Identifying Actionable Information on Social Media for Emergency Dispatch

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ABSTRACT

Crisis informatics researchers have taken great interest in methods to identify information relevant to crisis events posted by digital bystanders on social media. This work codifies the information needs of emergency dispatchers and first responders as a method to identify actionable information on social media. Through a design workshop with public safety professionals at a Public-Safety Answering Point (PSAP) in the United States, we develop a set of information requirements that must be satisfied to dispatch first responders and meet their immediate situational awareness needs. We then present a manual coding scheme to identify information satisfying these requirements in social media posts and apply this scheme to fictitious tweets professionals propose as actionable information to better assess ways that this information may be communicated. Finally, we propose automated methods from previous literature in the field that can be used to implement these methods in the future.

Keywords

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

INTRODUCTION

Researchers interested in utilizing social media to improve situational awareness have grappled with techniques to identify information that will be most relevant to emergency response. This study focuses on the information needs of public safety telecommunicators that dispatch emergency responders based on information provided over 9-1-1 phone calls answered at public safety answering points (PSAPs) in the United States.

First responders continue to seek out actionable, situational awareness information on social media that meets their specific information needs (Tapia et al. 2011). These needs vary depending on the roles and responsibilities of response agencies, and the particular emergency or crisis situation (Vieweg, Castillo, and Imran, 2014). However, recent research has tended to focus on identifying information available during a crisis at hand rather than focusing on information that addresses the specific needs of responders. Using various qualitative coding approaches, this research has identified situational information posted on social media during emergency events (Mazer et al., 2015; Olteanu, Vieweg, and Castillo, 2015; Saleem, Xu, and Ruths, 2014; Starbird, Palen, Hughes, and Vieweg, 2010; Vieweg, Hughes, Starbird, and Palen, 2010). These qualitative content analyses have, in turn, allowed the development of machine learning classifiers that can be used to automate the filtering of situational information (Herndon and Caragea, 2016; Imran, Castillo, Diaz, and Vieweg, 2014; Li, Caragea, Caragea, and Herndon, 2018).

Automated techniques have included methods to identify relevant tweets lacking keywords or hashtags related to a crisis event (Herndon and Caragea, 2016; Li et al., 2018). Techniques have also been developed to filter bots and other irrelevant information (Wang et al., 2014; Varol et al., 2017). As researchers have recognized that a great deal of information generated about crises are shared by news sources and external observers (Olteanu et al., 2015; Starbird et al., 2010), several studies have turned their attention to identifying eyewitness accounts that may be useful to first responders (Caragea, Squicciarini, Stehle, Neppalli, and Tapia, 2014). However, despite the extensive development of techniques to identify and filter event-relevant information, the question remains—what information do emergency dispatchers and first responders *really* need?

In this paper, we present criteria that would comprise a "golden tweet"- a post on Twitter containing actionable information for emergency dispatch and supporting the immediate situational awareness needs of first responders. We describe the two-stage process by which we elicited criteria characterizing actionable information from emergency dispatchers and responders, and then used these criteria to develop a qualitative coding scheme that can be used by researchers to identify actionable information posted on social media. We present these criteria and coding scheme as the main contributions of this paper and hope they will guide the development of automated methods to classify and filter information that can support the work of emergency dispatchers and first responders.

To understand criteria that would comprise a "golden tweet," we began by speaking with administrators, telecommunicators, and first responders about the way they themselves would create such a tweet in the face of an emergency. After asking them to create fictitious "golden tweets," we discuss the criteria they used to compose each message and held a conversation to evaluate one another's tweets. From this activity (and additional observations and interviews) we came to better understand protocols used to gather information from 9-1-1 calls, and gained insight into how criteria outlined in these protocols might be used to identify and filter actionable information on social media.

