Refining a Coding Scheme to Identify Actionable Information on Social Media

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ABSTRACT

This paper describes the use of a previously established qualitative coding scheme developed through a design workshop with public safety professionals, and applied the schema to social media data collecting during crises. The intention of applying this scheme to existing crisis datasets was to acquire training data for machine learning. Applying the coding scheme to social media data revealed that additional subcategories of the coding scheme are necessary to satisfy information requirements necessary to dispatch first responders to an incident. The coding scheme was refined and adapted into a set of instructions for qualitative coders on Amazon Mechanical Turk. The contribution of this work is a coding scheme that is more directly related to the information needs of public safety professionals. Implications of early results using the refined coding scheme are discussed in terms of proposed automated methods to identify actionable information for dispatch of first responders during emergency incidents.

Keywords

Dispatch, Public Safety Answering Point (PSAP), Social Media, Qualitative Coding.

INTRODUCTION

Researchers have been working for almost a decade to refine methods to identify information relevant to crises posted by digital bystanders on social media (Hughes & Palen, 2009; Imran, Elbassuoni, Castillo, Diaz, & Meier, 2013). Recently, new fieldwork with 9-1-1 call-takers at Public Safety Answering Points (PSAPs) in the United States has extended this work by identifying information requirements necessary to dispatch first responders (Kropczynski et al., 2018). Understanding information requirements is a helpful as a first step to automating methods to identify actionable information on social media such as requests for assistance and enhancing situational awareness (Vieweg, 2012). In this paper, we describe early work to apply these information requirements to social media data collected during crises using qualitative coding. We begin by describing the 6W (Where, What, Weapons, When, Who, Why) information requirements that must be satisfied to dispatch first responders identified through a design workshop with public safety professionals at a PSAP in the United States (Kropczynski et al., 2018). We then use manual coding to identify information satisfying these requirements in social media posts. Results are used to refine this coding scheme. Finally, we used the refined manual coding scheme to code social media data and develop insights about next steps to automate the detection of actionable information using machine learning techniques.

Previous work in coding and classifying information posted to social media has identified information that is informative (Imran et al., 2013), enhances situational awareness (Vieweg, 2012), or general relatedness to a crisis (Olteanu, Castillo, Diaz, & Vieweg, 2014). These works have evolved over several years to allow the development of machine learning classifiers used to automate detection of social media data that may be useful for situational awareness (Caragea, Silvescu, & Tapia, 2016; Herndon & Caragea, 2016). Equally important to these efforts are works to filter irrelevant information from bots (Wang et al., 2014), or to sort posts by news sources and external observers (Olteanu, Vieweg, & Castillo, 2015; Starbird, Palen, Hughes, & Vieweg, 2010). Despite this evolution, PSAPs in the United States do not currently utilize protocols that detect and respond to requests for assistance that are posted to social media. Instead, dispatch of first responders is based on information gathered through phone calls. In this trajectory to refine automated detection of useful information, it is important to consider the information requirements to dispatch first responders to a crisis.

Today, PSAP call-takers use computer-aided software to gather information from individuals that call 9-1-1, such as ProQA (https://prioritydispatch.net/discover_proqa/). ProQA software provides 9-1-1 call-takers with scripts that distill caller information into emergency types and results in the dispatch of firefighters, law enforcement, medical responders, or other first responders to resolve the request for assistance. Logic used by ProQA is rather complex, however, prior to the use of computer-aided software, 9-1-1 call takers utilized a basic information gathering protocol called the 5W's/6W's, in which call takers ask 1) *where* is the incident taking place, 2) *what* is the nature of the incident, 3) are there *weapons* involved, 4) *when* did the incident occur/is the incident ongoing, and 5) *who* is involved or how many people are involved. Some protocols include a sixth W, which retains any information about *why* the incident occurred. Table 1 shows the results of previous fieldwork with PSAP call takers, dispatchers, and first responders worked create a qualitative coding scheme to identify social media posts that contain information that is necessary to determine emergency types and send first responders to emergency locations.

