GRACE: Generating Cause and Effect of Disaster Sub-Events from Social Media Text

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ABSTRACT

In recent years, social media has emerged as a pivotal source of emergency response for natural disasters. Causal analysis of disaster sub-events is one of crucial concerns. However, the design and implementation of its application scenario present significant challenges, due to the intricate nature of events and information overload. In this work, we introduce GRACE, a system designed for generating the cause and effect of disaster sub-events from social media text. GRACE aims to provide a rapid, comprehensive, and real-time analysis of disaster intelligence. Different from conventional information digestion systems, GRACE employs event evolution reasoning by constructing a causal knowledge graph for disaster sub-events (referred to as DSECG) and fine-tuning GPT-2 on DSECG. This system offers users a comprehensive understanding of disaster events and supports human organizations in enhancing response efforts during disaster situations. Moreover, an online demo is accessible, allowing user interaction with GRACE and providing a visual representation of the cause and effect of disaster sub-events.

CCS CONCEPTS

• **Information systems** → Data mining; • **Disaster text event causal extraction** → *Natural language interfaces*; • **Computing methodologies** → Natural language processing.

KEYWORDS

Cause and Effect, Disaster Information System, Social Media Text

ACM Reference Format:
Xinxi Jiang, Xiang Li, Qifeng Zhou, and Qing Wang. 2024. GRACE: Generating Cause and Effect of Disaster Sub-Events from Social Media Text. In *Companion Proceedings of the ACM Web Conference 2024 (WWW '24 Companion), May 13–17, 2024, Singapore, Singapore.* ACM, New York, NY, USA, 4 pages. https://doi.org/10.1145/3589335.3651234

WWW '24 Companion, May 13–17, 2024, Singapore, Singapore

ACM ISBN 979-8-4007-0172-6/24/05
https://doi.org/10.1145/3589335.3651234

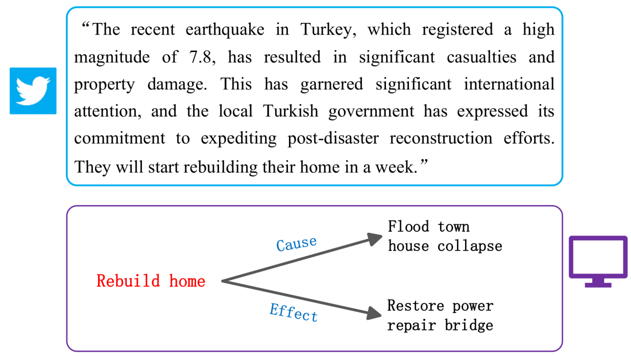

Figure 1: An example of generating cause and effect of sub-events from disaster-related text.

1 INTRODUCTION

Social media plays a crucial role in emergency response to natural disasters, with individuals leveraging these platforms to share real-time information, thereby contributing to efforts such as situational awareness and humanitarian relief. The rapid dissemination of this information is facilitated by the networked communication structure of social media platforms [9].

Causal analysis of disaster sub-events is an important application of using social media for disaster emergency response, which has attracted extensive interest [4, 8]. Figure 1 shows a brief application scenario for causal analysis: given a disaster-related social media text, the machine will automatically extract sub-events from the text and generate the corresponding cause-and-effect relationships [1]. Such an application is essential for both policymakers and emergency responders, serving to enhance situational awareness and facilitate humanitarian aid efforts.

Deploying this application practically faces three main challenges: identifying disaster-related social media text, extracting valid sub-events effectively, and comprehending relations among sub-events to generate plausible causes and effects. To address the above challenges, we develop GRACE, a system for generating causes and effects of disaster sub-events from social media text. Specifically, for Challenge 1, we train a text classifier based on the pre-trained language model (PLM) to determine whether a text is related to a disaster or not. To address Challenge 2, a sub-event extraction framework is proposed that combines dependency parsing [5] and AMR [3] parsing to maximize the recall of sub-events. For challenge 3, we first construct a disaster sub-event causal graph (DSECG) from CausalBank [6], and then we introduce a causal knowledge-based generation framework to produce the causes and effects of disaster sub-events.

