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Building Relatively Small Settlements' Capability for Disaster Response by a Human Dynamics-based Crowd-sourced Real-time Information Sharing System

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Vision and Goal

About 50 percent of urban inhabitants worldwide live in the built environment of the population size below half million residents. Such cities would need to significantly adjust their urban disaster coordination strategies via various preparedness and response activities across networks and scales, because growing populations and financial limits would put a wide range of constraints on their resources, the environment, and urban infrastructure. A variety of government agencies, nonprofit organizations, and individuals/volunteers have been actively participating in the different stages of disaster response.[\[1\]](#) Enhanced engagements and fusion of timely relevant data sets might reduce adverse impacts of disasters through maximizing the values of public and private investments. Human dynamics research can be developed to understand and analyze patterns, trends, and relationships embedded in human activities, behaviors, and communication in the context of disaster response. Such research would focus on the space-time modeling of information diffusion and the inter-correlation between online activities and real-world human behaviors, which is of considerable interest. More studies are needed to examine the applicability of theoretical frameworks to predicting and explaining human behavior in the context of meme diffusion for disaster response.

One of the fundamental and major research tasks in human dynamics studies is to identify, track, and predict how topics might emerge and spread within and across the online and real-world communities. Each human message can be treated as a meme from a communication perspective. Memes are replicable messages.[\[2\]](#) All electronic messages, images, and files can be defined as memes, although only a small number of all such memes will become socially significant, viral, and diffused to many individuals and groups.

A growing list of publications have documented how the memes and information spread in the widely-used online communication platforms, such as Facebook, Reddit, or Twitter. The hashtag is usually recognized as a representative of topics in Twitter, while such topics and events have to be extracted from the contents for news and articles using advanced natural language processing. A pioneering work by Bailey [\[3\]](#) modified and extended the disease-propagation Susceptible, Infected and Recovered (SIR) epidemiology model to explore the procedure of information diffusion.[\[4\]](#) The Linear Threshold (LT) model [\[5\]](#) and the Independent Cascade (IC) model [\[6\]](#) have been frequently employed to model such procedures.[\[7\]](#) Suen et al. employed social

dynamics to identify the evolution of topics and events in the social media.[8] The outcomes of human activities in response to disaster warnings are increasingly detectable and measurable due to the data availability especially human messages. The procedures of meme diffusion in the network environment can be modeled based on a variety of spatial diffusion approaches initiated by Hägerstrand,[9] followed by Pederson [10] and Berry.[11] However, such models are incapable of handling spatial diffusion integrating spatial and social network worlds.[12] The analysis of space-time correlations of human behaviors and response can be used to validate and calibrate computational models and support development of theory for better understanding human dynamics and spatio-temporal diffusion patterns of human messages, activities, and communications in a network environment.[13] Including spatial and temporal terms with classic statistics help distinguish various diffusion processes.[14][15]

Morrill, Gaile, and Thrall classified the models of spatial diffusion processes into stochastic and deterministic models, according to probabilistic or fixed forms.[16] A stochastic model allows for chance, indicating that the driving forces that involve a probability element would lead to the observed outcomes of spatial diffusion. However, a deterministic model suggests that the spatial diffusion follows certain fixed rules and parameters.[7]

Discovering the opinion leaders in an online community is critical for disaster response and information adoption, because these influential information spreaders would ensure the coverage maximization of information in a timely fashion, which is also refereed to as the social network influence maximization problem.[17] These methods need to deal with the resistance that might exist within social networks. The goal of such classical problem is to discover a group of seed nodes or top spreaders facilitating information adoption to a maximal number of nodes.[18] In addition, because misinformation might also diffuse based on such infrastructure or network, the early detection of misinformation or fake news in social networks is important to limit its social harm. Budak et al. explored the algorithms of minimizing the misinformation spread by adopting limiting campaigns to reduce the misinformation effects.[19]