Table 1. Original 6W Qualitative Coding Scheme (Kropczynski et al., 2018)

Label	Coding	Representative Examples in Fieldwork
Where	Place where help is needed; where an incident occurred; location of victim/suspect/witness; Directional guides/points of reference	"Northland Mall parking garage"; "in the corridor at univ high"; "@ st philip & george"; "headed west on I-26 at Ashley Phosphate"
What	Type of incident; indications of severity	"car accident"; "boat on fire lots of flames"
Weapons	Indication of whether weapons are present and if so, the type of weapons present	"#shooting"; "assault rifle"; "gun"
When	Time the incident occurred; indication of whether incident is still occurring; time lapse	"just now"; "7:32am"
Who	Number of people injured, or number of people armed; Description of victim/perpetrator/vehicle ; nature of observer (firsthand vs. secondhand account)	"3 injured"; "2 armed men"; "tall skinny white guy in blue jeans and a white v-neck tee.. 20 yrs old-ish.. Brown hair"; "we"
Why	Chain of events that led to emergency; Rationale for occurrence that may be helpful to an investigation	No examples

The 6W coding scheme has been applied to fictional social media posts generated by professionals working within a PSAP that were asked in a design workshop to "…construct a 280-character Tweet (Twitter's current character limit) that they perceived was descriptive enough for someone in their professional position to take action on" (Kropczynski et al., 2018). For each of these information labels, previous work has been identified to mine social media data for location information (Bilhaut, Charnois, Enjalbert, & Mathet, 2003; Daly & Thom, 2016; Grace et al., 2017; Han, Cook, & Baldwin, 2014; Intagorn & Lerman, 2010; Quercini, Samet, Sankaranarayanan, & Lieberman, 2010), incident types (Herndon & Caragea, 2016; Li, Caragea, Caragea, & Herndon, 2018; Mouzannar & Awad, 2018), using bag of word techniques or convolutional neural networks (Caragea et al., 2016) may be used to detect presence of weapons, timestamps aid in the identification of when an incident occurred, but no tools currently combine these techniques into one tool. This paper describes early work to move the trajectory of identification of actionable information forward in order to create such a tool.

Research Question

Although the 6W coding scheme has been applied to fictional social media posts, it has not yet been applied to social media posts generated during a crisis. The overarching research question guiding this work is: When applied to social media posts generated during a crisis, does the 6W coding scheme help to identify information that is actionable for dispatch of first responders according to previously established information requirements?

METHODS

The primary objective of this research is to verify the application of the 6W coding scheme to social media posts generated during a time a crisis using qualitative coding. As a large, pre-labeled dataset, the CrisisLex T6 dataset (Olteanu et al., 2014) was viewed as a viable dataset for the purposes of this analysis. The dataset contains data collected from Twitter during 6 different disasters between October 2012 and July 2103 in English-speaking countries. For each of these incidents, randomly selected tweets have been pre-filtered to label data as related/not related to a disaster, and either informative/not informative. Although this dataset has since been criticized when applied to establish, machine learning classifiers due to methods employed to collect data, for our purposes, our intention is only to qualitatively observe the presence of 6W information in social media generated during a crisis. The purpose of this activity is detection, but coding of relevant and informative data in order to establish whether the 6W coding scheme can be used to satisfy information needs of dispatch.

In the CrisisLex T6 dataset, 3926 tweets have been labeled as both related and informative to the crisis that they were collected during. Our method is to qualitatively code these pre-labeled tweets using the 6W coding schema. For each of these tweets, trained qualitative coders were asked to review contents, and if present, copy and paste the contents of tweets related to one the W's according to the coding schema into an associated column of a spreadsheet. The purpose of retaining content rather that indicating presence/absence of the W was to review the way that each of these W's are represented in actual tweets. In addition, there was some hope that text related to each W label might be used for training purposes for machine learning.

