be expressed by Eq. 3.1.

$$\mathbf{m}_i^n = f(\mathbf{V}_{sent_{\beta:\beta+K_{1_a}-1}} \circ \mathbf{W}^n + b_0). \tag{3.1}$$

Here f is the $ReLU$[84] as the activation function, $\circ$ is element-wise multiplication, $b_0 \in \mathbb{R}$ is a bias term. For $n \in [1,B]$, totally B ($B = 32$) filters with the $\mathbf{K}_{1_a}$ filter windows size, each filter can generate B feature maps, which represented as Eq. 3.2.

$$\mathbf{M} = [\mathbf{m}_1, \mathbf{m}_2, ..., , \mathbf{m}_B] \in \mathbb{R}^{(L-K_{1_a}+1)\times B}. \tag{3.2}$$

3.3.2.2 Primary Capsule Layer

The primary capsule layer is the first capsule layer, which transforms the features detected by CNN from scalar output to vector output. Such the output format is called the capsule, which lets the model learn the meteorological event attributes from a different viewpoint. Let $\mathbf{W}^p \in \mathbb{R}^{B\times d}$ represents the filter shared in different sliding windows, d is the dimension of the capsule ($d = 16$). $\mathbf{M}_i \in \mathbb{R}^B$ denotes each vector generated by N-gram convolution. A column list of capsules can be obtained by Eq. 3.3.

$$\mathbf{q} = (W^p)^T \{\mathbf{M}_i\}_{i=1}^{L-K_{1_a}+1} \in \mathbb{R}^{(L-K_{1_a}+1)\times d}, \tag{3.3}$$

Each capsule $\mathbf{q_i} \in \mathbb{R}^d$ in $\mathbf{q}$ can be calculated by Eq. 3.4

$$\mathbf{q}_i = g(\mathbf{s}_i), \tag{3.4}$$

where $\mathbf{s}_i = (\mathbf{W}^p)^T \mathbf{M}_i + b_1$, b_1 is the capsule bias term and g is the nonlinear squash function as the activation function, as shown in Eq. 3.5

$$g(\mathbf{s}_i) = \frac{\|\mathbf{s}_i\|^2}{1 + \|\mathbf{s}_i\|^2} \cdot \frac{\mathbf{s}_i}{\|\mathbf{s}_i\|}, \tag{3.5}$$

This layer totally has $C(C = 16)$ filters, the capsule feature maps can be rearranged as Eq. 3.6

$$\mathbf{Q} = [\mathbf{q}_1, \mathbf{q}_2, ..., , \mathbf{q}_C] \in \mathbb{R}^{(L-K_{1_a}+1)\times C\times d}, \tag{3.6}$$

$\mathbf{Q}$ contains a total of $(L - K_{1_a} + 1) \times C$ d-dimensional vectors.

3.3.2.3 Convolutional Capsule Layer

The capsule network introduces the child-parent structure to model the hierarchical relationship of internal knowledge representations in neural networks. In the convolutional capsule layer, each capsule is connected to the capsule in the lower layer (primary capsule layer). The capsules in the primary capsule layer multiple the transformation matrix to obtain a child-parent structure, and then the parent capsules in the convolutional capsule layer are obtained according to the dynamic routing algorithm (Algorithm.1).

Algorithm 1 Dynamic Routing Algorithm

```
procedure ROUTING(û_{j|i}, r, l)
    for all capsule i in layer l and capsule j in layer (l+1): b_{j|i} ← 0
    for r iterations do
        for all capsule i in layer l and capsule j in layer (l+1):
        c_{j|i} ← exp(b_{j|i}) / Σ_k exp(b_{ik})
        for all capsule j in layer (l+1):
        s_j ← Σ_i c_{j|i} · û_{j|i}
        for all capsule j in layer (l+1):
        v_j ← (||s_j||^2 / (1+||s_j||^2)) · (s_j / ||s_j||)
        for all capsule i in layer l and capsule j in layer (l+1):
        b_{j|i} ← b_{j|i} + û_{j|i} · v_j
    end for
return v_j
```

Let $\hat{\mathbf{u}}_{j|i}$ be the potential parent-capsule in the parent layer, which can be calculated as:

$$\hat{\mathbf{u}}_{j|i} = \mathbf{W}^c_j \mathbf{u}_i + \hat{b}_{j|i}, \tag{3.7}$$

where $\mathbf{W}_j^c$ is the j_{th} matrix in $\mathbf{W}^c \in \mathbb{R}^{K_2 \times C \times D \times d \times d}$, which represents the transformation matrixes. K_2 ($K_2 = 3$) is the receptive field size in this layer. $K_2 \times C$ is the number of child-capsules corresponding to each parent capsule. D ($D = 16$) is the number of parent capsules that child capsules are sent to. $\mathbf{u}_i$ is a child-capsules in a local region $K_2 \times C$, $\hat{b}_{j|i}$ is the capsule bias term. The dynamic routing algorithm obtains the feature maps in the parent-capsule, totally $(L - K_{1_a} - K_2 + 2) \times D$ d-dimensional capsules in this layer.

3.3.2.4 Fully Connected Capsule Layer

The capsules in the convolutional capsule layer are flattened into a list of capsules and fed into the fully connected capsule layer. These capsules multiple the transformation matrix $\mathbf{W}^f \in \mathbb{R}^{H \times E \times d \times d}$ to produce the final capsule $\mathbf{v}_j \in \mathbb{R}^d$ by the dynamic routing algorithm. H is the number of capsules in the convolutional capsule layer, and E ($E = 14$) is the number of meteorological event classes.

3.3.2.5 Capsule Average Pooling Layer

The outputs from the fully connected capsule layer are sent to the capsule average pooling layer to produce the class probability, thus determining the class of meteorological event.

3.4 Experiment

3.4.1 Dataset

The meteorological related posts in Sina Weibo are used as the dataset, totaling 1,123,000 items ($L = 1,123,000$). The Weibo posts in the dataset are arranged by post time.Table 3.1 shows the data representations in the training set, and Table 3.2 shows the data representations in the test set. The test set integrates the Weibo posts according to their post-time interval and combines all the Weibo posts and event labels in the same time interval. In the same time interval, the Weibo posts correspond to various meteorological event labels, indicating that Sina Weibo reflects all the meteorological events in this time interval. Since the proposed model is finally applied to the meteorological public opinion-mining platform, which achieves daily meteorological event detection on Sina Weibo, the experiment integrates the data in the test set with "day" as the time interval.

Table 3.1: Examples of the training and validation set. The meteorological events are marked in red fonts.

Weibo Posts	Post Time	Event
The CMA issued a blizzard blue warning at 6:00 on December 10.	2018/12/10 7:59	Blizzard
The cold wave hit, the temperature of the Heihe dropped to minus 30 degrees.	2018/12/10 7:57	Cold wave
The week with gale and heavy rain started.	2018/12/10 7:57	Gale
Ruian Meteorological Agency issued the Coastal Gale Warning and Weather Forecast at 07:00 on December 10.	2018/12/10 7:56	Gale
Tomorrow and the next two days, the impact of cold air is more obvious, gale, snow weather will be staged again.	2018/12/10 7:55	Gale
The CMA will continue to issue a cold wave blue warning at 06:00 on December 10.	2018/12/10 7:53	Cold wave
The cold wave is coming, the temperature is falling sharply, and snowfall continues everywhere.	2018/12/10 7:52	Cold wave

Table 3.2: Examples of the test set. The meteorological events are marked in red fonts.

Weibo Posts	Post Time	Event
Xinjiang Meteorological Observatory issues cold wave blue warning signal. The outside of the typhoon added cold air to the south, a pattering rain, the temperature dropped a lot. Cooling 6-8 degrees! There are rain and snow! The weather in our province will enter the "quick freeze" mode!......	2018/11/1	Cold wave, Typhoon, Gale, Hail, Blizzard, Frost, Haze

By observing the dataset, it can be found that most of the posts posted in a short period are descriptions of the same or co-occurring meteorological events. Such a data distribution facilitates the model to learn co-occurrence features within meteorological events and multiple semantic feature representations of the same meteorological event.

3.4.2 Implementation Details

The experiment is implemented based on NVIDIA GTX 1080Ti GPU. Adam[119] is used as the optimizer to minimize the margin loss over the training data. The dynamic learning rate is used, which starts at $1e-3$ and decreases by ten times each five epochs.

3.5 Results and Analysis

3.5.1 Evaluation Metric

The classification accuracy is used as the evaluation metric, which can be calculated by Eq.3.8.

$$Accuracy = \frac{1}{n}\sum_{i=1}^{n}\frac{\sum_{j=1}^{E}\left|G_i^j \cap P_i^j\right|}{|G_i \cup P_i|}, \tag{3.8}$$

G_i and P_i represents the ground truth and predicted result of instance x_i respectively, where

$$G_i^\lambda = \begin{cases} 1 & \text{if } x_i \text{ is belongs to class } \lambda \\ 0 & \text{otherwise} \end{cases}, \tag{3.9}$$

$$P_i^\lambda = \begin{cases} 1 & \text{if } x_i \text{ is predicted to class } \lambda \\ 0 & \text{otherwise} \end{cases}. \tag{3.10}$$

The label-based metrics summarized by Sorower[245] are also used to verify the performance of the SFMED model. It contains micro-averaged precision (P_{micro}), micro-averaged recall (R_{micro}), and micro-averaged F_1 ($F_{micro-1}$), which are often used in multi-label classification tasks[100, 200, 301]. These metrics are first computed on a single class and then averaged over all classes. The calculation of each metric is as follows:

$$P_{micro} = \frac{\sum_{j=1}^{E}\sum_{i=1}^{n} G_i^j P_i^j}{\sum_{j=1}^{E}\sum_{i=1}^{n} P_i^j}, \tag{3.11}$$

$$R_{micro} = \frac{\sum_{j=1}^{E}\sum_{i=1}^{n} G_i^j P_i^j}{\sum_{j=1}^{E}\sum_{i=1}^{n} G_i^j}, \tag{3.12}$$

$$F_{micro-1} = \frac{2 \cdot P_{micro} \cdot R_{micro}}{P_{micro} + R_{micro}}. \tag{3.13}$$

where n is the number of instances ($x_i \in n$), E is the number of meteorological events categories (in this task $E = 14$, $\lambda \in E$).

3.5.2 Baseline Methods

The CNN model proposed by Yoon Kim[117] is widely used in the event detection tasks[99]. This section uses the CNN model with the multi-level receptive fields as the baseline event detection network. The baseline methods also include a single-grained capsule network with a single-size receptive field of size 3.

In addition, the word vectors are introduced as the baseline language model to verify the advantage of sentence-level features in the meteorological event detection task. Specifically, the word vectors can be obtained by three initialization methods. (a) Rand: All word vectors are randomly initialized and used as parameters for optimization during the training process. (b) Static: The word2vec[181] model pre-trained on meteorological Weibo posts transforms all word vectors, and the vectors are fixed during the training process. Such word vectors have knowledge of the meteorological domain. (c) Non-Static: All word vectors are transformed by the pre-trained word2vec[181] model, but the vectors can be fine-tuned during the training process. Such word vectors have knowledge of the meteorological domain and can continuously learn new knowledge during the training process. The experiment uses the above three initialization methods in the comparison.

3.5.3 Quantitative Evaluation

Table 3.3 shows that the SFMED model achieves the best result compared to other baseline models. Specifically, the SFMED model captures more comprehensive features than the single-grained capsule network. Compared with the CNN model, which also has multi-level receptive fields, the SFMED model can better distinguish different meteorological events by learning semantic attributes. Such results prove the applicability of the SFMED model in the meteorological event detection task.

Table 3.3: Quantitative evaluation results of the SFMED model and other baseline models.

Language Model	Event Detection Network	Initialization Methods	$Accuracy$	P_{micro}	R_{micro}	$F_{1-micro}$
Word Vector	CNN[117]	Rand	0.889	0.673	0.637	0.654
		Static	0.891	0.788	0.630	0.700
		Non-Static	0.894	0.825	0.622	0.709
	Single-grained Caps	Rand	0.871	0.710	0.645	0.676
		Static	0.875	0.796	0.628	0.702
		Non-Static	0.876	0.731	0.647	0.686
	Wide-grained Caps	Rand	0.883	0.712	0.642	0.675
		Static	0.892	0.782	0.642	0.705
		Non-Static	0.886	0.792	0.653	0.709
BERT	CNN[117]	-	0.897	0.767	0.679	0.720
	Single-grained Caps	-	0.931	0.843	0.724	0.779
	SFMED	-	**0.941**	**0.862**	**0.738**	**0.795**

Table 3.3 also shows the experiment results using the fine-tuned BERT as the language model. It can be observed that the SFMED model has significant advantages in all metrics. The SFMED model has a multi-level receptive field similar to the CNN model[117], but the network structure of the SFMED model is based on the capsule network, and it also applies the receptive field of size 1. Such a structure can enable the model to learn the correlation among meteorological events from attributes and allow the model to learn independent meteorological event features. Compared with the single-grained capsule network, the SFMED model has more dimensionally receptive fields of learning the richer knowledge of the meteorological domain. The wide-grained capsule network of the SFMED model conforms to the real task features and is more suitable for the meteorological event detection task. Compared with the word vector initialization method of Rand, the other two initialization methods generally have better evaluation results, proving that the domain knowledge of meteorology positively impacts the whole meteorological event detection process. Except for P_{micro}, the wide-grained capsule network achieves the best results in the other two metrics; it performs the best in $F_{1-micro}$. Since $F_{1-micro}$ can measure P_{micro} and R_{micro} comprehensively, which proves that the capsule network with the wide-grained receptive field also has the advantage in the meteorological event detection process with the word vector as the language model.

It can also be seen that the advantages of using fine-tuned BERT as a language model are obvious compared to word vectors. In other words, the sentence-level features captured by the fine-tuned BERT model lay the foundation for the SFMED model to learn the correlation features between meteorological events. During the fine-tuning process, the fine-tuned BERT model can learn the correlation features of the events and endow them with meteorological domain knowledge, which results in a transformed vector with more distinct domain features. The word vectors only consider word-level features, which limits the use of features in Weibo posts and affects the performance of the whole model.

3.5.4 Effect of the Receptive Field Size

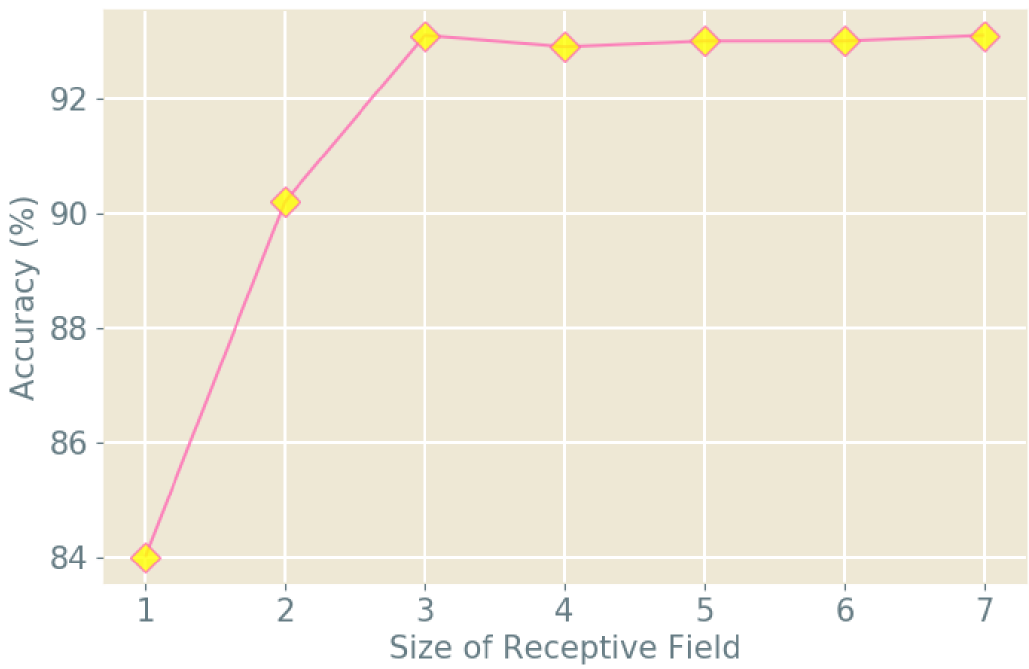

Figure 3.3: The effect of receptive field size on model performance.

This section discusses the effects of different receptive field sizes on the model performance using the single-grained capsule network with the fine-tuned BERT model. Fig. 3.3 shows that with the size of the receptive field increases, the model's accuracy increases gradually. When the receptive field size is 3, the model's accuracy tends to be stable. Such a conclusion also supports the setting of receptive field size.

Also, it can be found that the single-grained capsule network performs the worst when the receptive field size is 1. Because the model can only learn meteorological event features independently, it cannot learn from multiple angles about the various features of the same meteorological event and does not consider the correlation among meteorological events. As the size of the receptive field increases, the model can learn the richer features and achieves better performance.

3.5.5 Ablation Study

This section performs the ablation study to verify the model's validity with a receptive field of size 1. The ablation study is divided into two parts: comparing the SFMED model with a model having the receptive field of size $3,4,5$ and comparing the SFMED model with a model having the receptive field of size $2,3,4,5$, which are used to eliminate the effect of the size and number of receptive fields on the model.

Table 3.4: The results of the ablation study.

Receptive Field	{1,3,4,5} (SFMED)	{3,4,5}	{2,3,4,5}
Accuracy	**0.941**	0.934	0.936

By analyzing the results in Table 3.4, it can be found that the model's performance is improved when it contains the receptive field of size 1. This result proves that the receptive field of size 1 positively affects the SFMED model. Besides, the number of receptive fields also impacts model performance.

3.6 Conclusion

This chapter proposes the SFMED model for detecting meteorological events from Sina Weibo. The SFMED model consists of two modules: fine-tuned BERT as the language model and wide-grained capsule network as the event detection network. This joint structure considers the co-occurrence feature among meteorological events, making the SFMED model achieve the best results on all metrics compared with other baseline models. In subsequent chapters, the knowledge of extreme meteorological events detected by the SFMED model is used to guide and constrain the meteorological decision briefing generation and optimization process. This research has been published in Future Generation Computer Systems (CORE A).

CHAPTER 4

MULTIPLE KNOWLEDGE-ENHANCED METEOROLOGICAL DECISION BRIEFING GENERATION

4.1 Introduction

The emergency decision-making process requires comprehensive integration of multi-source information. Automatically generating meteorological briefings based on multiple Weibo posts is practical research. However, the weaker controllability of the generative model makes the generated briefing content easy to lose the core knowledge described in the source text[308]. This chapter proposes a **M**ultiple **K**nowledge **E**nhanced **S**ummarization (MKES) model to generate the content of the meteorological decision briefing. The MKES model applies the previously detected meteorological event knowledge and the manually labeled geographical location knowledge to constrain the summary generation process so that the generated summary retains the core knowledge in the source Weibo posts as much as possible.

The meteorological event knowledge with co-occurrence feature is the core description object of the meteorological briefing[4]. Meteorological briefings based on the multi-document summarization model need to consider all the meteorological event knowledge from each Weibo post. The event knowledge guidance model enhances the summary generation process by classifying the 14 previously detected extreme meteorological events[1]

[1]The extreme meteorological events include Typhoon, Rainstorm, Blizzard, Cold wave, Gale, Sandstorm, High temperature, Drought, Thunder, Hail, Frost, Fog, Haze, and Icing. These events are defined by the China Meteorological Administration (CMA) and also used as a national standard (General

based on the co-occurrence feature. Specifically, the module uses a generative structure to generate meteorological event knowledge because the structure considers previously generated event knowledge sequences when generating the new event knowledge. This characteristic promotes the model to mine the co-occurrence feature of meteorological event words.

In addition, geographical location knowledge is crucial to maintain the semantic consistency between the source Weibo posts and the generated summary. Therefore, this chapter designs the location knowledge guidance model that enhances the summary generation process by classifying 367 location knowledge[2] in the generated summary. Specifically, the model uses the single location knowledge emphasized classification structure to detect location knowledge. This structure is more controllable than the generative structure, sensitive to the knowledge of each location, and can achieve precise location-based rescue strategies. Based on the whole MKES model, this chapter constructs a meteorological briefing generation service framework, as shown in Fig.4.1. This framework has been applied to the Meteorological Public Opinion Mining Platform to visually display the meteorological trends of the day through meteorological briefings to provide decision support services.

The contributions of this chapter can be summarized as follows:

- This chapter constructs a **M**ultiple **K**nowledge **E**nhanced **S**ummarization (MKES) model to generate the meteorological briefing enhanced by meteorological event knowledge and geographical location knowledge. The structure makes generated briefing content focus on describing the source text's core knowledge. Compared with other baseline models, the MKES model achieves the best results.

- This chapter designs an event knowledge guidance model for introducing meteorological event knowledge. This module enhances the summary generation process by considering the co-occurrence feature between meteorological events in a specific period.

- This chapter designs a geographical location knowledge guidance model for introducing location knowledge. This module enhances the summary generation

Administration of Quality Supervision, Inspection, and Quarantine of the People's Republic of China & Standardisation Administration of the People's Republic of China, 2011).

[2]This chapter defines geographical location knowledge as 367 prefecture-level and above administrative regions in China, including 333 prefecture-level administrative regions and 34 provincial-level administrative regions. The classification criteria are defined by the administrative divisions of the People's Republic of China.

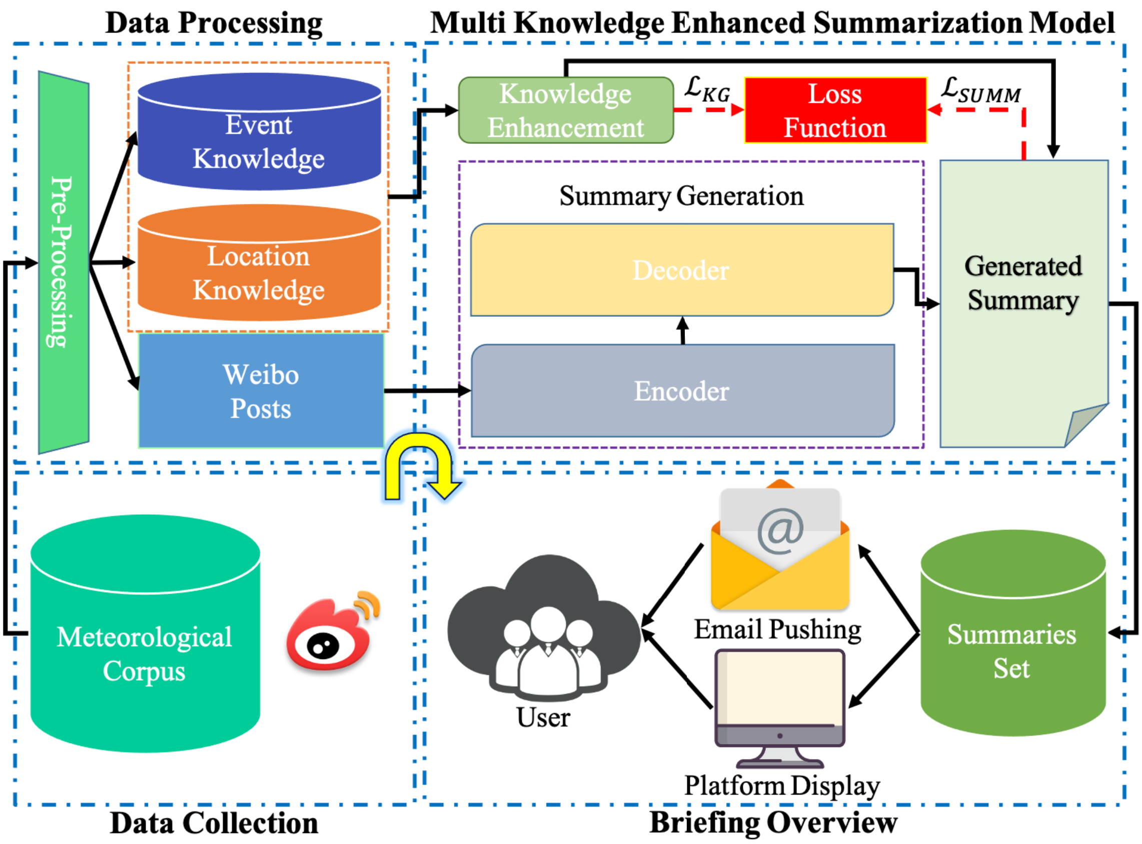

Figure 4.1: The framework comprises four modules: data collection, data processing, multiple knowledge enhanced summarization model, and briefing overview. Each of the modules is connected in a pipeline fashion.

process by considering the contribution of each location knowledge, making the generated summary provides fine-grained rescue decision support based on the characteristics of the specific geographical location.

