Searching Temporal Knowledge Graphs to Understand The Impacts of Disasters

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Abstract. Due to the increasing number of disasters, studies on responding to disasters using AI and big data technologies have received much attention. However, the diverse data collected during a disaster makes it difficult to utilize such data to understand disaster situations. Furthermore, state-of-the-art technologies are only limited to post-analysis disasters. To that end, in this paper, we first collect disaster data and generate a time-series temporal knowledge graph to establish relationships between different data types. Next, we discuss approaches to identifying critical keywords and analyzing disaster situations through graph exploration in real-time. As case studies, we select blackouts, typhoons, fires, and earthquakes to apply our approach, and the experimental results show that we can acquire disaster-specific information. Finally, we discuss how our approach can be applied to the government's disaster management system or policies, thereby increasing the overall understanding of disasters.

Keywords: Knowledge graphs · Graph search · Disaster impacts.

1 Introduction

Due to climate change, natural disasters have become more frequent and extensive, causing substantial losses of lives and property damage [9]. As the need to analyze the impact of disasters is steadily increasing, there are approaches using quantitative models to estimate the extent and intensity of disasters and the impact of disasters [11]. To better understand a disaster scene and predict its impacts on people, real-time data collected from disaster scenes are more valuable than numerical information about a disaster. However, since the types of disasters are very diverse and occur unexpectedly, it is difficult to assess and analyze the impact of a disaster in existing approaches. As a result, much effort to manage emergencies using IoT, big data, and AI has been made [1].

Recently, as social media platforms have been mainly used as a means of communication, research on using social media for disaster analysis has become mainstream [12]. In our prior work, we defined Temporal Knowledge Graphs

(TKGs) for various disasters from multiple data sources, including social media [7]. Using these knowledge graphs, we can classify disasters in real-time and better understand their emergencies [6]. In this paper, we present a graph search-based disaster analysis using TKGs to show the possibility of assessing damage situations, locations, and risk levels.

The rest of this paper is structured as follows. Section 2 compares our work and relevant approaches. In Section 3, we introduce how to search knowledge graphs for disaster analysis, and in Section 4, we show case studies. Section 5 describes the discussions and concludes in Section 6.

2 Related work

Recently, the use of social media in disaster management has driven a lot of attention because of its potential [5]. Many disaster response and damage assessment platforms use social media data to observe diffused information and social reactions [8] [3]. This study analyzes X (previously Twitter) activity before and after the occurrence of a specific hurricane and examines its relationship. It aggregates posts by location and performs a time-series analysis using a time stamp. Also, it analyzes the correlation between the severity of damage and social media activities. This platform evaluated losses based on reliable data such as household assistance grants and insurance claims, and compared disasters with similar intensity based on the estimated damage. Consequently, this study shows a correlation between the amount of X activity and the economic damage caused by disasters. In addition, real-time analysis of increasing online activities will enable us to evaluate the impact and damage on people.

Research on utilizing big data to monitor and detect disasters and support relief activities is increasing [13]. The following disaster monitoring system sources various information, such as satellite images, numerical simulation data, social media, and spatio-temporal data. Storing and processing large amounts of disaster big data is one of the challenges faced by government organizations responsible for disaster management [2]. To deal with disasters, it is necessary to collect heterogeneous data to fill the space between data sources and replace unreliable or noisy data. It enables an overall understanding of the event. However, it is required to integrate and filter data automatically for first responders or governments to make real-time decisions in disaster situations.

3 Proposed Approach

This section outlines the system overview and describes how to analyze disaster situations using TKGs. In addition, it shows ontology-based TKG and explains how to store disaster big data and extract keywords. Finally, we propose a method to explore graphs to understand what situations have occurred and how influential they are.

3.1 Approach Overview

Figure 1 shows the overview of the proposed approach. We start with monitoring disaster situations by generating TKGs at 1-minute intervals. We collect heterogeneous data for each disaster A, B, C, etc. in every minute, and store them in the pre-defined TKG structure. This approach includes detecting the occurrence of a disaster with an embedding value extracted from graphs using a graph neural network. This paper focuses on analyzing disaster situations through a detailed graph search with social media sub-graphs. Specifically, we analyze a disaster situation using keyword nodes with a relationship (i.e., an edge) with social media sub-graphs. For example, our approach enables us to identify specific types of disasters or analyze what happens at a disaster site.