RESULTS

Results showed that the majority of tweets labeled in the CrisisLex T6 dataset as informative and relevant contained *where*, *what*, *who*, and *why* information. Less prevalent was information related to *weapons* and *when*, however this varied by incident as only 2 of six incidents would be expected to mention *weapon* information (Boston Bombing and LA Airport Shooting). The low incidents of *when* information was anticipated because the implication of many tweets is that the information being posted is currently happening.

Table 2. Percent of Tweets Labeled by 6Ws

W Label	Percent
Where	78%
What	88%
Weapons	3%
When	5%
Who	68%
Why	72%

Although, the application of the 6W qualitative coding scheme demonstrated that many of the W's are present in these tweets, examination of the content contained in these tweets showed that very few tweets contained information requirements to dispatch first responders. Beginning with *where* information, this is necessary to identify a location to dispatch first responders. As written in the original coding scheme, *where* information is quite broad in its' description. This resulted in the contents of this coding to frequently include the name of a state, region, or town. Although this type of information may be quite helpful for situational awareness, it is the case that few tweets contained information that would satisfy the requirement of identifying a location where a first responder may be sent.

What information was present in the majority of tweets, however, the information requirement that this information must satisfy is to identify statements that can be associated with a type of incident to help understand the type of first responder to be deployed (fire, law enforcement, medical). As written, qualitative coding resulted in many statements that simply reiterated the subject of the tweet rather than information that helped identify a specific incident. Of all 6Ws, *weapons* information was most accurately coded in line with information aims—identifying the presence or absence of a weapon. *Who* information typically took the form of an @mention of another Twitter user, although a small number of tweets contained the number of victims or perpetrators involved in an incident. Finally, *why* information frequently included statements that were duplicated in *what* information, for example, "mandatory evacuations" may be *what* is happening in one tweet and the reason *why* is "flash flooding," however, flooding may also be considered *what* information. Based on these results, it was determined that the use of the 6W coding scheme, as written was not useful to identifying actionable information for dispatch.

REFINEMENTS TO CODING SCHEME

These early results indicated to our research team that further refinements to the coding scheme in terms of subcategories for each of the 6Ws would be necessary to focus on stratifying PSAP dispatch information requirements. The subcategory coding schemes contain subcategories that are intended to only focus on actionable information, provide a specific coding criteria, and examples borrowed from actual tweets in the dataset. Further, we have reduced the 6W coding scheme to a 5W coding scheme by eliminating the *why* information category due to the lack of actionable information for dispatch that is typically present in this category. These subcategories have been tested for clarity with qualitative coders on Amazon Mechanical Turk, but future work will be conducted to better understand the presence of these tweets within a larger dataset. Only a small sample of 200 tweets from the CrisisLex T6 dataset were used for the purposes of understanding if subcategories would be a viable method to refine the coding scheme.

Qualitative coders were given the following instructions: For each tweet, the coder should copy and paste words from the tweet that match the particular subcategory, if the information is present. If not present, the form should be left blank. Please keep in mind that the goal of this work is to help identify information that will be relevant to first responders during an emergency event. If something in a tweet seems important for a first responder to know, but does not fit into a category, please make a note under the “other” category. Also, if you find some of the coding descriptions confusing or misleading, you can also list that information under the “other” category.

Subcategories are described in sections that follow:

Where Information Subcategory Coding Scheme

Our results showed that state, region, and town are often considered as *where* information and although useful to situational information, it is assumed that in a tool that is used by dispatch, social media posts will likely be aggregated from a particular city, town, or regional bounding box. Therefore, tweets relating to an entire state is simply too broad to be actionable in most cases. The coding scheme subcategories have been updated as follows:

