

Early detection of emergency events from social media: A new text clustering approach

Lida Huang (✉ hld999@yeah.net)

Tsinghua University <https://orcid.org/0000-0002-2663-6221>

Panpan Shi

Tsinghua-Gsafety Joint Institute of Public Safety Research, Gsafety Company

Haichao Zhu

Tsinghua-Gsafety Joint Institute of Public Safety and Emergency Technology Research, Gsafety Company

Tao Chen

Tsinghua University

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Early detection of emergency events from social media: A new text clustering approach

Lida Huang^a, Panpan Shi^b, Haichao Zhu, Tao Chen^{a*}

^a Institute of Public Safety Research, Department of Engineering Physics, Tsinghua University, Beijing, China, 100084

^b Tsinghua-Gsafety Joint Institute of Public Safety and Emergency Technology Research, Gsafety Company, Beijing, China, 100094

Correspondence information: Tao Chen, Institute of Public Safety Research, Department of Engineering Physics, Tsinghua University, Beijing, China, 100084, chentao.b@tsinghua.edu.cn, 86-010-62796981

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Abstract

Emergency events need early detection, quick response, and accuracy recover. In the era of big data, social media users can be seen as social sensors to monitor real time emergency events. This paper proposed an integrated approach to early detect all the four kinds of emergency events including natural disasters, man-made accidents, public health events and social security events. First, the BERT-Att-BiLSTM model is used to detect emergency related posts from the massive and irrelevant data. Then, the 3W attribute information (What, Where and When) of the emergency event is extracted. With the 3W attribute information, we create an unsupervised dynamical event clustering algorithm based on *text-similarity* and combine it with the supervised logistical regression model to cluster posts into different events. The experiments on Sina Weibo data demonstrate the superiority of the proposed framework. Case studies on some real emergency events show the proposed framework has good performance and high timeliness. Practical applications of the framework have also been discussed, following by some future directions for improvement.

Keywords: Emergency event; early detection; social media; text clustering; Bi-LSTM; BERT

1. Introduction

Social media, like Twitter, Facebook, Sina Weibo, and WeChat, has become part of many people's daily lives. The rapid popularity of smart phones and the 5G network enables every citizen to report what is happening around him at any time. This behavior is not only limited to daily events, but also can be observed in emergencies. People tend to publish posts in social media to express their concerns and perceptions, providing a large amount of crowdsourcing information (Xiao et al. 2015; Cervone et al. 2016; Alamdar et al. 2017), through which emergency managers are enabled to be aware of the situation timely and effectively (Finch et al. 2016; Goswami et al. 2018). To take advantage of social media data, some projects have been implemented on awareness and assessment in several emergency events, such as infectious diseases (Chew and Eysenbach 2010), typhoons (Deng et al. 2016), hurricanes (Kryvasheyeu et al. 2016; Yuan and Liu 2018, 2020), floods (Cresci et al. 2015; Cervone et al. 2016), explosions (Shan et al. 2019; Deng et al. 2020), and nuclear disasters (Acar and Muraki 2011).

It is not easy to find informative data from massive unrelated and unnecessary social media tweets for analysis (Gao et al. 2011; Chae et al. 2014). With the help of natural language processing (NLP) and semantic web technology, social media data can be interpreted and used in emergency management (Middleton et al. 2014; Schnebele et al. 2014; Wang et al. 2015). To extract operational information, some previous work focused on text classification. These work specially on emergency detection was mainly centered on developing domain text classifiers, which aim to solve the problem of extracting features from the text for binary classification. Li et al. (Li et al. 2012) proposed a an event detection and analysis system based on Twitter, and applied it to detect traffic accidents in Houston. Machine Learning (ML) models like SVMs (Caragea et al. 2011) and Naïve Bayesian classifiers (Imran et al. 2013) have been used to classify and aggregate tweets about the 2010 Haiti earthquake and the 2011 Joplin

Tornado. Imran et al. (Imran et al. 2014) established a platform for automatically classifying crisis related tweets, and tested it in the 2013 Pakistan earthquake.

Although progress is satisfying, some challenges still exist. Detecting and characterizing the emergency-related event where the type of the event of interest is not known in advance is still a problem (Atefeh and Khreich 2015). There are many kinds of emergency events, including natural disasters, man-made accidents, public health events and social security events. For emergency managers, it is more practical to adopt one model that can cover all kinds of possible events rather than several special models for earthquakes or typhoons. The models for a type of emergency can achieve high classification accuracy, however, the results were poor when they tested on other types. Pekar et al.'s experiments on tweets of 26 different emergencies show that if a classifier trained for a specific type of emergency and evaluated for other types of emergency, its performance would be reduced by 70% (Pekar et al. 2016). Moreover, emergency response follows the territorial management and separate departmental management principle, which means, for the first-time situation awareness knowing the fine-grained 3W attribute information (What, Where, and When) is important.

Traditional text classification methods need to conduct feature engineering to express the text as high dimensional sparse feature vectors, and train the shallow classification model (Jurafsky and Martin 2009). Deep learning models do not need complicated artificial feature extraction, but automatically learn the text features by mapping all the text content into vectors with fixed length and then using multi-layer neural network to fit with tags. There are two kinds of deep learning models in text classification: Convolutional Neural Networks (CNNs) (Kim 2014) and Recurrent Neural Networks (RNNs) (Zhang et al. 2015). CNNs are able to learn the local response from the temporal or spatial data but lack the ability to learn sequential correlations. RNNs are specialized for sequential modelling, therefore, they are used more frequently in text classification. In recent years, RNNs with gating mechanism like Long Short Term Memory (LSTM) (Nowak et al. 2017; Liu and Guo 2019) have been widely used

in the field of NLP, as they can capture long-term dependencies and solve vanishing gradient and gradient explosion problems. Bidirectional Long Short Term Memory (BiLSTM) (Graves and Schmidhuber 2005) is a further development of LSTM and it combines the forward hidden layer and the backward hidden layer, which can access both the preceding and succeeding contexts.

2018 is an important watershed in NLP. In this year, Zhang et al. (Zhang et al. 2018) applied attention mechanism to text classification. Attention mechanism highlights the important information from the contextual information by setting different weights, and its combination with BiLSTM can further improve the classification accuracy. The more important event is the introduction of Bidirectional Transformers for Language Understanding (BERT) (Devlin et al. 2018). BERT based on Transformers instead of the usual RNNs refreshed the previous optimal performance record of 11 NLP tasks, and once published, it has brought a breakthrough development to the pre-training models.

This paper proposes an integrated approach using BERT and Attention-based Bi-directional Long Short Term Memory model (BERT-Att-BiLSTM) to detect 30 types of emergency events in social media. In our early research (Huang et al. 2020), we developed the similarity-based emergency event detection framework, consisting of three phases, the classification phase, the extraction phase, and the clustering phase. Here the overall process of the original framework is consistent, but we modify the specific models. The classification phase uses the BERT-Att-BiLSTM model to detect emergency related posts. The extraction phase extracts the What, Where and When information of the post. In the clustering phase, if all the 3W attribute information of post x is extracted, our defined *text-similarity* between post x and an event can be calculated, based on which an unsupervised dynamical text clustering algorithm is proposed to cluster social media posts into different events; otherwise, we will use the logistic regression model to determine whether post x describes a certain event.

Our study has two-fold contributions. First, it advances our capacity to classify different kinds of emergency events from massive social media data by a unifying and extensive method. Based on a certain amount of data accumulation, we refine the seed words for different types of emergencies to crawl the microblog posts and train the BERT-Att-BiLSTM model to discriminate the emergency related posts. These seed words are assigned with different weights, based on which emergency related posts can be classified into different events types. Second, we introduce a complete framework of social network data processing for early emergency event detection, which integrates text classification, attribute information extraction, and a new text clustering approach, and such framework has been proved to be feasible for case studies and practical applications. Our study could help to form a rapid, transparent and timely emergency reporting mechanism.

The remainder of this paper is structured as follows. Section 2 provides an overview of the Early Detection of Emergency Event (*EDEE*) framework we followed. Section 3 demonstrates the advantages of the *EDEE* framework through comparing its performance with baseline models and showing two specific case studies. Section 4 discusses the significance of our approach in practical applications and Section 5 proposes possible directions for future work.

2. Methodology

Here we describe our *EDEE* framework. Its workflow is offered in Figure 1. This framework has three phases. In Phase *I*, we collect microblog posts from Sina platform with seed words and preprocess them, and then pick out these emergency related posts using the BERT-Att-BiLSTM model. In Phase *II*, we recognize the event type based on the weight scoring method of the seed words, and extract the location and time entities of the posts. In Phase *III*, if all the three entities of post x are extracted, a similarity-based clustering algorithm will be used to cluster this post into an event; otherwise, it

will be input to the logistic regression model to determine whether it describes a certain event.

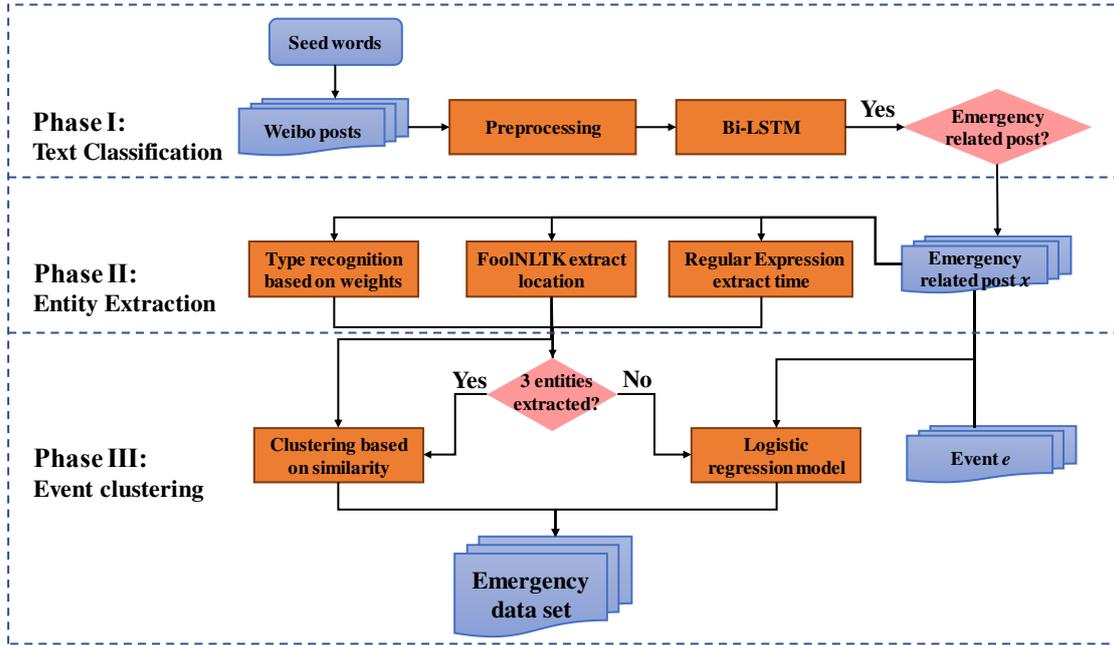


Figure 1: The process flow the *EDEE* framework.

