ANALYZING THE SPREAD OF SITUATIONAL INFORMATION ON SOCIAL MEDIA DURING THE COVID-19 PANDEMIC

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ABSTRACT
People utilise social media to get and share different kinds of information at a historic and unprecedented scale during the current coronavirus disease (COVID-19) epidemic. For the public and authorities to respond to the outbreak, only situational information is useful. In order to develop effective information publishing tactics for the COVID-19 pandemic, it is crucial to recognise this kind of situational information and comprehend how it is spread on social media. By using Weibo data and natural language processing methods to categorise COVID-19-related information into seven different forms of situational information, this paper aimed to close this gap. We discovered certain characteristics that helped us anticipate how much of each kind of material will be republished. The findings provide data-driven insights on public interest and information needs.

I. INTRODUCTION

The current coronavirus disease (COVID-19) epidemic in Wuhan, China, has resulted in a regional and worldwide public health emergency [1]. In times of disaster, such as the COVID-19 pandemic, people turn to social media channels to share their thoughts and get necessary information [2], [3]. Social media platforms offer a wide variety of information, and situational information—information that aids in the understanding of the emergency situation by the relevant authorities or individuals (including actionable information like asking for help or the number of people affected) [4]—helps the public and authorities direct their responses [5, 6]. The relevant authorities would benefit from recognising various kinds of information and forecasting their rate of dissemination in order to gauge public sentiment, information gaps between the public and the authority, and public information needs. After that, it would assist the government in developing appropriate emergency response plans [6].

The notion of situational information is still up for debate among the current research. Some people classified contributions and requests for assistance as situational information, while ignoring other kinds of situational information, such public criticism, which shows the public's worries, and emotional support, which shows the victims that others care about them [7]. Nonetheless, a thorough identification of situational information is required. Finding information pertaining to criticism, for instance, might assist authorities in understanding the public's primary issues and developing appropriate solutions. By identifying emotional support information, authorities may be able to better use these volunteer resources and understand the social support patterns of social media users. To make sure that the authorities may publish various kinds of situational information depending on the demands of the public, it is also crucial to determine the key characteristics that can forecast the dissemination size of situational information. In times of unexpected outbreaks like COVID-19, meeting such information needs is essential.

We addressed the following study issues using COVID-19-related conversations on Sina Weibo, the main microblogging platform in China (the Chinese counterpart of Twitter), in order to close these research gaps:

RQ1. How can situational information in social media be recognised and categorised?

RQ2. How predictably do the properties of the transmission scale of distinct situational information kinds vary?

II. LITERATURE SURVEY

"A modelling study for nowcasting and forecasting the possible domestic and international spread of the 2019-nCoV outbreak that originated in Wuhan, China,"

K. Leung, G. M. Leung, and J. T. Wu,

Context: The 2019 novel coronavirus (2019-nCoV) has been the cause of an atypical pneumonia epidemic in Wuhan, China, since December 31, 2019. Cases have been sent abroad and to other Chinese cities, raising the possibility of a worldwide epidemic. Here, we forecast the magnitude of the domestic and international public health risks of epidemics, taking into account social and non-pharmaceutical prevention interventions, and estimate the size of the Wuhan epidemic based on the number of cases exported from Wuhan to cities outside mainland China.

Methods: To estimate the number of infections in Wuhan from December 1, 2019, to January 25, 2020, we utilised data on the number of cases exported from Wuhan abroad from December 31, 2019, to January 28, 2020 (known days of symptom start from December 25, 2019, to January 19, 2020). The number of domestically exported cases was then approximated. Taking into consideration the impact of the Wuhan and adjacent city metropolitan-wide quarantine, which started on January 23–24, 2020, we projected the national and worldwide spread of 2019-nCoV. We utilised data on human movement in over 300 prefecture-level cities in mainland China from the Tencent database, as well as data on monthly aeroplane reservations from the Official Aviation Guide. The Chinese Centre for Disease Control and Prevention's bulletins included information on verified cases. Estimates of serial intervals were derived from earlier research on the severe acute respiratory syndrome coronavirus (SARS-CoV). The epidemics in all of China's main cities were simulated using a susceptible-exposed-infectious-recovered metapopulation model. Markov Chain Monte Carlo techniques were used to estimate the basic reproductive number, and the posterior mean and 95% confidence interval (CrI) were used to display the results.