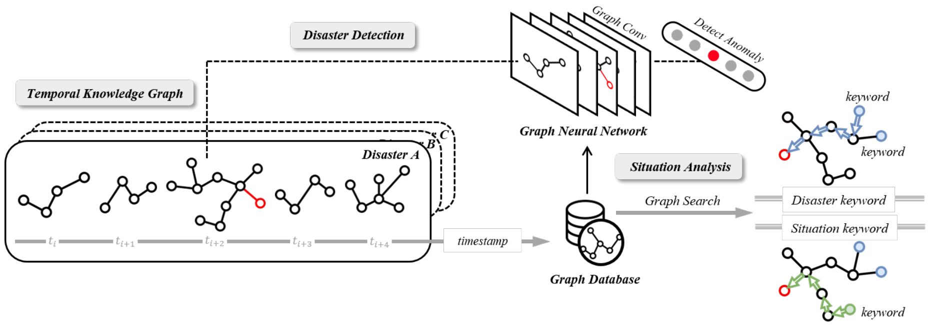

Fig. 1: Approach overview

3.2 Temporal Knowledge Graph Searching

Temporal Knowledge Graph (TKG) We construct a TKG to collect disaster big data and represent their relationship on a specific time basis. Figure 3 shows a part of the TKG. The graph consists of nodes, relationships, and their labels and properties. A node represents each disaster's object, and a relationship connects nodes and represents its actions. For example, node n_5 stores contents uploaded on social media and properties, including date, hashtag, user ID, place, post content, user name, and type. We store the keywords extracted from the node k and define the relationship between node k and node n_5 as $ExtractFrom$.

