Applying GNN Models for Diverse Disaster Detection using Temporal Knowledge Graphs

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***Abstract*—As unexpected disasters increase, the number of casualties and economic damages are increasing. Accordingly, efforts to collect and process data have been made to predict and respond to disasters. However, because the data collected from a certain disaster is enormous and diverse, it is difficult to identify an exact disaster type and its situations at the early stage of a disaster. To that end, in this paper, we first classify disasters into six categories according to their characteristics and extend our ontology-based temporal knowledge graphs to contain these characteristics. Finally, to detect a disaster from temporal knowledge graphs, Graph Neural Networks (GNN) or other deep learning techniques can be useful. For the evaluation, we selected four disasters belonging to six categories and constructed temporal knowledge graphs for each disaster. Then, to see how quickly a disaster can be detected from the constructed graphs, we tested three GNN models, including Graph Convolutional Network (GCN), SageConv, and Graph Attention Network (GAT). Our experimental results show that temporal disaster knowledge graphs can accurately represent the characteristics of various disasters, enabling the detection of disasters from heterogeneous data collected at disaster sites.**

***Index Terms*—temporal knowledge graphs, disaster classification, graph neural networks**

I. Introduction

Disasters cause damage to life or property due to changes in natural phenomena or artificial accidents. Recently, various unpredictable disasters have occurred frequently due to climate change, and we are quite vulnerable to them [1]. Although we can predict such disasters through scientific analysis, they are typically unpredictable, which makes it difficult to respond quickly or evacuate when disaster strikes [2]. Therefore, a disaster management system's importance is emphasized to respond as quickly as possible and minimize damage when a disaster occurs. Despite the massive amount of disaster data collected, there is a lack of knowledge sharing, making it challenging to manage the data comprehensively [3].

Therefore, there is a growing attempt to use knowledge graphs to monitor disasters in real time and organically integrate and analyze heterogeneous data [4]. Ontology-based knowledge graphs make it easier to reuse data by exposing the links between multiple sources of information [5]. We can combine machine learning or deep learning methods with these ontologies to derive additional knowledge. In addition, since each disaster has different characteristics, it is necessary to differentiate the data collection type or the analysis method according to the ontology structure.

In this paper, we classify disasters into six categories according to multiple disaster attributes. In addition, we generate Temporal Knowledge Graphs (TKGs) of each type of disaster and finally evaluate the previously trained GNN models. Through the generated TKGs, we can visualize the patterns of disaster changes and identify which data types are prominent in disasters. Depending on the evaluation results, it is possible to reconsider the data type to collect for each disaster category.

II. Related Work

There is an increasing number of studies to find disaster trends to manage and predict disasters [6]. These studies often focus on specific disasters. However, it is necessary to manage and analyze disasters according to their types because each disaster has its own characteristics. This paper shows the methods to detect such messages for unknown disasters, which include both natural disasters and artificial disasters [7]. It uses classification methods to identify reports, including potential emergencies. In addition to this data classification, it's critical to identify the disaster situation with the relevant data.

Although some factors can trigger disasters, it is frequently challenging to respond quickly because they often occur unexpectedly. When these unpredictable disasters occur, social media has become an important communication tool [8]. This paper analyzes the selected message streams from social media to acquire situational awareness and quantify the impact of disasters. However, due to the massive volume of data shared on social media, analyzing messages in disaster situations takes time and effort.

III. Diverse Disasters

This section addresses the classification of disasters according to their characteristics. In addition, we enumerate the disasters corresponding to each category and represent the relationship between disasters with a knowledge graph.

A. Disaster Classification

Generally, Federal Emergency Management Agency (FEMA) classifies disasters as natural(e.g., earthquakes, typhoons, floods, etc.) or technological hazards(e.g., materials