- Based on the MKES model, this chapter constructs a service framework for the automatic generation of meteorological briefings. This framework has been applied to the Meteorological Public Opinion Mining Platform to provide decision-makers with online decision support services.

The remainder of this chapter is organized as follows. Reviews on briefing generation and text summarization methods are given in section 4.2. Detailed descriptions of the MKES model are illustrated in section 4.3. Section 4.4 introduces the experimental process, including the datasets and implementation details. The results and analysis are in section 4.5. Section 4.6 performs the ablation study to verify each knowledge enhancement model's effectiveness. Section 4.7 performs the error analysis of the MKES model by taking the generated summaries as examples. The conclusion of this chapter are discussed in section 4.8.

4.2 Related Work

The massive number of users in social networks provide real-time and comprehensive information sources for emergency management of sudden meteorological disasters[236]. Multi-source information with specific knowledge as the core description object is essential to improve the efficiency of decision support service[238]. The decision support briefing is one of the effective ways to integrate multi-source information.

The current briefing construction methods are mainly based on the fixed template and the summary generation models[65, 237, 238]. Das et al.[65] extracted the briefing template from the written report, thus realizing the generation of briefing content that conforms to the fixed sentence structure. Mani et al.[171] generated the briefing content by reorganizing the generated summary based on the tree template, constraining the generated briefing content to conform to the laws of the natural language grammar.

The deep learning model provides a more powerful driving for the summary generation task[72, 308, 313]. The summary-based decision support services have been applied in many domains such as meteorology[237], legal[113], minutes of the meeting[173], and scientific documents[16]. The unsupervised multi-document summarization model is more flexible in understanding and representing knowledge in the source text. Chu et al.[54] realized the summary generation of Yelp and Amazon reviews with opinions by calculating the semantic mean between multiple texts. This research has played a positive role in guiding the follow-up research in unsupervised multi-document summarization. The research of Brazinskas et al.[36] encouraged the model to generate summaries that reflect public opinions and are semantically coherent by controlling the novelty of the generated summaries. Treating the task of summary generation as a noising and denoising problem, Amplayo et al.[15] preserved consensus information on multiple opinions by encouraging the model to remove noise from artificial references.

The substantial flexibility of the generative model makes the summary hallucinate due to deviation from the core description object in the source text. Researchers have explored controllable summary generation models by introducing prior knowledge[73, 74, 146, 319], whose carriers include knowledge graphs[137, 138, 326] and keywords[14, 25, 81, 133, 327]. Zhou et al.[326] proposed an entity-aware model for multi-document summarization by considering that the same entity may appear in different documents. The research of Li et al.[137, 138] verified that the text's relationship graph representation effectively detects the salient information in the document and improves the semantic coherence of the generated summary. Liu et al[146] constructed a document sentence graph and extracted sentences for summarization based on each sentence's neighborhood's similarity and relative distance.

The keywords make the generated summary focus on specific attributes such as topics, events, and emotions. Li et al.[133]'s research simulates that people first consider the keywords in the source text when writing a summary and thus proposed a multi-task learning architecture that promotes summary generation through keyword extraction. Gao et al.[81] learned potential summary topics in a vector space and embedded the sentences with topics into the summary generation system to generate summaries that consider sentence representation and topic assignment. Zhu et al.[327] first generated the topic tags of Wikipedia article paragraphs through a classifier and then decoded the sentence from topic-aware representations during the summary generation process to generate the summary centered on the topic of the source text. Bahrainian et al.[25] proposed a mechanism to control the underlying latent topic distribution of the generated summaries to satisfy the user's preference. Amplayo et al.[14] proved that content planning and sentiment characteristics help the model generate the summary with broader information coverage and smoother content. This chapter introduces the prior knowledge of meteorological events and geographical locations by designing a knowledge enhancement module. This module achieves knowledge enhancement by guiding and constraining the summary generation, making the generated summary maintains factual consistency with the source text.

4.3 Methods

4.3.1 Overview

This section illustrates the proposed **M**ultiple **K**nowledge **E**nhanced **S**ummarization (MKES) model. The model consists of two modules, the summary generation module and the knowledge enhancement module. The summary generation module is used to generate the summary based on multiple Weibo posts, and the knowledge enhancement module is used to guide and constrain the summary generation process. The structure of the MKES model is shown in Fig.4.2.

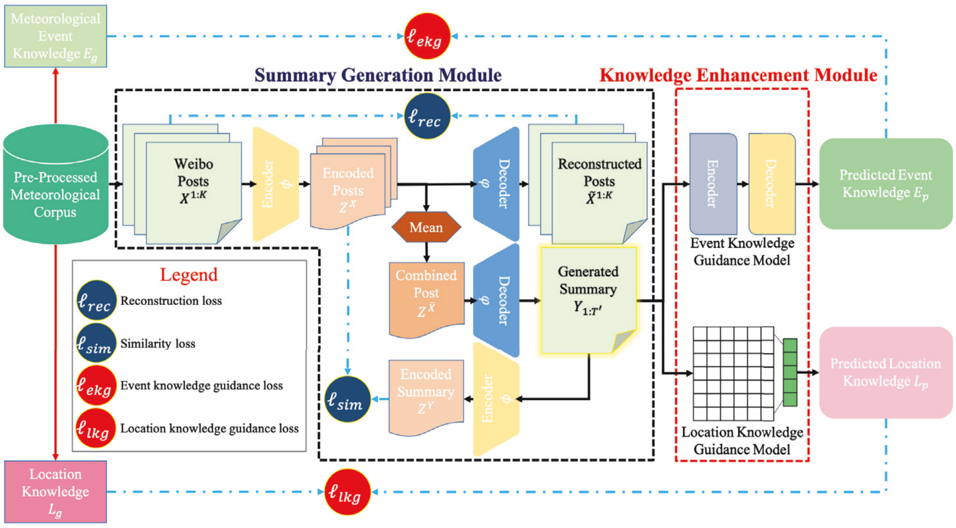

Figure 4.2: The structure of the multiple knowledge enhanced summarization model consists of two sub-modules: the summary generation module and the knowledge enhancement module.

The summary generation module consists of the reconstruction model and the similarity judgment model, which are based on the auto-encoder structure. The original Weibo posts are represented as $X^{1:K} \in \mathbb{R}^K$, where K is the size of the Weibo posts set that is intended to be summarized. $X^{1:K}$ are encoded into $\mathbf{Z}^X \in \mathbb{R}^{2\times K\times dim^\phi}$ by the encoder ϕ, the decoder φ reconstructs the encoded posts $\mathbf{Z}^X$ into the reconstructed posts $\widetilde{X}^{1:K}$, and compute the reconstruction loss ℓ_{rec} between $X^{1:K}$ and $\widetilde{X}^{1:K}$. Meanwhile, $\mathbf{Z}^X$ are combined by a mean function, and the decoder decodes the combined posts $\mathbf{Z}^{\bar{X}} \in \mathbb{R}^{2\times dim^\phi}$ to generate a multi-Weibo posts-based summary $Y_{1:T'} \in \mathbb{R}^{T'}$, where T' represents the length of the generated summary. Finally, the encoder encodes the $Y_{1:T'}$ into $\mathbf{Z}^Y \in \mathbb{R}^{2\times T'\times dim^\phi}$ and compute the cosine similarity ℓ_{sim} between the encoded posts $\mathbf{Z}^X$ and the encoded summary $\mathbf{Z}^Y$ to constrain the model to generate summary that is semantically similar to the $X^{1:K}$.

The knowledge enhancement module is divided into two sub-models: the event knowledge guidance model and the location knowledge guidance model. In the event knowledge guidance model, this section uses a generative encoder-decoder structure to generate the meteorological event knowledge sequence $E_p \in \mathbb{R}^{1:T^e}$, and compute the multi-label classification loss function ℓ_{ekg} between the ground truth meteorological event knowledge $E_g \in \mathbb{R}^{1:T^e}$ and E_p, where T^e is the length of the event knowledge sequence. In the location knowledge guidance model, this section uses a CNN-based structure to predict the location knowledge $L_p \in \mathbb{R}^{K^l}$ corresponding to $Y_{1:T'}$, and compute the multi-label classification loss function ℓ_{lkg} between the ground truth geographical location knowledge $L_g \in \mathbb{R}^{K^l}$ and L_p, where K^l is the number of the location knowledge.

4.3.2 Summary Generation Module

The proposed summary generation module is shown in Fig.4.3. The model comprises two sub-models, the reconstruction model and the similarity judgment model. Each of the sub-models is based on the auto-encoder structure.

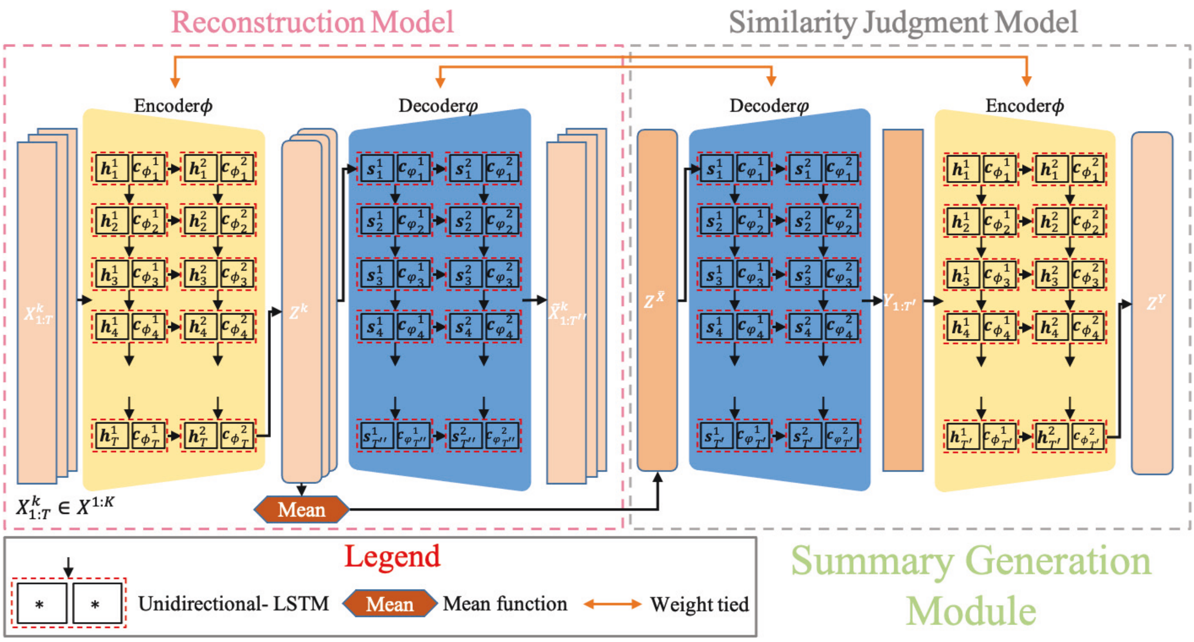

Figure 4.3: The structure of the summary generation module is consists of two models: the reconstruction model and the similarity judgment model.

4.3.2.1 Reconstruction Model

Let $X^k_{1:T} = \{x^k_1, x^k_2, \cdots, x^k_T\} \in \mathbb{R}^T$ be the k^{th} Weibo post with length T in $X^{1:K}$. The encoder of the reconstruction model is composed with a two-layer unidirectional-LSTM model. Let $\mathbf{h}^k_t \in \mathbb{R}^{1\times dim^\phi}$ and $\mathbf{c}_{\phi}{}^k_t \in \mathbb{R}^{1\times dim^\phi}$ be the hidden state and the cell state of the encoder at the time step t separately, and dim^ϕ be the dimension of the hidden state in the LSTM of the encoder ϕ. Let $\mathbf{Z}^k = \phi(X^k_{1:T}) = [\mathbf{h}^k_T, \mathbf{c}_{\phi}{}^k_T] \in \mathbb{R}^{2\times dim^\phi}$ be the encoded vector, which learns the representation of $X^k_{1:T}$.

The decoder φ is also based on a two-layer unidirectional-LSTM model. Let $\mathbf{s}^k_t \in \mathbb{R}^{1\times dim^\varphi}$ be the hidden state of the decoder at the time step t, and dim^φ is the corresponding dimension. The state of the decoder is initialized by $\mathbf{Z}^k$. Let $\widetilde{X}^k_{1:T''} = \left\{\widetilde{x}^k_1, \widetilde{x}^k_2, \cdots, \widetilde{x}^k_{T''}\right\} = \varphi\left(\mathbf{Z}^k\right) \in \mathbb{R}^{T''}$ be the reconstructed $X^k_{1:T}$. Following the research of Chu et al.[54], this section uses the cross-entropy loss with the teacher-forcing mechanism[287] to optimize this model. The loss function of the reconstruction model is as follows:

$$\ell_{rec} = -\sum_{k=1}^{K} log\left(p\left(X^k_{1:T} \mid \varphi\left(\phi\left(X^k_{1:T}\right)\right)\right)\right). \tag{4.1}$$

This section uses $\mathbf{Z}^{\bar{X}}$ to represent the combined vector of $X^{1:K}$, which can be calculated as Eq.4.2. $\mathbf{Z}^{\bar{X}}$ is also the initial state of the similarity judgment model, which makes the φ of the similarity judgment model generate $Y_{T'}$ by considering the semantic feature of each $X^k_{1:T} \in X^{1:K}$.

$$\mathbf{Z}^{\bar{X}} = \frac{1}{K}\sum_{k=1}^{K} \mathbf{Z}^k. \tag{4.2}$$

4.3.2.2 Similarity Judgment Model

The similarity judgment model is also based on the auto-encoder structure. The encoder and decoder are shared with them in the reconstruction model, and the weights are tied. The multi-document summary $Y_{1:T'} = \{y_1, y_2, \cdots, y_{T'}\} \in \mathbb{R}^{T'}$ is obtained by using decoder φ with the input of $\mathbf{Z}^{\bar{X}}$, $Y_{1:T'} = \varphi\left(\mathbf{Z}^{\bar{X}}\right)$.

To constrain the generated summary $Y_{1:T'}$ expressing semantic feature centered on $X^{1:K}$, this section re-encodes the $Y_{1:T'}$ to $\mathbf{Z}^Y$, and calculate the cosine similarity $cos(\cdot)$ between the hidden state $\mathbf{h}^k_T$ of each encoded $X^k_{1:T}$ and the hidden state $\mathbf{h}^Y_{T'}$ of the encoded $Y_{1:T'}$. This process makes the generated summary semantically similar to each $X^k_{1:T} \in X^{1:K}$. The calculation is as follows:

$$\ell_{sim} = \frac{1}{K}\sum_{k=1}^{K} cos(\mathbf{h}^k_T, \mathbf{h}^Y_{T'}). \tag{4.3}$$

Since the experiment do not have the ground-truth summary corresponding to $Y_{1:T'}$ and each of the generated word $y_t \in Y_{1:T'}$ are discrete, this section uses the straight-through gumbel-softmax[106, 167] to fit the generation process of $Y_{1:T'}$.

The loss function of the summary generation module can be calculated as Eq.4.4. Because the encoder and decoder are the same in the two sub-models, this section does not introduce the hyper-parameter to balance the $\mathcal{L}_{SUMM}$.

$$\mathcal{L}_{SUMM} = \ell_{rec} + \ell_{sim}. \tag{4.4}$$

4.3.3 Knowledge Enhancement Module

As shown in Fig.4.2, the knowledge enhancement module consists of two sub-models: the event knowledge guidance model and the location knowledge guidance model. Each of the sub-models is applied to constrain the summary generation process and makes the generated summary $Y_{1:T'}$ focus on describing the core knowledge in $X^{1:K}$.

4.3.3.1 Event Knowledge Guidance Model

Meteorological events are the core descriptive knowledge of meteorological-related Weibo posts, and there are common co-occurrence and evolutionary relationships between meteorological events. The model needs to make full use of this relationship to guide the summary generation process so that the model generates the summary that conforms to the meteorological event description of the facts in the source Weibo post. The generative structure can explore this relationship by considering the association between words. For this reason, the event knowledge guidance model is based on the encoder-decoder generative structure, and the event knowledge guidance process is encouraged to generate meteorological event knowledge consistent with $X^{1:K}$ by using $Y_{1:T'}$ as input. Specifically, the model is to assign a subset $E_p = \{E_{p1}, E_{p2}, \cdots, E_{pT^e}\} \in \mathbb{R}^{T^e}$ containing T^e labels in the meteorological event knowledge label space $EG = \{E_{g1}, E_{g2}, \cdots, E_{gK^e}\} \in \mathbb{R}^{K^e}$ to the generated summary $Y_{1:T'}$, where K^e is the number of meteorological event knowledge. The structure of the proposed model is shown in Fig.4.4.

The encoder of the event knowledge guidance model is a two-layer bidirectional-LSTM model, and the decoder is a two-layer unidirectional-LSTM model. Let $\mathbf{h}_i = \left[\overleftarrow{\mathbf{h}}_i, \overrightarrow{\mathbf{h}}_i\right] \in \mathbb{R}^{2\times dim^{EKG}}$ be the encoder's hidden state at the time step i, where dim^{EKG} represents the dimension of the hidden state in the event knowledge guidance model. This section introduces the attention mechanism[162] to mine the influence of different word weights in $Y_{1:T'}$ on E_{p_t} and use $\mathbf{c}_t \in \mathbb{R}^{2\times dim^{EKG}}$ to represent the context vector, which can be calculated as follows:

$$\mathbf{c}_t = \sum_{i=1}^{T'} \alpha_{t,i} \mathbf{h}_i, \tag{4.5}$$

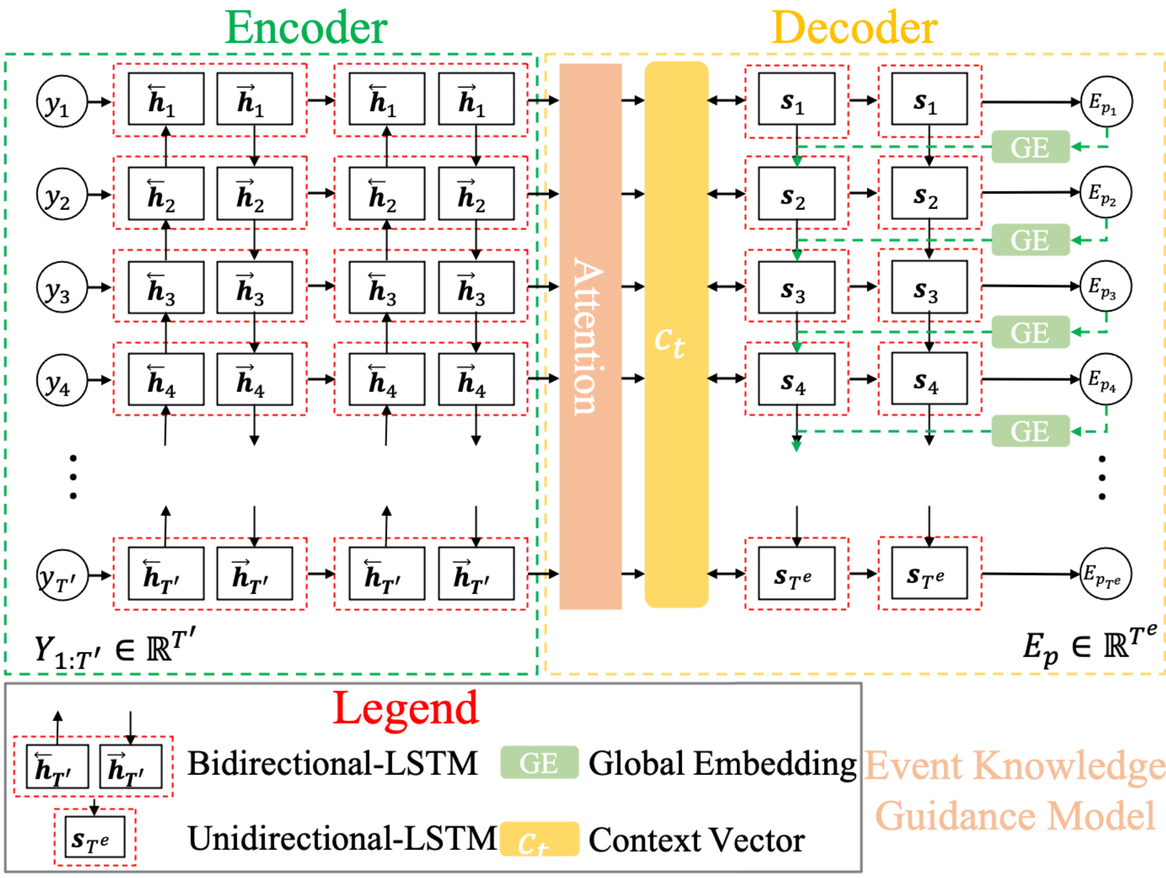

Figure 4.4: The structure of the event knowledge guidance model.

$$\alpha_{t,i} = \frac{exp(e_{t,i})}{\sum_{j=1}^{T'} exp(e_{t,j})}, \tag{4.6}$$

$$e_{t,i} = \mathbf{v}_{att}^T tanh(\mathbf{W}_{att}\mathbf{s}_t + \mathbf{U}_{att}\mathbf{h}_i), \tag{4.7}$$

where $\alpha_{t,i}$ represents the attention weight corresponding to y_i at the time step t. The $\mathbf{v}_{att}^T$, $\mathbf{W}_{att}$, and $\mathbf{U}_{att}$ represent the parameters and the $\mathbf{s}_t$ is the LSTM's hidden state of the decoder at the time step t. In the generative model, E_{p_t} at time step t depends on $E_{p_{t-1}}$, while E_{p_t} is obtained by calculating the maximum value of its probability distribution in all the meteorological event knowledge, ignoring its presence on the distribution of each of the event knowledge. Such the character allows E_{p_t} to inherit the error information and pass them if an incorrect $E_{p_{t-1}}$ is generated. For this reason, this section uses the global embedding[297] $GE(E_{p_{t-1}})$ to prevent the exposure bias by comprehensively integrating the probability distribution and features of all event knowledge at the time step t. Let $\mathbf{e}_g \in \mathbb{R}^{dim^{EKG}}$ be the embedding vector of the event knowledge that with the highest probability under the distribution of $E_{p_{t-1}}$, and $\bar{\mathbf{e}}_g \in \mathbb{R}^{dim^{EKG}}$ is the weighted average embedding at the time step t, which can be calculated as follows:

$$\bar{\mathbf{e}}_g = \sum_{i}^{K^e} P(E^i_{p_{t-1}})\mathbf{e}^i_g, \tag{4.8}$$

where $P(E^i_{p_{t-1}})$ is the i^{th} predicted event knowledge's probability distribution of $E_{p_{t-1}}$, and $\mathbf{e}^i_g$ is the embedding vector of the i^{th} predicted event knowledge. $GE(E_{p_{t-1}})$ represents the global embedded $E_{p_{t-1}}$, which passes the information to $\mathbf{s}_t$ at the time step t. It can be calculated as follows:

$$GE(E_{p_{t-1}}) = \mathbf{H} \odot \mathbf{e}_g + (1 - \mathbf{H}) \odot \bar{\mathbf{e}}_g. \tag{4.9}$$

Let $\mathbf{H} \in \mathbb{R}^{dim^{EKG}}$ be the transform gate that optimizes $GE(E_{p_{t-1}})$ by combining the original embedding and weighted average embedding. The model reduces the loss of mispredictions caused by the previous time step by considering the probability of each event knowledge. $\mathbf{H}$ can be calculated as follows:

$$\mathbf{H} = \sigma(\mathbf{W}_1\mathbf{e}_g + \mathbf{W}_2\bar{\mathbf{e}}_g), \tag{4.10}$$

where $\mathbf{W}_1 \in \mathbb{R}^{dim^{EKG} \times dim^{EKG}}$ and $\mathbf{W}_2 \in \mathbb{R}^{dim^{EKG} \times dim^{EKG}}$ are the weight matrices. By comprehensively considering the probability of each event knowledge contained in $E_{p_{1:t-1}}$, the model can reduce the risk of continuously transmitting wrong information. In addition, multiple $X^k_{1:T} \in X^{1:K}$ may describe the same meteorological event because they are in a similar publishing period. Therefore, in the training process, this section sorts and then merges the ground truth meteorological event knowledge E_g according to the number of occurrences in $X^{1:K}$, so that the meteorological event knowledge with high frequency can play the most positive guiding role.