2.1 Phase I: text classification

The seed words we used to collected Weibo data are shown in Table 1. 30 types of emergencies are considered, including 9 types of natural disasters, 13 types of man-made accidents, 6 types of public health events, and 2 types of social security events. These raw posts are preprocessed by removing URLs, whitespaces, and punctuations and then unified in the UTF-8 encoding format.

Table 1: Emergency events considered in this paper and their seed words.

Main type	Sub type	Seed words and their weights
Natural disaster	Flood	爆发山洪/洪水 0.5, 洪水 0.4, 山洪 0.4, 内涝 0.4
	Typhoon	台风登陆/路径 0.8, 台风 0.6, 风力 0.6
	Tornado	龙卷风 0.5, 龙卷 0.3, 龙吸水 0.3
	Rainstorm	暴雨 0.6, 强降雨 0.4, 雨 0.35, 降雨 0.35, 降水 0.35, 大雨 0.2
	Snowstorm	雪灾 0.7, 暴雪 0.6, 大雪 0.6, 雪 0.4, 降雪 0.15
	Earthquake	地震 0.4, 震源 0.2, 震中 0.2, 震感 0.2, 强震 0.2
	Landslide	滑坡 0.5, 泥石流 0.5
	Collapse	崩塌 0.6, 山体 0.2

	Forest fire	山林火灾 0.8, 林火 0.7, 森林大火 0.7, 森林火灾 0.7, 山火 0.7
Accident	Mine accident	矿难 0.7, 冒顶 0.7, 片帮 0.7
	Building collapse	坍塌 0.6, 倒塌 0.5, 建筑 0.1, 房屋 0.1, 脚手架 0.1, 塔吊 0.1
	Fire accident	火灾 0.6, 大火 0.6, 火情 0.2, 火警 0.2, 着火 0.2, 失火 0.2, 起火 0.2
	Explosion	爆炸 0.4, 爆燃 0.3, 巨响 0.2
	Leakage accident	泄漏 0.6, 燃气 0.1, 毒气 0.1
	Road accident	交通事故 0.4, 车祸 0.4, 撞死 0.35, 撞人 0.3, 撞车 0.3, 相撞 0.3, 追尾 0.3, 翻车 0.3, 肇事 0.1
	Drowning	溺亡 0.4, 溺水 0.3
	Capsize accident	翻船 1, 沉船 0.8
	Railway accident	脱轨 0.6, 火车事故 0.4
	Aviation accident	坠机 0.6, 空难 0.5, 坠毁 0.4, 坠落 0.2
	Falling accident	坠楼 0.6, 坠落 0.2
	Stampede event	踩踏 1
	Other accident	事故 0.5, 死亡 0.2, 身亡 0.1, 意外 0.1
Public health event	Avian influenza	禽流感 0.6
	Plague	鼠疫 0.6, 肺鼠疫 0.6
	COVID-19	新冠 0.4, 新型冠状病毒 0.4, 冠状病毒 0.2, 肺炎 0.1
	Swine fever	猪瘟 0.4, 猪瘟疫 0.3
	Food poisoning	中毒 0.4, 食物 0.1
	Other public health events	感染 0.1, 病毒 0.1, 疫情 0.1, 疫苗 0.1
Social security event	Major criminal case	刑事案件 0.7, 刑事拘留 0.7, 杀人/害 0.4, 猥亵 0.3, 暴打 0.3, 遇/被害 0.3, 嫌疑 0.3, 凶手 0.2, 砍死 0.2, 殴打 0.2, 斗殴 0.2
	Mass protest	群体性事件 0.8, 罢工 0.3, 游行 0.3, 非法集结 0.3, 暴乱 0.2, 暴动 0.2, 暴徒 0.2, 示威 0.2, 集会 0.2, 聚众 0.1

Emergencies are unconventional events that happens infrequently. Sometimes, although a post contains seed words, it does not describe the emergency. To solve this problem, the BERT-Att-BiLSTM model is applied in this phase. The architecture of this model is shown in Figure 2. First, the semantic representation of each post is obtained by the pre-trained BERT model; then, the semantic representation of each character in the post is input into the Att-BiLSTM model for further semantic analysis; finally, the softmax layer outputs the label 0 (false) or 1 (true).

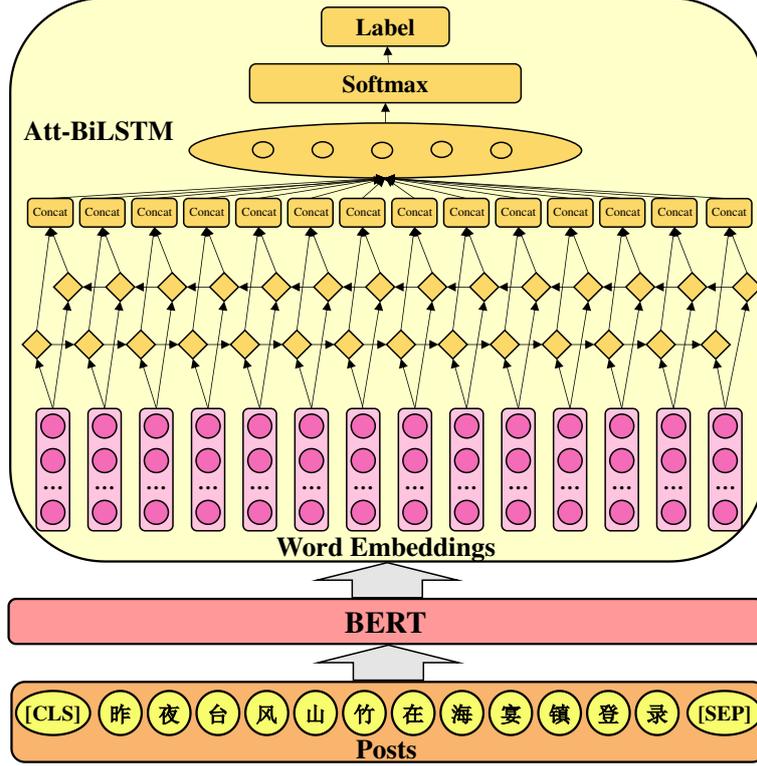


Figure 2: The BERT-Att-BiLSTM model architecture.

BERT is a word vector generation model that adopts bidirectional transformer architecture which analyzes the context to the left and right of the word. This paper uses the pre-trained BERT-Base-Chinese with 12 layers, 768-hidden, 12-heads, 110M parameters. It is available from the Google BERT model site.

The BiLSTM layer contains the forward LSTM (represented as \overrightarrow{LSTM}) and the backward LSTM (represented as \overleftarrow{LSTM}), and its outputs are stated as:

$$h_i^s = [h_i^{\overrightarrow{s}}, h_i^{\overleftarrow{s}}] \quad (1)$$

\overrightarrow{h}_i^s represents the forward information of word i in sentence s , \overleftarrow{h}_i^s represents the backward information, and h_i^s is the concatenated hidden vector. The attention weight of each word is expressed as follows:

$$e_i^s = v^T \tanh(\omega^s h_i^s + b^s) \quad (2)$$

$$\alpha_i^s = \frac{\exp(e_i^s)}{\sum_{j=1}^T \exp(e_j^s)} \quad (3)$$

where ω^s and b^s are represented as the weight and bias in the attention mechanism, $\tanh(\cdot)$ is hyperbolic tangent function, T is the number of words, and α_i^s is the attention weight of each word in the sentence s . The output of the context representations is:

$$F = \sum (\alpha_i^s * h_i^s) \quad (4.)$$

F is considered as the features for text classification. Then, the softmax layer is used to generate the conditional probabilities over the class space to achieve classification.

2.2 Phase II: entity extraction

For an emergency related post, three steps are needed to obtain its entity information, namely type recognition, location extraction, and time extraction.

(1) Type recognition

For a certain type of event, count the occurrence times of its seed words in the post, and calculate the weighted summation:

$$\omega_e = \sum_j c_j \omega_j \quad (5.)$$

c_j is the occurrence times of seed word j , and ω_j is the corresponding weight, whose value is shown in Table 1. If $\omega_e > 0.3$, the post will be labeled as type e . It should be noted that that one post may be labeled as more than one type.

(2) Location extraction

There are two ways to obtain location information. One is from the GPS tag in the post. This information is accurate but sparse. If the post contains no GPS tag, we will analyze the post content. The FoolNLTK package¹ is used to extract the location entity (e.g., Beijing, or Tiananmen Square) from the post content. If there is no location entity in the content, the location will be set as empty. Otherwise, we will call the Gaode APIs (<https://www.amap.com/>) to query the extracted location entity and extend it to four-level structured data, including the province, the city, the county/district, and the village/town.

¹ A Chinese word processing toolkit based on Bi-LSTM model, which is pre-trained for location extraction. The code can be download on <https://github.com/rockyzhengwu/FoolNLTK.git>

(3) Time extraction

The regular expression matching is used for time extraction. If the absolute time is contained in the post, like a certain day, or a certain hour/minute/second, we will extract it as the event time. Else, if there is only relative time contained, like yesterday, last week, or early morning, we will convert it to the absolute time based on the posting time. If there is no time information, the location will be set as empty.

2.3 Phase III: event clustering

This phase clusters posts into different events. If all the 3W entities of the post are extracted, a similarity-based clustering algorithm will be used to cluster this post into an event. Otherwise, if the location entity is empty, the post will be removed; if the time entity is empty, the post will be input to the logistic regression model to determine whether it describes a certain event.

(1) Similarity based clustering algorithm

The similarity between post i and post j is defined as:

$$similarity = s_c \times (0.5s_l + 0.5s_t) \quad (6.)$$

where s_c , s_l and s_t respectively represent the similarity of the event type, the similarity of the location, and the similarity of the time, and their values are assigned based on the rules in Table 2.

Table 2: Assignment rules of s_c , s_l and s_t .

Parameter	Value
s_c	If the event types are the same, $s_c = 1$; Else, $s_c = 0$.
s_l	If locations are the same at the village/town level, $s_l = 0.8$; Else if the locations are the same at the county/district level and at least one post lacks the village/street information, $s_l = 0.6$; Else if the locations are the same at the city level and at least one post lacks the county/district information, $s_l = 0.4$; Else if the locations are the same at the province level and at least one post lacks the city information, $s_l = 0.2$; Else, $s_l = 0$.

s_t If the time difference is less than 1 minute, $s_t = 0.9$;
 Else if the time difference is less than 1 hour, $s_t = 0.7$;
 Else if the time difference is less than 1 day, $s_t = 0.5$;
 Else if the time difference is less than 3 days, $s_t = 0.3$;
 Else, $s_t = 0$.