Results: According to our baseline scenario, as of January 25, 2020, there were 75,815 (95% CrI 37 304-130 330) infected people in Wuhan, and the basic reproductive number for 2019-nCoV was 2•68 (95% CrI 2•47-2•86). 6•4 days was the epidemic doubling time (95% CrI 5•8-7•1). According to our estimates, in the baseline scenario, Wuhan was the source of 461 (95% CrI 227-805), 113 (57-193), 98 (49-168), 111 (56-191), and 80 (40-139) infections imported by Chongqing, Beijing, Shanghai, Guangzhou, and Shenzhen, respectively. With a lag period of around 1-2 weeks behind the Wuhan outbreak, we deduced that epidemics are already expanding exponentially in other large Chinese cities if the transmissibility of 2019-nCoV were the same across the country and over time.

Interpretation: Other large Chinese cities are likely seeing localised outbreaks of 2019-nCoV as Wuhan is no longer containing the virus. If significant public health measures are not taken right away at the individual and population levels, large cities abroad with excellent transit connections to China may also turn into epidemic epicentres. Due to the significant exporting of presymptomatic patients and the lack of extensive public health measures, independent, self-sustaining epidemics in major cities throughout the world may become unavoidable. Plans for preparedness and mitigation measures should be ready for immediate implementation on a worldwide scale.

"Modelling the social media response to the terrorist attack in Woolwich: Tweeting the terror,"

Burnap, P. et al.

The elements that encourage the spread of information in online social networks after terrorist incidents are presently poorly understood. In this study, we used data from the well-known social networking site Twitter to build models to forecast the quantity and survival of information flows in the context of the 2013 terrorist attack in Woolwich, London. We characterise information flows as the spread of content on Twitter via retweeting across time. We used the zerotruncated negative binomial (ZTNB) regression approach after comparing it with other prediction techniques and taking into account the distribution shown by our dependent size measure. Because the Cox regression approach yields proportional hazard rates for independent metrics, it was utilised to model survival. The social, temporal, and content aspects of the tweet were included as predictors in both models after a principal component analysis was performed to minimise the dimensionality of the data. In the discussion section, we highlight the impact of emotive material on dissemination, given the event's expected emotional response. We provide new results from a sample of Twitter data (N=427,330) gathered after the incident, showing that the emotion in the tweet is statistically significant in predicting the extent and survival of such information flows. Additionally, both the stress conveyed in a tweet about survival and the quantity of offline news stories on the incident that were published on the day the tweet was written were significant predictors of size. Lastly, the co-occurrence of URLS and hashtags as well as the time gaps between retweets were shown to be relevant.

"Microblogging during two instances of natural hazards,"

L. Palen, K. Starbird, A. L. Hughes, and S. Vieweg

We examine microblog entries made on Twitter, a well-known microblogging platform, during two recent, simultaneous emergency situations in North America. We highlight messages from those who were "on the ground" during the Red River Floods in March and April 2009 and the Oklahoma Grassfires in April 2009, and we pinpoint information that might help improve situational awareness (SA). The purpose of this study is to provide guidance for future information extraction (IE) approaches that will be used to retrieve pertinent and helpful information during crises.

"Social media's contribution to the development of collective behaviour in the wake of natural disasters,"

R. Beck and A. Mukkamala,

User-generated material from catastrophe survivors has become more important with the rise of social media. Research to date has concentrated on classifying and taxonomising the kinds of information that users exchange during emergencies. Theorising about the links and dynamics of the identified categories is lacking, however. In this study, we used a probabilistic topic modelling technique to extract themes from Twitter data related to the Chennai catastrophe. The issues were manually analysed, further grouped into general categories and themes, and their evolution over the course of the disaster's days was tracked. Lastly, we construct a process model to investigate a new phenomena that appears on social media following a crisis. We contend that in order for individuals to feel, react, and behave as kinds of collective behaviour, certain circumstances and activities—such as collective awareness, collective concern, collective empathy, and collective support—are essential.