The hidden state $\mathbf{s}_t$ at the time step t can be calculated by Eq.4.11, and the first state of $\mathbf{s}_t$ is initialized by $\mathbf{h}_{T'}$.

$$\mathbf{s}_t = LSTM(\mathbf{s}_{t-1}, GE(E_{p_{t-1}}), \mathbf{c}_{t-1}). \tag{4.11}$$

The cross-entropy is used as the loss function of the event knowledge guidance model, which can be calculated as follows:

$$\ell_{EKG} = -\frac{1}{N}\sum_{n=1}^{N}\sum_{t=1}^{T^e} log(p(E_{g_t}^{(n)} \mid E_{p_{1:t}}{}^{(n)}, Y_{1:T'}{}^{(n)}, \theta^{EKG})). \tag{4.12}$$

The learning process makes the model to generate the meteorological event knowledge close to the ground-truth $E_{g_t} \in EG$ at the time step t by given $E_{p_{1:t}}{}^{(n)}$, $Y_{1:T'}{}^{(n)}$, and θ^{EKG} as inputs, where N is the number of samples, $E_{p_{1:t}}$ is the predicted meteorological event knowledge sequence till to the time step t, and θ^{EKG} represents the parameters of the event knowledge guidance model.

4.3.3.2 Location Knowledge Guidance Model

Meteorological Weibo posts often contain geographical location knowledge corresponding to meteorological events, also one of the core knowledge described in meteorological briefings. The briefing content without geographical location knowledge reduces the effectiveness of decision-making, especially for rescue. For this reason, this section proposes a location knowledge guidance model, which constrains the summary generation module to generate briefing content that conforms to the location knowledge contained in the source Weibo posts. Since the amount of location knowledge is much more than event knowledge and the correlation between location knowledge is insignificant, this section adopts a CNN-based structure in the location knowledge guidance module. Compared to the generative structure in the event knowledge guidance module, the CNN-based structure has lower complexity and higher computational efficiency. This section introduces a convolution kernel with a size of 1 to emphasize the guiding effect of a single location knowledge on the model, making the model more sensitive to the specific location knowledge. The structure of the proposed model is shown in Fig. 4.5.

Let $\mathbf{V}_{1:T'} \in \mathbb{R}^{T' \times dim^{LKG}}$ be the embedded vector of $Y_{1:T'}$ in the location knowledge guidance model, where dim^{LKG} is the dimension of the word embedding. $\mathbf{m} \in \mathbb{R}^{T'-f+1}$ is the feature map that resulted by convolution operation $*$, and $\mathbf{w}^f \in \mathbb{R}^{f \times dim^{LKG}}$ represents the conventional kernel with size $f, f \in [1,3,4,5]$. Each feature $\mathbf{m}_i \in \mathbf{m}$ can be calculated as follows:

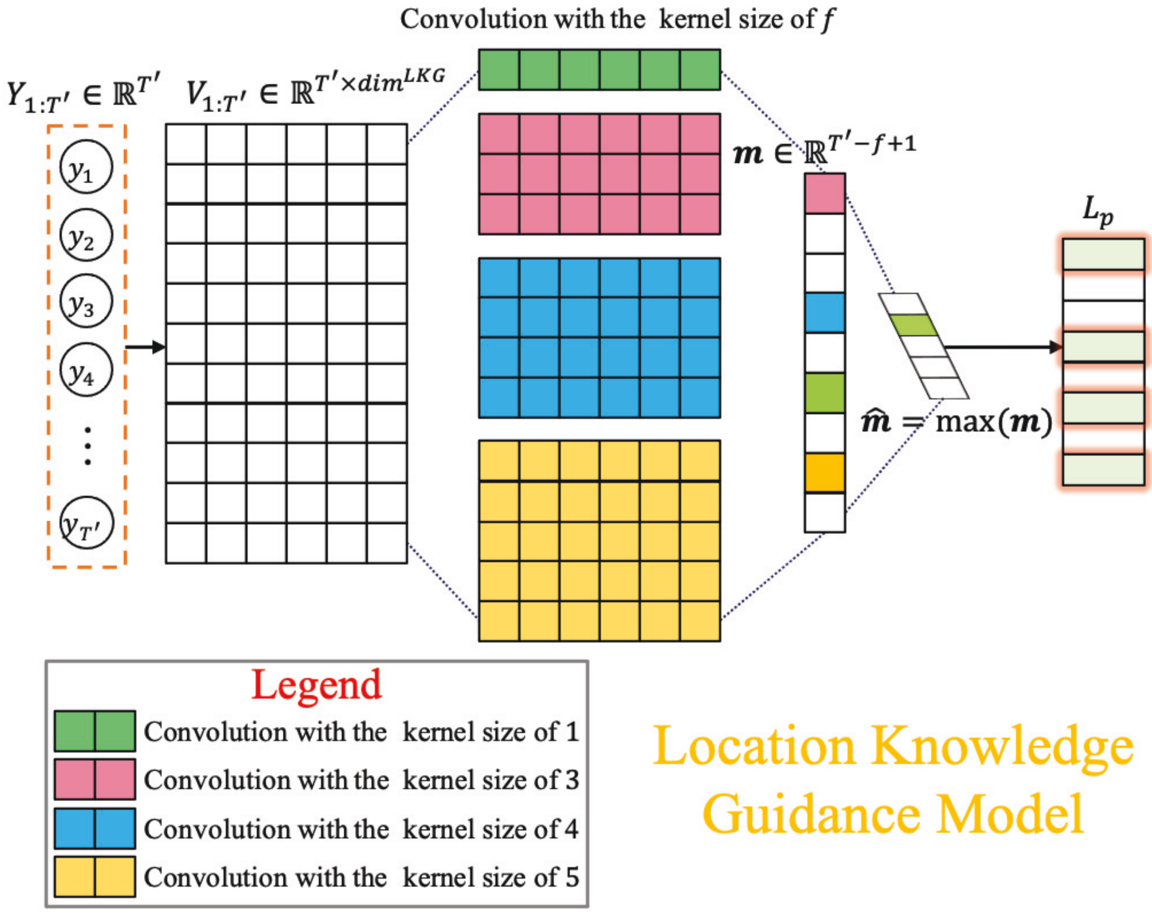

Figure 4.5: The structure of the location knowledge guidance model.

$$
\begin{aligned}
\mathbf{m}_i &= R(\mathbf{w}^f * \mathbf{V}_{1:T'})_i \\
&= R(\mathbf{w}^f \cdot \mathbf{V}_{1:T'[i-f+1:i]}) \\
&= R(\sum_{n=i}^{i+f-1} \mathbf{w}^f_n \mathbf{V}_{1:T'n}),
\end{aligned}
\tag{4.13}
$$

where R is $ReLU$[84] as the nonlinear activation function. The model then use the max-over-time pooling[57] $\hat{\mathbf{m}} = max(\mathbf{m})$ to capture the most significant feature of the corresponding location knowledge.

The loss function of the location knowledge guidance model is as follows:

$$
\ell_{LKG} = -\frac{1}{N} \sum_{n=1}^{N} log(p(L_g{}^{(n)} \mid Y_{1:T'}{}^{(n)}, \theta^{LKG})).
\tag{4.14}
$$

The learning process encourages the model to maximize the probability of the predicted location knowledge L_p close to the ground truth location knowledge L_g by giving the generated summary $Y_{1:T'}$ and the location knowledge guidance model's parameters θ^{LKG} as input, where N represents the number of samples.

The loss function of the whole knowledge enhancement module can be calculated as Eq.4.15. In multi-task learning, due to the different scales of multiple network structures and loss functions, the performance of the overall task is easily dominated by a single task, making the entire model unable to be optimized. For this reason, this section introduces λ_{EKG} and λ_{LKG} to balance the loss function of each knowledge enhancement model to make they have the most positive impact on the summary generation module.

$$\mathcal{L}_{KG} = \lambda_{EKG} \cdot \ell_{EKG} + \lambda_{LKG} \cdot \ell_{LKG}. \tag{4.15}$$

4.3.4 Training

The loss function of the MKES model is divided into two parts: $\mathcal{L}_{SUMM}$ and $\mathcal{L}_{KG}$, which are the loss function of each sub-module. The overall loss function $\mathcal{L}_{MKES}$ is as follows:

$$\begin{aligned} \mathcal{L}_{MKES} &= \mathcal{L}_{SUMM} + \mathcal{L}_{KG} \\ &= \ell_{rec} + \ell_{sim} + \lambda_{EKG} \cdot \ell_{EKG} + \lambda_{LKG} \cdot \ell_{LKG}. \end{aligned} \tag{4.16}$$

During the training process, the MKES model gradually learns the features related to E_p and L_p in $Y_{1:T'}$ by minimizing $\mathcal{L}_{MKES}$ continually. The summary generation module is encouraged to generate the knowledgeable word y_t with features significantly related to E_p and L_p. Such a structure allows the whole MKES model to retain the meteorological event knowledge and the geographical location knowledge described in $X^{1:K}$ as much as possible, making the generated summary focus on describing the core knowledge.

4.4 Experiment

4.4.1 Dataset

The dataset is constructed by the posts from Sina Weibo[3]. The Jieba[4] Chinese word segmentation tool is applied to segment the text into the word sequence.

The experiment cleans the data and screens high-quality posts by formulating nearly a hundred rules after investigating the original Weibo posts in the data processing. For example, the Weibo posts with empty content are removed, and special characters like '\u3000' and 'Emoji' are filtered out. Because the length of Weibo posts affects the quality of meteorological briefing, this section shows the boxplot and histograms of Weibo posts' length distribution in Fig.4.6, which helps to screen the posts with the length between 2 and 474 ($T \in [2, 474]$). In addition, this section filters out posts that do not have corresponding meteorological event knowledge and geographical location knowledge. The location knowledge not included in the prefecture-level administrative regions is expanded to the corresponding provincial-level administrative regions.

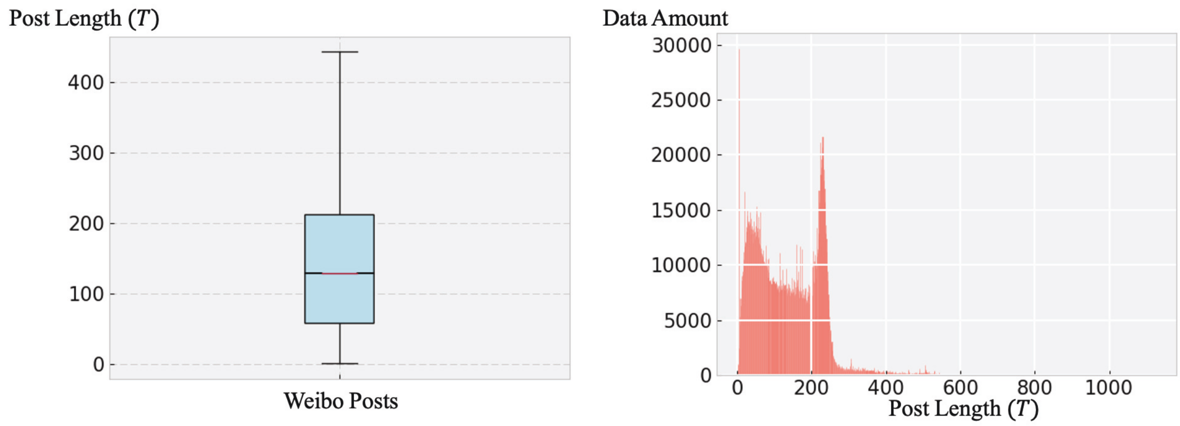

Figure 4.6: The box plot and histogram that reflect the length of Weibo posts in the dataset. The data not included in the whiskers of the box plot are not shown, which are the outliers of the length distribution.

After data preprocessing, approximately 7.2 hundred thousand Weibo posts are retained. The examples of the dataset are shown in Table 4.1.

[3] https://www.weibo.com/
[4] https://github.com/fxsjy/jieba

Table 4.1: Examples of the dataset. The event knowledge and location knowledge are respectively marked in red and blue fonts.

Weibo Posts	Event Knowledge	Location Knowledge
Beijing is haze again. Recently, I am lazy and eat a lot, and I am keen on various carbohydrates. Fortunately, I have insisted on running today.	Haze	Beijing
Cold wave come, the temperature dropped sharply in Laiwu, feeling cold.	Cold wave	Laiwu
On May 23, many places in Shenzhen encountered heavy rain. Among them, street flooding occurred in Guangming District. Shenzhen Meteorological Bureau issued a message at 15:00 that the orange warning of heavy rain in Baoan District and Guangming District was upgraded to red.	Heavy rain	Shenzhen

4.4.2 Implementation Details

The experiments are implemented based on the NVIDIA RTX 3090 GPU. Adam optimizer[119] is introduced to optimize the proposed model. The size of the Weibo posts set is 8 ($K = 8$), and the learning rate during the training process is 0.0001. The dimension of the word embedding is 256, and the dimension of the hidden state of the LSTM in the encoder ϕ and the decoder φ are 512 ($dim^{\phi} = 512$, $dim^{\varphi} = 512$).

In the event knowledge guidance model, the dimension of the word vectors of the LSTM model is 256 ($dim^{EKG} = 256$). Since $X^k_{1:T} \in X^{1:K}$ may describe the same meteorological event knowledge, the experiment merges multiple same event knowledge in $X^{1:K}$ into one, and the number of the event knowledge is 14 ($K^e = 14$).

In the location knowledge guidance model, the dimension of the word vectors is 256 ($dim^{LKG} = 256$). Since $X^k_{1:T} \in X^{1:K}$ may describe the same geographical location knowledge, the experiment merges multiple same location knowledge in $X^{1:K}$ into one, and the number of the location knowledge is 367 ($K^l = 367$).

The hyperparameter λ_{EKG} used to balance the event knowledge guidance model is 0.7 ($\lambda_{EKG} = 0.7$), and the hyperparameter λ_{LKG} used to balance the location knowledge guidance model is 0.5 ($\lambda_{LKG} = 0.5$). The subsequent section verifies the impact of different

λ_{EKG} and λ_{LKG} on the overall model performance.

4.5 Results and Analysis

4.5.1 Evaluation Metric

4.5.1.1 Content Evaluation

$ROUGE$[140] is a set of metrics commonly used in the text summarization task, which evaluates the similarity between the generated summaries ($Y_{T'}$) and the original Weibo post ($X^k_{1:T} \in X^{1:K}$). The experiment use $ROUGE-1$, $ROUGE-2$, and $ROUGE-L$ as the content evaluation metric of the proposed model, where $ROUGE-1$ and $ROUGE-2$ respectively calculate the unigram overlap and bi-gram overlap between $Y_{T'}$ and each $X^k_{1:T} \in X^{1:K}$. The final $ROUGE-1$ and $ROUGE-2$ are obtained by calculating the mean of each $ROUGE-1$ and $ROUGE-2$ in $X^{1:K}$. The calculation is as follows:

$$ROUGE-N = \frac{1}{K}\sum_{k=1}^{K}\frac{\sum_{gram_n \in Y_{1:T'}} Count_{match}(gram_n)}{\sum_{gram_n \in Y_{1:T'}} Count(gram_n)}. \tag{4.17}$$

The $ROUGE-L$ evaluates the overlap of the longest common subsequence between $Y_{T'}$ and each $X^k_{1:T} \in X^{1:K}$, which can be calculated as follows:

$$R_{lcs_k} = \frac{LCS(Y_{T'}, X^k_{1:T})}{T}, \tag{4.18}$$

$$P_{lcs_k} = \frac{LCS(Y_{T'}, X^k_{1:T})}{T'}, \tag{4.19}$$

$$F_{lcs_k} = \frac{(1+\beta^2)R_{lcs_k}P_{lcs_k}}{R_{lcs_k} + \beta^2 P_{lcs_k}}, \tag{4.20}$$

where $LCS(Y_{T'}, X^k_{1:T})$ is the length of the longest common subsequence of $Y_{T'}$ and $X^k_{1:T}$, β is a large constant $\beta \to \infty$ and F_{lcs_k} is the F-measure of R_{lcs_k} and P_{lcs_k}. The final $ROUGE-L$ can be calculated by Eq.4.21.

$$ROUGE-L = \frac{1}{K}\sum_{k=1}^{K} F_{lcs_k}. \tag{4.21}$$

4.5.1.2 Sentiment Evaluation

The sentiment feature is essential for public opinion, and it is also the feature that decision-makers focus on in meteorological decision briefings. The sentiment words are the common carrier for the sentiment features, making the sentiment evaluation reflect the semantic similarity of the original Weibo posts and the generated summary. This section conducts the sentiment evaluation using the sentiment attributes as an overall evaluation metric, judging whether the $Y_{T'}$ maintains the sentiment attributes distribution same with the $X^{1:K}$. Specifically, this section uses the general Senta[262] model to initial label each Weibo post $X_{1:T}^{k}$'s sentiment attributes and refine the labels manually. The sentiment value $\theta_{sent}^{X^k} = 1$ represents $X_{1:T}^{k}$ with a positive sentiment attribute, and $\theta_{sent}^{X^k} = 0$ represents $X_{1:T}^{k}$ with a negative sentiment attribute. This section uses $X_{1:T}^{k}$ as training data to construct a Text-CNN-based[117] model to fine-grained fit the semantic and sentiment features of the meteorological domain. This section calculates the $Accuracy$ (Acc), $Precision$ (P), $Recall$ (R), and the F_1 between the predicted sentiment attribute $\theta_{sent_p}^{X^k}$ and the ground-truth sentiment attribute $\theta_{sent_g}^{X^k}$, which can be calculated by Eq.4.22-Eq.4.25.

$$P = \frac{TP}{TP + FP}, \tag{4.22}$$

$$R = \frac{TP}{TP + FN}, \tag{4.23}$$

$$F_1 = \frac{2 \times P \times R}{P + R}, \tag{4.24}$$

$$Acc = \frac{TP + TN}{TP + TN + FP + FN}, \tag{4.25}$$

where TP represents the $\theta_{sent_g}^{X^k} = 1$ and $\theta_{sent_p}^{X^k} = 1$, TN represents $\theta_{sent_g}^{X^k} = 0$ and $\theta_{sent_p}^{X^k} = 0$, FP represents the $\theta_{sent_g}^{X^k} = 0$ and $\theta_{sent_p}^{X^k} = 1$, and FN represents $\theta_{sent_g}^{X^k} = 1$ and $\theta_{sent_p}^{X^k} = 0$. The test results of the sentiment evaluation model are shown in Table.4.2.

The results in Table.4.2 prove that this sentiment evaluation model can judge whether the generated summary maintains the same sentiment attributes distribution as the original Weibo posts. This section uses the trained sentiment evaluation model to predict

Table 4.2: The performance of the sentiment evaluation model.

Metric	Value
$Accuracy$	0.983
$Precision$	0.958
$Recall$	0.976
F_1	0.966

the sentiment attribute $\theta_{sent_p}^{Y_{T'}}$ of the generated summary $Y_{T'}$. The ground truth sentiment attribute $\theta_{sent_g}^{Y_{T'}}$ corresponding to $Y_{T'}$ can be labeled as Eq.4.26.

$$\theta_{sent_g}^{Y_{T'}} = \begin{cases} 1, \frac{1}{K}\sum_{k=1}^{K}\theta_{sent}^{X^k} \geq 0.5 \\ 0, \frac{1}{K}\sum_{k=1}^{K}\theta_{sent}^{X^k} < 0.5 \end{cases} . \tag{4.26}$$

4.5.2 Baseline Methods

This section uses the unsupervised multi-document summarization models as the baseline methods: the extractive summarization model[220], the MeanSum[54], and the Copycat[36]. The extractive summarization model is proposed by Rossiello et al[220]. Their model is a centroid-based method for text summarization, which exploits the compositional capabilities of word embeddings. The MeanSum is proposed by Chu et al[54], which achieves unsupervised multi-document summarization by considering the average semantic features among multiple documents. Brazinskas et al. proposed the Copycat[36], which pays more attention to the consensus opinions when generating summaries.

4.5.3 Quantitative Evaluation

The quantitative results of the content evaluation of the MKES model and other baseline models on the test set are shown in Table.4.3. It is evident that the MKES model achieves the best results in the $ROUGE-1$, $ROUGE-2$, and $ROUGE-L$.