Using these criteria, we develop a qualitative coding scheme to identify actionable information posted on social media and apply the coding scheme to the "golden tweets" composed by professionals during the design workshop. We subsequently refine our coding scheme to develop a preliminary understanding of how this type of information typically gathered from phone calls could be represented in a social medial post. After describing the coding scheme and content analysis of this dataset, we suggest computer-assisted methods based on existing work that might deploy and develop coding schemas to identify and filter information that more closely matches the information needs of professionals. Lastly, we identify challenges that point to opportunities for future work.

EXAMINING TELECOMMUNICATORS INFORMATION SEEKING NEEDS AND ACTIVITIES

This section describes two concatenated methods and results sections that further our goal of identifying actionable information on social media. These methods include a design workshop activity to understand the information seeking needs of emergency dispatchers and first responders, and the development of a qualitative coding scheme for identifying information posted on social media that addresses these needs.

Methods: Information Seeking Needs

To better understand the information seeking needs and activities of public safety telecommunicators, our research team held a design workshop at a PSAP in an urban, highly populated county in the United States that is responsible for 9-1-1 call-taking and emergency dispatch. This work was motivated by an interest on the part of the PSAP director to begin using information on social media to better respond to local requests for service. The workshop focused on helping to define criteria that can be used to identify "golden tweets" that contain both useful and actionable information. The activity was held in three sessions. The first included PSAP administrators (director, deputy director, and operations manager), the second was held with telecommunicators (floor supervisors, call takers, and dispatchers), and the third was held with first responders (police, fire, and emergency medical services).

Rather than requesting criteria directly, we began with an activity instructing participants to reflect on a recent incident in their community that they are familiar with, for example, an incident that they experienced or that they had direct interaction with in their job. Based on that incident they were asked 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. An emergency scenario was not assigned to allow variety in criteria used to create a post. After the session, participants were asked to describe the criteria they used for inclusion of information in their post. Further, participants were asked to read the tweets that they constructed and others were asked to comment on how they might attempt to address this type of information (how they would take action) or whether additional information is necessary in order to address the incident. A list was made of information that was missing and thought to be important.

Other activities in the workshop anecdotally supported findings, these include interviews with the administrators, telecommunicators, and information technology staff (IT manager, CAD supervisor, and CAD technicians), as well as approximately twenty hours of combined observation. During observation periods, the authors more closely examined the individual and cooperative workflows of 9-1-1 call takers, dispatchers, and resource managers, including the Computer-Aided Dispatch (CAD), GIS, radio, and associated systems used by telecommunicators for call-taking and dispatch.

Results: Information Seeking Needs

In writing a golden tweet, the majority of participants reflected on a recent storm, mall shooting, or traffic accident. When discussing criteria used to create an actionable social media post, participants began by communicating that location is key. As one participant stated, "obviously we can't respond if we don't know where." All agreed that they included location information when constructing their post. Following some discussion of location information, further descriptors of the number of people injured, direction that perpetrators fled when they left the scene, and other follow up questions came naturally to the telecommunicators. Eventually, the conversation turned to the protocol that telecommunicators typically use to intake information—what is asked first, what is asked second, and so forth. Based on discussion of criteria that is most important to telecommunicators, we learned that many call centers across the United States utilize the 5W's (also referred to as the 6W's) to request information from 9-1-1 callers. This was described to us by participants as "the 5W's plus weapons." Simply, the W's are: Where, What, When, Why, Who, and Weapons (Figure 1 Left). After some additional discussion, telecommunicators indicated that the priority of this information is: Where, What, Weapons, When, Who, and Why (Figure 1 Right).

Many call centers today use computer generated protocols, such as ProQA (https://prioritydispatch.net/discover_proqa/), which integrates with computer-aided dispatch (CAD), GIS, Smart911, and associated systems used by telecommunicators. These tools provide emergency-specific question scripts and caller instructions in standardized text entry forms. These scripts assist call takers in determining the chief complaint or incident code, the emergency classification that determines the type and level of emergency, and in turn, the police, fire, or EMS resources that will be dispatched. Prior to computer-aided software, call takers simply used the 5W's, which remains the default for many centers when computer systems are down.