"A systematic literature review on Twitter as a tool for emergency situation management and analysis,"

J. C. Rubio-Romero, M. Martínez-Rojas, and M. D. C. Pardo-Ferreira,

The appropriate handling of emergency situations depends on the timely, accurate, and efficient utilisation of the information that is available. New methods for disseminating and gathering crowdsourced data to support situational awareness and emergency management have been made possible in recent years by developing technology. In this sense, social media and the internet have shown the ability to be a useful tool for acquiring and sharing current knowledge. Twitter is one of the most widely used social networks, and studies have shown that it provides useful real-time data for making decisions. This work aims to provide a comprehensive literature review that highlights the problems and future research directions, as well as an overview of the current state of research on the use of Twitter to emergency management.

III. SYSTEM ANALYSIS AND DESIGN

EXISTING SYSTEM

Rudra et al. [7] classified sympathy for the victims, praise or criticism of the relief effort, post-analysis of the reasons behind the crisis, and information pertaining to donations into non-situational information. They defined situational information as notifications of casualties, injured/stranded people, or assistance with relief operations. The non-situational information described by Rudra et al. [7] was classified as situational information in the Vieweg (2012) [14] investigation.

She specifically divided situational information into three categories: constructed environment, social environment, and physical environment. Advice, caution, evacuation, fatalities, injuries, medical treatment, individuals missing, and giving assistance are all included in the social environment information. Information on the built environment includes the state of infrastructures and the damages brought on by the crisis. Environmental effect, general area information (hazard status), and general hazard information (weather report, for example) are all included in physical environment information [14].

Additionally, based on Vieweg's study, Imran et al. [15] further classified the situational information into seven categories: care and guidance, casualties and damage, gifts of cash, products, or services, persons who are missing, located, or seen, and information source. Initial information about the disaster, situation updates, criticism about inadequate attention, moral support, preparations, criticism and control rumours, help requests, offering help, self-organising support, and active volunteerism are among the ten categories of situational information that Mukkamala and Beck [4] categorised.

Posts that offer "tactical, actionable information that can aid people in making decisions, advise others on how to obtain specific information from various sources, or offer immediate post-impact help to those affected by the mass emergency" are considered situational information, according to Vieweg [14].

PROPOSED SYSTEM

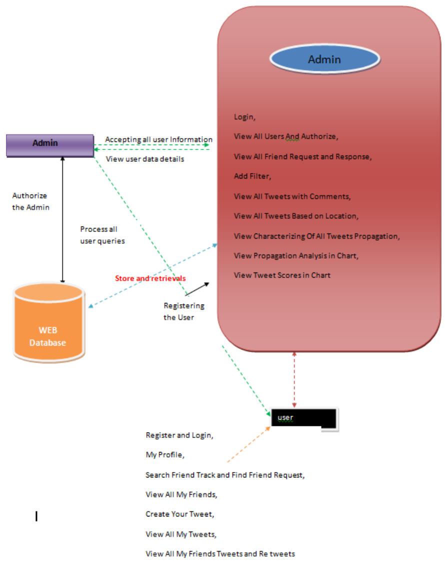
As outlined in the literature, we extracted five categories of data to determine the main elements that may reliably predict the propagation scale (reposted quantity) of each kind of situational information [33], [32]. The following are the extracted characteristics (names are italicised).

Emotional elements: affect, anxiety (anx), rage, sorrow words (sad), negative emotion (negemo), and positive emotion (posemo) in the postings and Percept, see, hear, and feel are perception-related elements.

Affiliation-related variables include risk, reward, power, affiliation, and accomplishments. 4) Features connected to people: the number of followers (Followers (log)), the number of followers (Followees (log)), whether or not the event is nearby (NearCity), whether or not they reside in a developed city (BigCity), and whether or not they are verified users.

Content-related indicators include the post's length, whether or not it contains a hashtag or URL, and when it was published (in hours).

System Architecture:



IV. IMPLEMENTATION

Modules

Admin

The Tweet Server must be logged in with a working username and password in order to utilise this module. After successfully logging in, he may do certain tasks such See Every User And Give Permission, See Every Friend Request and Reaction, Put a filter in. See Every Tweet with a Comment, See Every Tweet by Location, View Propagation Analysis in Chart, View Tweet Scores in Chart, and View Characteristics of All Tweets Propagation.

View and Authorize Users

The administrator may see a list of all registered users in this module. Here, the administrator may see the user's information, like name, email, and address, and they can also grant the user permissions.