Define a set of vectors $\chi = \{x^{(1)}, x^{(2)}, \dots, x^{(l)}\}$, in which $x^{(i)} \in \mathbb{R}^3$ is the vector consisting of the type, location and time of post i . The purpose of the algorithm is partitioning these posts into the event set $\mathcal{E} = \{e_1, e_2, \dots, e_k\}$. $e_j \in \mathbb{R}^3$ is the vector consisting of event j 's type, location and time. The process of the clustering algorithm is as follows:

- (a) Calculate the *similarity* between post $x^{(i)}$ and event e_j based on Equation (6). If the *similarity* > 0.5 , merge $x^{(i)}$ into e_j . Otherwise, take $x^{(i)}$ as a new event e_{k+1} .
- (b) If there are new posts merging into event e_m in step (a), compare location and time of these posts with those of e_m , and then update e_m by the most accurate description.
- (c) If there is no updating in step (b), the algorithm will finish. Otherwise, take these updated events as new posts, and return to step (a).

(2) Logistic regression model

For a post that time is empty, we will compare it with the events of the same type detected within one week. Here we use the Logistic Regression (LR) model. Three independent variables are considered: N_w , the number of words both in post x and event e ; Δt , the time difference between the posting time of x and the occurrence time of e ; N_p , the number of posts in event e . N_w is calculated as follows. First, select the latest 60 posts in event e . Then, these posts and post x are segmented with the Jieba toolkit, and stop words are removed. N_w is counted based on the remaining words. The output of the LR model is 0 or 1, which means post x describes event e or not.

3. Experiments and case studies

3.1 Experiments

(1) Text classification

For this task, we collected 890,938 Weibo posts using seed words, among which 70,927 posts are emergency related, and 820,011 are unrelated. These emergency related posts are annotated with type labels, and the statistics are given in Figure 3.

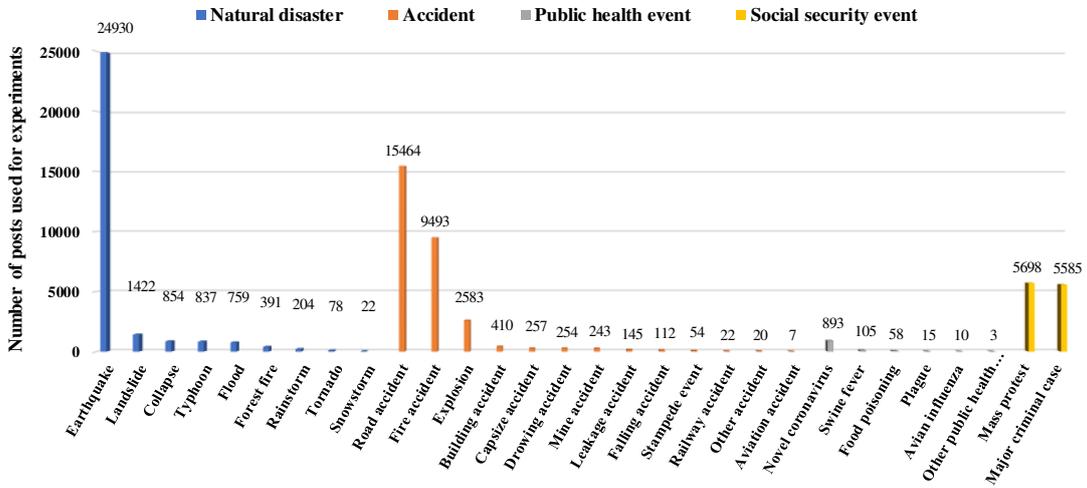


Figure 3: The number of posts related to different types of emergencies.

The dataset is divided into the training set, the validation set, and the testing, with the ration of 6:2:2. To verify the validity of the BERT-Att-BiLSTM model, we use Word2Vec-Att-BiLSTM and BERT as comparison baselines. The results are shown in Table 3. It can be seen that BERT can improve the classification performance a lot, and the combination of BERT and Att-BiLSTM further improves the recall rate.

Table 3: Classification performance of different models.

Model	<i>Precision</i>	<i>Recall</i>	<i>F1-measure</i>
Word2Vec-Att-BiLSTM	0.76	0.79	0.77
BERT	0.84	0.89	0.86
BERT-Att-BiLSTM	0.85	0.93	0.89

(2) Entity extraction

The 70,927 emergency related posts are used to test the word-based event type recognition method. The accuracy is 90.58%, which is better than all model-based methods in our previous study (Huang et al. 2020). To test the location and time extraction models, we randomly select 27000 posts in these 70,927 posts, and annotate them with the location and time labels. Results show that the accuracy of the FoolNLTK package to extract location is 94.7%, and the accuracy of the regular expression matching to extract time is 96.9%, which are believed acceptable.

(3) Event clustering

We select 20,000 posts that have been detected in a certain week to evaluate the event clustering method. Among these posts, 18,714 have all three entities, and 1,286 have empty time entity. The accuracy of the similarity based clustering algorithm is 94.15%. For the Logistic regression model, we use 60% of the 1,286 posts for training and the rest for testing, and the testing accuracy is 84.91%. The overall accuracy of our event clustering approach is 93.56%.

3.2 Case studies

In this part, we apply the *EDEE* framework to real-time Weibo data, and select two cases to show its effect. One case is an accident (Xiangshui Explosion), and the other is a public health event (COVID-19).

(1) Xiangshui Explosion

Xiangshui Explosion occurred on March 21, 2019 is a huge accident that resulted in the death of 78 people and the injury of 617 (Zhang et al. 2019). At about 14:48, the first fire flame was observed in a plant in Xiangshui County, Yancheng City, Jiangsu Province. Then, a small explosion was heard, followed by a loud explosion several seconds later. Later, a M2.2 earthquake with a focal depth of 0 m, equivalent to the energy of more than 2 tons of TNT, was detected by China Seismic Network (CSN).

We collected Weibo data from 14:00 to 23:59 and applied the *EDEE* framework. The distribution of related posts been detected is shown in Figure 4. At 14:50, the first

related post published by CSN was detected, and it was judged as Xiangshui Earthquake. At about 14:54, only 6 minutes after the explosion occurred, a post containing the words “earthquake” and “explosion” was detected, and Xiangshui Explosion was first detected. At 15:00, a post mentioning the occurrence location as Guannan County (a county adjacent to Xiangshui County) was detected, and it was judged as an earthquake and an explosion. After 15:00, there were more and more posts related to Xiangshui Explosion, while the posts related to the other three events were gradually decreased.

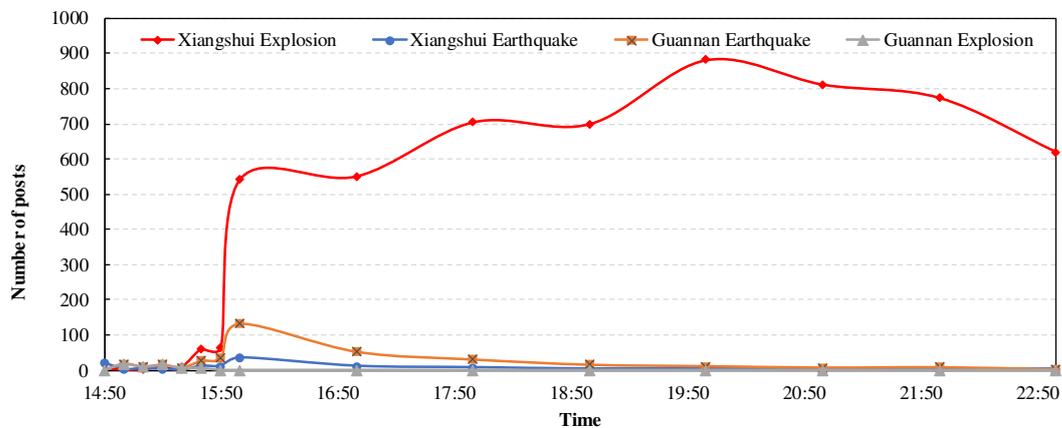


Figure 4: Publishing time distribution of posts related to Xiangshui Explosion from 14:00 to 23:59 on March 21.

To intuitively show the information of these emergency events, we extract high-frequency nouns, verbs, and adjectives from the posts of these four events and use the alluvial diagram for visualization (Rosvall and Bergstrom 2010), seen in Figure 5. Here the blocks in the diagram represent high-frequency nouns and verbs, while the stream fields represent high-frequency adjectives. It can be seen that from 14:00 to 15:59, the posts about Xiangshui Explosion also mentioned “earthquake”. In these posts, people speculated that there might have been an earthquake or an explosion. And these posts are judged as an explosion as well as an earthquake. Similarly, posts about Guannan Earthquake and Guannan Explosion both contain “earthquake” and “explosion”. That is because CSN published a message at about 15:00, reporting that an earthquake with a focal depth of 0 km (a suspected explosion) occurred in Guannan, and the message

related to SARS (Severe Acute Respiratory Syndrome Coronavirus), while the official refuted the rumors of SARS. From Jan. 19, Wuhan municipal government begun to hold regular presses conference and answered questions on COVID-19, people's attention continued to grow, and the number of related posts remained high.

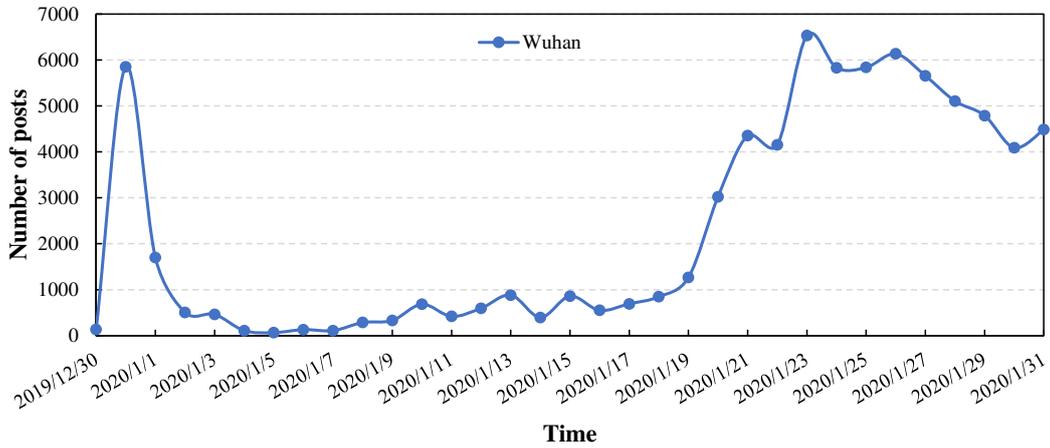


Figure 6: Publishing time distribution of posts related to COVID-19 in Wuhan.



