Using Social Media to Geo-Target Emergency Management Efforts

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ABSTRACT

The ubiquity of social media data has increased their use in emergency management (EM) in real-time. For instance, during Haiti Earthquake (2010) and Hurricane Harvey (2017), Ushahidi and Twitter were used respectively for emergency response and rescue operations. Social media data tend to contain [ir]relevant information to be useful for disaster analytics for emergency response efforts. In this study, geo-tagged tweets obtained for 2013 Colorado flooding were analysed to determine (i) what kind of situational awareness (SA) information could be extracted from tweets for emergency response? and (ii) what is the spatio-temporal distribution of such information? The results indicate that tweets generated before September 12th (day of heavy precipitation) were non-relevant, but tweets generated on and following September 12th contained crisis information, warnings, preparatory information. Next phase of this study will focus on developing a framework to integrate SA information with physical risk and social vulnerability to geo-target EM efforts.

CCS CONCEPTS

• **Information systems → Content analysis and feature selection**; *Data analytics*.

KEYWORDS

situational awareness, crisis informatics, emergency management, natural language processing

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1 INTRODUCTION

Gaining insight into what happened before, during and after a disaster event is essential for emergency response and recovery efforts. Traditionally, socio-economic and geospatial data sets available from census and other conventional sources are used for these efforts. These data sets (i) are not available in real-time, and (ii) do not capture a communityâĂŹs response and recovery needs. By contrast, social media data (e.g., tweets) are available in near real-time, contain information about usersâĂŹ feelings and needs.

Among many social media platforms, Twitter has become a platform for risk communication because it is free, instantaneous, globally distributed, and rich in context [3]. A very good example is the Twitter earthquake detector, developed by USGS, that disseminates alerts within few minutes of receiving information from seismometers and tweets [1]. Twitter has also been used for coordinating relief efforts, raising awareness [7, 14]; and helping with emergency preparedness [13]. Significant number of studies have used tweets to extract information about damages sustained, level of threat, among others based on usersâĂŹ posting habits, tweet volume and sentiments [5, 6].

Despite the increase in tweet characters from 140 to 280, the information disseminated by a single tweet can be confusing and may not contain relevant and reliable information to be of use by emergency managers. Information available from tweets also tend to vary across disaster events [4, 9]. Tweets tend to be âĂIJnoisyâĂİ and biased by user demography, and may contain [ir]relevant information for disaster analytics [4, 8]. Currently, several tools and data sets containing crisis-related terms (e.g. CrisisLex, EMT Terms, VerbNet) and using linguistic expressions to classify tweets into various categories are available to be used for emergency management [10–12]. Because situational awareness (SA) information is contextual, it is crucial to classify tweets into categories representative of emergency management (EM) phases [12]. The first part of the study focused on analyzing geo-tagged tweets obtained for 2013 Colorado flooding to determine (i) the types of SA information that could be extracted from tweets before, during and after the flooding events, and the spatio-temporal distribution of SA information in relation to impacted counties.

The paper is organized into following sections. A brief review of the existing techniques and tools to classify tweets related to disasters is presented in section 2. The data and methodology used to answer the research questions are discussed in section 3. The results are presented in section 4 followed by a discussion of the findings followed by conclusion and future research direction is presented in section 5.

2 JUSTIFICATION OF WORK

Kongthon et al. [?] investigated the different type of SA information that were available from tweets during 2011 flood in Thailand. The authors found an overall increase in tweet volume before the flood event, and an increase in number of retweets for certain users who provided locational and situational information about the flood event. Their analyses also revealed that most tweets provided up-to-date information about the flood, road conditions, and contained requests for relief efforts. In a similar study, Shaw et al.[?] developed a typology of Twitter usage during 2010 Queensland flood in Australia. Takahashi, Tandoc and Carmichael (2015) examined Twitter usage during and after Typhoon Haiyan that impacted Philippines in 2013 based on time and geographic location of users, and their extent of social media engagement. The authors found that the Twitter use varied among users, and stakeholders used Twitter to disseminate different information, such as the public used Twitter to coordinate relief efforts and journalists used Twitter for sharing information. Wang and Zhuang [?] analyzed tweets generated during 2012 Hurricane Sandy by governmental organizations (GO), non-governmental organizations (NGO) and news agents using five key performance indicators âĂŞ impression, like, mention, response time and retweet count. The authors found that news agents generated a large volume of tweets, but the retweet count was higher for tweets generated by GO and NGOs.