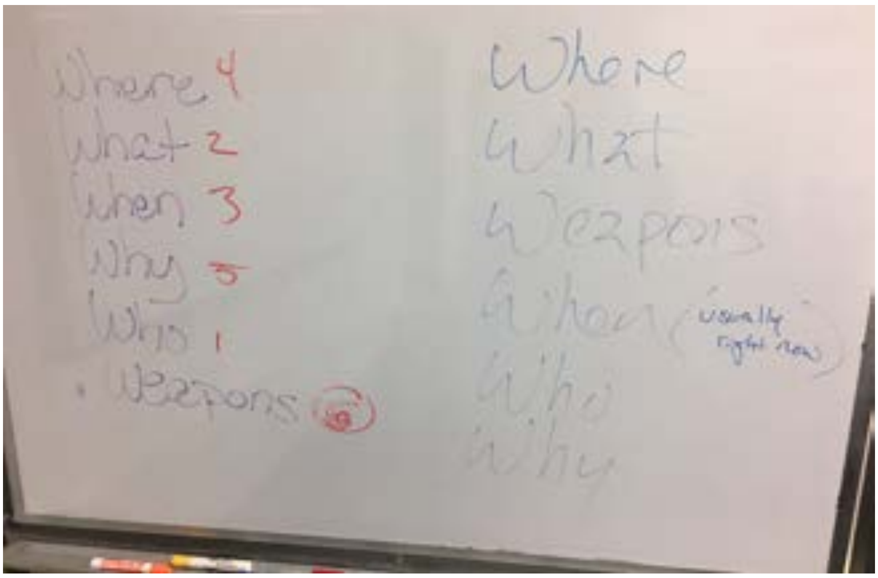

Figure 1. The "5 W's + Weapons" shown in order of protocol (left) and preferred order (right)

Methods: The Coding Scheme

To learn more about the 5W's and develop a coding scheme for each, we requested telecommunicators training manuals from the PSAP that we worked with, reviewed information available on the web created for telecommunicators in other areas (Craven County, n.d.; *Telecommunicator I: Basic Caller*, 2011), and reviewed information used to educate the public about the types of questions that 9-1-1 call takers will ask (Mundelein, n.d.; Office, n.d.). In each instance, there was general consistency among the descriptions of each of the 5W's. Because the purpose of this coding scheme is to identify information relevant to emergency dispatchers and first responders, we have adapted all W's into the coding scheme that will be henceforth referred to as the 6W's.

After translating the properties of each of the 6W's into a coding scheme (see Table 1) to be used for content analysis, we analyzed the content of the 34 fictional posts generated by administrators, telecommunicators, and first responders. Our analysis adopted the content analysis research process employed by Neuendorff (2002) which includes evaluative criteria, reliability as measured by intercoder agreement, and relevance. The fictional posts created in our design workshop were used to test relevance of the coding scheme because they were intended to be actionable tweets based on the participants' professional experience and were more likely to contain the 6W's. It was our interest to use these posts to recognize how the 6W's would be represented in a post to develop a qualitative coding scheme that can be applied to qualitative analysis of actual social media posts generated in emergencies in the future.

To develop the qualitative coding scheme, a preliminary codebook was created based on a review of materials written about the 6W's. The preliminary codebook was then applied to the 34 fictional posts by two researchers to ensure inter-coder reliability. As with other qualitative coding schemes (Kropczynski, Cai, and Carroll, 2015; Stromer-Galley, 2007), the code is applied in two phases. The first phase involves identifying words and phrases that communicate a line of thought; a line of thought may be communicated in a word, a set of words, or a complete sentence. Coding at the thought-level is an approach that has been adopted in qualitative analysis of social media posts to draw clear boundaries around portions of text. The second phase involves labeling relevant lines of thought with one of the 6W's according to the coding scheme. Since the purpose of this approach is to identify actionable information, other thoughts and phrases were not coded.