Figure 7: The post that has been first detected (a) and the post with maximum forwarding times (b) about the COVID-19.

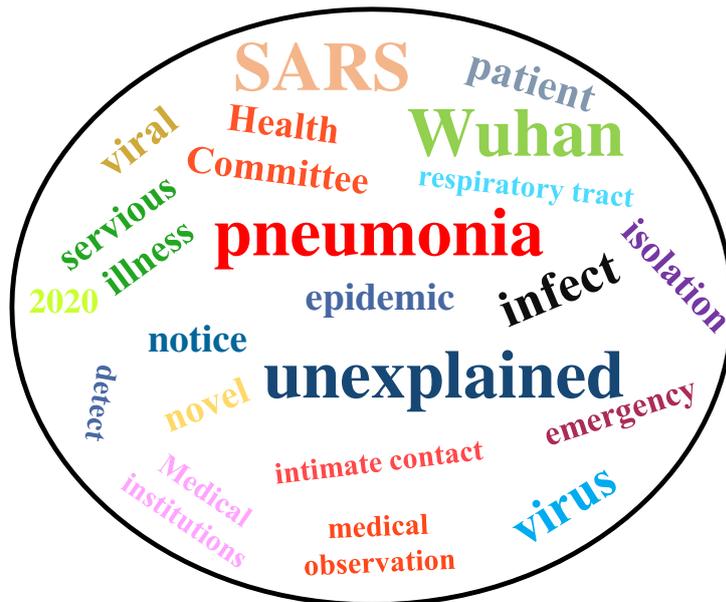


Figure 8: Word clouds of posts about COVID-19 from Dec. 30, 2019 to Jan. 6, 2020.

After Jan. 19, COVID-19 related posts were detected in other provinces and cities outside Hubei Province. On Jan. 19, relevant posts were detected in Guangdong and Shanghai, and on Jan. 20, they were detected in Beijing, followed by Hunan, Henan, Jiangxi, Sichuan and Chongqing. In other cities besides Wuhan in Hubei Province, like Huanggang, Jingzhou and Jingmen, COVID-19 related posts were also detected one after another. Figure 9 shows the time distribution of COVID-19 related posts been detected in other cities of Hubei Province (a) and other provinces (b). Compared Figure 9 with the daily confirmed cases of these cities or provinces, it can be found that the time when the first related post was detected basically coincides with the time when the first case was published. Besides, there is a certain correlation between the number of posts and the number of cases in cities of Hubei Province, but the correlation is weak in provinces outside Hubei. This is because in cities of Hubei, the economic development and population structure are relatively similar, and the proportion of people who use Weibo and their posting frequency are also similar. While it is quite different at the national scale. People from economically developed regions like Beijing and Shanghai use Weibo more frequently, so the number of related posts in these regions is significantly higher than that in other regions.

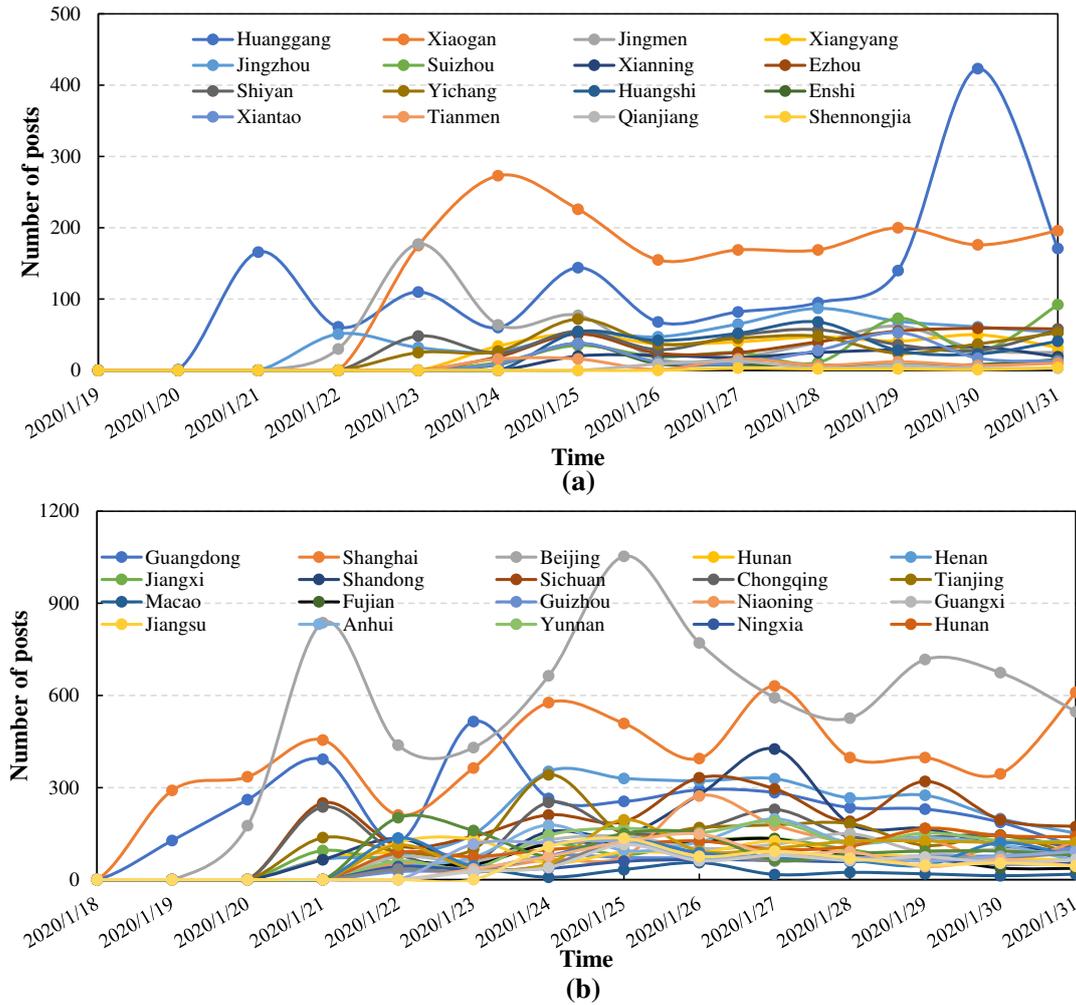


Figure 9: Publishing time distribution of posts related to COVID-19 in other cities and province.

4. Practical applications and discussion

Based on the *EDEE* framework, we developed a cloud service system for emergency event detection with social media data. The system includes PC terminal and mobile terminal, and the interface is shown in Figure 10. The homepage of the system shows the heatmap of emergencies been detected in recent 5 days, the hot emergencies ranking according to the hot degree (which is represented by the number of relative posts), the time distribution of the four categories of emergencies in recent 30 days, the sentiment analysis results of the posts, the regional public opinion hot

degree, and the personalized push service setting module. Click on an emergency, you will go to the emergency information page, where the emergency related posts are shown in detail. The personalized push service setting module support the user to set the location and event type that they interested in, by which user can receive alerts that satisfy their conditions in the WeChat application.

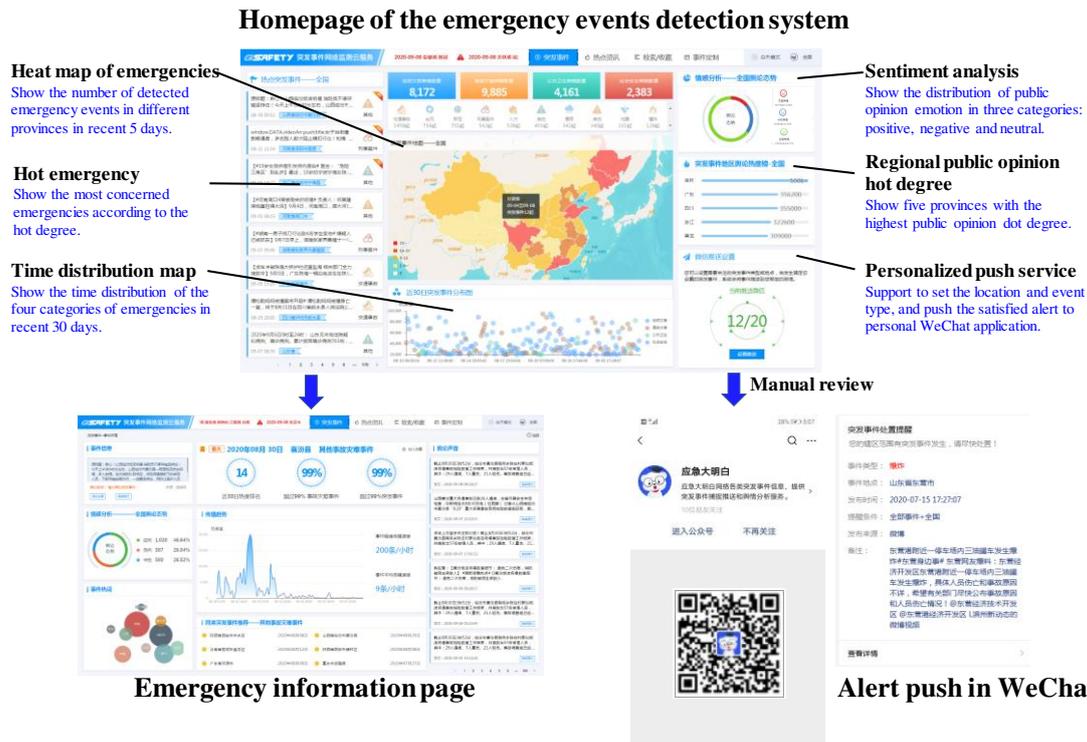


Figure 10: The system interface.

The system has been in operation since June 2020 and now it has more than 400 users. On average, about 80 emergency events will be detected every day. We counted 3170 events with more than 100 related posts during the six months from June to November 2020, as seen in Figure 11. It can be seen that the man-made accident has the largest number of 1319 (accounting for 42%), followed by the natural disaster with the number of 1121 (accounting for 35%) and the social security event with the number of 500 (accounting for 16%), and the public health events has the smallest number of 230 (accounting for 7%). In terms of the specific types of emergencies, there are more traffic accidents and major criminal cases, followed by fire accidents, rainstorms, earthquakes and typhoons. As for public health events, due to the continuous pandemic

of COVID-19, 195 related events have been detected. In addition, it is worth noting that 6 other types of public health events have been detected, including swine foot-and-mouth disease infection in Leizhou, Guangdong Province on July 11, dengue infection in Taipei on October 2, concentrated tuberculosis infection in Xuzhou, Jiangsu Province on October 14, and norovirus infections in Bayan County of Harbin City on October 24 and Zigong City of Sichuan Province on November 25. These events are not in our detection list, but they were still detected because we adopted some common seed words for public health events. If we need to strengthen the detection of these events, more detailed seed words can be included.