The generated TKGs are stored in a graph database. Then, we can extract *post_keyword* from the TKG's *post* in a specific time range using a declarative graph query language. The following query returns extracted keywords:

```
MATCH (k:key:X)-[r:ExtractFrom]->(n5:post:X {type:'Post'})
WHERE start_date <= k.date < end_date
RETURN k.post_keyword
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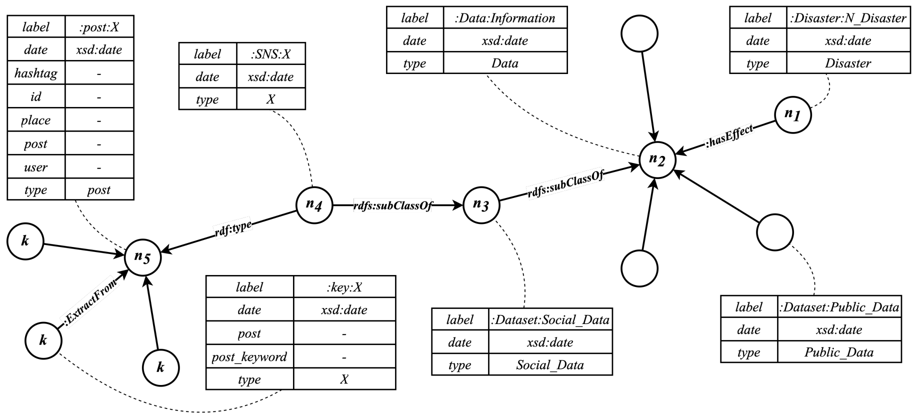


Fig. 2: Disaster Knowledge Graph

MATCH clause can specify patterns to search in the graph database. In addition, we select node k and node n_5 with each node's label and property. The *key*, X, and *post* are the labels of each node. We select *ExtractFrom* as the relationship, r, connecting two nodes. In this case, we use rounded brackets for nodes and square brackets to express the relationship.

WHERE phase filters results. We can set the time condition of the node k we want to extract. To search for the specific time range between *start_date* and *end_date*, we can assign a relationship with *date*, the attribute value of node k.

RETURN phase can specify what to include in the query result. The query returns the attribute value of *post_keyword* extracted from node k.

Graph Search Using the generated disaster TKGs, it is possible not only to detect the occurrence of a disaster but also to analyze what kind of disaster has occurred, which situation is progressing, and how dangerous it is. Figure 3 shows part of the disaster knowledge graph.

When a disaster (kko:Disaster) occurs, various types of data are generated, including sensor data, news data, public data, and social data. A subclass (*rdfs:subClassOf*) of a data node (:Data) represents each data. For example, a subclass of social data is X (:X). In the TKG generated in a 1-minute interval, uploaded posts are stored in each sub-graph. In addition, we use an analyzer to extract nouns from the posts and store the extracted words as keywords (*:key*). We calculate the frequency of keywords and use the most frequent keyword to determine a disaster type. Then, the type attribute value of a disaster node (kko:Disaster) initially set to 'Unknown' is updated with a high-frequency keyword. In addition, we can understand the status of the disaster site with situation- or damage-

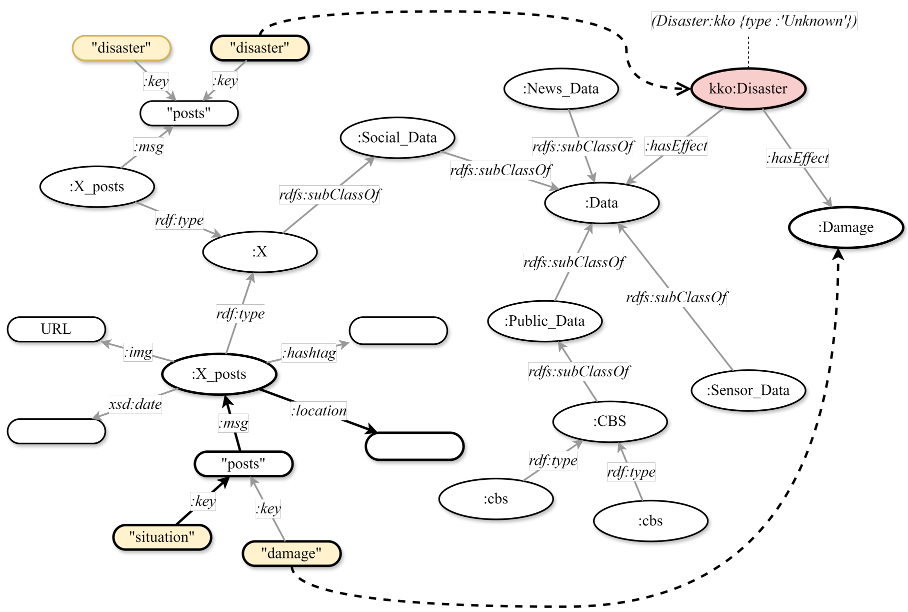


Fig. 3: Disaster Knowledge Graph Searching

related keywords. In particular, we use a node type, attribute values of an edge, and a time range to search for keywords.

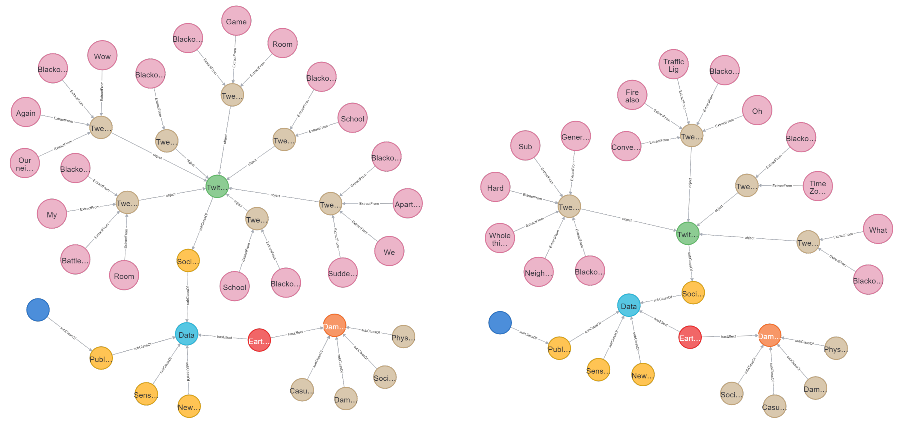
Moreover, people frequently share images or videos about disasters on social media. We evaluate the field situation and pinpoint the location using keywords from such posts. Additionally, we can ascertain the risk level of uploaded social media content through image processing. Finally, we store the analyzed damage information in the damage (:Damage) sub-graph for future disaster risk analysis.

4 Case Studies

In this section, we choose four disasters as case studies to explore the TKGs. We extract keywords from the TKG to understand disaster scenes.

Blackout: A blackout is an unpredictable disaster. Therefore, the duration or location of the blackout is likely to fluctuate. When it occurs, many people tend to upload relevant content on social media, including the current situation at their location. Figure 4 shows TKGs of a blackout that occurred on December 6, 2023, around 15:37. Figure 4a and 4b are TKG generated 1 minute and 2 minutes after the disaster occurrence.

Among the keywords analyzed in the context of the post, the most common word is 'Blackout'. Therefore, we update the disaster type to a blackout. In ad-



(a) (b)

Fig. 4: TKGs of a blackout