103 thoughts were identified and coded as relating to one of the 6W's, the two researchers found 86% agreement upon initial coding. After initial coding, the two researchers met to discuss items that were coded differently and discussed each until agreement was reached. The differences of opinion were used as an opportunity to elaborate on coding schemes to prevent error due to ambiguous phrasing of the codebook. Below is the Coding Scheme used to identify the 6 W's in the tweets along with representative examples from the fictional tweets.

Table 1. 6W Coding Scheme

Label (the W)	Coding	Representative Examples
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

Results: The Coding Scheme

This section first discusses frequencies of observation in the primary coding scheme and then describes the use of the 6W's in social media posts by participants. In the next section, we will interpret these findings and relate them to a refined coding scheme for further qualitative analysis. We will also review methods to automate these methods and discuss their implications for design rationale.

By employing the coding scheme, we were able to identify and count the use of each W in a tweet.

Table 2. Count of Tweets Containing Each of the 6W's

Label (the W)	Count (N = 34)	Percentage
Where	34	100%
What	34	100%
Weapons	12	35%
When	6	18%
Who	17	50%
Why	0	0%

None of the posts went beyond the 280-character limit, three of the posts indicated the inclusion of a picture or video (either hand drawn or a notation). Content analysis using the coding scheme reveals that participants perceived *where* and *what* information as most important to creating a social media post that would produce actionable information. The priority of this information was evidenced by the finding that every tweet composed by dispatchers and responders included some form of *where* and *what* information. *Where* information was written as intersections, buildings (i.e. points of reference), and in some cases, specific street addresses were added. *What* information was clearly articulated in tweets, but few included many details beyond the nature of the incident and did not discuss the severity of the incident. All posts that related to a shooting incident gave some indication if *weapons* were present. Few posts indicated *when* information, but, as the telecommunicators and responders expressed, we can often assume that events described in a social media post likely occurred just before the post was written, additionally, messages posted on social media include timestamps. Moreover, a few posts used the word "just" indicating that the event had happened at that moment, while others included a specific time that the incident occurred. Of posts that did not include *who* information, the large majority were related to a storm incident that occurred. In other posts that did not include *who* information, it might be assumed that the user posting the information is the *who* is involved in the incident, however, our coding scheme focused on the content of the tweets rather than extracting profile information. None of the tweets included *why* information. We might assume that this is because that information is either unnecessary for action to be taken or difficult to explain quickly within a 280-character post. The next section reflects on these findings and methods to automate qualitative content analysis.

DISCUSSION

The ISCRAM community has worked for many years to find new ways to make better use of social media data to aid responders. Over the last few years, several computational methods have been proposed to automate the processing of social media data for emergency and crisis management. These techniques aim to solve various challenges ranging from parsing unstructured and brief content, to handling overload by filtering noisy content, and the summarization of relevant information (Castillo, 2016; Imran, Castillo, Diaz, and Vieweg, 2015).

Following from the results, we discuss the implications of our preliminary coding scheme for automated methods to detect each W within real time social media streams. Information scientists have long worked to automate qualitative coding schemes as a method to scale coding techniques to large datasets and make use of coding schemes in real-time (Crowston, Liu, and Allen, 2010). Our interest in developing this coding scheme is no different. We do this by first reiterating the emergency dispatch and response activity associated with each of the W's, and then review prior work utilizing automated methods to uncover this type of information. In this section, we have identified existing work that relates to each of the 6W's. Lastly, although, much work in this area has been accomplished, we acknowledge outstanding challenges and future work needed to better match automated methods for classifying and filtering information posted on social media with the information needs of emergency response.

Table 3 provides a summary of this section. This is not intended to be a comprehensive summary of existing resources, but rather a suggestion for starting points to develop automated methods that can identify actionable information posted on social media associated with each of the 6Ws. We further discuss the aims, existing resources, and future work for each W below.