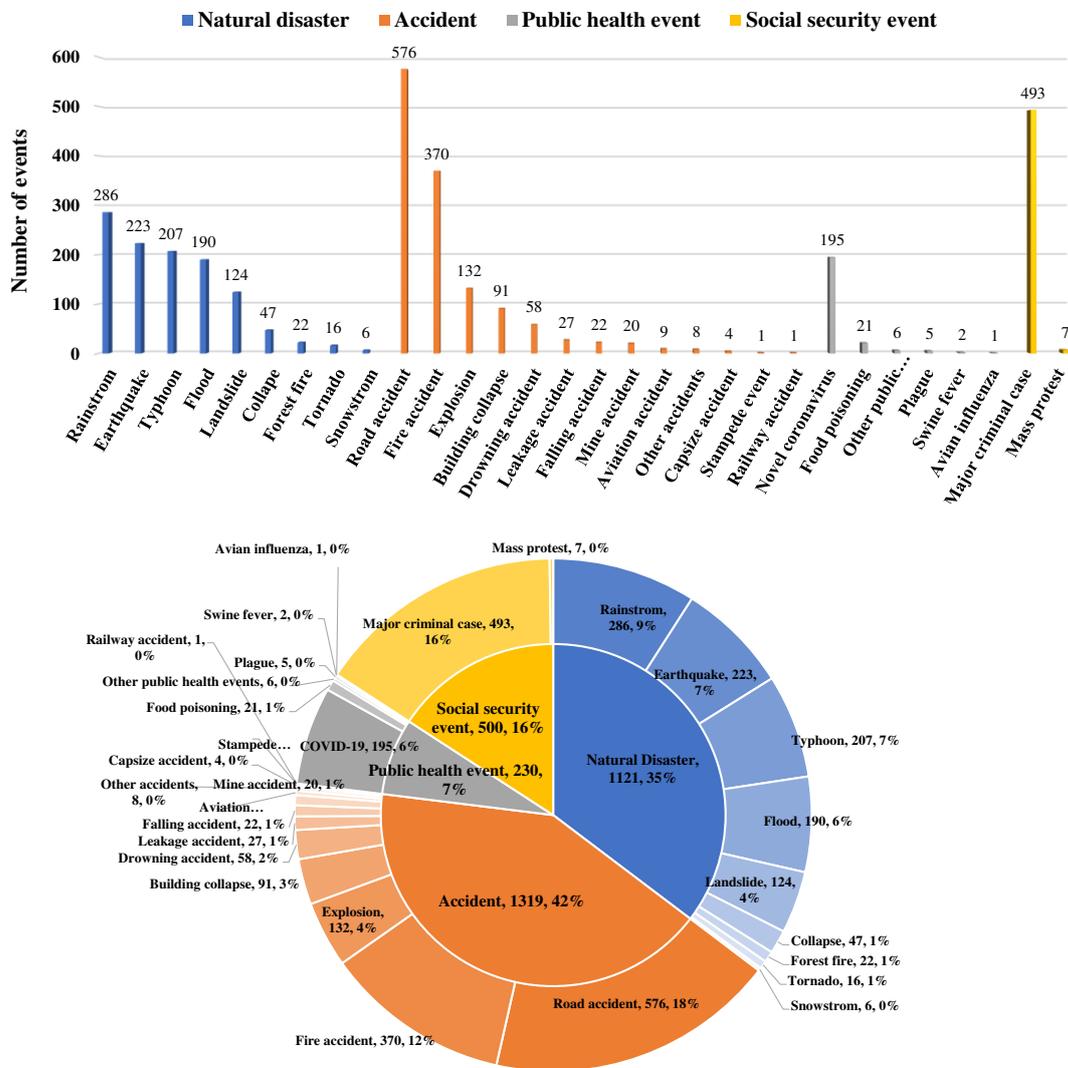


Figure 11: Statistical chart of detected emergencies from June to November 2020.

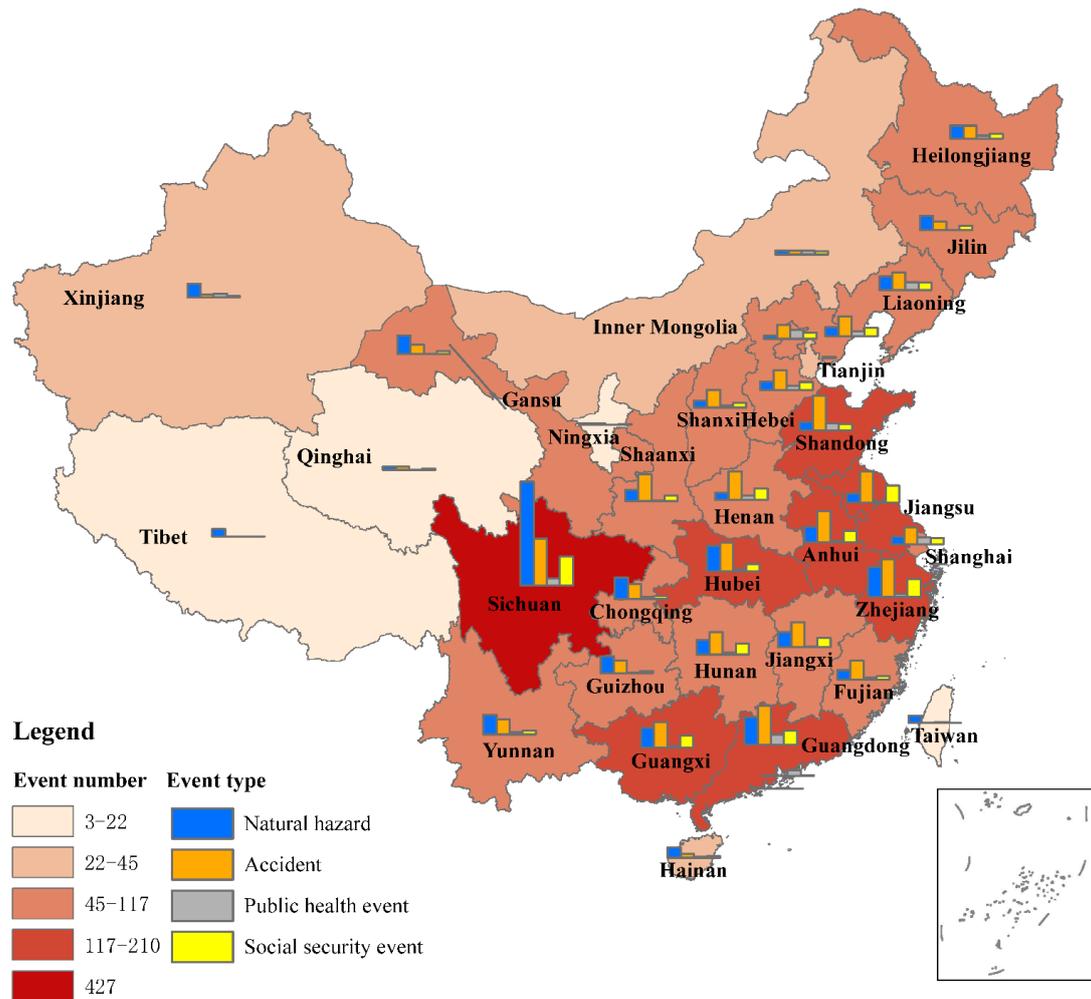


Figure 12: Location distribution map of the detected emergencies.

Figure 12 shows the location distribution of the detected emergencies. It can be seen that the regional distribution of emergencies in China is very uneven. According to the comprehensive statistics, there are many kinds and high frequency of emergency events in the southeast, which gradually decrease to the northwest. In particular, Sichuan Province has the largest number of emergency events, especially for the natural disasters. Sichuan Province is located in the earthquake zone with many mountains. In 2020, Sichuan not only suffered from a lot of large and small earthquakes, but also experienced the heavy rainstorm in August, with many secondary disasters such as landslides and floods.

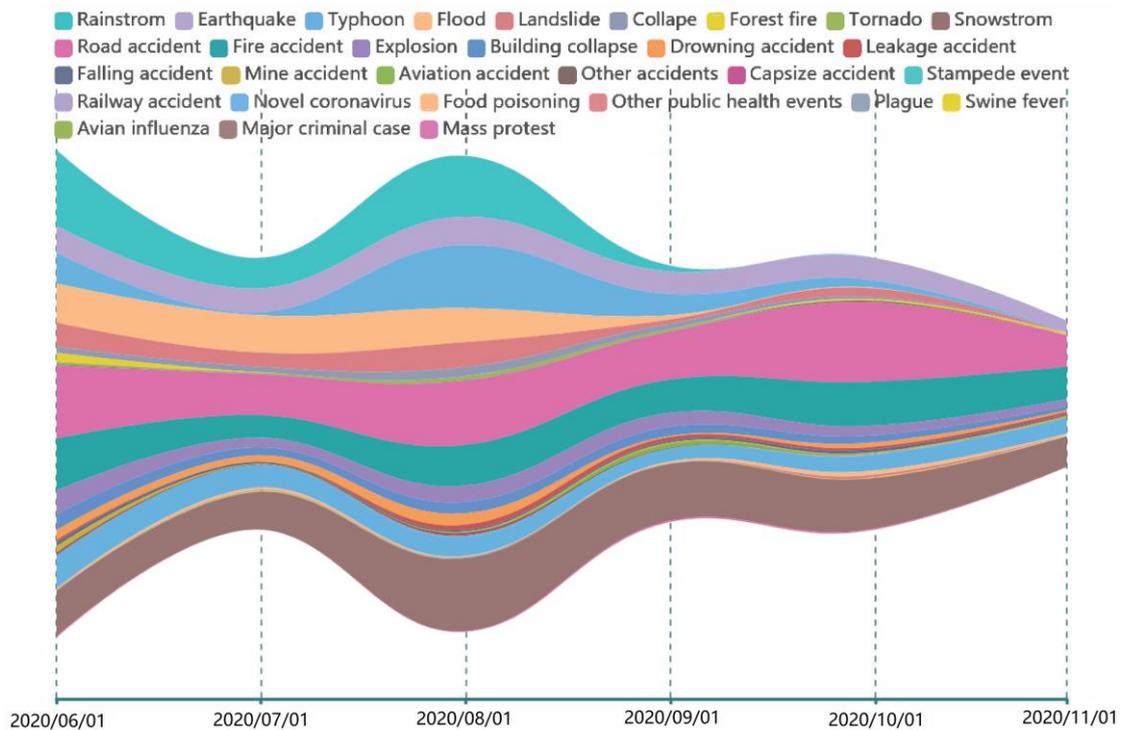


Figure 13: Streamgraph of detected emergencies of different types.