In summary, this study presents a scenario leveraging social media for the causal analysis of catastrophic sub-events. The proposed system, GRACE, harnesses the abundant News and reports and timely user-generated information on social media to provide a rapid, comprehensive, and real-time analysis of disaster intelligence. We also develop an online demo with an easy-to-use user interface for interactively visualizing GRACE data. It offers decision-makers critical insights and information regarding disaster events.

2 SYSTEM ARCHITECTURE

Figure 2 illustrates the system architecture, it comprises three primary functional modules: 1) disaster-related text identification, 2) disaster sub-event extraction, and 3) sub-event causal generation. The implementation of the three main functional modules are introduced in detail below.

2.1 Text Classification

In this section, we first describe the settings for data preprocessing, and then introduce our classification model followed by the evaluation results on the benchmark dataset.

2.1.1 Data Preprocessing. We first preprocess the original text to remove the noisy content. Three preprocessing settings are introduced to explore its impact on classification performance: 1) remove URLs, dates, mentions, symbols, emoticons, punctuation, numbers, hashtags, and stop words. 2) only remove URLs, dates, and mentions. 3) keep all original text content.

2.1.2 Classification Model. Our classification model is based on the PLM and we fine-tune it using the prescribed fine-tuning procedure. As shown in Figure 3, we first encode the text using the PLM and take the hidden state of the token [CLS] from the last layer as text representation. Then, we feed it to a linear layer to output the predicted label (binary classification, i.e., related or unrelated).

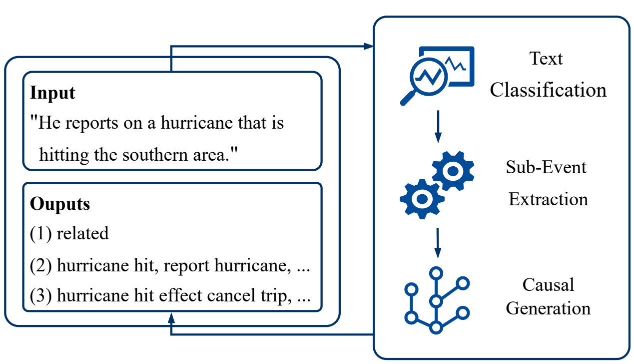

Figure 2: System architecture of GRACE.

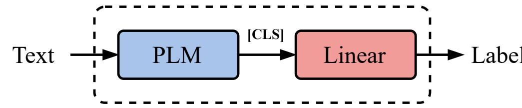

Figure 3: Classification model.

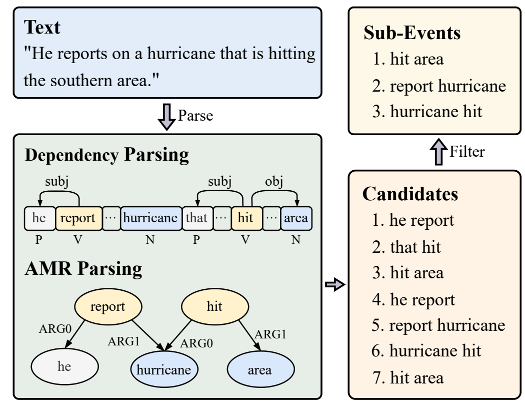

Figure 4: Framework of sub-event extraction.

2.1.3 Training and Evaluation. We train and evaluate our classification model on the benchmark dataset CrisisBench [2], and we follow the official data split, with 109,796/16,008/31,095 samples for training/development/testing, respectively.

Our classification model is initialized with RoBERTa-large [7], same as the previous SOTA [2]. We use weighted average precision (P), recall (R), and F1-measure (F1) as evaluation metrics. The results are shown in Table 1, where RoBERTa-1/2/3 denote the three preprocessing settings introduced in § 2.1.1, respectively. Based on the results, RoBERTa-2 achieves the best performance on all three evaluation metrics, which indicates that text classification performance can be improved by preprocessing, but excessive preprocessing will lose subtle clues (e.g., symbols, hashtags) in the text and lead to lower performance.

2.2 Sub-Event Extraction

In this section, we introduce our framework for sub-event extraction. As shown in Figure 4, we first parse the text to extract the candidate sub-events, and then we filter the candidates to remove the duplicate or meaningless sub-events.

2.2.1 Text Parsing. A semantically complete sub-event (noun-verb pair, i.e., NV pair) can be considered to be triggered by a *predicate* and represented by *<subject, predicate>* (SP) or *<predicate, object>*

Table 1: Evaluation results on the test set.