In addition, this section uses the trained sentiment evaluation model to test the sentiment consistency between the generated summaries and the original Weibo posts. The sentiment evaluation results are shown in Table.4.4, where the MKES model achieves the best results on P, R, F_1, and the MeanSum achieves a better result on Acc. Since

Table 4.3: Quantitative results of the content evaluation of the MKES model and other baseline models.

	ROUGE-1	ROUGE-2	ROUGE-L
Extractive[220]	0.1661	0.0564	0.1472
MeanSum[54]	0.1869	0.0589	0.1640
Copycat[36]	0.1874	0.0632	0.1587
MKES	**0.2025**	**0.0807**	**0.1740**

the sentiment attributes of the Weibo posts in the test set are imbalanced, the F_1 metric can better illustrate the advantages of the MKES model. Such a result proves that the summary generated by the MKES model maintains more similar sentiment attributes and semantic features with $X^{1:K}$.

Table 4.4: Quantitative results of the sentiment evaluation of the MKES model and other baseline models.

	Acc	P	R	F_1
Extractive[220]	0.779	0.438	0.500	0.467
MeanSum[54]	**0.862**	0.633	0.625	0.619
Copycat[36]	0.824	0.602	0.617	0.610
MKES	0.857	**0.657**	**0.656**	**0.656**

4.5.4 Qualitative Evaluation

This section takes the summaries generated by the MKES model and other baseline models as examples to illustrate the advantages of the MKES model in generating the semantics reasonable briefing content that takes the event and location knowledge in the source text as the core description object. The comparison results are shown in Table.4.5.

The core knowledge described in the source mainly consists of four parts, including 1. Typhoon Jongdari landed in Shanghai, 2. Sichuan encountered heavy rain, 3. Central Meteorological Observatory issued a blue warning of heavy rain, and 4. Beijing issued a blue warning of heavy rain. This section evaluates the MKES and baseline models qualitatively by considering whether the generated summary contains the above-mentioned core knowledge. The summary generated by the Extractive[220] model incorrectly describes "Typhoon Jongdari" as "Typhoon Ampil". The lack of a detailed description of "Typhoon

Table 4.5: The qualitative evaluation results of the MKES model and other baseline models. The event knowledge and location knowledge are respectively marked in red and blue fonts.

Source	X^1: Are you enter the eye of the typhoon? How can you see the blue sky and white clouds? Shanghai Kangqiao. X^2:During the typhoon, the railway department will pay close attention to the changes in the path of the typhoon and dynamically adjust the train operation plan to ensure the safety of passengers. Shanghai Railway will release the latest train operation information in a timely manner. X^3:Typhoon Jongdari. Always pay attention, safety first. The barrier of Shanghai is finally breaking. X^4: I just watched the real-time typhoon track, and Jongdari is 72KM away from Shanghai, getting closer and closer. Everyone must take precautions. X^5: Heavy rain stormed Guangyuan, Sichuan, cars swimming on the street. X^6: Sichuan was hit by heavy rain. X^7: The Central Meteorological Observatory continued to issue a blue heavy rain warning at 06:00 on August 3. From 08:00 on August 3 to 08:00 on August 4, there is heavy rains or torrential rains in the parts of southwestern Sichuan Basin, northern Zhejiang, southwestern Jiangsu, eastern Anhui, western Guangxi, southeastern and western Yunnan, northeastern Inner Mongolia, central Heilongjiang, northeastern Qinghai, etc. X^8: This morning, Beijing Haidian issued a blue warning for heavy rain. It was sunny and sultry in Beijing on weekends and the highest temperature was 33 degree.
Extractive[220]	Typhoon Ampil. This year's No. 12 Typhoon Jongdari affected a thunderstorm in the early hours of the 11th.
MeanSum[54]	This year the (Typhoon) Jongdari landed in our country and there were thunderstorms and gale. Heavy rain occurred in some parts of the southeast coast.
Copycat[36]	Affected by the tropical depression in the South China Sea, Shanghai will experience moderate rains and local heavy rains.
MKES	**Typhoon Jongdari invaded Shanghai. There were heavy rains in parts of Guangyuan, Sichuan, northern Zhejiang, and Yunnan. Among them, the Sichuan Basin and other places have moderate to heavy rains, and local heavy rains. Blue warning of heavy rain in Beijing.**

Jongdari" makes this summary confusing and can hardly provide valuable support for decision-making. The summary generated by the MeanSum[54] model describes the appearance of "Typhoon Jongdari" and points out the meteorological event of heavy rain. However, the generated summary mistakenly described the location experiencing heavy rain as the southeast coast and incorrectly generated a gale event, interfering with the decision-making process. The summary generated by the Copycat[36] model describes the location of "Shanghai" contained in the source but mistakenly describes its meteorological event as "heavy rain" and the event's cause. Such a summary can easily induce decision-makers to make wrong decision strategies. Compared with the summaries generated by the baseline models, the summary generated by the MKES describes the three ($\frac{3}{4}$) parts of core knowledge in the source text. More importantly, the MKES model generated summary more accurately retains the core meteorological event knowledge as typhoon and heavy rain while also pointing out the location of their occurrence, which is essential to improve the efficiency of decision support.

4.6 Ablation Study

This section performs the ablation studies to verify the effectiveness of the event knowledge guidance model and the location knowledge guidance model.

4.6.1 Event Knowledge Guidance Model Verification

4.6.1.1 Quantitative Evaluation

The quantitative evaluation result of the event knowledge guidance model verification is shown in Table.4.6 and Table.4.7, where "w/o EKG" represents the model without the event knowledge guidance model. Obviously, both the content evaluation and sentiment evaluation results of the MKES model achieve a significant improvement. Such results prove that the event knowledge guidance model positively impacts the performance of the MKES model.

Table 4.6: Quantitative results of the content evaluation of the event knowledge guidance model verification.

	ROUGE-1	ROUGE-2	ROUGE-L
w/o EKG	0.1935	0.0652	0.1637
MKES	**0.2025**	**0.0807**	**0.1740**

Table 4.7: Quantitative results of the sentiment evaluation of the event knowledge guidance model verification.

	Acc	P	R	F_1
w/o EKG	0.821	0.636	0.637	0.636
MKES	**0.857**	**0.657**	**0.656**	**0.656**

4.6.1.2 Qualitative Evaluation

Table. 4.8 shows the qualitative evaluation results of the event knowledge guidance model verification. It is shown that there is three meteorological event knowledge in source Weibo posts (X^1-X^4: heavy rain, X^5-X^6: gale, X^7-X^8: thunder). Due to intense convective weather, these meteorological events often co-occur in a short period with the feature of co-occurrence. The model without the event knowledge guidance model describes the one category ($\frac{1}{3}$) of meteorological event knowledge in the source. In comparison, the MKES model describes the three categories ($\frac{3}{3}$) of meteorological event knowledge in the source.

Table 4.8: Qualitative evaluation results of the event knowledge guidance model verification. The meteorological event knowledge is marked in red fonts.

Weibo Posts		Event Knowledge
Source	X^1: The continuous heavy rains and floods in Sichuan were like beasts, and the turbulent waters really washed the Dragon Temple. X^2: Things around Nujiang. In response to the recent obvious rainy weather and the increase in heavy rains that have caused frequent occurrences of natural disasters such as rolling rocks, slope landslides, and mudslides along the roads in Lushui city, the Lushui Highway Sub-bureau ensures that rescue personnel, vehicles, materials, and equipment are in place and do their best to maintain the roads in the rainy season and ensure that they are flooded.	Heavy rain

	X^3: Affected by the heavy rain, the Shanxi Provincial Department of Land and Resources and Meteorological Bureau jointly issued a yellow warning for meteorological risks of geological disasters. X^4: Cloudy turned to thunderstorms on the 13th, and local heavy rains and high temperature weather eased. Released in Shenzhen.	
	X^5: At 10 o'clock this morning, the Central Meteorological Observatory issued a severe convective weather warning. From this afternoon to tomorrow, Beijing-Tianjin-Hebei, western Liaoning, northern Shandong may have strong convective weather such as gale over 8 levels or hail, and short-term heavy rainfall. X^6: Xingtai City Meteorological Observatory issued important weather information: It is expected that there will be a significant precipitation process in the city from the morning of the 13th to the night of the 14th, and the strongest rainfall period will occur from day to night on the 13th. The local area may be accompanied by strong convective weather such as short-term gale and heavy precipitation.	Gale
	X^7:Shexian Meteorological Observatory distributed the yellow warning signal of thunder at 20:28 on July 12, 2018. X^8: Shangluo Meteorological Observatory issued a yellow warning signal of thunder at 20:10 on July 12, 2018.	Thunder
w/o EKG	Shanxi early warning information. Sichuan, Nujiang, and Beijing-Tianjin-Hebei were affected by heavy rains. Shangluo Meteorological Bureau reminded us to pay attention to the weather, heavy precipitation and short-term heavy precipitation. Partial heavy rain in Shenzhen. Handan.	Heavy rain

MKES	**Shanxi risk yellow warning. Affected by heavy rainfall, there were heavy rains in parts of Sichuan, Shangluo, and Beijing-Tianjin-Hebei, and local heavy rains in Shenzhen, accompanied by strong convective weather such as short-term heavy rain, gale, and hail. Thunder yellow warning in Handan.**	**Heavy rain, Gale, Thunder**

The summary generated by the model without the event knowledge guidance model generates the heavy rain event based on the semantic probability. In the natural law, heavy rain, gale, and thunder often occur together. The event knowledge guidance model introduces prior knowledge to provide a reference for the summary generation module. The MKES model can perceive various meteorological events in a fine-grained manner by considering the co-occurrence feature and semantic probability so that the generated summary also describes the event knowledge of gale and thunder that is accomplished by the heavy rain accurately.

4.6.2 Location Knowledge Guidance Model Verification

4.6.2.1 Quantitative Evaluation

The quantitative evaluation result of the location knowledge guidance model verification is shown in Table. 4.9 and Table. 4.10, where "w/o LKG" represents the model without the location knowledge guidance model. The MKES model with the location knowledge guidance model achieves better content evaluation and sentiment evaluation results, proving that the location knowledge guidance model also positively impacts the MKES model's performance.

Table 4.9: Quantitative results of the content evaluation of the location knowledge guidance model verification.

	ROUGE-1	ROUGE-2	ROUGE-L
w/o LKG	0.1937	0.0652	0.1625
MKES	**0.2025**	**0.0807**	**0.1740**

Table 4.10: Quantitative results of the sentiment evaluation of the location knowledge guidance model verification.

	Acc	P	R	F_1
w/o LKG	0.835	**0.727**	0.587	0.650
MKES	**0.857**	0.657	**0.656**	**0.656**

4.6.2.2 Qualitative Evaluation

Table. 4.11 shows the qualitative evaluation results of the location knowledge guidance model verification. It is shown that there is six location knowledge in source Weibo posts (X^1-X^3: Ningbo, X^4: Beijing, X^5: Jiangsu, X^6: Hangzhou, X^7: Chongqing, X^8: Shaoxing). The model without the location knowledge guidance model describes the two categories ($\frac{2}{6}$) of location knowledge in the source. In comparison, the MKES model describes the five categories ($\frac{5}{6}$) of location knowledge.

Table 4.11: Qualitative evaluation results of the location knowledge guidance model verification. The geographical location knowledge is marked in blue fonts.

	Weibo Posts	Location Knowledge
Source	X^1: The Ningbo Meteorological Observatory issued a yellow warning for heavy fog. Please take precautions. X^2: The warning is issued. Ningbo Meteorological Observatory issued a heavy fog yellow warning at 19:33 on December 15, 2018. Affected by the warm and humid air currents, it is expected that fog with visibility less than 500 meters will appear in most areas of our city from tonight to tomorrow morning. Please take precautions.	Ningbo

	X^3: Yellow warning sign of heavy fog. Yuyao (Ningbo) Meteorological Observatory issued a heavy fog yellow warning signal at 18:56 on December 15, 2018. At present, heavy fog with visibility less than 500 meters has appeared in some areas of our city. It is expected that the fog will continue from tonight to tomorrow morning. Please pay attention to traffic safety.	
	X^4:Beijing issued a yellow warning for heavy fog and heavy air pollution.	Beijing
	X^5: Hongze Lake in Jiangsu ushered in heavy fog, and the mist was misty like a fairyland.	Jiangsu
	X^6: It was raining heavily in Hangzhou today, and the dense fog fell into the low mid-air, giving a very depressed scene.	Hangzhou
	X^7: The Central Meteorological Observatory's weather forecast announced that there will be many sunny places from tomorrow to Wednesday, and heavy fog in Zhejiang, Anhui, Sichuan, and Chongqing. Take precautions and alert to traffic safety.	Chongqing
	X^8: Xinchang County (Shaoxing) Meteorological Observatory issued a heavy fog yellow warning at 19:10 on December 15, 2018. At present, heavy fog with visibility less than 500 meters has appeared in our county. It is expected that there will be heavy fog with visibility less than 500 meters in some areas of our county tonight. Please take precautions.	Shaoxing
w/o LKG	A yellow warning for heavy fog is issued. The fog warning is issued. The current early warning signal for heavy fog is a yellow early warning signal. There are foggy weather in Ningbo, Beijing and other places.	Ningbo, Beijing

MKES	**Warning information. Ningbo Meteorological Observatory issued a yellow warning signal for heavy fog. The Beijing Meteorological Observatory issued a yellow warning signal for heavy fog. Heavy fog in Jiangsu, Hangzhou, and Chongqing.**	**Ningbo, Beijing, Jiangsu, Hangzhou, Chongqing**

In the source, three posts describe the fog in Ningbo, so this location knowledge occupies a more significant weight. In addition, fog often occurs in Beijing in the natural environment, making the words fog and Beijing have a strong correlation in vector space. Table. 4.11 shows that the model without the location knowledge guidance model only generates summaries describing the weather in Ningbo and Beijing based on semantic probability. In contrast, the summary generated by the MKES model also describes the weather in Jiangsu, Hangzhou, and Chongqing. The results prove that the location knowledge guidance model can make the summary generation module more sensitive to minority locations when the semantic correlation is insignificant.

4.6.3 λ Selection

In this section, the $ROUGE-1$, $ROUGE-2$, and $ROUGE-L$ are used as the metrics to verify the influence of the hyperparameters λ_{EKG} and λ_{LKG} on the model performance. The results are shown in Fig.4.7. It is obvious that the $ROUGE-1$, $ROUGE-2$, and $ROUGE-L$ achieve the highest value when $\lambda_{EKG} = 0.7$ and $\lambda_{LKG} = 0.5$. This result proves that the event knowledge guidance model and the location guidance model have the most positive impact on the summary generation module when $\lambda_{EKG} = 0.7$ and $\lambda_{LKG} = 0.5$ separately. Such a conclusion supports the selection of λ_{EKG} and λ_{LKG} in the experiment.

4.7 Error Analysis

This section randomly selects one hundred unsatisfactory summaries generated by the MKES model for error analysis. The errors are divided into four categories, namely 1. confusing content, 2. missing description, 3. wrong direction, and 4. numeric error. The remainder of this section will analyze the causes of each error and propose potential solutions.

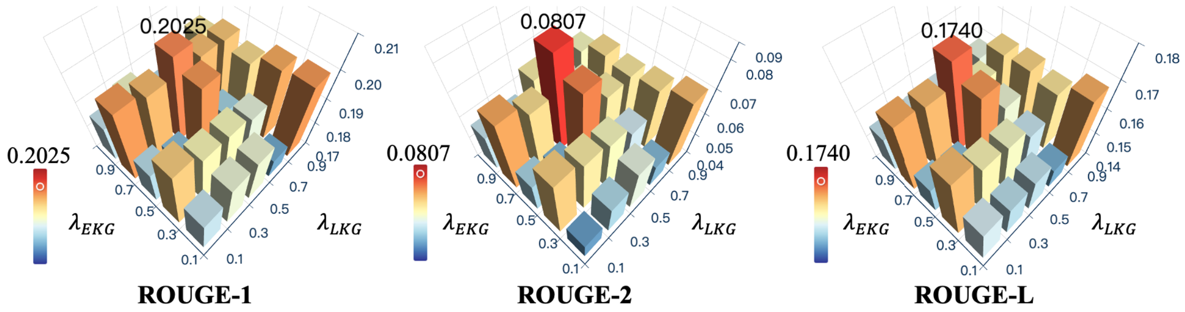

Figure 4.7: The verification histogram of the effect of λ_{EKG} and λ_{LKG} on model performance.

4.7.1 Confusing Content

The confusing content is an abstract error category, which refers to the generated summary that does not conform to natural language logic and makes people difficult to understand. An example is shown in Table.4.12.

Table.4.12 shows that the MKES model mistakenly generates "Haven't put it on yet", which is a confusing expression. This type of error is common in $X^{1:K}$, which primarily consists of Weibo posts from personal accounts.

The main reason for this error is that the personal Weibo posts have a more flexible language style and more colloquial words than the posts posted by official accounts. However, due to the differences between dialects in various regions, there may be multiple descriptions of the same object. The lack of formalized language style makes the model unable to control the source text's various grammatical features and vocabulary, which proves the necessity of briefing optimization in improving the efficiency of decision support services.

4.7.2 Missing Description

The missing description refers to the fact that there are more same or similar posts in $X^{1:K}$ so that the generated summary focuses on describing the posts that occupy a large proportion in $X^{1:K}$ while ignoring the description of posts that account for less in $X^{1:K}$. An example is shown in Table.4.13.

Table.4.13 shows that most of the Weibo posts ($\frac{7}{8}$) in the source describe the fog in Pulandian, Liaoning Province, and only one item ($\frac{1}{8}$) describes the yellow thunder warning signal in Datong. The generated summary only describes the fog in Liaoning, ignoring the description of the thunder in Datong.

Table 4.12: The error analysis of "Confusing Content".

Source	X^1: The sun is so big in the morning, and it is heavy rain in the evening. Is the weather in Wuhan dying? X^2: Heavy rain in Shenzhen. How can the rain be popular searching every time. X^3: Heavy rain in Shenzhen. The Pingan Building was hit. X^4: Heavy rain in Shenzhen. I would like to ask if there is no heavy rain in Shenzhen. But the rain is always gone in ten minutes, and then it continues hot hot hot hot. X^5: When I went to buy the chicken soup pot, it rained heavily. It should be the last night before Wuhan is officially hot. X^6: Beijing subway news announces heavy rain, let the storm come harder, let the heavy rain come harder. X^7: Nanning will have a temperature of 26-36 degrees tomorrow. Recently, the high temperature has continued, so everyone must pay attention to sun protection and heatstroke prevention. X^8: The highest temperature in Xujiahui today reached 32.9 degrees Celsius, and the body feels a bit stuffy. However, the easterly air currents from Typhoon Denas brought a variety of flowing clouds and crystal sky to Shanghai. Tomorrow Shanghai will be cloudy to overcast with scattered showers. The highest temperature tomorrow will be 31 degrees and the lowest temperature will be 27 degrees. Shanghai will be affected by showers from time to time on weekends, and the temperature will continue to rise to 34 degrees on Sunday and 35 degrees next Tuesday.
MKES	There have been heavy rains in Shenzhen and Wuhan in the past few days. **Haven't put it on yet**. High temperature in Nanning, and Shanghai is hot.

There are two main reasons for this error. One is that meteorological events are sudden and emergency events, which will attract many people's repost in a short time. Each new reposts provides a new information source for the Weibo post. This section does not remove the Weibo posts with repeated content in the corpus at the pre-processing stage because the decision-makers can focus on the Weibo posts that increase rapidly in a short time. However, the disadvantage caused by this strategy is that the content repeated Weibo posts in $X^{1:K}$ will have a dominant role in the generated summary. The second reason is that the model gives the same weight to each Weibo post in $X^{1:K}$ when generating the summary, making the generated summary more inclined to focus on the posts that occupy a large proportion. The future research needs to ensure the dominant role of posts with a large proportion in $X^{1:K}$ in the generated summary; also, the future research can design a weight punishment method based on semantic similarity to make

Table 4.13: The error analysis of "Missing Description". X^2 to X^4, X^5 and X^6, X^7 and X^8 are the same Weibo posts.

Source	X^1: Datong Meteorological Observatory issued a thunder yellow warning signal. Affected by the convective cloud system, it is expected that there will be thunder activities in the early warning area in the next 6 hours, which may be accompanied by strong convective weather such as short-term heavy rain, thunderstorms, and hail. The warning area is the whole city. $X^2 - X^4$: Orange warning sign of heavy fog. It is expected that there will be dense fog with visibility less than 200 meters in the Pulandian area and some areas of the coastal waters. Please take precautions. Released by the Liaoning Provincial Meteorological Disaster Monitoring and Early Warning Center. X^5, X^6: Pulandian District Meteorological Observatory issued a heavy fog orange warning signal. It is expected that there will be dense fog with visibility less than 200 meters in the Pulandian area and some areas in the coastal waters. Please take precautions. X^7, X^8: Orange warning sign of heavy fog. It is expected that there will be dense fog with visibility less than 200 meters in the Jinpu New Area and some parts of the surrounding sea. Please take precautions. Released by the Liaoning Provincial Meteorological Disaster Monitoring and Early Warning Center.
MKES	Orange warning sign of heavy fog. It is expected that some areas of Pulandian may experience dense fog with visibility less than 200 meters in the future. Please take precautions. Released by the Liaoning Provincial Meteorological Disaster Monitoring and Early Warning Center.

the generated summary consider the posts with a small proportion.

4.7.3 Wrong Direction

The wrong direction means that the model does not accurately generate the direction words corresponding to meteorological events in the source. Meteorological-related Weibo posts often contain words describing the direction of the meteorological event, which are used to more finely describe the specific area (east, south, west, north, etc.) where the meteorological event occurs. However, the current model is easy to confuse direction words when generating the summary. An example is shown in Table.4.14.

Table 4.14: The error analysis of "Wrong Direction".

Source	X^1: Yellow warning for heavy rain in Longmen. At present, the heavy rain cloud system affecting our county has weakened, but it is expected that there is still obvious heavy rain weather in our county tonight. Longmen County Meteorological Observatory downgraded the heavy rain orange warning signal to heavy rain yellow. Please take precautions. X^2: The arrival of heavy rain has quenched the thirst of drought in the province. Affected by the tropical depression in the South China Sea, the whole province of Hunan ushered in a round of large-scale rainfall from the evening of the 25th, with heavy rains in some places. This round of rain is expected to last until the 31st. After the rainfall ends, the drought in most places **south** of central Hunan will be basically relieved. X^3: Note that Guangxi will have sustained heavy rain. From tonight to tomorrow, Beihai, Qinzhou, Fangchenggang, Yulin, Guigang, Laibin, Nanning, Chongzuo, Wuzhou, Hezhou and other cities will have heavy convective weather such as heavy rains, local heavy rains or short-term thunderstorms and strong winds. On the 30th, there were heavy rains, local heavy rains or short-term thunderstorms and strong winds in most areas of **southern** and **western** Guangxi. X^4: Level 3 early warning of meteorological risk of geological disasters in Heyuan City. Affected by the low pressure of the monsoon, there was moderate rain in our city, and local heavy rain. X^5: The Lanzhou Meteorological Bureau reminded that due to the influence of the southerly airflow outside the subtropical high, there were scattered showers in the **northern part** of the city. Affected by the cold air, there was an obvious rainfall process in our city, and the rainfall in the city was mainly moderate rain. Among them, the **southern part** of Qili River, Honggu District, and **southern** Yuzhong County have heavy rain, with moderate to heavy rain. X^6: National weather. Today and tomorrow, Inner Mongolia, Heilongjiang, Jilin, Liaoning, Shandong, Gansu, Fujian, Guangdong, Guangxi and other parts of the heavy rain, local heavy rain. Heavy rain warning. X^7: Dark clouds, heavy rain warning. Red warning for heavy rain in Xiamen.