Table 3. Aims, existing, resources and challenges summary of each of the 6W's

	Aim	Existing Resources	Challenges/Future Work
WHERE	Latitude/Longitude of incident, or specific boundary box	Geotags (Intagorn & Lerman, 2010; Daly & Thom, 2016); NLP entity extraction and gazetteer databases (Bilhaut et al. 2003; Quercini et al. 2010; MacEachren et al. 2011); Social Triangulation (Grace et al. 2017); Location Indicative dialect (Han et al. 2012; Han et al. 2014)	Large portion of messages do not contain geographic metadata; those that contain geotag may provide a location different from the location of the incident; multiple "where" descriptors may or may not appear together in text
WHAT	Associate incident with incident code used by PSAP	NLP, extracting activity; intensity (Halse et al. 2016); classification based on images (Mouzannar & Awad, 2018)	Use of emojis, incident classification and categorization; detection of event scale
WEAPONS	Specify type of weapon or at least identify presence of weapon	Bag of words; Convolutional Neural Networks (Caragea et al. 2016)	Any object may be a weapon; image recognition
WHEN	Understand if it is a current, ongoing emergency that requires a first responder	Typically now; Day/time rules; tense; metadata such as timestamp	Most tweets don't include time, so we might assume that "just now" is implied
WHO	Full description of victims and/or suspects and/or vehicles; know how many people are injured/armed; understand if information is posted by an eyewitness	Bag of words; NLP; NER; Name in Twitter Profile; @mention	Includes a variety of information that may be difficult to predict with NLP alone, such as the entity varying from a person to a vehicle, it may also include a count of people, and detailed descriptions
WHY	Information typically used for a police investigations	Information contained in pictures and videos	Twitter privacy policy does not allow use of API to monitor individuals; many posts do not include "why" information

WHERE: Information Aims, Existing Resources for Automation, and Automation Challenges

Aim: Location information is critical to emergency response. Simply put, without an incident location it is very difficult to provide a response. Consequently, the aim of discovering where an incident has occurred is the priority of responders. Location identification first attempts to identify specific latitude and longitude coordinates indicating where resources should be dispatched. If precise coordinates are unavailable, a secondary attempt involves identifying an area in which the incident has occurred, often in relation to a point of reference (i.e. such as a building or intersection), in order to dispatch a response to that area.

Existing Resources: Geographic metadata (e.g. geotags) have provided a useful source of location information to the crisis management community (Intagorn and Lerman, 2010). Geographic metadata has also been obtained through mining and classifying image posts for its EXIF data (Daly and Thom, 2016), however, Twitter has adopted a policy of scrubbing images of this information. In addition to quickly changing policies that make harvesting geospatial knowledge from social metadata difficult, it also known that on average, 1-3% of all tweets are geotagged (Morstatter et. al., 2013).

As a result, a number of other tools have been developed to geolocate the precise location of a tweet, or identify a particular geographic region from which it likely originates. Natural language processing tools (NLP) have been used to extract entities that identify geographic points of reference (Yin et al., 2012) through named entity recognition (NER). Studies have also used these geographic references with gazetteer databases, to infer users' locations (Mahmud, Nichols, and Drews, 2014), and have built on these approaches with rule-based (Bilhaut, Charnois, Enjalbert, and Mathet, 2003) and machine-learning methods (Quercini, Samet, Sankaranarayanan, and Lieberman, 2010). Senseplace2, for example, extracts named entity information from twitter data and geocodes locations with coordinates of the best matching location returned from the Geonames.org web service (MacEachren et al., 2011).

General location information has also been deduced using users' social networks, including geo-location inferencing based on the number of local organizations a user follows known as Social Triangulation (Grace et al., 2017). Additionally, the use of location-indicative dialect, such as the words "yinz" and "dippy" used in Pittsburgh, or semi-local words that refer to some features of a relatively limited subset of cities (Han, Cook, and Baldwin, 2012, 2014), have been deployed to identify users in a geographic area.

Challenges/Future Work: From our review of actionable tweets composed during the design workshop, it is clear that even a geotagged tweet may provide the wrong location information for the purposes of emergency dispatch. One participants' tweet, for example, indicated that anyone headed to the mall should turn around due to an active shooter there. General location references such as "mall" can point to multiple locations, and, require analysts to make further inferences to ascertain the location of an incident. Such challenges fall under the *where* category. As the coding scheme notes, several conditions help describe types of *where* information and each could utilize a different method to automate coding: where help is needed; where an incident occurred; where are the locations of victim/suspect/witness; as well as directional guides (i.e. direction a vehicle is moving in) in relation to points of interest.