Subcategory:	Street address
Coding:	(If present, please write) Number of building and name of street
Example:	123 Main St.; 456 East Ave.; 789 MLK Rd.
Subcategory:	Building name
Coding:	(If present, please write) Name of well-known building
Example:	Sears Tower; Kirkland Mall; the Courthouse
Subcategory:	Location within building
Coding:	(If present, please write) If building name is known, this information specifies a floor, room, or orientation within a building
Example:	Near the east entrance; the southwest corner of the building; Near Taco Bell in the Mall
Subcategory:	Intersection
Coding:	(If present, please write) Location of incident in the form of the intersection of two streets. Both streets must be named to be an intersection.
Example:	Main and Vine; Main St. and Vine St.
Subcategory:	Words that indicate a moving target (vehicle in motion)
Coding:	(If present, please write) direction of moving target (i.e. north, south, east, west) or area that moving target is heading in the direction of (i.e. toward Main St.; toward Taco Bell)
Example:	headed north on Main Street; took off in the direction of Taco Bell
Subcategory:	Situational awareness in neighborhood/city/region
Coding:	(If present, please write) Name of neighborhood, city, or region
Example:	Highland Neighborhood; Townville, Low Country

Information that is not actionable: reference to state

By employing the above subcategories, none of the coders indicated that coding information are unclear. Results showed that the sample of 200 tweets contained 19 street addresses, 12 building names, 3 locations within a building, 7 intersections, 3 moving targets, and 90 tweets that contained information that may be useful for situational information.

What Information Subcategory Coding Scheme

Results of original coding scheme found that *what* information was often interpreted as the subject of the sentence, based on this result, two subcategories were created to better satisfy information requirements for dispatch. These subcategories asked qualitative coders to specifically identify requests for assistance and words that indicate there is an emergency situation or a situation that can/should be addressed by a first responder.

Subcategory:	Request for assistance
Coding:	(If present, please write) Information that relates to the type of assistance being requested - or full request for help
Example:	in need of rescue; building collapse; stranded

Subcategory:	Words that indicate there is an emergency situation or a situation that can/should be addressed by a first responder
Coding:	(If present, please write) Information about a crisis event taking place
Example:	Fire, flood, crash

None of the coders indicated that the coding scheme for these subcategories are unclear. Of the 200 tweets coded, 10 contained requests for assistance and 143 contained information that coders believed would be useful information for first responders. This information often contained very general words such as “flood”, “shooting”, or “wildfire” which indicates that this category should be further explored. In many instances, it is simply the case that the tweet did not originate from an eyewitness or victim of an event, but instead originated from a news source or outside observer of the event on social media. Techniques currently being used to better filter tweets by eyewitnesses (Caragea, Squicciarini, Stehle, Neppalli, & Tapia, 2014; Li et al., 2018) will help to further refine work in this category.

Weapons Information Subcategory Coding Scheme

Although this category already produced useful information, we attempted to further refine to two subcategories in line with information requirements which includes information that indicates a weapon is present and words that indicate what kind of weapon is present.

Subcategory:	Words that indicate that weapon is present
Coding:	(If present, please write) This information may simply indicate that a weapon is present, but does not indicate what kind of weapon
Example:	shooter, shots, explosion, loud pops

Subcategory:	Words that indicate what kind of weapon is present
Coding:	(If present, please write) Indication of type of weapon present
Example:	gun, bomb, rifle, AK47, baseball bat, mace, tire iron

None of the coders indicated that the coding scheme for these subcategories are unclear. Of the 200 tweets, 66 related to incidents where a weapon may have been present (Boston Bombing and LA Airport Shooting). Of those, 61 contained information coded was words indicating that a weapon is present and 11 contained words that indicate what kind of weapon is present. In the case of the kind of weapons present, many wrote “bomb” or “rifle,” based on this result, a bag of words technique where weapon types are pre-loaded may be more useful for detection of this subcategory. None of the tweets from incidents related to natural disasters (wildfires, flooding) contained information coded as *weapons* information.

When Information Subcategory Coding Scheme

This category was further refined into three subcategories, information that indicates that a situation is ongoing, happened in the past, or will happen in the future.