	X^8: Life in Fuzhou. The city continued to rain heavily, the weather geological disaster meteorological risk warning level is high, especially Baisha Town, Minhou County.
MKES	Heavy rain warning. The **southwest** Fujian, Guangdong, Guangxi, Hunan, Hainan and other parts of the region will have heavy rain, local heavy rain. There were heavy rains in **southern** Jiangxi, **western** and **southern** Guangdong, **southern** Gansu, and **western** and northern Fujian.

Table.4.14 shows that the summary generated by the MKES model describes the heavy rain event and generates the corresponding province words as location knowledge accurately. However, the model is hard to generate specific direction words corresponding to location knowledge.

The main reason for this error is that the location knowledge granularity is defined as a prefecture-level city in the current design of the location knowledge guidance model, but direction belongs to more fine-grained location knowledge. In addition, there is a certain correlation between location knowledge and specific meteorological event knowledge (e.g. Chongqing often experiences high temperatures, etc.), so the model can refer to meteorological event knowledge when generating location knowledge. However, there is no significant correlation between direction words and meteorological event knowledge, making the model unable to use the prior knowledge introduced by the meteorological events. Future research will design a more fine-grained location knowledge guidance model to associate location and direction knowledge.

4.7.4 Numeric Error

The numeric error refers to the model does not accurately generate numerical information in the source. Meteorological Weibo posts often contain numerical description information such as date, meteorological event intensity, and location. The current model cannot summarize the numerical information accurately. An example is shown in Table.4.15.

Table 4.15: The error analysis of "Numeric Error". X^1 and X^2 are the same Weibo posts.

Source	X^1-X^2: Yutu (tropical storm scale), the **26th** typhoon of this year, was located about **75** kilometers to the northwest of Dongsha Island at **20:00** today, with the maximum wind force of Force **8** (**18**m seconds) near the center. Yutu is expected to move southwest at about **5** kilometers per hour, gradually losing strength. By its influence Chongwu to Dongshan coastal wind up to **7** to **8** today night. X^3: The center of this year's No. **26** Typhoon Yutu at **11:00** on the **2nd** is located at **21.0** degrees north latitude and **116.3** degrees east longitude, about **320** kilometers south of Dongshan County. The maximum wind force in the center is **8** (a tropical storm of **20** meters per second). It will gradually decrease in intensity when moving to the northeast at a speed of about **5** kilometers per hour. X^4: This year's **26th** typhoon Yutu at **20** o 'clock today center is located in the East of Fujian Dongshan about **350** kilometers south of the South China Sea, is at **20.8** degrees north latitude, longitude **116.2** degrees. Maximum wind force **8** (**18**m second tropical storm force) near the center. The future will be stalled in the waters near the East Sand Islands or circling tonight. X^5: Yutu, the **26th** typhoon of this year, was centered at **20.8** degrees north latitude **116.2** degrees east longitude at **20:00** today, which is about **75** kilometers to the northwest of Dongsha Island in the sea. It is about **355** kilometers away from Dongshan Mountain in Fujian, and the maximum wind force near the center is **8** (a tropical storm of **18** meters per second). In the future, it will stagnate in the waters near the Dongsha Islands or turn around tonight. X^6: Typhoon news. Typhoon Yutu (tropical storm scale), the **26th** typhoon of the year, was centered at **20.8** degrees north latitude and **116.2** degrees east longitude over the northeastern South China Sea, about **330** kilometers southeast of Guangzhou, with maximum force **8** winds (**18** meters per second) near the center. Yutu is expected to move southwest at about **6** kilometers per hour.

	X^7: The center of Typhoon Yutu No. **26** this year is at **20.8** degrees north latitude and **116.2** degrees east longitude, about **345** kilometers south of Dongshan County. The maximum wind force near the center is level **8** (a tropical storm level of 18 meters per second), and it will move to the southwest at a speed of about **6** kilometers per hour, and the intensity will gradually weaken. X^8: Typhoon Yutu (Tropical Storm) was **664** kilometers away from Fuzhou at **20** o'clock on November **2**, **2018**, with a pressure of **1005** hPa, a maximum wind force of **8** near the center, and a moving speed of **6** kmh.
MKES	Typhoon Yutu landed along the coast with a gale of **312** level. It was located on the **350**-kilometer sea surface of Fuzhou at **5** a.m. on July **11**. The maximum wind force near the center was **8** (**20** meters per second), and the lowest pressure at the center was **1005** hPa.

Table.4.15 shows that all posts in the source are numerically describing the movement of Typhoon Yutu. There is a slight difference in the numerical description of Typhoon Yutu due to the different posting times of Weibo posts in the source. However, although the generated summary accurately describes this meteorological event knowledge, the description of the numerical information is quite different from that in the source.

The main reason for this error is that numerical information is challenging to generate through probabilistic modeling, making the current model unable to accurately capture numerical information in the source. In future work, specific numerical information such as time, meteorological event intensity, and speed in Weibo posts can be defined and identified through templates, and numerical information in the source can be directly applied through the copy mechanism.

4.8 Conclusion

This chapter proposes the MKES model, which provides a new idea for meteorological decision support service by automatically generating the meteorological briefing. Compared with other baseline models, the proposed MKES achieves the best quantitative and qualitative evaluation results. In addition, this chapter constructs a framework for the automatic generation of meteorological decision briefing based on the MKES model. This framework has been applied to a prototype application based on meteorological decision briefing, which can provide timely and effective decision support services for decision makers and assist them in the decision-making process.

CHAPTER 5

METEOROLOGICAL EVENT KNOWLEDGE-ENHANCED DECISION BRIEFING OPTIMIZATION

5.1 Introduction

The social sensor signal-based meteorological briefings have shortcomings, such as poor formalization of text style, confusing content, and colloquial text, which affect decision-makers' efficiency in obtaining information and further interfere with decision-making. Formalizing the decision briefings' content from informal to formal texts can enhance and optimize the content of the generated decision briefings, which is conducive to further improving the application ability of domain knowledge in decision briefing. Content optimization of meteorological decision briefing refers to the use of artificial intelligence methods to realize the transfer of briefing content from informal to formal text style and enhance the readability without changing the core knowledge description in the source text, thus improving the efficiency of decision support services based on meteorological decision briefings.

For optimizing the previous generated briefing content, this chapter proposes a meteorological event knowledge guided briefing formalization module consisting of three models: the text form judgment model, the formalization words detection model, and the **E**vent **K**nowledge **G**uided **T**ext **F**ormalization (EKGTF) model. The text form judgment model is designed to screen out the source text with significant formalization features. The formalization words detection model is designed to detect the formalization words in the screened source text and build the memory word sets with formalization features. As the core model in this module, the EKGTF model is composed of two submodules, the text formalization module and the meteorological event knowledge guidance module, which are designed to transform the meteorological briefing content from informal text to formal text. This chapter uses the 14 types of meteorological events[1] detected by the sentence-level feature-based meteorological event detection model as guidance knowledge, enhancing the formalized briefing content that focuses on describing the core meteorological event knowledge in the source text. Since the complexity of the briefing optimization process is significantly higher than that of the briefing generation model, and the content of the briefing to be optimized already with the corresponding geographic location knowledge, the briefing optimization process do not introduce additional location knowledge as an enhancement. Based on the meteorological briefing formalization module, this chapter develops a meteorological briefing formalization service framework. The structure of this pipeline framework is shown in Fig. 5.1.

The contributions of this chapter can be summarized as follows:

- This chapter specifically develops a meteorological briefing formalization module to realize the formalization processing for the briefing content in the meteorological domain. The module contains three models: the text form judgment model, the formalization words detection model, and the **E**vent **K**nowledge **G**uided **T**ext **F**ormalization (EKGTF) model.

- The crucial model in the meteorological briefing formalization module is the EKGTF model with the event knowledge guidance module structure. Such a structure enhances the formalized texts to focus on describing specific meteorological events in the source text. Compared to other baseline models, the EKGTF model achieves the best results.

- The BERT model with meteorological knowledge is fine-tuned to introduce prior knowledge to the EKGTF model. This knowledgeable fine-tuned language model is more sensitive to meteorological events.

- Based on the meteorological briefing formalization module, the service framework for the meteorological briefing formalization is constructed. This framework has

[1]The events include typhoons, rainstorms, blizzards, cold waves, gales, sandstorms, high temperatures, drought, thunder, hail, frost, fog, haze, and icing. These events are defined by the China Meteorological Administration (CMA) and used as a national standard (General Administration of Quality Supervision, Inspection, and Quarantine of the People's Republic of China & Standardization Administration of the People's Republic of China, 2011).

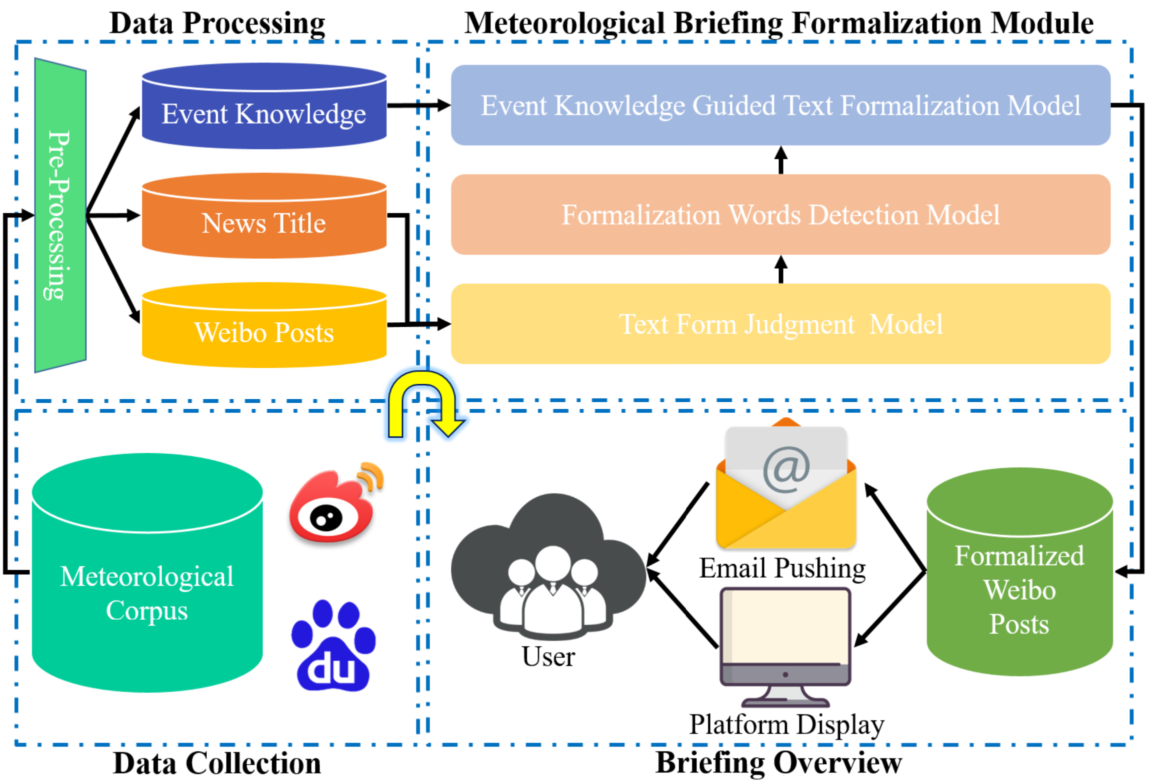

Figure 5.1: The framework is divided into four modules: data collection, data processing, meteorological briefing formalization module, and briefing overview. Each of the modules is connected in a pipeline fashion.

been applied to the Meteorological Public Opinion Mining Platform as an online service.

The remainder of this chapter is organized as follows. Reviews on briefing generation and text style transfer are given in section 5.2. Detailed descriptions of each model in the meteorological briefing formalization module are illustrated in section 5.3. Section 5.4 introduces the experimental process, including the datasets and experimental settings. The results and analysis are in section 5.5. The ablation study to verify the effectiveness of the fine-tuned BERT model and the event knowledge guidance module of the EKGTF model are given in section 5.6. Section 5.7 performs the error analysis of the EKGTF model by taking the formalized items as examples. The conclusion of this chapter are discussed in section 5.8.

5.2 Related Work

Decision-makers need to integrate different information comprehensively when making decisions, and social networks are among the key information sources[18, 248]. However, the quality of the information on social networks is uneven, there are often many rumors, and the text style is confusing, which seriously interferes with decision-making[163, 314, 330]. How to screen valuable knowledge to enhance decision-making efficiency has become the focus of researchers[11, 32, 155, 307]. As an efficient method for screening knowledge, briefing generation has been gradually applied to solve the above problems[79, 127, 171, 172, 252].

Although the briefing generation model can screen the source text's core knowledge, the resulting briefing content still suffers from text style confusion. Research by Reiter et al.[216] shows that people are more inclined to read the briefing content generated by the NLG system because the content has a unified and formalized language style, which avoids the ambiguity of human understanding. Such a conclusion illustrates the importance of formalizing the text style of briefing content. The text style transfer model refers to rewriting text from one style to another specific style, which can be introduced to solve the above problem[192]. The current models are mainly divided into two categories: supervised models and unsupervised models[211, 292]. Due to the lack of parallel data, research based on supervised models is rare for this task[41, 107, 279, 316].

By contrast, unsupervised models are widely used, most of which are based on the encoder-decoder structure. The model proposed by Prabhumoye et al.[210] learns the latent representation of input by the language-translation model and then uses adversarial generation techniques to output the desired style of the text. Mueller et al.[185] proposed a model based on a recurrent variational autoencoder (VAE) and an outcome-predicting neural network. Their model achieves text style transfer by continuously optimizing the latent factors. Similarly, the model proposed by Zhao et al.[320] is based on the Wasserstein autoencoder (WAE), which achieves flexible training of deep latent variable models with discrete structures. Targeting the problems existing in the seq2seq-based model, Wu et al.[289] proposed the PTO model to solve problems such as weak content interpretation. Most of the current models need to disentangle style and content in the latent space[110, 142, 275, 295]. For example, Liu et al.[144] pointed out that the explicit disentanglement of the content and the attributes is indispensable for the text style transfer task. However, some researchers think that such a method may ignore subtle interactions in the natural language[161, 249]. The model proposed by

Dai et al.[63] does not consider the potential disentangled representation of the source sentences and uses the attention mechanism to achieve better style conversion and content preservation.

In text style transfer tasks, researchers have gradually explored knowledge-enhanced models to meet personalized requirements[308]. Zhang et al.[315] controlled the specific language style through model parameters, in which shared model parameters are used to capture generic language characteristics and private model parameters are used to capture special style characteristics. Logeswaran et al.[151] applied reconstruction loss and adversarial loss to enable the model to control multiple attributes simultaneously. Hu et al.[97] achieved controlled text style transfer through a model combining the VAE model and holistic attribute discriminators. This chapter uses specific meteorological events as guidance knowledge to guide and constrain the content of formalized text.

The current application of text style transfer models is mostly focused on sentiment modification[130, 134, 241, 244, 291]. There are also other applications, such as cipher cracking[47, 302] and political slant transfer[250]. It is worth mentioning that some researchers have also applied these studies to formality transfer[85, 93, 105, 109, 132], which provides valuable references for this research.

5.3 Methods

5.3.1 Overview

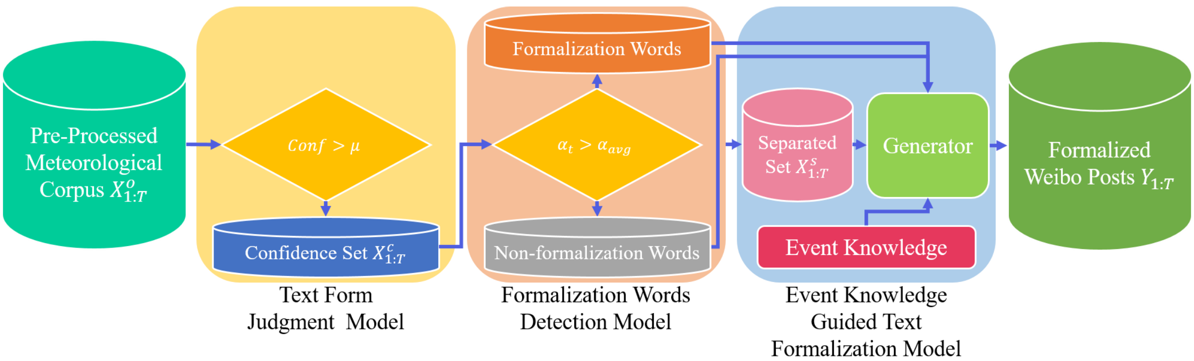

Figure 5.2: The processing flow of the meteorological briefing formalization module. This module consists of three models: the text form judgment model, the formalization words detection model, and the EKGTF model.

This section illustrates the proposed meteorological briefing formalization module. It contains three models: the text form judgment model, the formalization words detection model, and the EKGTF model. Each of these models is trained independently. The processing flow is shown in Fig. 5.2.

The text form judgment model is used to filter the input source text $X^o_{1:T}$ with the insignificant formalization features through the text form classification task. Because news titles have stronger formal requirements than Weibo posts, the model is trained by labeling news titles as formal text and Weibo posts as informal text. This model outputs not only the predicted label of $X^o_{1:T}$ but also its corresponding confidence ($Conf$) that is used to screen out $X^o_{1:T}$ with significant formalization features. The input source text $X^o_{1:T}$ with $Conf$ greater than the threshold (μ) will be retained and build the confidence set $X^c_{1:T}$, otherwise it will be filtered.

The formalization words detection model is used to detect the formalization words in $X^c_{1:T}$ through a bidirectional LSTM-based classifier with the attention mechanism. α_t is the corresponding attention weight of the $t-th$ word x^c_t, where x^c_t with α_t that is greater than the averaged attention weight (α_{avg}) is defined as the formalization word; otherwise, it is defined as the non-formalization word. The formalization words set contains two memory words sets with the bipolar formalization knowledge, which are the formal words memory set ($M_F \in \mathbb{R}^\gamma$) and the informal words memory set ($M_I \in \mathbb{R}^\gamma$), where γ is the size of each memory set.

The EKGTF model is the crucial model of the entire module, which is used to generate the formalized Weibo posts $Y_{1:T}$. The original Weibo post after separating the formalization words is represented as $X^s_{1:T}$, which is the word sequence that only contains the non-formalization words. Here, the generator is a seq2seq-based autoencoder structure. As enhancement knowledge, the event knowledge in the event knowledge guidance module is used to guide and constrain the generated content.

The rest of this section will introduce each of the models in detail.

5.3.2 Text Form Judgment Model

This model classifies the text form by using a convolutional classifier. Let $\mathbf{V}^o_{1:T} \in P^{T\times dim^v}$ be the embedded word vectors of the input text $X^o_{1:T}$, where T is the length of $X^o_{1:T}$ and dim^v is the dimension of the word vector. Compared to the traditional Text-CNN model[117], the model introduces a convolution kernel of size 1, which focuses on the contribution of each word to the text form. The convolution operation $*$ between two vectors $\mathbf{w}^k \in \mathbb{R}^{k\times dim^v}$ and $\mathbf{V}^o_{1:T}$ results in the feature map $\mathbf{f}^{TFJ} \in \mathbb{R}^{T+k-1}$, and each feature

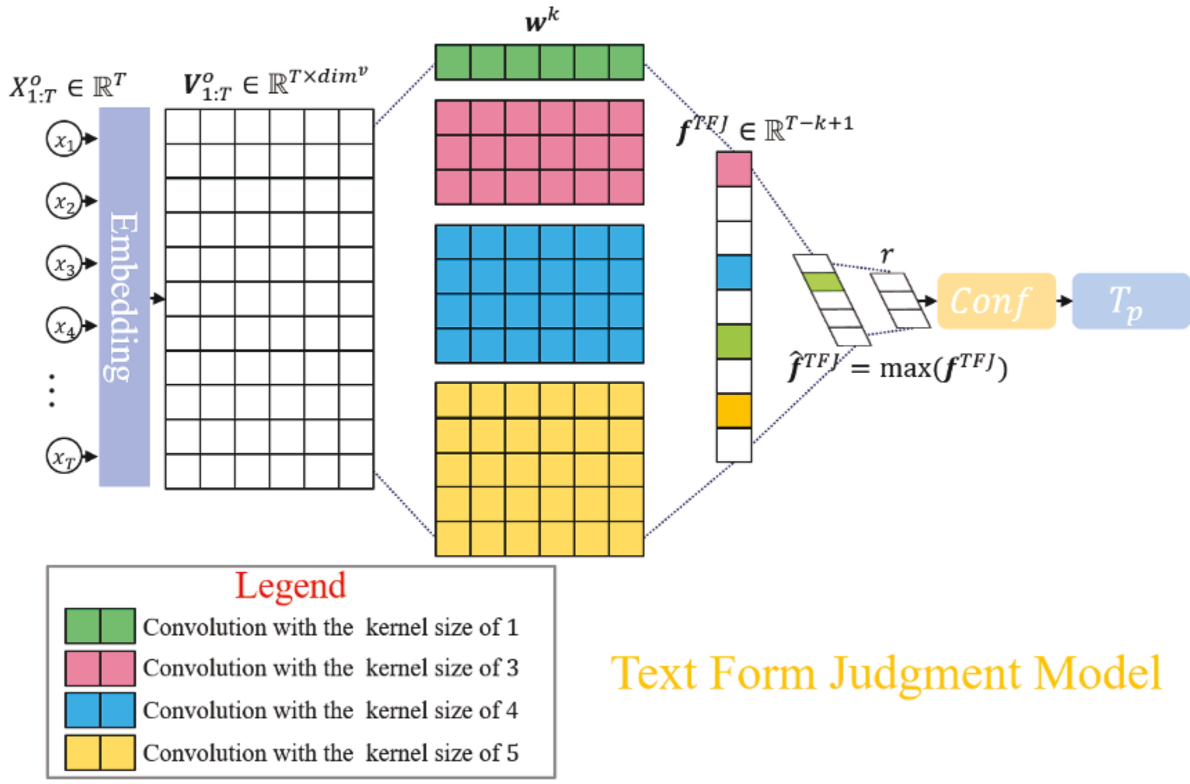

Figure 5.3: The structure of the text form judgment model. The model outputs not only the final classification result (T_p) but also the confidence ($Conf$) of each class.