Numerous social and behavioral theories from the individual level to the macro level have been applied to predict and explain human behaviors, such as healthcare seeking and response to public health disasters, as well as human response to controversial topics such as anti-vaccination and gun control debates.[20] For example, Paek et al. adopted survey data from a representative sample of 1,302 adults living in Georgia to

demonstrate that self-efficacy to manage an emergency, as well as subjective and perceived norms related to preparing for an emergency, were associated with an individual's level of emergency preparedness.[21] In addition, risk perception theory has been applied to understanding influences on public health workers' readiness and willingness to report to duty in emergencies, and their ability to effectively communicate risk to the public. [22]

The concept of network communities was suggested by Rosvall and Bergstrom.[23] Fortunato demonstrated how clustered people form communities in real space or virtual space and form the entities in social networks that allow us to study, model and predict meme diffusion processes.[24] Community structure has been demonstrated to affect information diffusion.[25] It was also the basis for studying the activities of individuals and the speed of diffusion. Although the use of network communities as a concept to study meme diffusion is not new,[5] Ye et al. [26] and Dang et al. [27] proposed to use agent-based simulations to model the spread of memes so that we not only model different forms of diffusion processes with simulations but also enable prediction of ways that meme diffusion may proceed over social networks.

Researchers have been actively investigating spatio-temporal effects in the information diffusion process across a wide range of disciplines. Baybeck and Huckfeldt investigated the spatial and temporal diffusion of political information within urban areas.[28] Zhang et al. explored an information diffusion theory-based methodology for spatio-temporal risk assessment of natural disasters.[29] Doo presented an activity-based social influence model based on an activity-enhanced heat diffusion kernel and a suite of algorithms.[30] Cao et al. suggested a visualization design, "Whisper", for tracing the process of information diffusion in social media in real time.[31] Their design highlights three major characteristics of diffusion processes in social media: the temporal trend, the social-spatial extent, and the community response for a topic of interest. Spatio-temporal visualization can be applied to intuitively reflect the complex process of information diffusion. These visualization techniques allow analysts to iteratively and interactively explore a dataset and thus gain deeper understanding of the origination, propagation, and clustering of information. Chen and Ye implemented both public attention value and geographical distance decay to show how temporal and spatial factors would influence such diffusion across social network.[32]

We envision first examining and assessing gaps and opportunities for some representative communities in the Mississippi River Watershed (MRW) regarding their practices, goals, and needs for seeking and using data related to disasters. Then, we

would build a tool utilizing citizens as sensors to enhance a community's management strategies and response to a wide variety of disasters (e.g., a tornado, flooding, etc.) taking into account the complicated mechanisms of human communications in both cyberspace (online) and the real world (offline). We will develop a cloud-based platform that utilizes citizen-generated event information with three data components (video/photo, narration, and location) from mobile devices to support community decision making. The research will integrate community-relevant practical applications with computational techniques, including multimedia spatial databases, crowd-sourcing and mobile computing, and visualization and human-machine interfaces. The aim is to also identify the most salient theoretical constructs which can then be used to inform public efforts utilizing meme diffusion strategies to enhance community resilience.

Intellectual Merit

There is growing recognition of the importance of spatially and temporally dynamic relationships in explaining processes relevant to human behaviors, public health, and social activities. By using both computational methods and social science approaches, we can help social scientists trace, monitor, and analyze human dynamics in different domains, including public response to disaster alerts, controversial social topics, social movements, urban planning, political campaigns, and public opinions. These research efforts can help us understand the diffusion of innovations and the dynamic relationships of human activities, behaviors, and communications. The development of HPC solutions and web-accessible GIS tools can provide an innovative solution for visualizing diffusion patterns of social media messages and constitute transformative social science analysis tools. New insight from social media analytics can also help to verify existing social-behavioral theories as well as contribute to problem solving in a range of areas vital for the current mobile and data-rich age. We seek to capitalize on the interdisciplinary intellectual, paradigmatic, and methodological capabilities of scholars uniquely suited to addressing problems for which new insights can lead to better policy and prediction. As new models of human dynamics reflected in

cyberspace continue to be refined, insights into such dynamics will become increasingly predictive and explanatory.