dition, among the analyzed keywords, it is possible to predict that a disaster has occurred at places such as 'School', 'Room', 'Apartment', and 'Convenience store'. We can explore the location information of posts with the following keywords to know where the user uploaded them. Additionally, it is possible to predict which objects the blackout has affected using keywords like 'Traffic light' and 'Generator'.

Typhoon: We can predict typhoons through meteorological analysis. However, it affects many different areas and lasts for a long time. Many people prepare even before the typhoon makes landfall, but it also causes unpredictable secondary damage due to heavy rain and flooding accompanying the typhoon. In addition, people have a lot of conversations on social media about the typhoon before and after it comes. We selected Typhoon, which landed on August 10th, 2023, around 9:20 a.m., as the case study. Figure 5 lists keywords extracted from the generated typhoon TKGs based on the number of frequencies.

The highest frequency of the keyword 'Typhoon' indicates that the generated TKG is a typhoon-related graph. In addition, we searched for a post with the keyword 'Damage' around 9:22 A.M. to find the area where the typhoon landed. An hour later, the frequency of specific local names increased, showing that the typhoon had moved. We can understand the current weather conditions with keywords like 'Wind', 'Rain', and 'Rainstorm'. A TKG generated at 9:22 A.M. shows that due to the effects of the typhoon, the 'Jamboree' participants carried out indoor programs. Moreover, we can know the flooded area through the upload location of the post with the keyword 'Flooding'.

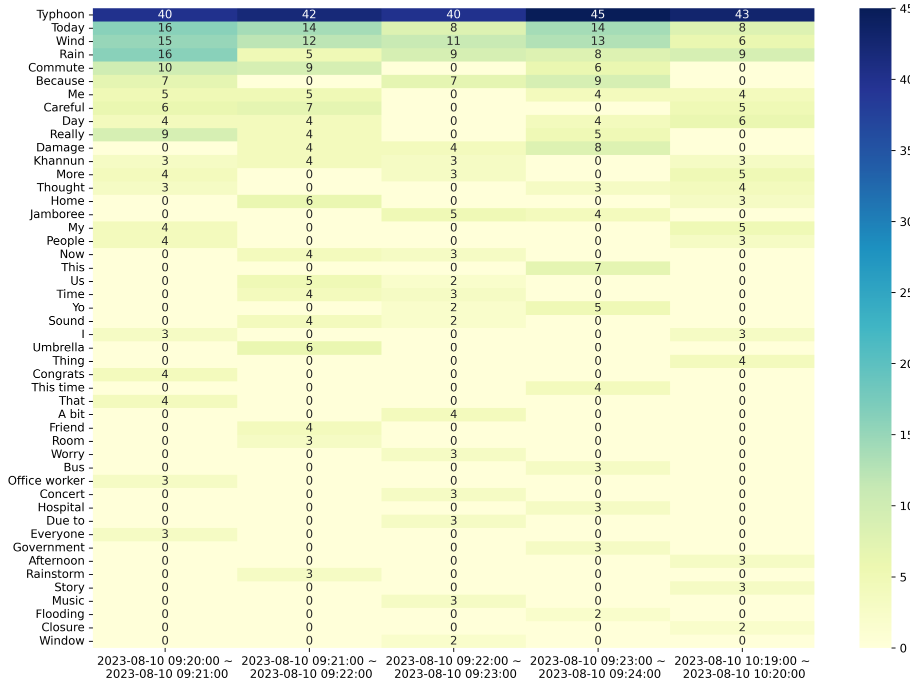
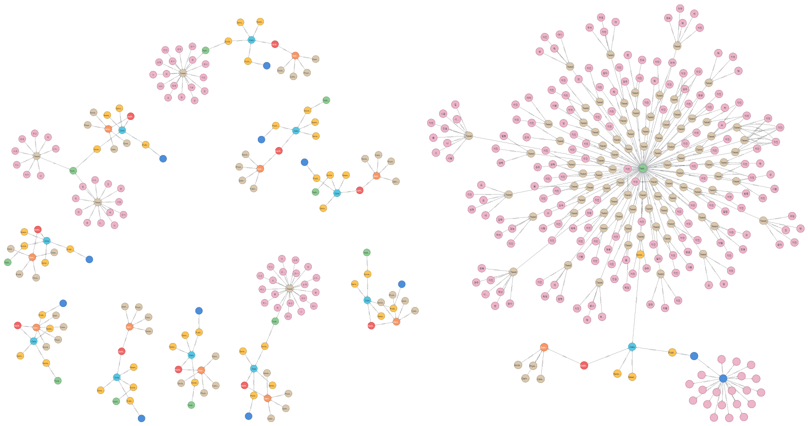


Fig. 5: Keyword frequencies over time(Typhoon TKG)

Fire Fires are unpredictable, affect large areas (e.g., wildfires), and may last for a long time or may occur in local areas for a short period. Social media users may post photos or videos about the current situation when a fire breaks out. When generating TKGs, we store the media and its storage path in a database. By analyzing the media, public safety agencies, including fire stations and police stations, can recognize the fire before receiving official reports and identify the situation on-site before they arrive at the disaster scene. As a case study, we handled a traffic accident-induced fire around 6:20 P.M. on December 10, 2023. Figure 6a visualizes the TKGs generated after the accident during 10 minutes and photos uploaded to social media.

As shown in Figure 6a, some sub-graphs include accident-related contents collected from social media. We integrate dynamic social media data with the base graph structure to represent relevance in 1-minute intervals. As a result of analyzing the content keywords, we can extract ‘Roadway’, ‘Fire’, ‘Highway’, and local names as keywords. Through these keywords, we can grasp the location and status of the accident. In addition, it can improve situational awareness by monitoring and evaluating situations in real-time.



(a) TKGs of a fire (b) TKGs of an earthquake

Fig. 6: TKGs from different disasters

Earthquake Earthquakes are unpredictable and can affect large areas but occur in a short time. Figure 6b shows the TKGs collected within a minute after the November 30, 2023 earthquake around 04:55 a.m.