Figure 13 shows the streamgraph of different types of emergencies. The colored stream flowing (narrow or wide) maps the decreased or increased of the number of a certain type of emergency event over time. From the figure it can be seen that the frequency of natural disasters changes greatly with time, while the frequency of other events is relatively stable. Especially, affected by the rainy season, rainstorms, typhoons, floods and other events occurred more frequently in June and August, and in September the frequency of these events slowed down.

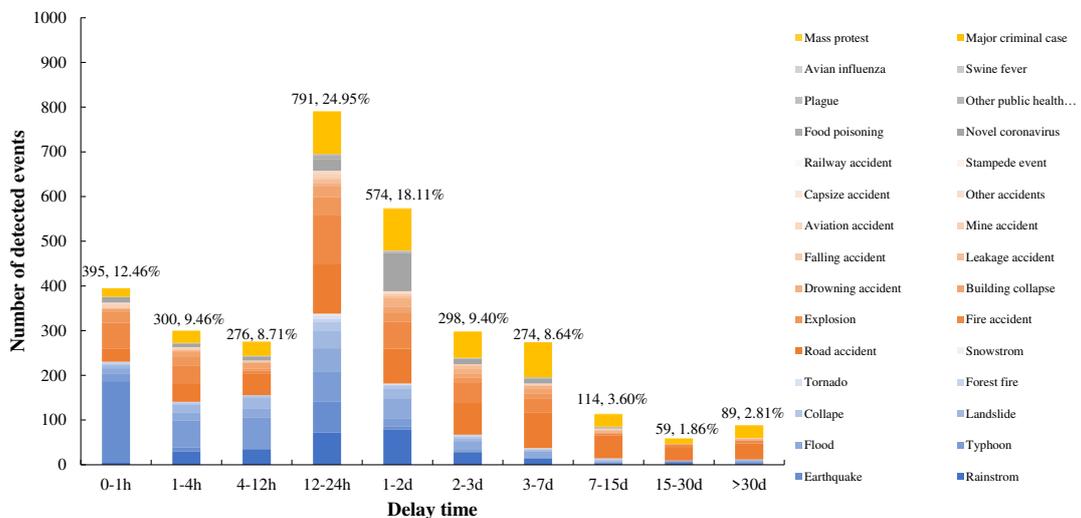


Figure 14: The interval between the time of the emergency been detected and the time of the emergency occurred.

We also compare the interval between the time of the emergency been detected and the time of the emergency occurred, as shown in Figure 14. In general, most emergencies (about 55.6%) can be detected within one day. 12.46% of these events were detected within 1 hour, 9.46% within 1-4 hours, 8.71% within 4-12 hours, and 24.95% within 12-24 hours. This demonstrates the effectiveness of our system in the early detection of emergencies. Considering different types of events, most natural disasters can be detected within one day, and a few will be detected within 1-3 days. For man-made accidents and social security events, the time interval distribution is relatively scattered. Most of these events were detected between 12-24 hours, while some events were detected after many days, such as traffic accidents and major criminal cases. This is because these major traffic accidents and criminal cases may be adjudicated by the court after a period of time, and relevant posts are detected. Since the event clustering approach only considers the events that occurred in the last week, these events are judged as new events. This problem could be solved by considering a longer period of time for event clustering. As for public health events, the COVID-19 epidemic became normal between June and November 2020, and people's attention became low. Many of the COVID-19 related posts we detected were officially released, summarizing the case information of the previous day, so time intervals are mainly concentrated in 1-2 days.

The system has already been applied to the practical work of Ministry of Emergency Management of China (MEM). Attendants review and summarize the event information detected by this system and that directly submitted by the local department, and then push to relevant persons for disposal according to the urgency and severity of the events. Here the definitions of the severity of different types of events are different. For example, for an earthquake, if its magnitude is more than 5 and the population density in the area 50 *km* away from the epicenter reaches 200 people per *km*², the

earthquake will be handled; for an explosion accident, as long as it happens in an enterprise, it needs to be dealt with. The recognition of emergency severity is done manually, and it can be processed automatically by extracting more text information and making relevant rules in the future.

Practical application has proved that, about 5 to 10 important emergency events can be first found by our system every day, and staff of MEM will check with the local department as soon as they receive the alarm information. This effectively restrains staff of local departments from delaying to report or concealing emergencies, so as to improve the efficiency of emergency disposal. While, it should be pointed out that not all emergencies can be detected at the first time, as sometimes no one uses Weibo immediately after an emergency. At 2 p.m. on January 10, 2021, an explosion happened at a gold mine in the rural areas of Qixia City, Shandong Province, with 22 miners trapped underground. The explosion was not reported to the local emergency department until 20:48 on January 11, and the first Weibo post was detected at 23:51. We do not see this as a vital limitation, because the types of social media become more and more various, with its prevalence steadily increasing. We can improve the efficiency of emergency detection by using more data source like WeChat Moments and TikTok.

5. Conclusion

In this paper we have proposed a new framework aiming at early detecting emergency events from social media. The framework integrating the emergency related text classification, the 3W attribute information (What, Where, and When) extraction, and the emergency event clustering contributes to detecting emergencies and discovering the valuable knowledge to which is difficult to be detected by humans from a large collection of texts. For text classification, massive Weibo posts have been used to train different models, and results show that the BERT-Att-BiLSTM model works

well in discriminating different types of emergency related posts. Based on the extracted 3W attribute information, we create an unsupervised dynamical event clustering algorithm based on *text-similarity* and combine it with the supervised logistical regression model, which makes the event clustering accuracy reach 93.56%.

The research is facilitated to form the fast and transparent emergency reporting mechanism that makes information transmit in time. The practical application verifies that emergency event detection through the proposed method is effective and has a great significance for efficient of emergency disposal.

We plan to further refine the emergency event detection framework in a number of directions. First, some emergency events that occur in the same location within a short period have chain relationships, like rainstorms and landslides, and fires and explosions. These event chains should be identified and analyzed as a topic. Second, more text information, like the earthquake magnitude, the explosive material and the casualty, should be extracted to judge the severity of the emergency events and then push them to different people. Third, more social media data could be added to our framework.

Compliance with Ethical Standards

I certify that this manuscript is original and has not been published and will not be submitted elsewhere for publication while being considered by Natural Hazards. No data have been fabricated or manipulated (including images) to support our conclusions. No data, text, or theories by others are presented as if they were our own.

Conflicts of interest: The authors declare that they have no conflict of interest.

Ethical statements: This article does not contain any studies with human participants or animals.

Consent for publication: All individual participants were informed and agreed to publish this manuscript.

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Figures

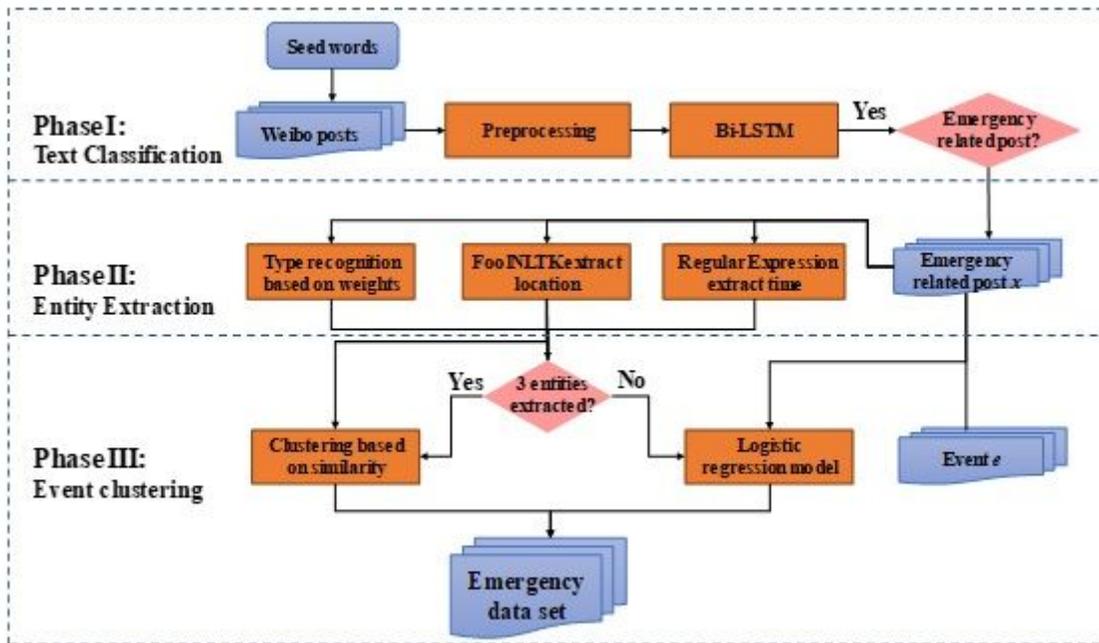


Figure 1

The process flow the EDEE framework.

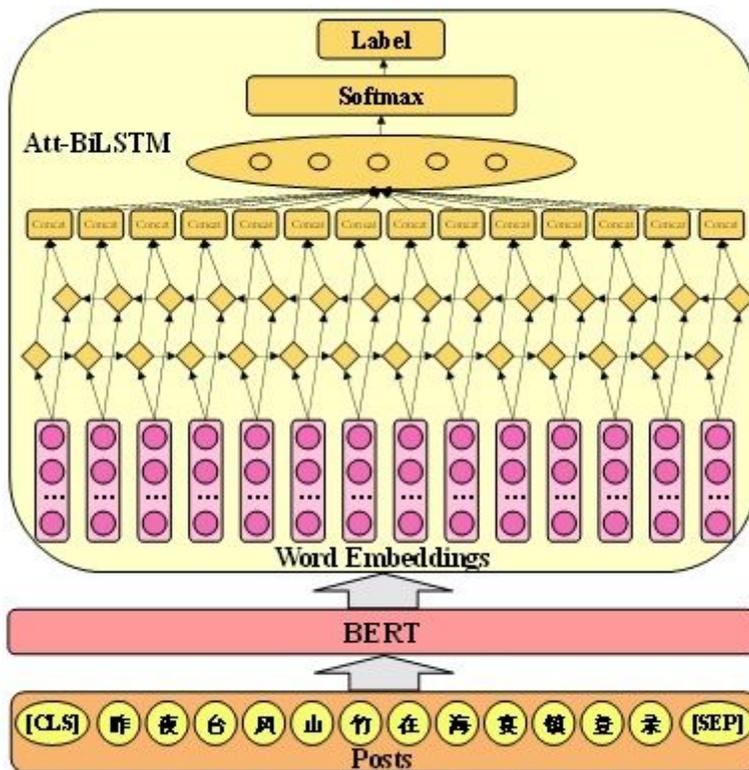


Figure 2

The BERT-Att-BiLSTM model architecture.