Subcategory:	Indication that situation ongoing
Coding:	(If present, please write) Any information that indicates that the situation still requires the help of a first responder
Example:	Just now, a minute ago, breaking, latest, exact time mentioned by user, but not the timestamp of tweet

Subcategory:	Indication that situation happened in the past
Coding:	(If present, please write) Any information that indicates that the situation happened in the past and may not still require the help of a first responder
Example:	earlier today, yesterday, ambulance just left, but not the timestamp of tweet

Subcategory: Indication that situation may occur in the future
Coding: (If present, please write) Any information that indicates that there is an impending threat of emergency that is about to occur and will require the help of a first responder
Example: threat, headed this way, worried about possible

None of the coders indicated that the coding scheme for these subcategories are unclear. Of the 200 tweets coded, 15 contained information that indicated that a situation is ongoing, 10 contained information that indicated a situation happened in the past, 11 contained information that indicated a situation may occur in the future.

Who Information Subcategory Coding Scheme

Results of our analysis showed that *who* information may be interpreted as an original poster of a tweet, news source or agency mentioned in a tweet, which is not often actionable information. Subcategories focused on actionable information now indicate who is in need of assistance and who is the perpetrator.

Subcategory: Who needs assistance
Coding: (If present, please write) Any description of a person in need that will help a first responder identify them, or information that will help a dispatcher identify number of resources to send to the scene
Example: Lady on ground, person in red car, three children, a busload of people

Subcategory: Who is the perpetrator
Coding: (If present, please write) Any description of a person that law enforcement or a first responder should be aware of
Example: Person in yellow jacket; black SUV

None of the coders indicated that the coding scheme for these subcategories are unclear. Of the 200 tweets, 21 contained information related to who is in need of assistance. None of the tweets contained information about a perpetrator.

Other Information Identified During Coding

As mentioned in the coding instructions, Amazon Mechanical Turkers were given the option to share any information that they thought may be important to a first responder but does not fit into any category. They were also encouraged to state any notes related to coding instructions that may have been confusing or misleading. None of the coders stated that coding instructions were confusing or misleading. Some coders included words that seemed useful to situational awareness for citizens such as “emergency declaration” or “campus closed” but no theme emerged that led to the inclusion of a new category.

CONCLUSION AND FUTURE WORK

Based on these results, we believe that the 5W coding scheme with categories included show promise for the development of tools to automate detection of actionable information. While this is the case, of the 200 tweets coded for refinement of this coding scheme, few contained actionable information. An original aim of this work was to utilize actionable information present in social media posts generated during a crisis, however, in attempting to identify these tweets for machine learning training using manual coding, we found that the dataset we have utilized contained few incidents of actionable information. For many of the subcategories, other techniques or dataset may be useful for the automated coding of actionable information that does not require large datasets of actionable information. These subcategories include: street address, building name, intersection, neighborhood/city/region, presence of a weapon, type of weapon, and past/present/future tense words. Categories that will need attention in the future include requests for assistance. Existing presorting techniques may be employed before attempting to find this type of data in future work.

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REFERENCES

Bilhaut, F., Charnois, T., Enjalbert, P., & Mathet, Y. (2003). Geographic reference analysis for geographic document querying. *Proceedings of the HLT-NAACL 2003 Workshop on Analysis of Geographic*

References, 55–62. https://doi.org/http://dx.doi.org/10.3115/1119394.1119403

Caragea, C. ., Squicciarini, A. ., Stehle, S. ., Neppalli, K. ., & Tapia, A. . (2014). Mapping moods: Geo-mapped sentiment analysis during hurricane sandy. *ISCRAM 2014 Conference Proceedings - 11th International Conference on Information Systems for Crisis Response and Management*, (May), 642–651. Retrieved from http://www.iscram.org/legacy/ISCRAM2014/papers/p29.pdf

Caragea, C., Silvescu, A., & Tapia, A. (2016). Identifying informative messages in disaster events using convolutional neural networks. *ISCRAM 2016 Conference Proceedings – 13th International Conference on Information Systems for Crisis Response and Management*, (May). Retrieved from http://idl.iscram.org/files/corneliacaragea/2016/1397_CorneliaCaragea_etal2016.pdf

Daly, S., & Thom, J. A. (2016). Mining and Classifying Image Posts on Social Media to Analyse Fires. *13th International Conference on Information Systems for Crisis Response and Management*, (May), 1–14.