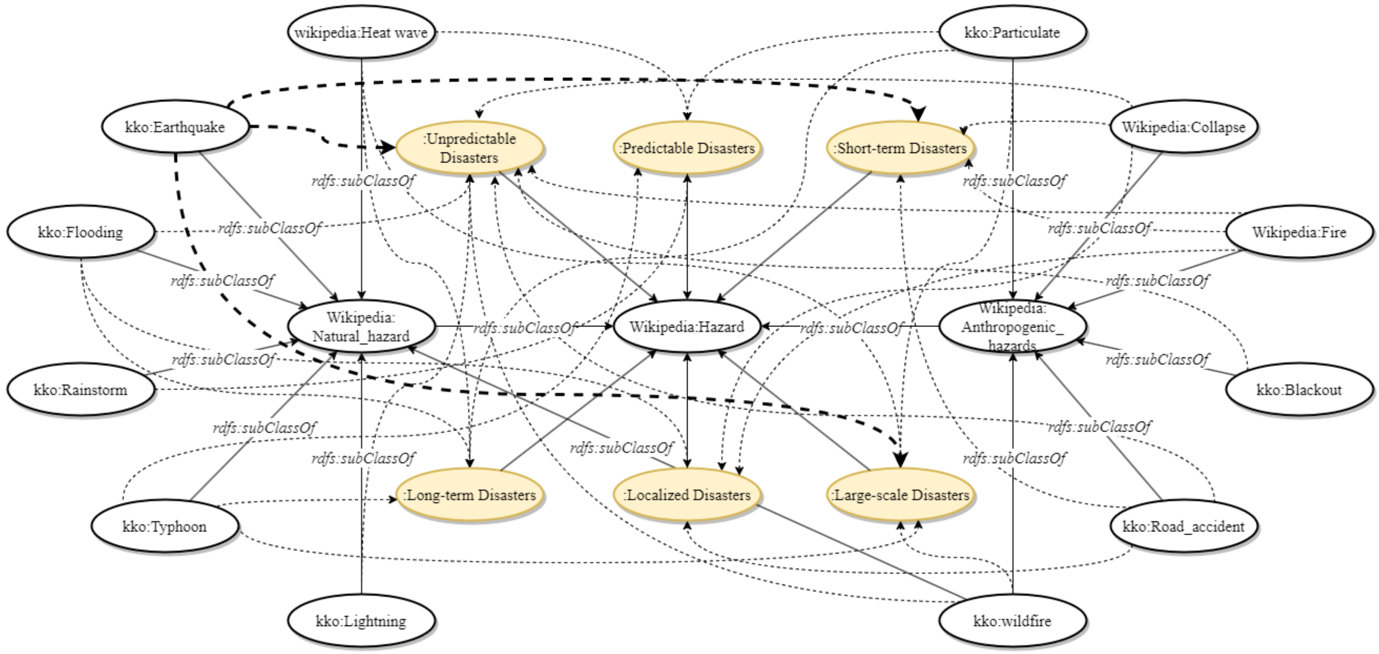

Fig. 1. Diverse Disaster

incidents, chemical emergencies, etc.) [9]. However, disasters within the classified group need to be reclassified regarding disaster management since each has different characteristics. We classify disasters into 6 categories based on predictability, temporal features, and spatial features. Figure 1 shows the disaster classification represented with a knowledge graph.

We classify disasters into unpredictable disasters, predictable disasters, short-term disasters, long-term disasters, localized disasters, and large-scale disasters. According to the figure, 'kko:Earthquake' is classified into ':Unpredictable Disasters', ':Short-term Disasters', and ':Large-scale Disasters'.

Unpredictable Disasters: Unpredictable disasters are increasing due to rapid climate change. Such disasters cannot be prepared in advance, making it difficult to respond immediately. When a disaster strikes unexpectedly, many people post on social media about the damaged situation or their feelings, such as uncertainty, surprise, or fear. It indicates that social media will play a significant role in judging and analyzing disaster situations. Unpredictable disasters include road accidents, fires, wildfires, lightning, earthquakes, blackouts, collapses, and flooding.

Predictable Disasters: In contrast to unpredictable disasters, some disasters are predictable through scientific analysis. For example, even though particulates, heat waves, rainstorms, and typhoons can be predicted in advance, they can cause severe damage because of their unpredictable behaviors. Typhoon-induced collapse and rainstorm-induced flooding are examples of such situations.

Short-term Disasters: Short-term disasters represent events occurring over a short period, such as road accidents, fires, lightning, and collapses, and they are considered unpredictable disasters. Because they occur in a short time, there are only a few witnesses to the disasters. As a result, social data is rarely generated in these cases.

Long-term Disasters Long-term disasters include events occurring over a relatively long period, such as particulates, heat waves, typhoons, and flooding. Because such long-term disasters have particular patterns, they are often predictable. Even though we try to predict and prepare for these disasters, they often cause huge damage because of their inevitable nature. Therefore, people constantly have relevant conversations over social media before, during, and after a disaster.

Local Disasters: Disasters such as road accidents, fires, collapses, and flooding are classified as localized disasters because they have relatively limited impacts on areas. However, the fact that the damage area is limited does not imply that the amount of damage is minor. Instead, many casualties may occur since the impacted areas tend to be close to residential areas. As a result, it is important to collect social data containing information about sudden changes to detect such disasters early.