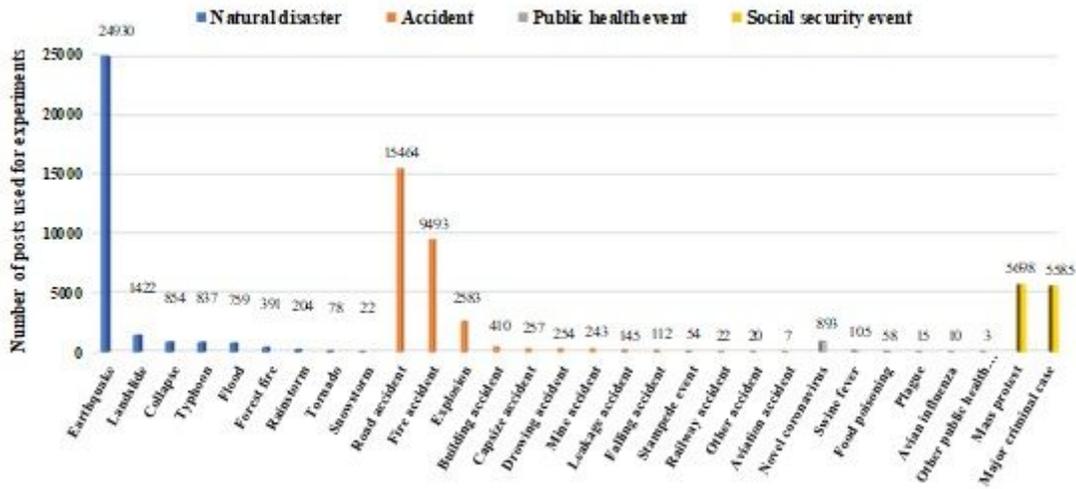


Figure 3

The number of posts related to different types of emergencies.

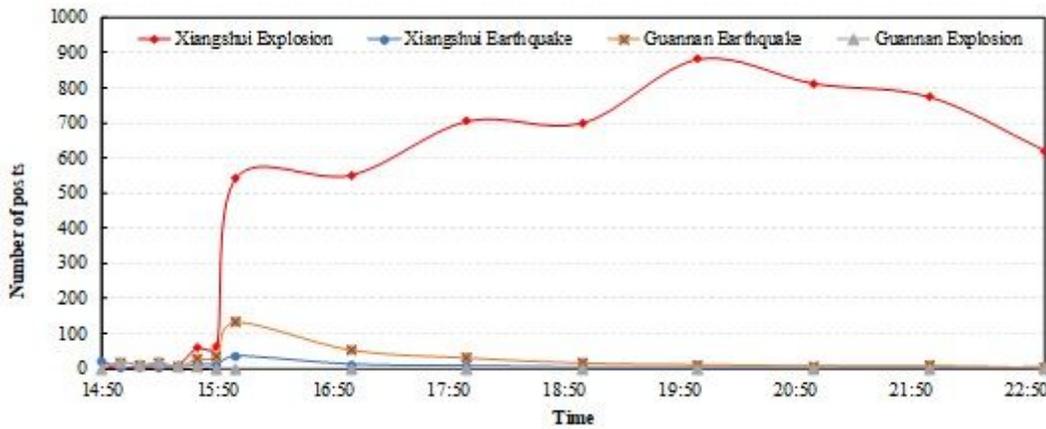


Figure 4

Publishing time distribution of posts related to Xiangshui Explosion from 14:00 to 23:59 on March 21.



(a)



(b)

Figure 7

The post that has been first detected (a) and the post with maximum forwarding times (b) about the COVID-19.

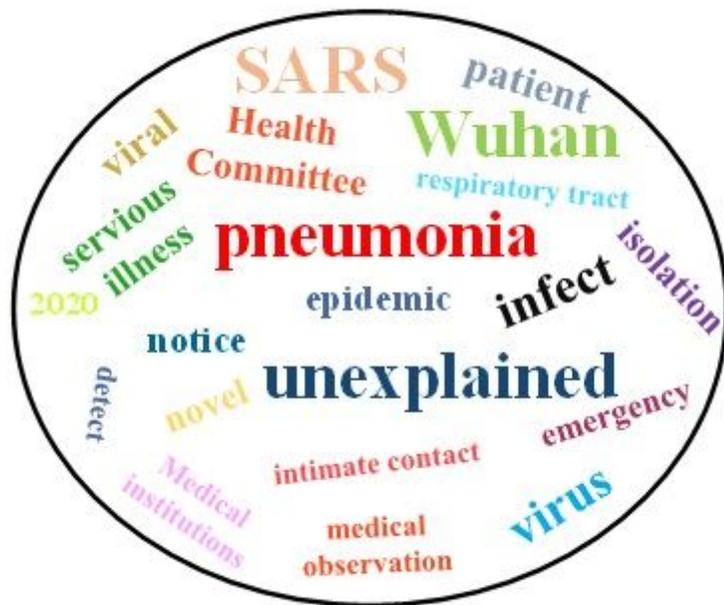


Figure 8

Word clouds of posts about COVID-19 from Dec. 30, 2019 to Jan. 6, 2020.

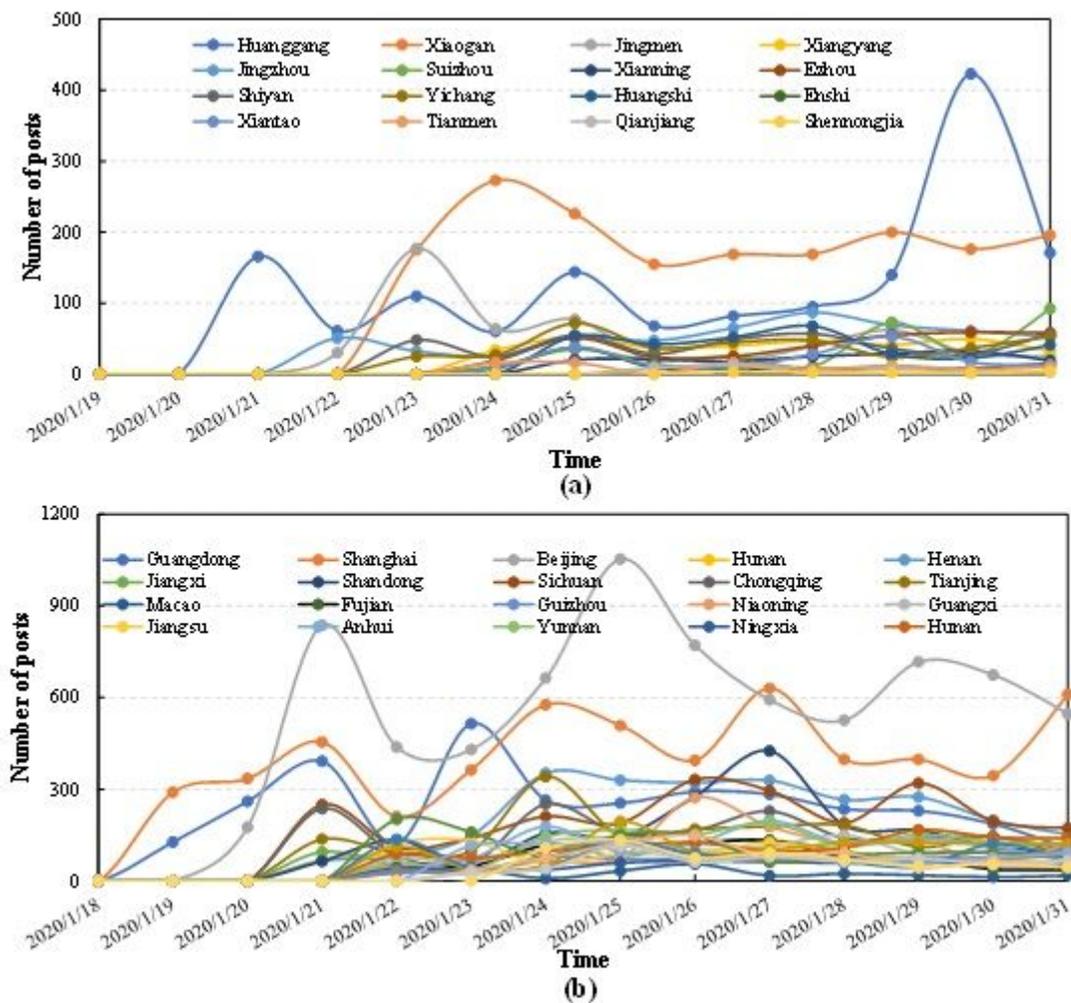


Figure 9

Publishing time distribution of posts related to COVID-19 in other cities and province.

Homepage of the emergency events detection system

Heat map of emergencies
Show the number of detected emergency events in different provinces in recent 5 days.

Hot emergency
Show the most concerned emergency events according to the hot degree.

Time distribution map
Show the time distribution of the four categories of emergencies in recent 30 days.

Sentiment analysis
Show the distribution of public opinion emotion in three categories: positive, negative and neutral.

Regional public opinion hot degree
Show five provinces with the highest public opinion hot degree.

Personalized push service
Support to set the location and event type, and push the satisfied alert to personal WeChat application.



Emergency information page



Alert push in WeChat

Figure 10

The system interface.