Grace, R., Kropczynski, J., Pezanowski, S., Halse, S., Umar, P., & Tapia, A. (2017). Social triangulation: A new method to identify local citizens using social media and their local information curation behaviors. In *Proceedings of the International ISCRAM Conference* (Vol. 2017–May).

Han, B., Cook, P., & Baldwin, T. (2014). Text-based twitter user geolocation prediction. *Journal of Artificial Intelligence Research*, *49*, 451–500. https://doi.org/10.1613/jair.4200

Herndon, N., & Caragea, D. (2016). An evaluation of approaches for using unlabeled data with domain adaptation. *Network Modeling Analysis in Health Informatics and Bioinformatics*, *5*(25). https://doi.org/https://doi.org/10.1007/s13721-016-0133-6

Hughes, A. L., & Palen, L. (2009). Twitter adoption and use in mass convergence and emergency events. *International Journal of Emergency Management*, *6*(3/4), 248. https://doi.org/10.1504/IJEM.2009.031564

Imran, M., Elbassuoni, S., Castillo, C., Diaz, F., & Meier, P. (2013). Practical extraction of disaster-relevant information from social media. In *Proceedings of the 22nd International Conference on World Wide Web - WWW '13 Companion*. https://doi.org/10.1145/2487788.2488109

Intagorn, S., & Lerman, K. (2010). Harvesting Geospatial Knowledge from Social Metadata. *Proceedings of the 7th International ISCRAM Conference*, (May), 1–10. Retrieved from http://www.isi.edu/integration/papers/intagorn10-iscram.pdf

Kropczynski, J., Grace, R., Halse, S., Obeysekare, E., Bénaben, F., & Tapia, A. (2018). Identifying Actionable Information on Social Media for Emergency Dispatch. *In Proceedings of ISCRAM Asia Pacific 2018*.

Li, H., Caragea, D., Caragea, C., & Herndon, N. (2018). Disaster response aided by tweet classification with a domain adaptation approach. *Journal of Contingencies and Crisis Management*, *26*(1), 16–27. https://doi.org/10.1111/1468-5973.12194

Mouzannar, H., & Awad, M. (2018). Damage Identification in Social Media Posts using Multimodal Deep Learning, (May).

Olteanu, A., Castillo, C., Diaz, F., & Vieweg, S. (2014). CrisisLex: A Lexicon for Collecting and Filtering Microblogged Communications in Crises. *Proc. of the 8th International Conference on Weblogs and Social Media*, 376. https://doi.org/10.1.1.452.7691

Olteanu, A., Vieweg, S., & Castillo, C. (2015). What to Expect When the Unexpected Happens: Social Media Communications Across Crises. *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing - CSCW '15*, 994–1009. https://doi.org/10.1145/2675133.2675242

Quercini, G., Samet, H., Sankaranarayanan, J., & Lieberman, M. D. (2010). Determining the spatial reader scopes of news sources using local lexicons. *Proceedings of the 18th SIGSPATIAL International Conference on Advances in Geographic Information Systems - GIS '10*, 43. https://doi.org/10.1145/1869790.1869800

Starbird, K., Palen, L., Hughes, A. L., & Vieweg, S. (2010). Chatter on the red: what hazards threat reveals about the social life of microblogged information. *CSCW '10 Proceedings of the 2010 ACM Conference on Computer Supported Cooperative Work*, 241–250. https://doi.org/10.1145/1718918.1718965

Vieweg, S. (2012). *Situational Awareness in Mass Emergency: A Behavioral and Linguistic Analysis of Microblogged Communications*. University of Colorado at Boulder.

Wang, A. H., Hai, A., Detecting, W., Bots, S., Networking, S., Machine, S. A., & Wang, A. H. (2014). Detecting Spam Bots in Online Social Networking Sites : A Machine Learning Approach To cite this version : HAL Id : hal-01056675 Detecting Spam Bots in Online Social Networking Sites : A Machine Learning Approach, 0–8.