Method	P	R	F1
Previous SOTA	0.883	0.884	0.883
RoBERTa-1	0.886	0.886	0.886
RoBERTa-2	**0.891**	**0.892**	**0.891**
RoBERTa-3	0.889	0.89	0.889

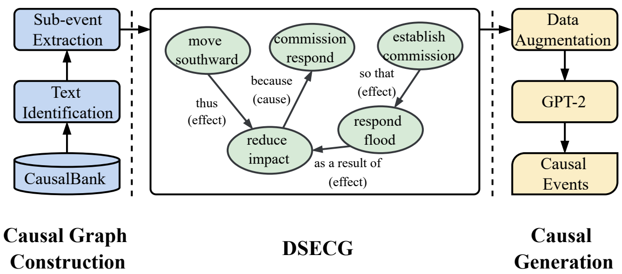

Figure 5: Framework of causal generation for disaster sub-event.

Table 2: Causal patterns and relations in the CausalBank.

Pattern	Relation
Cause	as, as a consequence of, because, because of, result from, ...
Effect	bring about, induce, result in, in order to, thereby, therefore, thus, ...

(PO). Thus, our goal is to use dependency parsing and AMR parsing to analyze the text and find sub-events that satisfy the form SP or PO. Additionally, we lemmatize all tokens during parsing, e.g., the token "hitting" will be converted to "hit".

For dependency parsing, we first employ spaCy's dependency parser [5] to parse the text and generate a dependency tree. Then, we traverse the tree and extract all child and parent nodes when one is a *predicate* (verb) and the other is a *subject* or *object*, i. e., when the dependency between two nodes is "subj" or "obj", as illustrated in Figure 4. For AMR parsing, we first use the state-of-the-art AMR parser amrlib to parse the text into an AMR graph. Then, we traverse the graph and extract all pairs of nodes whose edges are either ARG0 or ARG1, where ARG0 and ARG1 denote predicate-specific roles, representing the *subject* and *object*, respectively.

2.2.2 Sub-Event Filtering. After parsing, we obtain candidate sub-events from the text. To ensure that the final sub-events are both unique and semantically complete, we begin by deduplicating candidate sub-events and then remove any sub-events containing stop words or those that do not form noun-verb pairs. For example, we remove the sub-events <*he*, *report*> because it contains the stop word "he", and it is not a noun-verb pair (e.g., "report" is a verb, but "he" is a pronoun).

2.3 Causal Generation

In this section, we introduce our causal generation framework for disaster sub-events, as depicted in Figure 5. First, we construct a causal knowledge graph of disaster sub-events (DSECG) from the causal corpus CausalBank [6] using the methods in § 2.1 (text classification) and § 2.2 (sub-event extraction). Then, we generate causal sub-events by fine-tuning GPT-2 on the DSECG.

2.3.1 Causal Graph Construction. CausalBank is a large sentence-level causal corpus, containing 314M text pairs stored as <text A, relation, text B>. The relations can be divided into two causal patterns: Cause and Effect (refer to Table 2). For pattern Cause, the text pair can be represented as <text A, cause, text B>, indicating that B is the cause of A. Likewise, for pattern Effect, the text pair <text A, effect, text B> indicates that B is the effect of A.

Taking a text pair <text a, pattern, text b> as an example, we first feed the concatenation of text a and text b ([text a; text b]) into the text classification model (§ 2.1.2) to identify whether it is disaster-related, then we use the extraction framework (§ 2.2) to extract sub-events from text a and text b respectively (if disaster-related), finally we pair the sub-events into the form <sub-event a, pattern, sub-event b>.

With the method described above, we identified 716,208 disaster-related text pairs from CausalBank and extracted 196,022 sub-event pairs (containing 130,110 sub-events). Eventually, we integrate all sub-event pairs to construct the DSECG. Figure 5 shows a subgraph of the DSECG.

2.3.2 Sub-Event Generation. We utilize the pre-trained language model GPT-2 (124M) as the generator and fine-tune it on the DSECG to learn specific disaster domain knowledge.