User

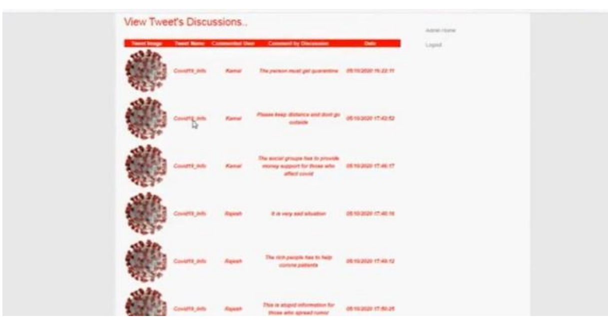
A total of n users are present in this module. Before beginning any actions, the user needs register. Following registration, the user's information will be entered into the database. Following a successful registration, he must use his password and authorised user name to log in. After successfully logging in, the user will do several tasks such as viewing their profile, searching for friend requests, and tracking friends. See Every One of My Friends, Post Your Own Message, See Every One of My Friends' Messages, and Retweet.

V. SCREEN SHOTS

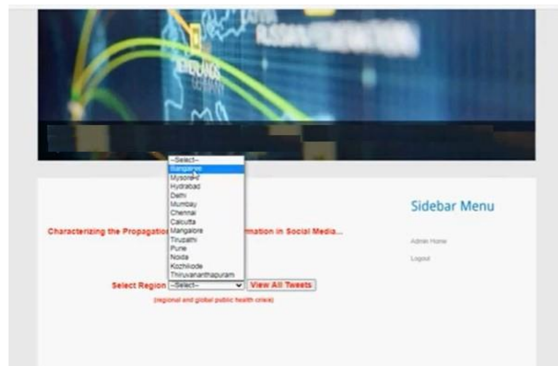
HOME PAGE:


Add Filter Details...
Existing Filter Details ...


User Mohan's Information...
Sidebar Menu


View Tweet's Discussions..


Sidebar Menu
View Tweet's Discussions..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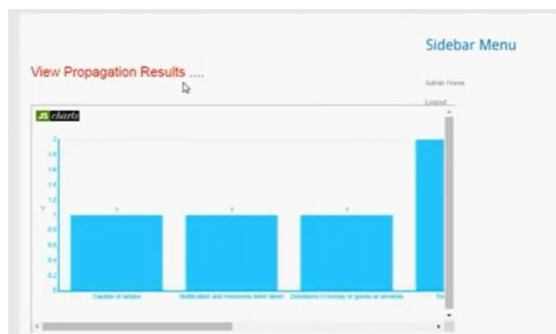
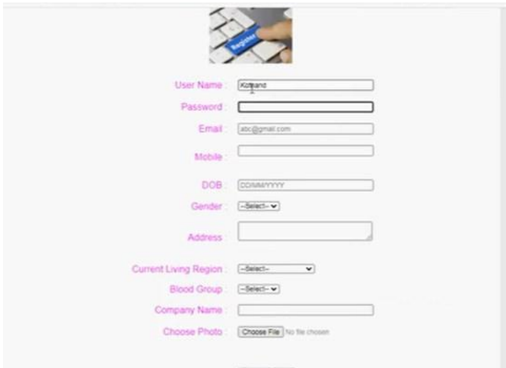

Sidebar Menu
View Propagation Results ....


Sidebar Menu
View Health Tweet Score Results ....



VI. CONCLUSIONS

The results of this paper show that various kinds of situational information need distinct information dissemination methodologies. The characteristics chosen for the various situational information categories may also teach the authorities how to structure their COVID-19-related postings to increase or minimise the number of reposts. Researchers or practitioners who want to create successful social media-based emergent response programs and crisis information systems may also find the situational information definitions helpful.

There are restrictions on this article. First, due to Sina API limitations, we were only able to get a portion of social media data. To acquire more data in the future, we will work with the data suppliers. Second, owing to a lack of data, we were only able to train three conventional NLP-based classifiers to recognise the different forms of situational information content. To identify the content kinds more accurately in the future, we will train deep learning techniques using additional data [34], [35]. Third, the process of manually labelling crisis data takes a lot of time and may affect how well crisis information sharing is described. To get around this restriction in the future, we want to use automated labelling techniques [6], [36].

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