WHAT: Information Aims, Existing Resources for Automation, and Automation Challenges

Aims: The *what* category, as it applies to the work of dispatch, identifies the type of incident but also associates that type with the appropriate resources and personnel needed for response. As we learned in our fieldwork, computer-aided dispatch (CAD) software helps call takers and dispatchers associate information obtained from 9-1-1 callers with emergency-related incident codes that first responders use to understand the nature and response requirements of an emergency. Future systems stand to improve this categorization work by gathering information related to an emergency that can assist the determination of incident codes, and provide additional, contextual information that can guide first responders' decision-making processes.

Existing Resources: Prior research has utilized keywords associated with particular emergencies in order to detect incidents such as traffic accidents (Gu, Qian, and Chen, 2016), or, for disasters, developed lexicons to assist in the collection and filtering of social media to identify crisis-related information (Olteanu, Castillo, Diaz, and Vieweg, 2014). In addition, NLP can be used to extract activity words associated with emergencies using language models based on social media users' communication patterns (Kumar, Jiang, and Fang, 2014). Other techniques include sentiment analysis measures of language intensity that can indicate information posted on emergencies (Halse, Tapia, Squicciarini, and Caragea, 2018). Most recently, scholars have begun extracting this type of information from images embedded within posts (Mouzannar and Awad, 2018).

Challenges/Future Work: One challenge raised by a participant was that individuals wishing to express unfolding events quickly may use emojis rather than text to express, for example, that a shooter is present, or use "praying hands" to indicate that they are in need of help. Researchers are working on new methods to conduct search and information retrieval based on these words, but little work has been done to categorize emojis most often associated with emergency incidents.

WEAPONS: Information Aims, Existing Resources for Automation, and Automation Challenges

Aims: Participants consider this an important category because it directly relates to the type of response that will be dispatched, and provides first responders with critical situational information about potential hazards. The minimum critical information is to know if a weapon is present, however, it is ideal to know the exact kind of weapon present on the scene.

Existing Resources: Some cities in the United States utilize audio-based gunshot detection systems to alert authorities to the use of weapons in an area (Valenzise et al. 2007). Few papers have addressed this issue, and this issue may be more apparent in some countries than in others. One potential direction is to utilize a bag of words approach may work for identifying potential weapons. ProQA and other computer-aided systems have developed codes for PSAPs to classify weapons to be entered into these systems and these lists might be used to develop a bag of words.

Challenges/Future Work: One challenge with automated detection is that anything can be used as a weapon and the way that people describe the presence of weapons will evolve over time. Researchers (Caragea, Silvescu, and Tapia, 2016) have shown that Convolutional Neural Networks can show significant improvement over the bag of words approach for detecting information during a major event and that approach may be applicable here.

WHEN: Information Aims, Existing Resources for Automation, and Automation Challenges

Aims: This information is used by dispatch to determine if the incident is an ongoing emergency that requires a response.

Existing Resources: In many studies, the timestamp of the tweet is used to indicate the time of the incident. Day/time rules could be applied to attempt to find this type of information in a tweet. The tense of the tweet might also be used to indicate whether the tweet is actively taking place or if it is something that happened in the past. Our study showed that some professionals working in this field indicated *when* the incident had taken place, but this may have been based on their own knowledge of the 6W's and an interest in including as much relevant information as possible.

Challenges/Future Work: In our experience, many tweets did not contain a time, so it is an assumption that the incident is still ongoing.