Large-scale Disasters: Large-scale disasters include particulates, heat waves, typhoons, earthquakes, and wildfires. In these cases, the amount of damage is enormous and continues for a long time, as the affected areas are wide. As a result, we need to collect data containing both sudden changes and information about the damages people suffered during the early stages of the disaster. Based on such information, it is possible to accurately predict potential damage due to the disaster.

IV. Temporal Disaster Knowledge Graphs

This section briefly describes the designed structure of the TKGs. We selected four disasters (i.e., earthquake, blackout, typhoon, and fire) that occurred in 2023 according to the disaster categories. Then, we generated TKGs with SNS data and public data to show how each disaster TKG is changed to a specific pattern over time.

A. Graph Structure

TKG is a knowledge graph that has a set of facts and information or knowledge dependent on time [10]. In our prior work, we designed a disaster knowledge graph structure to represent the relationship between heterogeneous disaster data [11]. Figure 2 shows the structure of the disaster knowledge graph, especially earthquakes. When a disaster occurs, various types of data are generated. This graph structure has ':Social_Data', ':Public_Data', ':News_Data', and ':Sensor_Data' as types of ':Data', which are expressed as relationships '*rdfs:subClassOf*'. Depending on the disaster's type, we can expect numerous kinds of data to be generated. Each type of disaster is likely to produce distinct data, and some data may contain more meaningful information than others.

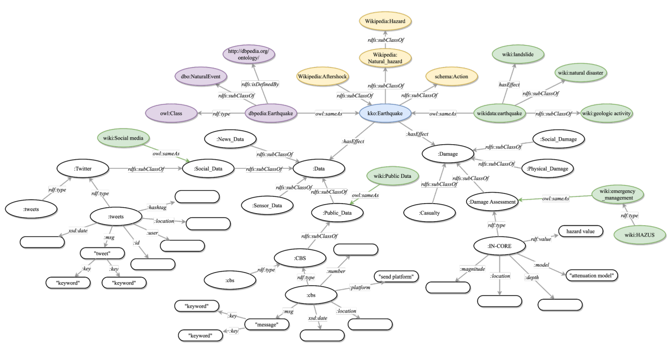

Fig. 2. The structure of a disaster knowledge graph

B. Case Studies

We chose the following four disasters as case studies to analyze the TKGs changing patterns by disaster category. The structure of the graph follows the structure of the proposed disaster knowledge graph.

Earthquake: Earthquakes are classified as unpredictable disasters, short-term disasters, and large-scale disasters. Figure 3 shows 1-minute interval TKGs of an earthquake that occurred on November 30, 2023, around 04:55 a.m. As shown in the figure, at time (c), the number of nodes in the Twitter sub-graph increases rapidly. In addition, an emergency alert message was issued in time (c), represented by a sub-graph with a blue node on the right side. Many people continued to upload situations or feelings related to the earthquake even after the disaster had occurred, and it gradually decreased.

Blackout: Blackouts are classified as unpredictable disasters. The duration of time and the range of areas that occur may vary depending on the situation. Figure 4 shows TKGs of a blackout that occurred on December 6, 2023, around 15:37; it lasted for two hours. Many people were confused; the traffic lights went out, and the elevator stopped working. From the time the blackout occurred in (d), a few people uploaded tweets related to the outage. However, the emergency alert message was issued at 15:54, 17 minutes after the power outage.

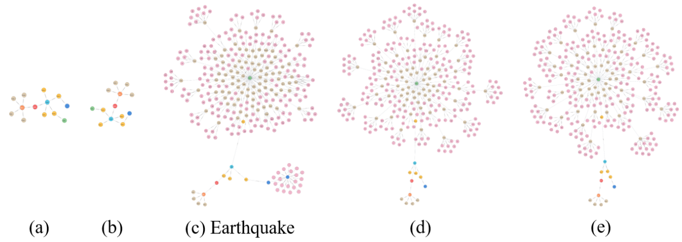

Fig. 3. TKGs with earthquake

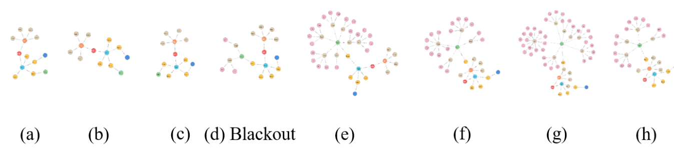

Fig. 4. TKGs with blackout

Typhoon: Typhoons are classified as predictable disasters, long-term disasters, and large-scale disasters. The following figure 5 shows the TKGs of Typhoon Khanun, which landed inland on August 10th, 2023, around 9:20 a.m. Typhoons affect many people even before they impact inland since heavy rains often accompany them. Therefore, we frequently have conversations about preparation on Twitter both before and after the typhoon comes. In addition, the government issues disaster alert messages frequently according to the typhoon's expected path. Typhoons typically cause significant damage due to their vast size and duration.