One of the biggest challenges a community faces is acquiring real time information about an ongoing event. Increasingly members of the public share situational data through mobile devices in the form of text, pictures, audio, and video, usually on social media. However, while social media is often discussed as having the potential to enhance traditional community data flows, there are potentially serious problems regarding the reliability and validity of these data. First, spatial location is often not given or not accurate enough to locate event position in a community. Second, incoming data are noisy and intermittent, which hinders their use in real time tasks. Hence, the utility of social media as a real-time data source has so far proven unsatisfactory. We plan to develop a cloud-based system that efficiently utilizes crowd-sourced information from people within the community. It can enhance existing response systems and provide near-real-time and trustworthy insights for community responders. These "citizens as sensors" data may potentially be utilized to support and enhance a community's capability regarding situational awareness and emergency response.

Reliable, punctual, and spatially accurate data are vital for event response and management. In some instances, this may be planned, such as monitoring activities around a public celebration, monitoring rainfall or snowmelt flooding, or treating road cracks and potholes. It also may be severe and unforeseen, such as a tornado or an active shooter(s). A useful tool for all of these events would be a scale-able solution that includes multiple data inputs and that can be processed and turned into actionable knowledge in near real-time. We propose to develop a human-centered Smart and Connected Disaster Response integrated conceptual framework, which connects people living in a relatively small settlement, through smart computational techniques and infrastructures. It will greatly improve a community's promptness and effectiveness in its responses to disaster events with the integration and utilization of abundant, just-in-time event information. A multimedia spatial database in the cloud could process and manage real-time event information including videos, pictures, audios, and comments. The data is acquired and shared through a mobile App by community volunteers who are on the ground, in or around an event as it unfolds. The system could answer spatial-temporal queries based on location, time, and semantic information in an operation center, so that decision makers and responders attain situational awareness and make proper decisions. Users can interact with the data and

other users through an intuitive visual interface, while the behavior of the crowd sources can also be studied and managed.

Broader Impact

The dual threat of increasing urban populations coupled with climate change creates a circumstance where cities urgently need to work toward identification and mitigation of potentially devastating problems. We will develop new smart and connected community techniques that collect, share, manage, and visualize multiple forms of reliable event data for disaster response. We plan to build the system on cloud platforms and design user-friendly interfaces which can be easily adopted and leveraged by different communities. The system will operationalize “citizens as sensors” in terms of people on the ground, being in or around an event as it unfolds, and who can collect vital information that can be used in the response. Clearly, a new collaborative approach is needed to speed up scientific and technological advances, along with the software tools that focus on sustainable urban management, in order to support urban vulnerability policy and management.

Our proposed techniques and tools can be used by the public, city employees, and city technology managers with their full participation in terms of improving what and how data are collected, and how to maximize their utility. Through meetings with city managers of some typical small communities, we can identify several use scenarios as test cases to evaluate both the public uptake of the system, the quality of the database system, and the effectiveness of the end-user tools. This platform can be developed with deep engagement from some typical (relatively small) communities, considered representative those which currently lack capabilities, in terms of IT infrastructure and staffing levels, to utilize new computing and data technologies. We expect that outcomes from the proposed research will be generalizable by providing other communities a city operation tool to efficiently leverage their data to become more effective and coordinated in managing complex and sometimes competing priorities in emergency scenarios.

In addition to the system being transferable to other communities, and the types of events characterized for each location, what we propose will revolutionize emergency management and disaster science. Hence, this framework will facilitate sustainable funding opportunities beyond the planning grant period, as well as a tool for municipalities with practice-based approaches. Currently response to any disaster is reliant on three primary data flows: 911 calls, response teams, and remotely-sensed imagery. While social media appears to add additional insight, the lack of content

validation and spatial precision leaves it an under-utilized data source. This system will harness the benefits of social media, with citizens as sensors, while providing data flows that lead to content validation and spatial precision. By turning these real-time data uploads into usable data, response to an event will be greatly enhanced. This transformational system will also contribute to more effective spatially-focused warning systems that evolve according to the flow of data. This effort can facilitate the transformation of social and behavioral science research through computational modeling, simulation, and prediction applications.

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