$\mathbf{f}^{TFJ}{}_i$ in $\mathbf{f}^{TFJ}$ is as follows:

$$\begin{aligned} \mathbf{f}^{TFJ}{}_i &= R(\mathbf{w}^k * \mathbf{V}^o_{1:T})_i \\ &= R(\mathbf{w}^k \cdot \mathbf{V}^o_{1:T[i-k+1:i]}) \\ &= R(\sum_{m=i}^{i+k-1} \mathbf{w}^k_m \mathbf{V}^o_{1:T\,m}), \end{aligned} \tag{5.1}$$

where R is the ReLU[186] as the nonlinear activation function and $\mathbf{w}^k$ is a convolution kernel of size $k, k \in \{1,3,4,5\}$. The model applies max-over-time pooling[57] to take the maximum value $\hat{\mathbf{f}}^{TFJ} = max(\mathbf{f}^{TFJ})$, which captures the most significant feature. Let r represent the output after the fully connection with dropout. The confidence of each class can be obtained by $Conf = softmax(r)$, and T_p represents the final classification result. Each item in $X^o_{1:T}$ with a corresponding $Conf$ greater than the threshold μ will be retained to construct the confidence set $X^c_{1:T}$.

The loss function of this model is as follows:

$$\mathcal{L}_{TFJ} = -\frac{1}{N}\sum_{n=1}^{N} p(T_g^{(n)} | \mathbf{V}^o_{1:T}{}^{(n)}, \theta^{TFJ}), \tag{5.2}$$

where T_g is the ground truth label corresponding to T_p and θ^{TFJ} represents the parameters in the text form judgment model. By continuously optimizing $\mathcal{L}_{TFJ}$, the model gradually learns the more distinguishing features, thus producing more meaningful and precise $Conf$.

5.3.3 Formalization Words Detection Model

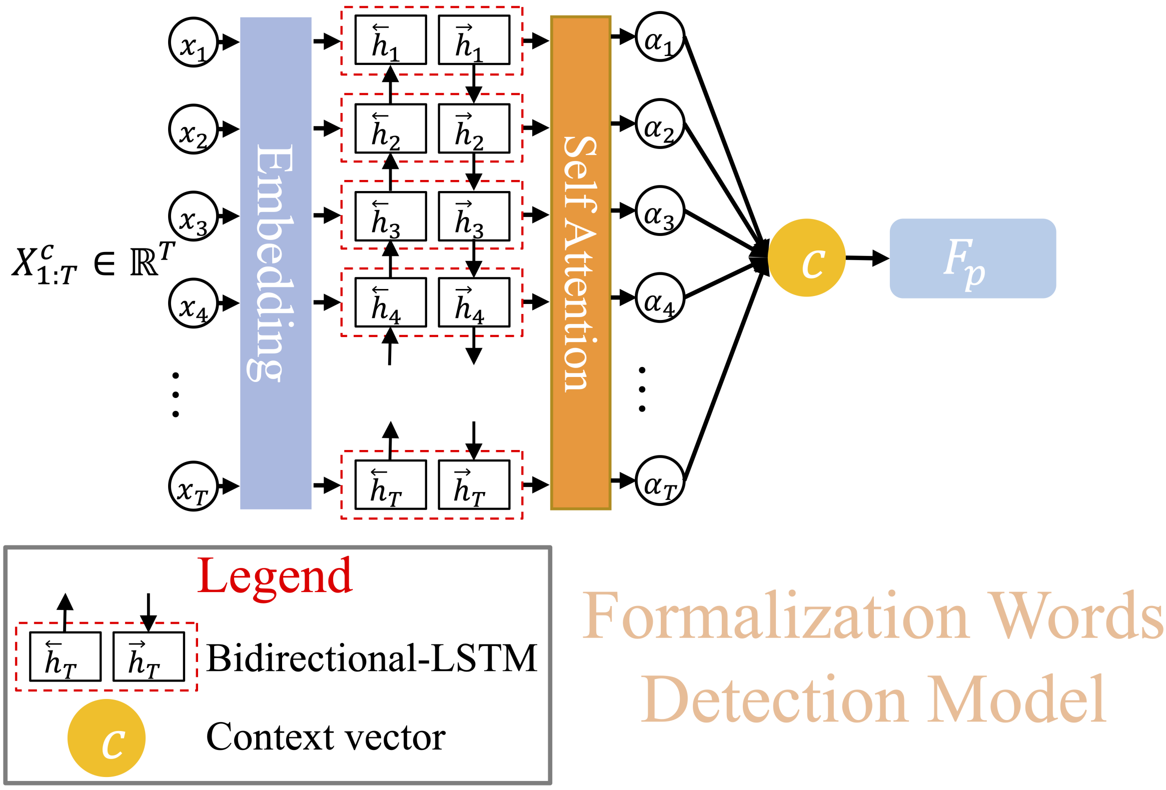

Figure 5.4: The structure of the formalization words detection model. The model outputs not only the final classification result (F_p) but also the attention weight (α_t) of each word.

Following the structure proposed by Yang et al.[298], this section trains the formalization words detection model based on the bidirectional LSTM model with a self-attention mechanism. Let $\mathbf{h_t} = \left[\overrightarrow{\mathbf{h_t}}; \overleftarrow{\mathbf{h_t}}\right] \in \mathbb{R}^{1\times 2dim^l}$ be the hidden state of the bidirectional LSTM at time step t and dim^l be the dimension of the hidden state in the bidirectional LSTM. The context vector $\mathbf{c}$ can be obtained by:

$$\mathbf{c} = \sum_{t=1}^{T} \alpha_t \cdot \mathbf{h}_t, \tag{5.3}$$

where α_t is the attention weight of each $x_t^c \in X_{1:T}^c$. The context vector $\mathbf{c}$ is fed into the fully connected layer to predict the text form polarity of $X_{1:T}^c$. Because each x_t^c in $X_{1:T}^c$ contributes to the final classification result, this section calculates the contribution of each x_t^c through the corresponding α_t. Specifically, x_t^c is the formalization word with α_t greater than x_t^c, which is the non-formalization word. Therefore, α_t can be used to distinguish whether x_t^c is a formalization word or not.

The sum of α_t corresponding to each x_t^c is equal to 1, and there are several x_t^c in $X_{1:T}^c$, which results in a lower distinguishability within α_t. The model expects that the value of each α_t is closer to 0 or 1 to further obtain a greater distinction, so the model maps α_t following Kim et al[118].

$$\alpha_t = sigmod(\mathbf{v}^T \mathbf{h}_t), \tag{5.4}$$

where $\mathbf{v}$ is the parameter vector. However, α_t here is still a continuous value, and the model expects that it is the Bernoulli distribution for more apparent distinction. Following Xu et al.[294], the model applies the averaged attention value α_{avg} to obtain $\hat{\alpha}_t$, which is the discretization value. It can be obtained as follows:

$$\hat{\alpha}_t = \begin{cases} 0, \alpha_t < \alpha_{avg}, x_t^c \text{ is the non-formalization word} \\ 1, \alpha_t \geq \alpha_{avg}, x_t^c \text{ is the formalization word} \end{cases} \tag{5.5}$$

Therefore, $\hat{\alpha}_t$ can be used to identify whether x_t^c is the formalization word or is the word without formalization information. The formalization words splits two memory sets: the formal words memory set $M_F \in \mathbb{R}^\gamma$ and informal words memory set $M_I \in \mathbb{R}^\gamma$. In this task the model only applies M_F to formalize the Weibo posts.

In this model, the cross-entropy is applied as the loss function, which is shown in 5.6.

$$\mathcal{L}_{FWD} = -\frac{1}{N}\sum_{n=1}^{N} p(F_g^{(n)} | \mathbf{V}_{1:T}^{FWD^{(n)}}, \theta^{FWD}), \tag{5.6}$$

where F_g is the ground truth label corresponding to F_p, which is the predicted text form polarity. θ^{FWD} represents the parameters in the formalization words detection model. By minimizing $\mathcal{L}_{FWD}$ continually, the model can predict more accurate results and calculate more distinguishing attention weights.

5.3.4 Event Knowledge Guided Text Formalization Model

The event knowledge guided text formalization model is the key model of the meteorological briefing formalization module. It consists of two submodules: the text formalization

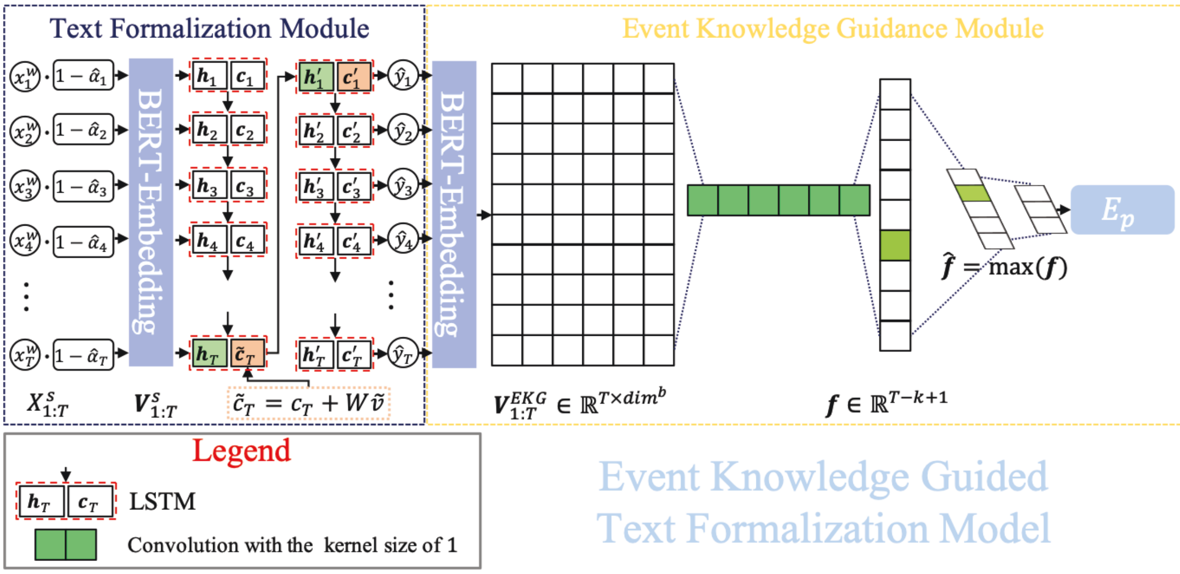

Figure 5.5: The structure of the event knowledge guided text formalization model.

module and the event knowledge guidance module. The event knowledge guidance module is used to guide and constrain the content generated by the text formalization module, enhancing the generated content centered on the descriptions of the specific meteorological event expressed in the source text.

5.3.4.1 Text Formalization Module

The main structure of the text formalization module is based on the LSTM autoencoder model. Let $X^w_{1:T} = x^w_1, ..., x^w_T$ be the original Weibo post. Because $\hat{\alpha}_T$ can be used to identify the formalization words, $(1-\hat{\alpha}_T)$ can be used to identify the non-formalization words. The non-formalization sequence of $X^w_{1:T}$ can be represented as $X^s_{1:T} = (1-\hat{\alpha}_1)x^w_1, ..., (1-\hat{\alpha}_T)x^w_T$, which is the input of the encoder. Unlike the other two models, the word embedding applied here is initialized by the fine-tuned BERT model, which is based on the "BERT-Base, Chinese" [2] model and fine-tuned through the meteorological events classification task. Such embedded vectors are more sensitive to meteorological events and have more significant meteorological event features.

The model uses $\mathbf{V}_{MF} \in \mathbb{R}^{dim^b \times \gamma}$ to represent the embedded vectors of the formal words memory set $M_F \in \mathbb{R}^{\gamma}$, where γ is a hyperparameter to control the size of M_F and dim^b is the dimension of the vectors transformed by the fine-tuned BERT model. In addition, the formal words in $X^w_{1:T}$ are continually updating $\mathbf{V}_{MF}$. The model introduces a vector

[2] https://storage.googleapis.com/bert_models/2018_11_03/chinese_L-12_H-768_A-12.zip

$\mathbf{s}^{fml} \in \mathbb{R}^{dim^b}$, which is the sum of the embedded vectors $\mathbf{V}^{w}_{1:T} \in \mathbb{R}^{T\times dim^b}$ corresponding to the formalization words in $X^{w}_{1:T}$. This vector contains the text form information and can be obtained as follows:

$$\mathbf{s}^{fml} = \sum_{i=1}^{T} \hat{\alpha}_i \cdot \mathbf{v}^{w}_{i}, \tag{5.7}$$

$\mathbf{v}^{w}_{i} \in \mathbb{R}^{1\times dim^b}$ is the embedded vector of $x^{w}_{i} \in X^{w}_{1:T}$. The model applies the attention mechanism to find the column in $\mathbf{V}_{MF}$, which is the most relevant to $\mathbf{s}^{fml}$. The attention weight $\alpha^{fml} \in \mathbb{R}^{\gamma}$ is as follows:

$$\alpha^{fml} = softmax((\mathbf{s}^{fml})^T \mathbf{V}_{MF}). \tag{5.8}$$

After the model obtains α^{fml}, a mask matrix $\mathcal{M} \in \mathbb{R}^{dim^b} \times \gamma$ can be obtained by calculating the outer product between $\mathbf{s}^{fml}$ and α^{fml}. This calculation is as follows:

$$\mathcal{M} = \mathbf{s}^{fml} \otimes \alpha^{fml}. \tag{5.9}$$

This mask is used to capture and screen the distinct features of the formal words by updating $\mathbf{V}_{MF}$ continually, and the processing is as follows:

$$\mathbf{V}_{MF} = \mathbf{V}_{MF} + \mathcal{M}. \tag{5.10}$$

Moreover, the model assists the decoder stage by using the non-formalization words. The vector $\mathbf{s}^{non} \in \mathbb{R}^{dim^b}$ is the sum of the embedded vectors of the non-formalization words, which is more likely to be generated associated with the formalization words at the decoder stage. It can be obtained as follows:

$$\mathbf{s}^{non} = \sum_{i=1}^{T} (1 - \hat{\alpha}_i) \cdot \mathbf{v}^{w}_{i}. \tag{5.11}$$

The model also computes the attention weight $\alpha^{non} \in \mathbb{R}^{\gamma}$ of $\mathbf{V}_{MF}$ to find the column that is most relevant to $\mathbf{s}^{non}$, which can be calculated as follows:

$$\alpha^{non} = softmax((\mathbf{s}^{non})^T \mathbf{V}_{MF}). \tag{5.12}$$

The sum of the most relevant weighted columns in V_{MF} can be expressed as:

$$\tilde{\mathbf{v}} \in \mathbb{R}^{dim^b} = \sum_{j=1}^{\gamma} \alpha^{non}{}_j \cdot \mathbf{V}_{MF j}, \tag{5.13}$$

where $\alpha^{non}{}_j$ is the $j-th$ value in α^{non} and $\mathbf{V}_{MF j}$ is the $j-th$ column in $\mathbf{V}_{MF}$. $\tilde{\mathbf{v}}$ is used to update the last cell state of the encoder and can be expressed as:

$$\tilde{\mathbf{c}}_T \in \mathbb{R}^{dim^b} = \mathbf{c}_T + \mathbf{W}\tilde{\mathbf{v}}, \tag{5.14}$$

where $\mathbf{c}_T$ is the original last cell state of the encoder and $\mathbf{W}$ is the parameter matrix. As Fig. 5.5 shows, the updated state $(\mathbf{h}_T, \tilde{\mathbf{c}}_T)$ of the encoder is the initial state of the decoder.

The generated sequence can be represented as $\hat{Y}_{1:T} = \{\hat{y}_1, ..., \hat{y}_T\}$. During the training process, the decoder is encouraged to restore $X^s_{1:T}$, and the loss function is as follows:

$$\mathcal{L}_{FMA} = -\frac{1}{N} \sum_{n=1}^{N} \sum_{t=1}^{T} p(X_t^{s(n)} | \hat{Y}_{1:t}^{(n)}, X^s_{1:T}{}^{(n)}, \theta^{FMA}), \tag{5.15}$$

where $\hat{Y}_{1:t}$ is the generated sequence until time step t and θ^{FMA} represents the parameters of the text formalization module.

5.3.4.2 Event Knowledge Guidance Module

The poor controllability of the generative model makes it possible for the formalized sequence to lose the core knowledge contained in the source text $X^w_{1:T}$. Because of this defect, this section proposes the event knowledge guidance module to guide and constrain the formalized content to enhance it centered on the specific meteorological event described in $X^w_{1:T}$. Let $\mathbf{V}^{EKG}_{1:T} \in \mathbb{R}^{T \times dim^b}$ be the vectors of $\hat{Y}_{1:T}$ embedded by the fine-tuned BERT model that is shared with it in the text formalization module. Specifically, the higher-order features of each word vector $\mathbf{v}^{EKG}_t$ in $\mathbf{V}^{EKG}_{1:T}$ are extracted by a convolution kernel $\mathbf{w}^{EKG} \in \mathbb{R}^{1 \times dim^v}$ with size 1. This structure can handle the indeterminate length of summary formalized by the text formalization module, and the feature map produced by this module can be expressed as $\mathbf{f}^{EKG} \in \mathbb{R}^T$. Each feature $\mathbf{f}^{EKG}_i$ in $\mathbf{f}^{EKG}$ can be obtained as follows:

$$\begin{aligned} \mathbf{f}^{EKG}_i &= R(\mathbf{w}^{EKG} * \mathbf{V}^{EKG}_{1:T})_i \\ &= R(\mathbf{w}^{EKG} \cdot \mathbf{V}^{EKG}_{1:T\;[i]}), \end{aligned} \tag{5.16}$$

where R is the ReLU[186] as the nonlinear activation function. To compare the effect of the receptive field size and amount on the model performance, the max-over-time pooling[57] is then applied to capture the most significant word feature that is most relevant to the corresponding meteorological event.

The loss function of the event knowledge guidance module is as follows:

$$\mathcal{L}_{EKG} = -\frac{1}{N}\sum_{n=1}^{N} p(E_g^{(n)}|\mathbf{V}_{1:T}^{EKG(n)}, \theta^{EKG}). \tag{5.17}$$

The learning process encourages the model to maximize the probability of generating the predicted label $E_p \in \mathbb{R}^{1\times e}$ close to the ground truth label $E_g \in \mathbb{R}^{1\times e}$ by giving the formalized sequence vector $\mathbf{V}_{1:T}^{EKG}$ and θ^{EKG} as inputs. θ^{EKG} represents the parameters in the event knowledge guidance module, and e is the number of meteorological events. Such a structure makes the model tend to capture the more significant word features that are related to the corresponding meteorological event.

5.3.5 Training

During the training process, each of the models is trained independently by optimizing their loss function. The output of each model is stored in the file for subsequent model applications. It should be noted that the loss function of the EKGTF model is divided into two parts: $\mathcal{L}_{FMA}$ and $\mathcal{L}_{EKG}$, which are the loss functions of each submodule. The overall loss function $\mathcal{L}_{EKGTF}$ of the EKGTF model can be calculated as follows:

$$\mathcal{L}_{EKGTF} = \mathcal{L}_{FMA} + \lambda \cdot \mathcal{L}_{EKG}. \tag{5.18}$$

Because the loss function scale is different in multitask learning, the overall loss may be dominated by one of the tasks. This result will cause the loss function of other tasks to be unaffected by the entire model's learning process. Therefore, this section introduces a hyperparameter λ to balance the overall loss function, ensuring that the event knowledge guidance module can positively impact the entire model. During the training process, the model gradually learns the salient features related to E_p in $\hat{Y}_{1:T}$ by minimizing $\mathcal{L}_{EKGTF}$ continually. Furthermore, the text formalization module is encouraged to generate the word $\hat{y}_t$ with features significantly related to E_p. While formalizing the Weibo posts, such a structure allows the model to retain the knowledge of meteorological events as much as possible and generates the formalized content centered on the specific event knowledge contained in the source text.

5.4 Experiment

5.4.1 Dataset

The dataset items consist of two parts: posts in Sina Weibo[3] and news titles in Baidu News[4]. These two sites are among the most well-known social networks and news websites in China. Because news titles have a formalized text style, the experiment regards them as the target style in the experiment and transform the style of Weibo posts to it. The Jieba[5] word segmentation tool is applied to segment the text into the word sequence.

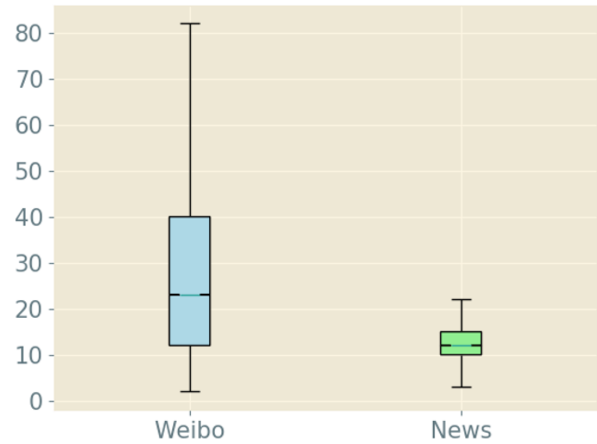

Figure 5.6: The boxplot reflects the length of items for Weibo posts and news titles. Any data not included between the whiskers are not shown, which are the outliers of the text length distributions.

The experiment cleans the data through data preprocessing. By investigating original Weibo posts and news titles, approximately one hundred rules have been formulated for use in screening high-quality items. For example, the empty content items are removed, and special characters such as "\u3000" and "Emoji" are filtered out. Because this model is applied to the meteorological briefing overview platform, each item's length in the briefing is required to be short. For this reason, this section uses a boxplot in Fig. 5.6 to display the length distribution of Weibo posts and news titles and screen items less than 25 in length ($len < 25$). Histograms of data counts corresponding to Weibo posts and news titles are shown in Fig. 5.7.

[3]https://www.weibo.com/
[4]https://news.baidu.com/
[5]https://github.com/fxsjy/jieba

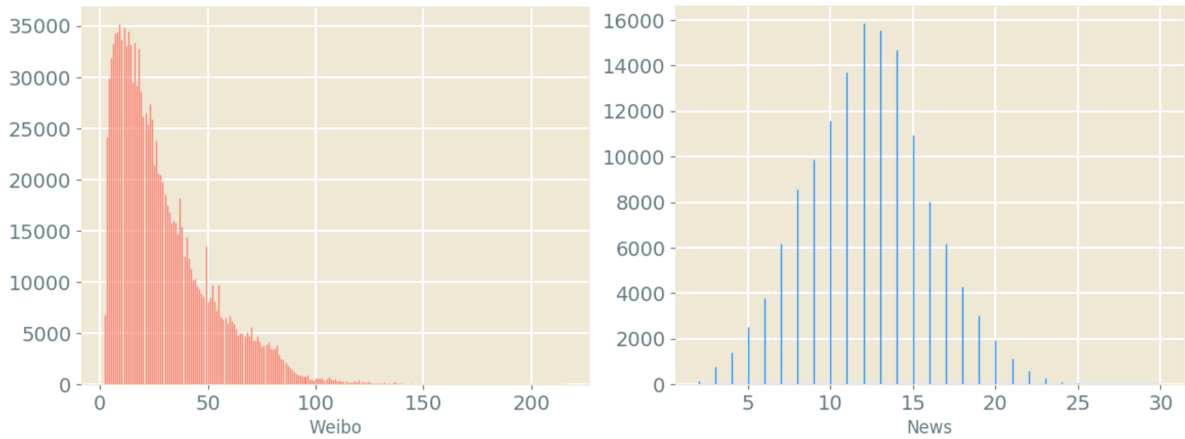

Figure 5.7: Histograms of item length in posts and news titles.