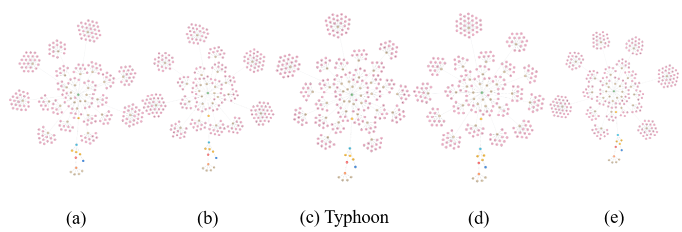

Fig. 5. TKGs with typhoon

Fire: Fires are classified as unpredictable disasters, short-term disasters, and localized disasters. A fire can divide into a forest fire depending on where it occurs or can be derived from car accidents. Figure 6 shows the TKGs of fires caused by traffic accidents on the highway. It took approximately thirty minutes to extinguish, and it was a small-scale accident in which no disaster alert message was issued. Only a few witnesses shared images from the site and tweets about what happened on Twitter. The fire-related tweet generated at (c) before the event contains content related to the fire at another location. Furthermore, witnesses uploaded tweets about the event 16 minutes later at (j).

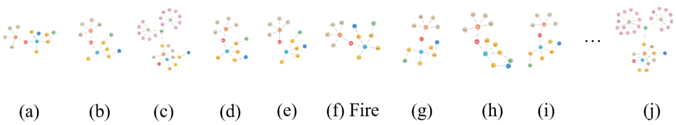

Fig. 6. TKGs with fire

V. Applying GNN models to TKGs

We apply three GNN models, including GCN, SageConv, and GAT, primarily used to capture and analyze local and global information in time series digraphs. Then, to extract the features of each node and edge of TKG, we use degree centrality values, keyword vectors, and large language models. This section describes the datasets collected for the model training and how to assign the labels. In addition, we show disaster detection results using those models and examine which disaster patterns enable early detection.

A. Dataset and Labels

In our prior work, we trained GNN models to detect the occurrence of disasters [12]. We selected 50 earthquakes for the dataset and generated TKGs for 2 hours at 1-minute intervals for each disaster. For model training, we assigned labels of 'non_eq', 'eq', and 'after_eq' to each digraph, which follows the structure of TKG.

B. Disaster Detection Results

We evaluate whether various types of disasters can be detected using GNN models trained with 50 earthquake datasets. The dataset collected for model training includes social data and public data. We assess its applicability to other disasters. The following Table I shows the disaster detection results of the four disasters.

TABLE I
Disaster detection results with various disasters

	GCN	SageConv	GAT
Earthquake	Detected in 1 min	Detected in 1 min	Detected in 1 min
Blackout	Detected in 2 mins	Detected in 1 min	Detected in 2 min
Typhoon	Detected sporadically	Detected sporadically	Not detected
Fire	Rarely detected	Rarely detected	Not detected

All three models predicted the occurrence of the earthquake within a minute, and the blackout, which showed similar Twitter upload patterns, detected the event within two minutes. However, typhoon-related tweets were uploaded for a long time; even before the occurrence, the disaster was detected sporadically. In addition, localized disasters such as fires are rarely detected or tend not to be detected.

VI. Conclusion and Future Work

In this paper, to detect the occurrence of various types of disasters, we first classify diverse disasters into six disaster categories according to their characteristics. Then, we use temporal knowledge graphs to represent disaster patterns that determine disaster categories. For the evaluation, we generated temporal knowledge graphs for four disasters and analyzed their change patterns to see how effectively GNN models can identify disaster occurrences with knowledge graphs. The detection result shows different data types can capture different disaster characteristics, which affect the disaster detection ability. Therefore, it is important to collect appropriate data representing the characteristics of a disaster. For future work, we will further evaluate which data type is crucial in a specific disaster and design a new graph neural network model. More accurate disaster detection will be possible by collecting additional data suitable for the characteristics of the disasters.

Acknowledgment

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