We can see many post-subgraphs and one emergency alert message sub-graph in the lower right. The government issues emergency alert messages for large-scale disasters such as earthquakes. It has better reliability than social media because it notifies users of the actual results of a sensor. Therefore, we can set significant weight values for the edges connecting the sub-graphs. We can extract keywords such as ‘Southeast’, ‘Magnitude’, ‘Caution’, ‘Response’, and local names from the messages. We can also find such keywords in keywords extracted from social media. Table 1 shows the ten keywords extracted from social media collected within two minutes after the earthquake occurred.

Through social media, we can obtain disaster-related information and emotion-related keywords such as ‘Surprised’ and ‘Shock’. In addition, we expect that

Table 1: Keywords of Earthquake TKG

Time	Keywords and Frequencies
2023-11-30 04:55:00 ∼ 2023-11-30 04:56:00	(‘Earthquake’, 195), (‘What’, 25), (‘Text message’, 10), (‘**Surprised**’, 8), (‘Damn’, 7), (‘**Oh**’, 6), (‘Alert’, 4), (‘Disaster’, 4), (‘Hmm’, 2),(‘**Magnitude**’, 1)]
2023-11-30 04:56:00 ∼ 2023-11-30 04:57:00	(‘Earthquake’, 1556), ‘**Surprise**’, 127), (‘Alarm’, 125), (‘Disaster’, 85), (‘Dawn’, 24), (‘Suddenly’, 23), (‘**Shock**’, 19), (‘**Caution**’, 4), (‘**Southeast**’, 2), (‘**Response**’, 2)]

keywords such as ‘Collapse’ and ‘Fire’ help us understand the secondary disaster situations caused by the earthquake.

5 Discussion

This section discusses how we can apply our studies to real-world disaster management based on interviews with government officials.

Integration with Disaster Management Systems The Korean government operates a disaster management system to share and manage disaster information efficiently [10]. It provides disaster type, document number, and transmitter information by sharing a situation broadcast message with related organizations in the event of a disaster. The manager determines whether or not the situation is influential using empirical knowledge. Therefore, we can apply the proposed graph searching methods to automatically classify important messages and understand if there is a lot of impact on people. This study can make several policy contributions. Analyzing disaster patterns can help government agencies take preventive measures by predicting the likelihood of disaster occurring in specific areas. In addition, it can contribute to a sustainable disaster response system by establishing a long-term disaster management strategy based on data.

Automatic Report Generation The National Disaster Management Research Institute in South Korea analyzes disaster issues and trends using the Social Big Board [4], which analyzes social big data in real time. The proposed TKG search can contribute to identifying the time and location of a disaster based on social media data and monitoring the damage situation through keyword analysis. In addition, we can select important messages before and after the event through TKGs and generate a report by organizing heterogeneous information related to the event through graph search.

6 Conclusion and Future Work

This paper presents a novel approach for searching disaster knowledge graphs to understand disaster situations. We extracted keywords by exploring social media sub-graphs from TKG to collect information and understand secondary disaster situations. In addition, we generated TKGs for four disasters for case studies and searched for the critical keywords. However, due to linguistic complexity, it is expected to be challenging to determine whether the post is disaster-related. In future work, we will apply Large Language Models (LLM) to train vast amounts of textual data. This approach is intended to analyze complex structural patterns of content effectively and improve the accuracy of situation analysis. In addition, we will further expand the types of data and disasters to see if each type has distinct characteristics.

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