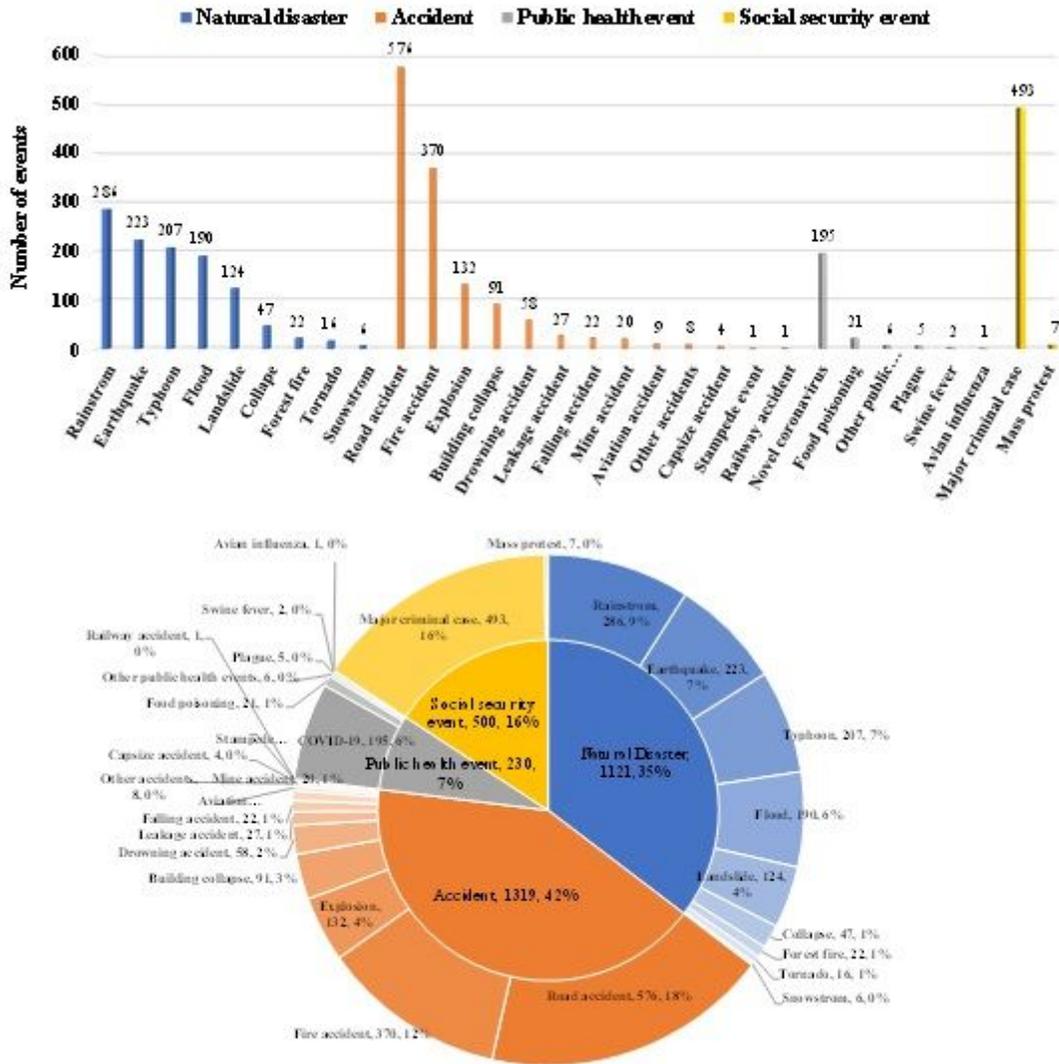


Figure 11

Statistical chart of detected emergencies from June to November 2020.

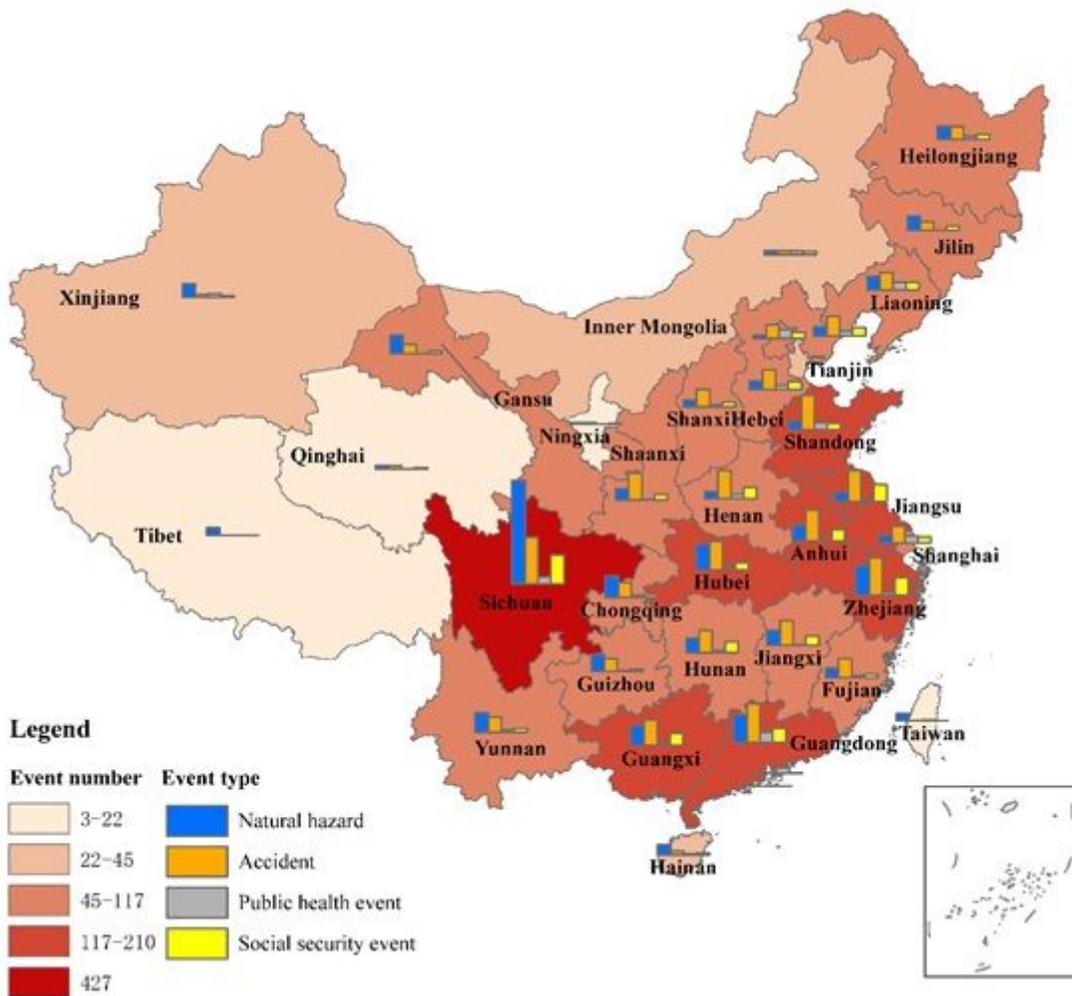


Figure 12

Location distribution map of the detected emergencies. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

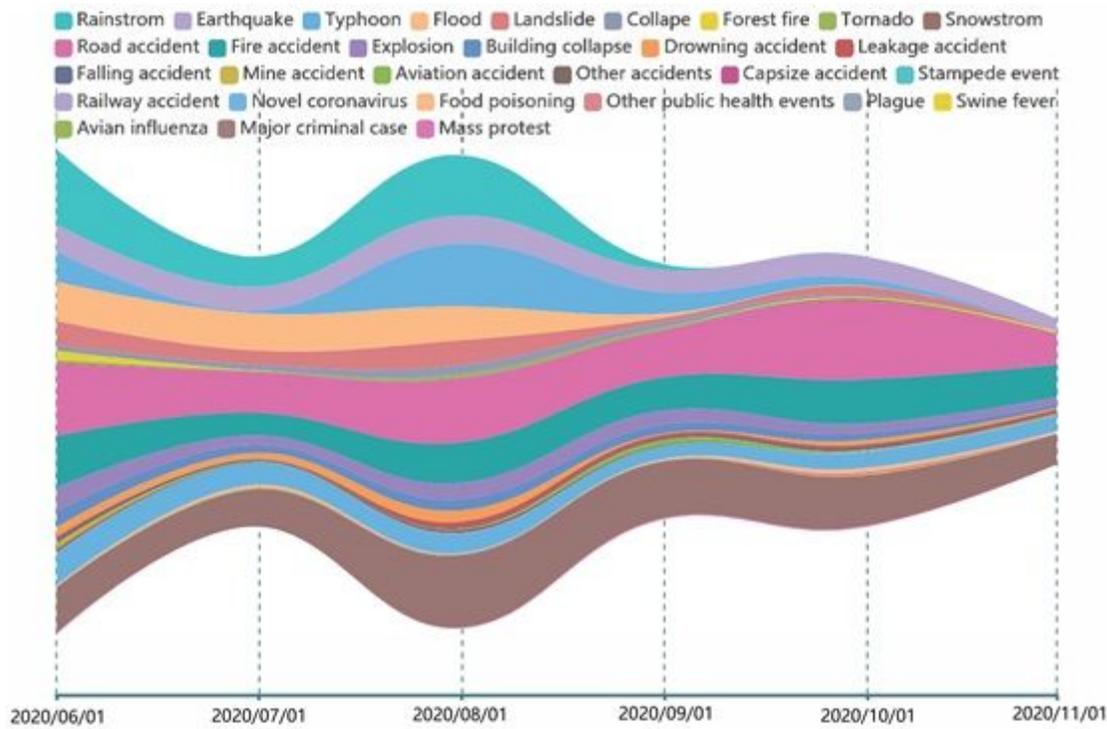


Figure 13

Streamgraph of detected emergencies of different types.

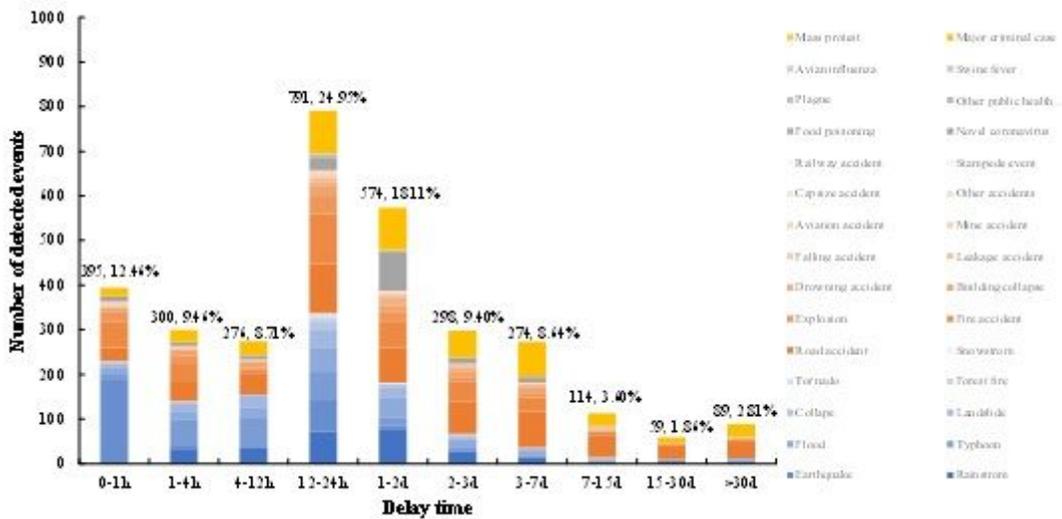


Figure 14

The interval between the time of the emergency been detected and the time of the emergency occurred.