After data preprocessing, approximately 1.3 million Weibo posts and 0.15 million news titles are retained. Examples of the dataset are shown in Table 5.1.

Table 5.1: Examples of the dataset. The meteorological event knowledge is marked in red fonts.

Weibo	News	Event Knowledge
The weather is so "good" for going out, it is gale and rainy.	Beijing issued a blue warning for the gale of up to the 8th scale on the 5th.	Gale
What should we do? This year, the two sides of the Yellow River are suffering severe drought.	Mainly cloudy in the next 10 days, attention! High temperature and drought is coming.	Drought
Typhoon Mangosteen is wreaking havoc on the Pacific Ocean reaching 255 kilometers per hour.	The national meteorological center continued to issue a yellow warning for typhoon at 10:00 am on August 16.	Typhoon
I heard that there was hail somewhere in Beijing today, and it is sunny here.	Weifang issued an orange hail warning, reminding citizens to pay attention to safety.	Hail

There are many thunder warnings today, but no rain is seen.	The black clouds over the city, Luzhou issued a yellow warning signal of thunder.	Thunder

5.4.2 Experiment Settings

The experiments are implemented based on a NVIDIA GTX 1080Ti GPU. The Adam[119] optimizer is applied for all of the models. In the text form judgment model, the learning rate is 0.001, and the dimension of word embedding is 300 ($dim^v = 300$). The learning rate of the formalization words detection model is 0.001, and the dimension of the hidden state in the bidirectional LSTM is 128 ($dim^l = 128$). In the event knowledge guided text formalization model, the learning rate is 0.1, and the dimension of the vectors transformed by the fine-tuned BERT model is 768 ($dim^b = 768$). The number of meteorological events is 14 ($e = 14$), which are defined and illustrated above. The size of each memory set used in the text formalization module is 60 ($\gamma = 60$), and the hyperparameter used to balance the overall loss function is 0.2 ($\lambda = 0.2$).

5.5 Results and Analysis

5.5.1 Evaluation Metric

Because the text form judgment model and the formalization words detection model are both binary classification tasks and the number of items is not balanced, this section uses the precision (P), recall (R), F_1 score (F_1), and accuracy (Acc) as the evaluation metrics of these two models. The calculations are as follows:

$$P = \frac{TP}{TP + FP}, \tag{5.19}$$

$$R = \frac{TP}{TP + FN}, \tag{5.20}$$

$$F_1 = \frac{2 \times P \times R}{P + R}, \tag{5.21}$$

$$Acc = \frac{TP + TN}{TP + TN + FP + FN}. \tag{5.22}$$

For each of these two models, TP is the number of positive classes predicted as positive, TN is the number of negative classes predicted as negative, FP is the number of negative classes predicted as positive, and FN is the number of positive classes predicted as negative.

BLEU[198] is a bilingual evaluation metric used to evaluate the similarity percentage of n groups of words between source and reference. P_n is the modified $n-gram$ precision score. BP is the brevity penalty, where c is the length of the transferred sequence and r is the length of the reference. The final BLEU is calculated as Eq. 5.25, where w_n is the geometric mean coefficient; in this experiments, $w_n = \frac{1}{4}$.

$$P_n = \frac{\sum_{C \in \{Candidates\}} \sum_{n-gram \in C} Count_{clip}(n-gram)}{\sum_{C' \in \{Candidates\}} \sum_{n-gram' \in C'} Count(n-gram')}, \tag{5.23}$$

$$BP = \begin{cases} 1, \text{if } c > r \\ e^{1-\frac{r}{c}}, \text{if } c \leq r \end{cases}, \tag{5.24}$$

$$BLEU = BP \times exp(\sum_{n=1}^{N} w_n log P_n). \tag{5.25}$$

5.5.2 Baseline Methods

The experiments use the CAE[235], MAE[78], and SMAE[317] as the baseline models. CAE is the cross-aligned autoencoder model proposed by Shen et al.[235], which uses a shared latent content space to separate the features of content and style. MAE is the multidecoder autoencoder model proposed by Fu et al.[78]. Their model learns the input sentence representation only containing content information and then generates a corresponding text with a specific style through a multidecoder model that acquires different style features. SMAE is the sentiment memory-based autoencoder model proposed by Zhang et al.[317]. Their model can automatically extract appropriate text style features from the acquired style memory according to the specific context and then realize text style transfer.

5.5.3 Quantitative Evaluation

Table 5.2 shows the quantitative evaluation results of the EKGTF model and other baseline models on the test set. It is evident that, compared with other baseline models, the EKGTF model achieves better results in the BLEU score.

Table 5.2: The quantitative evaluation results of the EKGTF model and the baseline models.

Model	BLEU
CAE[235]	5.873
MAE[78]	8.705
SMAE[317]	17.688
EKGTF	**21.489**

In addition, this section also shows the quantitative evaluation results of the text form judgment model and the formalization word detection model. The results are shown in Table 5.3 and Table 5.4, respectively.

Table 5.3: The quantitative evaluation results of the text form judgment model.

P	R	F_1	Acc
0.871	0.830	0.834	0.978

Table 5.4: The quantitative evaluation results of the formalization words detection model.

P	R	F_1	Acc
0.881	0.889	0.874	0.926

Both Table 5.3 and Table 5.4 show satisfactory results. Such results encourage the model to build more accurate memory sets (M_F and M_I), thus improving the entire model's performance.

5.5.4 Qualitative Evaluation

This section takes the text formalized by the EKGTF model and other baseline models as examples to illustrate the advantages in the qualitative evaluation of the EKGTF model. The comparison results are shown in Table 5.5.

The core knowledge described in the source text is that there is heavy rain in Guangzhou accompanied by continuous thunder now. From the example, it can be observed a mood word "Oh" in the source text, which is often used in informal spoken expressions and does not often appear in the formal text. Except for the CAE model, each of the models detects this word and removes it. The text formalized by the MAE model mistakenly adds the ordinal word "first" and turns the declarative sentence into a question, which is quite different from the source text. The formal text transferred by the SMAE model describes the term "Guangzhou" through a colon. Although this is different from the source text since it adds punctuation that does not exist in the source text, it expresses a similar meaning. Such a result formalizes the style of the source text to some extent. By contrast, the text generated by the EKGTF model is as consistent as possible with the source, and it also has a formalized style. More importantly, the word "now" describing the time is not lost after the formalization, which is crucial for meteorological briefings with timeliness requirements.

Table 5.5: The qualitative evaluation results of the proposed EKGTF model and the baseline models.

Source: Oh Guangzhou is now falling the heavy rain and continuous thunder.
CAE[235]: Oh Guangzhou fall the heavy rain, the rain with continuous thunder.
MAE[78]: Guangzhou first fall the heavy rain and continuous thunder?
SMAE[317]: Guangzhou: fall the heavy rain and continuous thunder!
EKGTF: Guangzhou now appears the heavy rain that with continuous thunder!

5.5.5 Effect of the Receptive Field Size in Event Knowledge Guidance Module

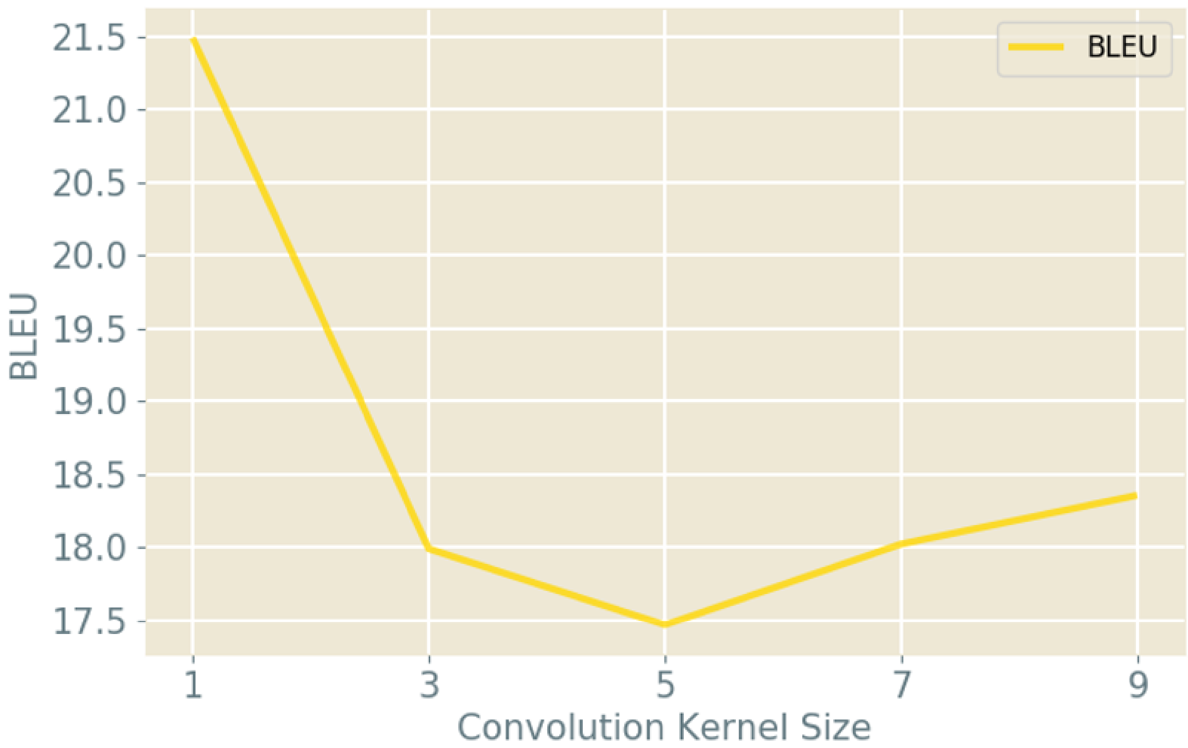

Figure 5.8: Effect of receptive field size in the event knowledge guidance module on model performance.

This section verifies the effect of the receptive field size on the model performance in the event knowledge guidance module. The results are shown in Fig. 5.8. The model achieves the highest BLEU score with the receptive field of size 1 and achieves the lowest BLEU score with the receptive field of size. 5. This is because, the larger the convolution kernel size is, the richer the $n-gram$ word features captured are. However, such characteristics dilute the event word's features and bring unnecessary noise to the model, thus affecting model performance. In contrast, when the size of the convolution kernel is 1, the event word features captured by the model are the most significant, thus effectively exerting the most positive impact on the text formalization module. Furthermore, the model tends to capture the global sentence features when the convolution kernel is larger. Compared with the features of partial words, the sentence features are more significant, but they are far less significant than the features of a single event word.

5.5.6 Effect of the Receptive Field Amount in Event Knowledge Guidance Module

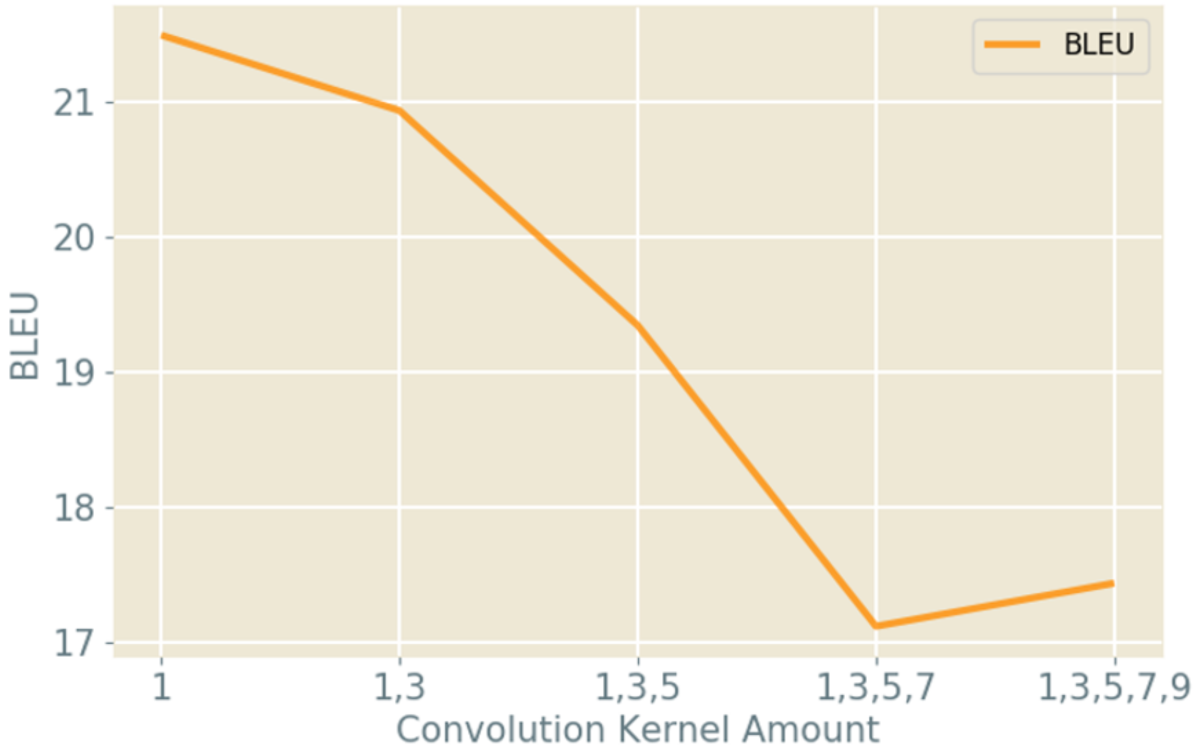

Figure 5.9: Effect of receptive field amount in the event knowledge guidance module on model performance.

This section verifies the effect of the receptive field amount on the model performance in the event knowledge guidance module. The results are shown in Fig. 5.9. The model achieves the highest BLEU score when the event knowledge guidance module only contains one receptive field with a size of 1, and it achieves the lowest BLEU score when the event knowledge guidance module contains four receptive fields with sizes of $[1,3,5,7]$. The performance of the model decreases as the receptive field amount increases. The reason for this result is similar to the effect of the receptive field size in the event knowledge guidance module because richer convolution kernels bring unnecessary noise to the model. Similarly, when the convolution kernel of size 9 is included in the module, the model tends to introduce global sentence features, which are slightly more significant than partial word features. However, these features still weaken the significance of the single event word feature.

5.5.7 Effect of the Memory Size

Figure 5.10: Effect of memory size in the text formalization module on model performance.

This section verifies the effect of memory size in the text formalization module on model performance. The results are shown in Fig. 5.10. When each memory set's size is 60 ($\gamma = 60$), the model achieves the best performance. Such a conclusion also supports the choice of γ in the experiment. Unexpectedly, the larger γ caused the model performance to decrease. It can be speculated that this is because a larger γ will prevent the model from applying the words well and make the formalized content more diverse, which causes its controllability to decrease. Such a characteristic limits the flexibility of the model. Maintaining the model performance with the increase of γ is worth studying in future work.

5.6 Ablation Study

This section performs an ablation study to verify the effectiveness of the fine-tuned BERT model and the event knowledge guidance module in the EKGTF model.

5.6.1 Fine-tuned BERT Model Verification

This section verifies the effectiveness of the fine-tuned BERT model by quantitative evaluation. The results are shown in Table 5.6.

Table 5.6: The quantitative evaluation results for fine-tuned BERT model verification, where "w/o BERT" represents the word embedding in the EKGTF model initialized randomly.

Model	BLEU
w/o BERT	20.011
EKGTF	**21.489**

It can be observed that the EKGTF model that uses the fine-tuned BERT model to initialize the word embedding achieves a better result, which proves that the fine-tuned BERT model has a positive impact on the EKGTF model.

5.6.2 Event Knowledge Guidance Module Verification

This section verifies the effectiveness of the event knowledge guidance module by quantitative evaluation and qualitative evaluation. Furthermore, this section also explores the impact of hyperparameter λ on model performance.

5.6.2.1 Quantitative Evaluation

Table 5.7 shows the quantitative evaluation results of the event knowledge guidance module. It is obvious that, compared to the model "w/o EKG," the EKGTF model with the event knowledge guidance module has a significant advantage and achieves a better result.

Table 5.7: The quantitative evaluation results for the event knowledge guidance module, where "w/o EKG" represents the model without the event knowledge guidance module.

Model	BLEU
w/o EKG	18.941
EKGTF	**21.489**

5.6.2.2 Qualitative Evaluation

Table 5.8 shows the qualitative evaluation results of the event knowledge guidance module. The main knowledge expressed in the source text is that today's haze is serious, so it is necessary to pay attention to safety when going out. The core meteorological event described in the source is haze. The "w/o EKG" model incorrectly replaces the meteorological event "haze" with "fog," which loses the core knowledge expressed in the source text and affects the accuracy of the meteorological briefing. In contrast, the content generated by the EKGTF model not only captures the core event knowledge in the source text but also formalizes the text style, thereby generating more accurate briefing content.

Table 5.8: The qualitative evaluation results for the event knowledge guidance module, where "w/o EKG" represents the model without the event knowledge guidance module.

	Weibo Posts	Event Knowledge
Source	Today the haze is very serious, pay attention when you go out.	Haze
w/o EKG	Today is a foggy day, pay attention to safety when you go out.	Foggy
EKGTF	**Today's haze is severe, and you should pay attention to safety when you go out.**	**Haze**

5.6.2.3 λ Selection

This section verifies the effect of hyperparameter λ on model performance. The results are shown in Fig. 5.11. It can be observed that the EKGTF model achieves the best performance when the value of λ is 0.2. Based on this result, it can be speculated that, when $\lambda = 0.2$, the event knowledge guidance module has the most positive impact on the text formalization module. Such a conclusion supports the choice of λ in the experiments.

5.7 Error Analysis

This section randomly examines 100 unexpected examples generated by the EKGTF model for the error analysis, and tries to identify common errors and divide them into three typical categories: (1) Confusing Content; (2) Unchanged; and (3) Number of Events. The remainder of this section will analyze these categories in detail.

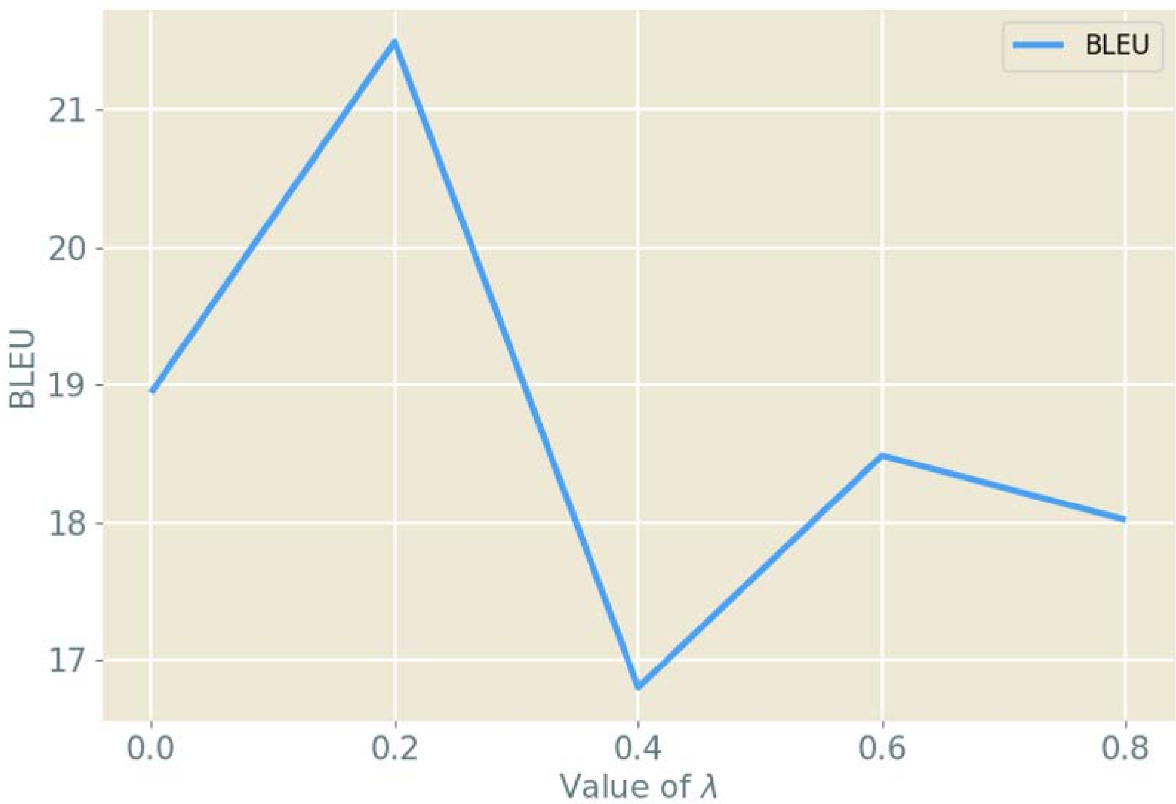

Figure 5.11: The verification curve of the effect of λ on model performance. It is obvious that the model achieves the best performance when $\lambda = 0.2$.

5.7.1 Confusing Content

"Confusing Content" means that the model generates messy formalized content that is hard to understand. Because the model is based on the generative seq2seq structure, this results in poor controllability of the generated content, which is a common defect of the seq2seq-based model. The most apparent manifestation of this defect in the model is the generation of repetitive words. An example is shown in Table 5.9.

Table 5.9: The error analysis of "Confusing Content."

Source: Nanjing finally experienced the haze that is the same standard level as Beijing.
EKGTF: Nanjing **experienced experienced experienced** the haze that is the same standard level as Beijing.

The text formalized by the EKGTF model in Table 5.9 contains the repeatedly generated word "experienced," which misinterprets the source text's meaning and makes the generated text confusing, thus resulting in the model not properly formalizing the source text. Some researchers focus on this problem[231]. The current EKGTF model can be further optimized in future work.

5.7.2 Unchanged

"Unchanged" refers to the model that does not modify and formalize the content in the source text. An example is shown in Table 5.10.

Table 5.10: The error analysis of "Unchanged."

Source: **National Meteorological Center of CMA** continues to issue a cold wave blue warning at 10:00 on December 26.
EKGTF: **National Meteorological Center of CMA** continues to issue a cold wave blue warning at 10:00 on December 26.

Some of the meteorological-related Weibo posts are posted by official accounts, such as the National Meteorological Center of CMA shown in the example. The posts posted by these official agencies often have a formalized text style, so the model does not need to address them. The example text formalized by the EKGTF model in Table 5.10 does not make any changes to the source text, demonstrating that the model performs well in identifying text styles.

5.7.3 Number of Events

"Number of Events" means that, due to the accompanying relationship among meteorological events (e.g., gales often occur before rainstorms and blizzards often accompany icing), some Weibo posts contain descriptions of multiple meteorological events. However, the formalized text only correctly generates a description of one event. An example is shown in Table 5.11.

Table 5.11: The error analysis of "Number of Events."

Source: Both **cold wave** and **blizzard** warnings have been issued together, when the raging of this round of cold air be stopped.
EKGTF: **Cold wave** and **binary typhoons** came together to strike, and cold air landings raged seriously affecting the temperature.