Studies have also used tweets from multiple disaster events to develop frameworks for classifying tweets accurately into hazard and EM related categories, such as death, injury, warnings, damages, etc., and develop a database of EM terms to aid with tweet classification for emergency response efforts. Zhang and Vucetic [15] used a semi-supervised approach (crowdsourcing to manually classify tweets, and Logistic Regression to classify tweets based on their scoring) to classify tweets obtained during six disasters that occurred between October 2012 and July 2013: Sandy Hurricane, Boston Bombings, Oklahoma Tornado, West Texas Explosion, Alberta Floods, Queensland Floods. By using unlabelled tweets with a trained classifier, the authors found that the choice of algorithm and corpus of tweets impacted classification accuracy. Imran and Castillo [2] used human experts and Latent Dirichlet Allocation method to classify tweets obtained during several disasters, including wild fire, flood, typhoon, earthquakes from different counties to develop a framework to classify tweets into information categories, such as hazard type, damages, sympathy/opinion, etc. Temnikova, Castillo and Vieweg [12] developed a database known as EMTerms that contains terminologies related to hazard events and emergency management to aid with tweet classification. The authors classified 500 tweets each from four different events (i.e., 2013 Russia-China floods, 2013 Pakistan-Afghanistan floods, 2013 Bohol earthquake (Event3), 2012 Colorado wildfires) manually and using Conditional Radom Fields method (a probabilistic method used in NLP) to develop a sequence of terms for different EM related topics. The authors developed a trained model using the classified data set, which they used subsequently on 35 anthropogenic and natural hazard events to develop the final EMTerms list for classification of tweets generated during disasters. Olteanu et al. [10] used tweets from six different disasters that occurred in the USA, Canada and Australia (included hurricane, bombing, tornado, flood and explosion) to create CrisisLex âĂŞ a dictionary of crisis related terms similar to EMTerms.

Currently, CrisisLex contains 380 terms and EMTerms contains 23 categories and 7,200 terms that could be used to classify tweets related to disasters (CrisisLex 2018). Because Twitter use varies across different phases of a disaster, dependent on the type, location and time of the event, and related with user demography, it is crucial to understand what SA information could be extracted from Twitter to aid with emergency response efforts. This study, therefore, focuses on developing a framework to analyse tweets for SA before, during and after an event to help with EM efforts, and associate the SA information with physical risk and social vulnerability to geo-target response activities related to communities and infrastructures. The framework can be used to undertake strategic crowdsourcing activities to help with EM efforts by emergency management agencies and first responders.

3 DATA AND METHODS

For this preliminary study, 1,195,183 firehose tweets were obtained from Twitter Inc. during September 9th to 17th for the 2013 Colorado flood. Among the tweets, 85% were in English, and 1.38% were geo-tagged. From the 15,154 geotagged tweets, 4,829 tweets posted by 2,039 unique users located within Colorado were extracted. For each tweet, special characters and encoding, such as #, , RT, etc. were removed, and apostrophes (e.g. ĂŹ) were replaced with a stroke (i.e.
âĂŹm) to differentiate text from the string wrapper. Half of the tweets (training data set) were manually classified into four broad categories Information, Conversation, Others and Not Relevant and thirteen classes Information category - Preparation, Sharing, Warning, Loss, Location; Conversation category - Positive, Negative, Humour, Concerns, Neutral; Others - Advertisement, Help; Non-relevant. Each word in a tweet was tokenized and converted into a string vector to examine the relationship between their occurrence and a specific category/class. A few machine-learning algorithms, such as J48, NaÃŕve Bayes Multinomial (NBM), Sequential Minimal Optimization (SMO) and Random Forest (RF) were evaluated based on percentage of correct prediction, kappa statistics, confusion matrixes and Areas under the ROC Curve. Based on the percentage of correct prediction, kappa statistics, Confusion matrixes and Areas under the Receiver Operating Characteristics Curve, the results of Sequential Minimal Optimization (SMO) used to classify tweets is presented below. The spatio-temporal distribution of tweet classes were also analysed for each day during the 9-day (September 9th âĂŞ September 17th) period to understand which contextual tweets were predominant before, during and after the flood event.