WHO: Information Aims, Existing Resources for Automation, and Automation Challenges

Aim: This category has many aims depending on the response context. From the design workshop, the most common aims for this category were to obtain descriptions of victims and/or suspects at the scene of an incident, to know the number of people injured or armed, and to discern whether the post originated from an eyewitness or a secondary source. In cases such as the storm events participants created posts about, *who* information was not necessary used to take action. Moreover, we also found that the *who* can refer to a person or, in some cases, a vehicle (see notes in coding scheme). These layers of complexity are why the *who* category may be the most complex, and one that finds limited related research in the literature.

Existing Resources: Qualitative content analyses find that eyewitness remain limited among social media users during crisis (Starbird et al., 2010). Analyzing information posted on social media across multiple disasters, Olteanu et al. (2015) find that eyewitness reports- direct observations of events- account for only 9% of all disaster-related posts collected from Twitter. Consequently, identifying eyewitness information remains a challenge for automated methods required to classify sparse reports within large datasets of derivative or unrelated information.

Several recent studies attempt to use machine learning and other methods to detect whether a post originated from an eyewitness or another source (Caragea et al., 2015; Tanev et al. 2017). In our coding of tweets, we identified *who* language such as "I" or "we" that can suggest the post originated from an eyewitness. Similarly, bag of words approaches have been adopted to identify eyewitness accounts, including methods that take into account accompanying information.

Named Entity Recognition models may also be used here to identify names in the tweet and simple tags within the tweets such as @mentions. It could be an indication of someone involved. However, we believe that it would be somewhat unlikely that an @mention would be used to direct link to a victim or perpetrator. Another simple technique would be to simply extract the name of the poster from profile information since they may be the person involved and it could be helpful to identify them by name when responding to the incident.

Challenges/Future Work: As previously mentioned, this category contains a variety of information that may be difficult to categorize using NLP models alone because an entity may vary from a person to a vehicle or includes numbers of people involved in an incident or warrant a complete description of the individual. As suggested for the *where* category, it would be important to develop classifiers for each type of *who* information mentioned in the coding scheme: Full description of victims and/or suspects and/or vehicles; know how many people are injured/armed; and understand if information is posted by an eyewitness.

WHY: Information Aims, Existing Resources for Automation, and Automation Challenges

Aim: From our review of literature describing the 6W's, it would appear that this is not often used on the scene, but rather it may support police investigations after a first responder has addressed the situation.

Existing Resources: Information contained in pictures and videos as well as the content of the tweets have been used to support police investigations in the past.

<u>*Challenges*</u>: An immediate challenge of this category, is that from our small sample of fictitious tweets intended to provide actionable information, no tweets included *why* information. More pressing is that the Twitter Privacy Policy does not allow companies that utilize their API or Firehose to monitor individuals for investigation. This type of information may create conflicts in data gathering.

CONCLUSION

This work is guided broadly by the overarching research question—what information do emergency dispatchers and first responders *really* need when it comes to using social media data for situational awareness? We take steps to answer this question through concatenated methods to inquire into public safety telecommunicators information needs when dispatching emergency responders, and then utilizing knowledge of information needs to understand how this type of information would be represented on social media.

The primary contribution of this paper is the development of a qualitative coding scheme that can be used to identify actionable information posted on social media for emergency dispatchers and first responders. Significantly, this coding scheme matches the protocols for information seeking and gathering that are commonly used by PSAPs in the United States. We also help to identify existing automated methods to gather this data in order to point to directions for future work.

A limitation of this preliminary work is that the coding scheme has only been utilized to evaluate fictitious tweets. Future work in this area will apply the coding scheme to posts extracted from Twitter to develop more specific classifiers. Other efforts to extend this work involve developing an interface to view social media data separated by the 6Ws. Just as we have worked to identify information that best meets the information needs of public safety telecommunicators, future work would attempt to present the information in a way that can be best integrated into the established work flows of emergency dispatchers and first responders.

While a great deal of work has been done over the past decade to prove the relevance of social media in emergency and crisis management by identifying social media posts that may be relevant to situational awareness, these methods have not been specifically tailored to the information needs of emergency dispatchers and first responders. By considering the 6W's we present a more nuanced approach to identify actionable information that supports the information needs of emergency response.

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