In the training stage, we add the description of the opposite pattern of each sub-event pair to the training sample for data augmentation. For sub-event causal pairs, the two causal patterns (Cause and Effect) are mutually transformable, e.g., if sub-event b is the effect of sub-event a, then conversely sub-event a can be considered as the cause of sub-event b. Specifically, taking the sub-event pair <sub-event a, cause, sub-event b> as an example, we add a description of its opposite pattern <sub-event b, effect, sub-event a> to the training samples. After that, the number of our training samples (sub-event pairs) increased from 196,022 to 392,044.

In the generation stage, we take the causal pattern as a guide word, and input the concatenation of the query event and the causal pattern into the model. The generation length is set to 2 (i.e., two words). In addition, to generate results with diversity, we set the parameter *temperature* to 0.8 and set the number of results to 5.

2.3.3 Case Study. We show the causal generation results of two query sub-events ("shut airport" and "water rise") in Table 3 to investigate the effect of DSECG, where GPT-2 denotes the original model and GPT-2* denotes the model fine-tuned on the DSECG. From the results, we can make the following observations: 1) GPT-2 has been able to generate common-sense answers, which benefits from the pre-training on a large-scale corpus. 2) GPT-2* is able to learn disaster domain knowledge in DSECG and generate structured causal sub-events (NV pair), which are attributed to the fact that the sub-event pairs used for training are strictly aligned (<NV, pattern, NV>). For example, in the query "shut airport", GPT2 generates "an unfortunate" and "a terrorist" causes, while GPT2*(ours) generates "earthquake hit" and "hurricane strike", the former we think is a kind of common sense, not helpful for our causal analysis, while the latter is a better way to capture the cause of the event. We can also find the similar results from the "water rise" query that GPT2 generates "the warming" and "high temperatures" while GPT2* generates "rain fall" and "glacier melt".

Table 3: A case study to investigate the impact of DSECG on the causal generation results.

Query	GPT-2		GPT-2*	
	Cause	Effect	Cause	Effect
shut airport	the weather	another crisis	volcano erupt	strand people
	an unfortunate	more fear	earthquake hit	close resort
	a terrorist	service disruption	hurricane strike	block highway
water rise	the warming	the collapse	rain fall	build bridge
	high temperatures	increased risks	create dam	evacuate people
	increased groundwater	higher levels	glacier melt	flood occur

3 DEMONSTRATION

We have developed an online demo for GRACE, implemented as a web application and powered by Streamlit[1]. As illustrated in Figure 6, GRACE has an intuitive user interface designed to interactively visualize the results of the system's three main functional modules. The demonstration video and source code of GRACE are now publicly available[2].

Visualization of text classification. When GRACE receives a text, it first preprocesses the text and then feeds the preprocessed text to the classification model. The output of the classification model is the probability value of two labels (related or unrelated), which sum to 1. These probability values are visualized using a bar chart, where the blue bar represents the probability of being related, and the green bar represents the probability of being unrelated.

Visualization of sub-event extraction and causal generation. If the text is predicted to be disaster-related, GRACE will extract sub-events from the text and display the extraction results through radio buttons, from which users can select a query sub-event and feed it into the fine-tuned causal generator (GPT-2) to generate the corresponding cause and effect sub-events. The generated causal sub-events are visualized through a relationship graph, where the blue node is the query sub-event selected by the user, the green and yellow nodes are the cause and effect sub-events, respectively. Furthermore, users can click on the legend buttons (Query, Cause, and Effect) to specify which type of nodes are displayed.

Case Analysis. Based on the above functional modules,we extract a real-time text from social media, i.e. "The heavy snow block all the road." In the "block road" query, five causes and five effects are quickly generated, allowing decision makers to combine existing information in the causes to get the most likely cause of disaster, helping decision makers to take measures to solve the problem.

4 CONCLUSION

This paper introduces GRACE, a system designed to automatically generate causes and effects of disaster sub-events from social media text. GRACE identifies disaster-related text, extracts sub-events, and generates corresponding causal and effect sub-events. Additionally, an online demo is available for users to interact with GRACE easily.

ACKNOWLEDGEMENTS

This work is partially supported by National Natural Science Foundation of China (Grant No. 62171391).

[1]https://streamlit.io/
[2]https://github.com/lixiangxmu/GRACE-DEMO

Figure 6: The user interface of GRACE.

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