4 RESULTS AND DISCUSSION

Of the geocoded tweets, 35% were non-relevant, 42% contained flood-related information, 22% were conversations about the event, and 1% were classified as âĂIJOthersâĂİ. From the informational tweets, about 54% was âĂIJsharingâĂİ news/updates about the event, 22% contained warning messages, 16% reported self-identified location, 5% reported damages/losses, and the remaining 3% provided advice for disaster preparation. Among the 16% locational tweets, some provided contextual information (e.g. who they were with) or reported building/institution names. About 52% of the âĂIJconversationâĂİ tweets contained neutral discussion about the event. The remaining âĂIJconversationâĂİ tweets expressed positive emotions (11%), negative emotions (13%), concerns (12%) and humor (12%). Of the tweets categorized as âĂIJOthersâĂİ, 46% contained disaster-related advertisements (e.g. plumbing, locksmith) and 54% contained solicitations about assistance 1.

About 30 âĂŞ 70% of tweets generated before and after September 12th and 13th (the days when heavy precipitation occurred) were non-relevant. On Sep 12th, 86% of tweets was relevant and contained neutral discussions (18%), news/updates about the event (28%), warnings and alert messages (19%), concerns (4%), humor (6%), location information (3.5%), positive and negative emotions (4.5%), and damages and preparatory information (3%). A similar trend was observed on Sep 13th with 79% of tweets being relevant, and contained neutral discussions (16%), sharing (31%), warnings (9%), concerns (6%), humor (3%), location information (2.7%), positive and negative emotions (6.5%), and damages, preparatory information and solicitation for help (4.8%).

About 70 to 80% of the geo-tagged tweets were clustered in the moderately to worst damaged counties of Morgan, Logan, Boulder, Larimer, Clear Creek, Jefferson, Adams, Arapahoe, El Paso, and Fremont. Tweets providing advertisements, preparatory, loss and damage information were concentrated in Denver and Broomfield cities, Boulder, Arapahoe, Adams, Jefferson and El Paso counties (worst damaged counties with high population concentration). Given that the 2013 flooding impacted the Front Range area (Denver MSA, Boulder and Larimer County), and the towns of Jamestown and Lyons (Boulder County) and Estes Park (Larimer County) were isolated by water, it is not surprising that the tweets pertaining to the event, and those containing negative and positive emotions are concentrated in these heavily impacted areas.

Among the machine-learning algorithms examined, SMO performed the best with a correct percentage of 76% in category prediction and 68.7% in class prediction 1. The classifier was acceptable in labeling most classes under âĂIJInformationâĂİ (i.e. âĂIJPreparationâĂİ, âĂIJWarningâĂİ, âĂIJLocationâĂİ and âĂIJLossâĂİ) except âĂIJSharingâĂİ probably due to its diverse nature (e.g. embedded links and multimedia). Among conversation classes, the classifier was more confused in the âĂIJHumorâĂİ and âĂIJNeutralâĂİ classes. Due to the ironic and sarcastic nature, the former meme is often filled with polarized context-specific keywords; whereas the âĂIJNeutralâĂİ class suffers from its vague and broad nature. Due to the small sample sizes in training data for âĂIJPreparationâĂİ, âĂIJPositiveâĂİ and âĂIJHelpâĂİ classes, the classifier performed poorly.