The source of Table 5.11 contains two meteorological events, cold waves and blizzards, but the text formalized by the EKGTF model only correctly describes the cold wave event. The reason is that the event knowledge guidance module's current structure design has not yet considered the situation in which multiple meteorological events are contained in one Weibo post. The future work can further optimize and improve the model to address this problem.

5.8 Conclusion

This chapter proposes a meteorological event knowledge-enhanced briefing formalization module, consisting of the text form judgment model, formalization words detection model, and the EKGTF model. The three models are connected in series to realize the content optimization of meteorological decision briefing based on social sensor signals. The EKGTF model applies the fine-tuned BERT model as the language model to introduce the meteorological domain prior knowledge, and the event knowledge-guided module is applied to constrain the text formalization process so that the formalized decision briefing content focuses on the core meteorological events expressed in the source posts. Compared with other baseline models, the EKGTF model achieves the best results. In addition, this chapter develops a framework for meteorological decision briefing optimization services based on the EKGTF model. This framework has been applied to a prototype application based on meteorological decision briefing to optimize the content and improve decision-making efficiency. This research has been published in Information Processing & Management (CORE A).

Chapter 6

Meteorological Decision Briefing-based Application

In sudden meteorological disaster scenarios, decision-makers are faced with tasks at multiple granularities such as strategic, regional, and personal. They need to achieve cross-domain, cross-department, and cross-platform meteorological data linkage. Based on the social network platform, the social sensor senses the meteorological disaster environment through the fusion of human senses, which can break the data barriers between various departments. Therefore, the research of this thesis uses social sensor signals to design a prototype application based on the meteorological briefing. By segmenting, reorganizing, and distributing the knowledge in the meteorological domain, this thesis realizes the automatic encapsulation of decision knowledge carried by decision briefing and provides real-time, efficient, flexible, and intelligent decision support services for decision-makers. This prototype application can realize the dynamic interaction among meteorological big data, knowledge, and decision-makers, integrate decision-making knowledge in sudden meteorological disaster scenarios accurately and in a timely manner, and transform it into a hierarchical and multi-task decision support service. This application has been deployed on the Meteorological Public Opinion Mining Platform. Since its deployment, it has provided decision-makers of the China Meteorological Administration (CMA) with decision support services in sudden meteorological disaster scenarios, including the 2021 Henan rainstorm.

This chapter explains the prototype application in terms of process and decision-

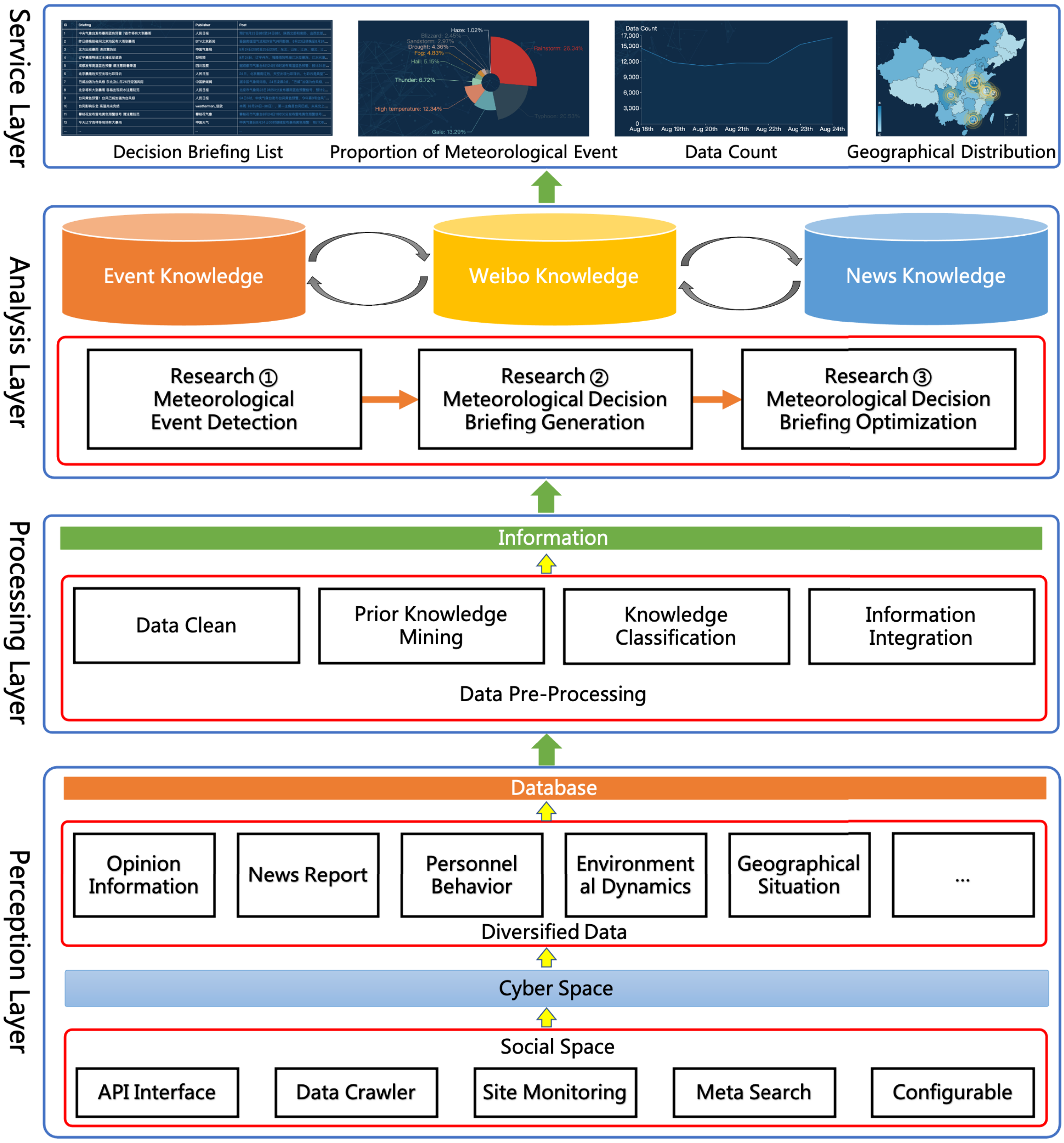

Figure 6.1: The process of the meteorological decision briefing-based application.

making function. The remainder of this chapter is organized as follows. Section 6.1 details the prototype application process based on the meteorological decision briefing. Section 6.2 takes the data of July 21, 2021, as an example to describe each module's decision support service function in the prototype application. The conclusion of this chapter is discussed in section 6.3.

6.1 Application Process

This section introduces the prototype application process based on the meteorological decision briefing, as shown in Fig. 6.1. The process includes the layers of perception, processing, analysis, and service. The rest of this section introduces each layer's processing capabilities in detail.

Perception Layer: This layer uses data collection methods such as the official API interfaces, data crawler, site monitoring, meta-search collection, and configurable collection to perceive social sensor signals in the real space and map the social sensor signals to the network space. Compared with physical sensor signals, social sensor signals can provide feedback on more diverse meteorological characteristics, including qualitative characteristics such as public opinion, news, personnel behavior, environmental dynamics, and geographic location. Finally, a database with specific service capabilities is constructed based on the application requirements.

Processing Layer: This layer screens and filters the original data by using a data preprocessing method that conforms to the characteristics of the meteorological domain. Specifically, it includes raw data cleaning based on rules and other methods, domain prior knowledge mining with meteorological events as the core knowledge, information classification based on information application functions, and core information integration with meteorological decision briefing services as application requirements.

Analysis Layer: This layer is the functional module of the prototype application. The preprocessed information is passed through the sentence-level feature-based meteorological event detection model, the multiple knowledge-enhanced summarization model, and the meteorological briefing formalization module. It extracts, refines, and expresses the core knowledge in the meteorological domain, generating formalized decision briefing content driven by the meteorological event knowledge and meeting the emergency decision-making requirements of sudden meteorological disasters. Finally, the knowledge base is constructed by the decision support knowledge generated by each intelligent model, including the event knowledge base, Weibo posts knowledge base, and news knowledge base.

Service Layer: This layer enables the dynamic interaction with decision-makers through the user interface. The meteorological decision service knowledge base is applied in this layer to provide intelligent decision support services. The service layer provides application scenarios for each decision-making support function.

6.2 Decision Support Function

The July 2021 Henan rainstorm was one of China's most severe meteorological disasters in recent years[1]. This section uses the Henan rainstorm data as an example to demonstrate the prototype application based on the meteorological decision briefing, as shown in Fig. 6.2. This application can generate and display the formalized meteorological briefings online through the aforementioned innovative model, detect and mine current hot meteorological events, and provide meteorological decision support services oriented to the environmental characteristics of sudden meteorological disasters using data statistics and location mapping methods. This application can integrate the content of the meteorological decision briefing for a specific period and send the generated briefing to the email address of the designated decision-maker. Specifically, the application consists of four functional modules: the briefing list, the proportion of meteorological events, the data count, and the geographic distribution. The rest of this section details the specific decision-making functions of each module and illustrates its application value in meteorological decision support services through cross-validation with the meteorological events in the real environment.

6.2.1 Briefing List

This is the core component of the meteorological briefing overview platform. It shows the source Weibo posts with clickable links, the generated briefing content, and each post's publisher. Through this component, decision-makers can comprehensively and efficiently understand public opinion and situations in relation to meteorological events.

In the example in Fig. 6.2, the source Weibo posts displayed in the list describe the rainstorm and the related meteorological events which occurred in Henan province on that day. Vital fine-grained features such as rain warning signals, rain situation forecasts, and rescue resources are screened and retained. This functional module summarises and refines the crucial knowledge through the proposed intelligent model, avoiding the influence of irrelevant information in the source Weibo post on the efficiency of the decision-making process. Using this module, decision-makers can obtain a more detailed understanding of the qualitative information of meteorological events in social sensor signals and then efficiently formulate suitable, diverse, real-time, and flexible decision-making strategies.

[1]https://en.wikipedia.org/wiki/2021_Henan_floods

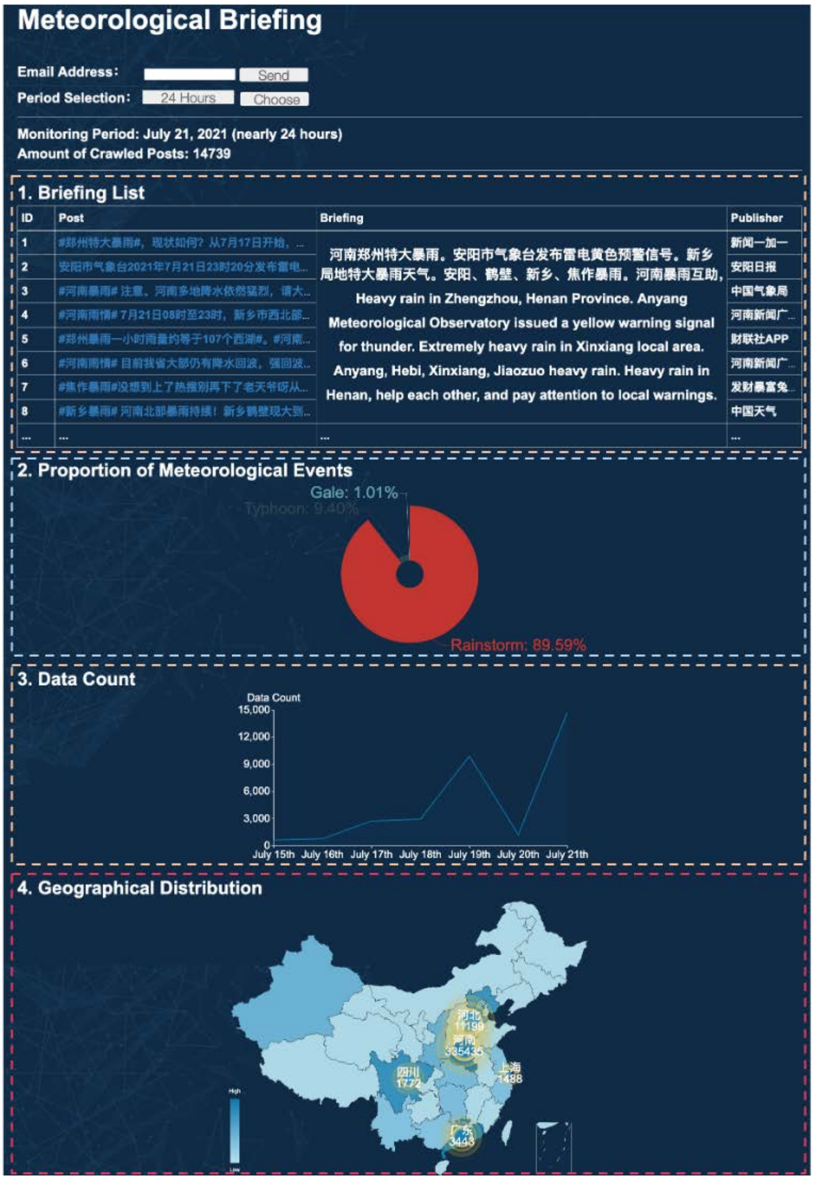

Figure 6.2: The example of the meteorological decision briefing-based application.

6.2.2 Proportion of Meteorological Events

This component identifies the current hot meteorological events which have attracted immense public attention. The event heat is quantified by the area of the sector and the corresponding percentage. The larger the sector area, the higher the percentage, and the more public attention. Through this component, decision-makers can intuitively understand the current meteorological events that attract the public's attention.

As can be seen from Fig. 6.2, there are three types of meteorological events that are of wide concern in the current period: rainstorm, typhoon, and gale. Of these, the rainstorm has the highest event attention, which is in line with the characteristics of meteorological events in the real space of the day[2]. This result also verifies the solid situational awareness and event detection capabilities of the proposed sentence-level features-based meteorological event detection model. Based on this module, decision-makers can intuitively understand hot-spot meteorological events with great attention in the current period and formulate decision-making strategies that meet the characteristics of corresponding events according to the meteorological attributes and event heat.

6.2.3 Data Count

This component shows changes in the amount of data in the meteorological Weibo posts within a week. The higher the data count, the more posts that were posted that day. This component provides decision-makers with a visual understanding of trends in public attention to meteorological events.

The data statistics curve in Fig. 6.2 shows that the total amount of data from July 19th to 21st is at a high level, which is consistent with the heavy rain event in Henan in real space. On July 19th, there was an obvious upward inflection point in the data statistics curve, which coincided with the time of the red rainstorm warning signal issued by Zhengzhou City, Henan province on July 19[3]. This trend also proves that real-time rainstorm warning signals can stimulate extensive discussion in cyberspace. During the rainstorm disaster, the microblogging social network, Sina Weibo, became the main information dissemination channel for feedback on the situation in real space. The release of a large amount of information led to a surge in the amount of data as shown by the curve. This module can help decision-makers intuitively understand the trends in public attention in relation to meteorological-related content within a week, providing a reference for decision makers to analyze the changes in public attention to meteorological events and predict the evolution of events in cyberspace.

6.2.4 Geographical Distribution

This component shows the geographical distribution of meteorological events on a map, showing the five provinces with the most significant public attention to meteorological events. The larger the circle and the number, the higher the attention to the corre-

[2] http://www.cneb.gov.cn/2021/07/21/ARTI1626800164258636.shtml
[3] http://www.cneb.gov.cn/2021/07/19/ARTI1626704330709780.shtml

sponding meteorological events in the province. Henan received the most significant attention, accurately mapping the heavy rain event that day. This component supports the formulation of fine-grained meteorological emergency decision strategies following geographical location characteristics.

The example in Fig. 6.2 shows that Henan province has the largest aperture and the highest attention value on the map. This result accurately maps the catastrophic rainstorm events in Henan province at the current time in real space. The heavy rain has also affected Hebei province, giving it a higher degree of attention on the map. In addition, Guangdong province is also active on the map. After checking the meteorological events in real space, it was found that Typhoon Chapaka landed in Guangdong on July 21st[4], which is consistent with the map. This functional module can support decision-makers in formulating more accurate, fine-grained, and more applicable decision-making strategies that conform to the multi-dimensional characteristics of the corresponding provinces, such as geography and meteorology.

6.3 Conclusion

This chapter introduces the prototype application based on the meteorological briefing from the application process and decision support function. It describes the functions of each module in the prototype application in detail. The practicality of the social sensor-based meteorological briefing is further demonstrated by cross-validating the results displayed by each functional module in the 2021 Henan rainstorm event with the meteorological events in real space. The research in this chapter has been applied to the Meteorological Public Opinion Mining Platform.

[4]http://www.cneb.gov.cn/2021/07/20/ARTI1626791198918797.shtml

Chapter 7

Conclusion and Future Research

7.1 Thesis Conclusion

In modern civilization, the coupling degree between humans and nature is gradually growing, and the characteristics of complex systems are more obvious. Complex systems are often relatively fragile, and emergencies are likely to become the key factor in destroying the stability of the whole system. The human is the most critical and vulnerable carrier of sudden meteorological disaster environments and the core social sensor unit in disaster environments. Compared with traditional physical sensors, human-based social sensors are more convenient to deploy, more flexible, have a lower cost, and provide faster feedback. More importantly, social sensors can obtain feedback from public opinion information and psychological behavior. This is an important data source in decision support services based on "event - public opinion communication - psychological behavior", which fills the social factor which is missing in traditional emergency decision support services. As an effective carrier of decision-making schemes in sudden meteorological disasters, decision briefings can filter, screen, and summarize the original social signal by refining the core decision knowledge. The automatic generation method of flexible decision reports in a sudden meteorological disaster environment can provide efficient decision support services for decision-makers.

The emergency management of sudden meteorological disasters has the characteristics of scenario dependence. When making decisions, the scenario should be considered as the primary background of scientific research and the basic assumption of problem structure. This thesis takes the sudden meteorological disaster environment as the decision support application scenario. In conclusion, this thesis proposes a method for generating the formalized meteorological briefing based on meteorological social event knowledge. This method takes the meteorological briefing as the carrier and provides the decision-makers with intelligent, real-time, diverse, and efficient meteorological emergency decision support services. The innovations of this thesis are as follows:

1. Co-occurrence Feature-based Sudden Meteorological Event Detection: Given the problems of limited coverage, poor flexibility, and the low interactivity of traditional physical sensor signals in extreme meteorological environments, this thesis proposes a sentence-level feature-based meteorological event detection model, which uses social sensor signals to perceive specific meteorological events. Of these, the structure of the wide-grained capsule network considers the independent characteristics and co-occurrence characteristics of meteorological events to efficiently detect meteorological events. The experimental results show that the proposed model achieves 0.941, 0.862, 0.738 and 0.795 respectively in terms of $Accuracy$, P_{micro}, R_{micro} and $F_{micro-1}$, outperforming the other baseline models significantly. This model has been applied to the Meteorological Public Opinion Mining Platform for detecting specific meteorological events.

2. Multiple Knowledge-enhanced Meteorological Decision Briefing Generation: Given the problems of rigid content, single perspective, and complicated processes in the current decision briefing generation method that relies on specific templates, this thesis proposes a multiple knowledge-enhanced summarization model, which automatically generates the meteorological briefing based on multiple posts from Sina Weibo. The MKES model comprises a summary generation module and a multiple knowledge enhancement module. The multiple knowledge enhancement module guides and constrains the summary generation process using meteorological event knowledge and geographical location knowledge, ensuring the generated summary focuses on describing the specific knowledge in the source text. The experiment results show that the proposed model achieves 0.2025, 0.0807, 0.1740 and 0.656 respectively in terms of $ROUGE-1$, $ROUGE-2$, $ROUGE-L$ and $F_{micro-1}$, outperforming the other baseline models significantly. This model has been applied to the Meteorological Public Opinion Mining Platform to generate the content of a meteorological decision briefing.

3. Meteorological Event Knowledge-enhanced Decision Briefing Optimization: Given the problems of weak formalization, strong colloquialisms, and chaotic text styles in social sensor-based decision briefing, this thesis proposes an event knowledge-guided meteorological decision briefing optimization module to formalize the generated meteorological decision briefing content. This module includes a text form judgment model, a formalization words detection model, and an event knowledge-guided text formalization model. Through the joint application of these models, the detection, optimization, and text language style transfer are realized, where meteorological event knowledge is used to guide the language style transfer process so that the content of the formalized decision briefing can retain the knowledge of the meteorological events described in the source text. The experiment results show that the proposed model achieves a quantitative evaluation result of 21.489 in terms of $BLEU$, outperforming the other baseline models significantly. This model has been applied to the Meteorological Public Opinion Mining Platform to optimize the content of the generated meteorological decision briefing.

In conclusion, this thesis takes social sensors as signal sources for situational awareness of sudden meteorological disasters, meteorological emergency decision support services as demanding guidance, and meteorological decision briefing as service carriers. It completes the knowledge transfer and decision intelligence of social sensor signal $\longrightarrow$ information $\longrightarrow$ knowledge $\longrightarrow$decision support services. Based on the application scenario of the meteorological decision briefing, the decision support service in extreme meteorological environments is realized, and intelligent decision support is enhanced by knowledge service automation.

7.2 Future Research

The intelligent decision support service technology for extreme meteorological environments is still in its early stages. It needs further expansion in terms of theoretical research, technical methods, and industrial applications. To extend the research undertaken in this thesis, the following research directions will be pursued:

1. Time series prediction of meteorological situation based on multi-modal social signals: In recent years, various short video applications have become mainstream, generating substantial economic and social benefits and becoming an essential part of the social network ecology. High-performance devices such as GPUs have made it possible to process video signals efficiently. Compared with text and image signals, video signals are multi modal signals that can express text, images, and audio in a unified manner. The time-series features have more comprehensive situational awareness, information dissemination abilities, public opinion mining capabilities, and higher data credibility. The real-time time-series analysis of social sensor-based video signals is a research focus of future work. This research will improve the trustworthiness of social sensor signals with a potential information error correction capability in video time features.

2. Multi-source extreme meteorological environment situational awareness technology integrating physical and social sensor signals: Massive social sensor signals have the advantages of comprehensive coverage, diversified perspectives, and a strong description ability to perceive extreme meteorological events. However, compared with social sensor signals, physical sensor signals have more accurate situational awareness and more robust data reliability. Fusing the two types of sensor signals and building an intelligent meteorological decision support service platform based on multi-source data is a research focus of future work. The two signals complement and cross-validate each other, providing more data-driven applications for building intelligent, accurate, and formalized meteorological knowledge service applications.

3. Real-time public opinion guidance intervention combined with the trend of sudden meteorological events: Rumors in the sudden meteorological environment have become a vital hazard factor that causes social shocks, damages public interests, and interferes with decision-making. The networked structure of social media provides a convenient and fast link for the dissemination of rumors, resulting in various social media platforms becoming the hardest-hit areas for rumors to ferment when sudden meteorological events occur. Combining the characteristics of sudden meteorological events, predicting the development of public meteorological opinion, and actively guiding the negative public opinion related to meteorological events from knowledge popularization is a research focus of future work. The timely identification, discovery, and intervention of meteorological-related rumors it is of great significance to reduce social panic, maintain public security, and improve the efficiency of decision support services.

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