5 CONCLUSION

The analyses of the tweets indicated that prior to the event a large proportion of tweets were not relevant to the event. During and following the event, the proportion of tweets providing warning, preparatory information, risk information pertaining to loss and damages, and location information increased. The tweets relevant to the event are also concentrated in the areas that experienced severe and moderate damages (Figure 3). However, the tweets providing warning information were generated in areas that were not impacted by the event at all, such as Weld County that is close to Larimer County that experienced severe damages, and Estes Park in Larimer County was waterlocked. Hence, it could be assumed that the tweets containing warnings were generated in areas that were severely impacted as a precautionary measure to alert residents of the event, and help them take appropriate actions (such as evacuate) if needed. Tweets containing location information were concentrated in areas that experienced significant damages. However, these tweets did not provide any specific information about shelters, roads and bridges that were damaged or underwater rather they contained second-hand information that could be used for search and rescue operations instead of response efforts. The Front Range area also had higher concentration of non-relevant tweets, and tweets providing loss and damage information, and those containing positive and negative sentiments.

The findings suggest that tweet volume increases in areas that are significantly impacted by a disaster event and in close proximity to areas at high risk from the event. Temporal distribution of tweet volume also matched the days when the flooding was severe. Because of the low volume of geo-tagged tweets and their concentration in impacted counties, the SA information derived here should be combined with physical risk, social vulnerability and extent of damage to geo-target EM efforts. Next phase of the study will focus on (i) analyzing emojis and URLs to extract SA information, (ii) integrating SA information from emojis with content analysis outputs, (iii) assessing physical risk and social vulnerability of the impacted counties, (iv) relating these factors with situational information obtained from tweets, and (v) establishing a framework to integrate tweets with geospatial data to help prioritize emergency management activities in impact areas. Further analysis will be conducted to classify tweets into the four phases of emergency management activities so that integration of SA information with risk and vulnerability will help create a resilient index for impacted communities to help with EM activities.

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REFERENCES

[1] Guy M. Buckmaster R. Ostrum C. Horvath S. Earle, P. and A. Vaughan. [n.d.]. *Seismological Research Letters* 81 ([n. d.]). Issue 2.

[2] M. Imran and C. Castillo. 2015. Towards a Data-Driven Approach to Identify Crisis-Related Topics in Social Media Streams. In *Proceedings of the 24th International Conference on World Wide Web*. 1205–1210.

[3] Song X. Finin T. Java, A. and B. Tseng. 2007. Why We Twitter: Understanding Microblogging Usage and Communities. In *Proceedings of the Joint 9th WEBKDD and 1st SNA-KDD Workshop. San Jose, CA*. 56–65. https://doi.org/10.1145/1348549.1348556

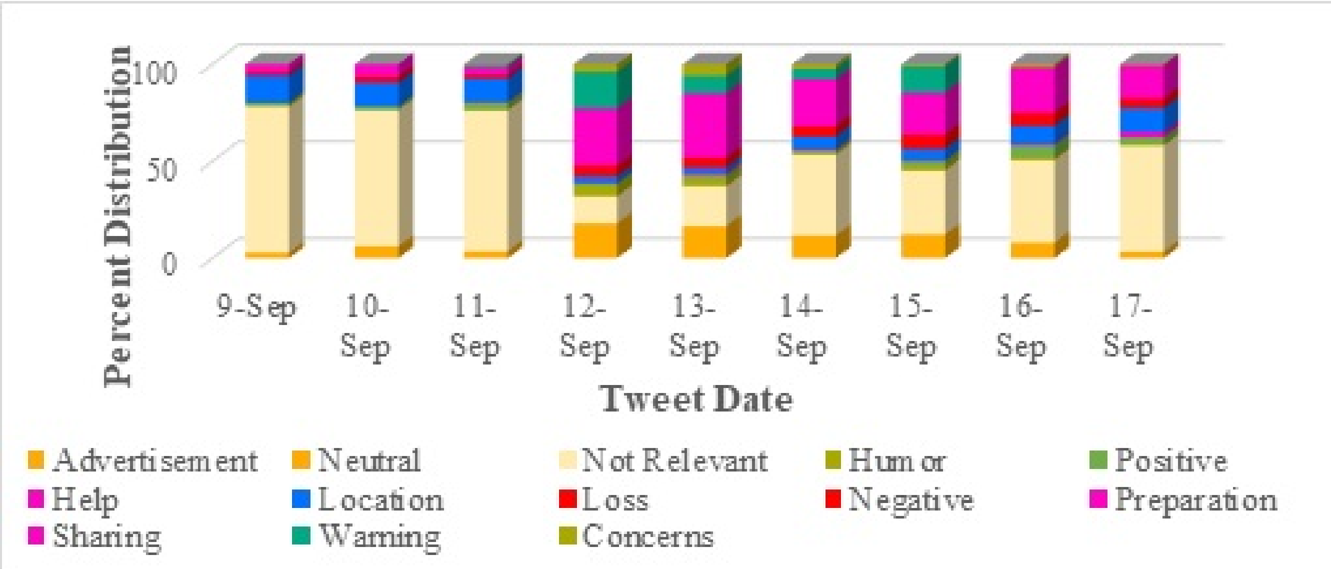

Figure 1: Temporal Distribution of Tweets

	Actual	Conversation	Information	Not Relevant	Others	TP Rate	FP Rate	ROC Area
4*Predicted	Conversation	336	63	86	0	0.711	0.122	0.834
	Information	96	798	94	0	0.808	0.114	0.874
	Not Relevant	128	92	659	2	0.748	0.12	0.871
	Others	7	8	4	13	0.406	0.001	0.715

Table 1: Table 1: Summary statistics of categorical classification accuracy

[4] N. Kanhabua and W. Nejdl. 2013. Understanding the Diversity of Tweets in the time of Outbreaks. In *WWW 2013 Companion*.

[5] J. D. Kent and H. T. Capello. [n.d.]. *Cartography and Geographic Information Science* 40 ([n. d.]). Issue 2.

[6] Chen H. Obradovich N. Moro E. Van Hentenryck P. Fowler J. Cebrian M. Kryvasheyeu, Y. 2016. Rapid Assessment of Disaster Damage using Social Media Activity. *Sci. Adv.* (2016).

[7] P. M. Landwehr and K. M. Carley. 2014. *Social Media in Disaster Relief.* Springer.

[8] Kar B. Zhang C. Liu, X. and D. Cochran. 2018. Evaluating Relevance of Twitter Data for Risk Communication. *International Journal of Digital Earth* (2018). https://doi.org/10.1080/17538947.2018.1480670

[9] R. Munro and C. D. Manning. 2012. Short Message Communications: Users, Topics, and In-language Processing. In *Proceedings of the 2nd ACM Symposium on Computing for Development*. https://doi.org/10.1145/2160601.2160607

[10] Castillo C. Diaz F. Olteanu, A. and S. Vieweg. 2014. CrisisLex: A Lexicon for Collecting and Filtering Microblogged Communications in Crises. In *Proceedings of ICWSM*.

[11] Vieweg S. Olteanu, A. and C. Castillo. 2015. What to Expect When the Unexpected Happens: Social Media Communications Across Crises. In *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work and Social Computing*. 994–1009. https://doi.org/10.1145/2675133.2675242

[12] Castillo C. Temnikova, I. P. and S. Vieweg. 2015. EMTerms 1.0: A Terminological Resource for Crisis Tweets. In *Proceedings of the International Conference on Information Systems for Crisis Response and Management*.

[13] Hughes A. L. Starbird K. Vieweg, S. and L. Palen. 2010. Microblogging during Two Natural Hazard Events: What Twitter may Contribute to Situational Awareness. In *Proceedings of the SIGCHI conference on Human Factors in Computing Systems*. 1079–1088.

[14] Hovy E. Wang, H. and M. Dredze. 2015. The hurricane Sandy Twitter Corpus. In *Association for the Advancement of Artificial Intelligence*. 20–24.

[15] S. Zhang and S. Vucetic. 2016. Semi-supervised Discovery of Informative Tweets During the Emerging Disasters. In *4th International Workshop on SWDM, co-located with CIKM*.