Classifying User Types on Social Media to inform Who-What-Where Coordination during Crisis Response

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ABSTRACT

Timely information is essential for better dynamic situational awareness, which leads to efficient resource planning, coordination, and action. However, given the scale and outreach of social media—a key information sharing platform during crises, diverse types of users participate in discussions during crises, which affect the vetting of information for dynamic situational awareness and response coordination activities. In this paper, we present a user analysis on Twitter during crises for three major user types—*Organization*, *Organization-affiliated* (a person's self-identifying affiliation with an organization in his/her profile), and *Non-affiliated* (person not identifying any affiliation), by first classifying users and then presenting their communication patterns during two recent crises. Our analysis shows distinctive patterns of the three user types for participation and communication on social media during crises. Such a user-centric approach to study information sharing during crisis events can act as a precursor to deeper domain-driven content analysis for response agencies.

Keywords

User Classification, Social Media, Crisis Coordination, Organization, Organization-affiliated.

INTRODUCTION

Social media has empowered citizens to contribute to situational awareness of crisis response teams (Vieweg et al., 2010), who share time-critical observations (Imran et al., 2013) and report needs and offer to help (Purohit et al., 2013), in addition to being instrumental in community healing (Glasgow et al., 2016). Albeit, the consequence of this citizen empowerment has also led to an overload of information, described as big crisis data (Castillo, 2016), which challenges response organizations to leverage citizen-generated data on social media for crisis response coordination (Hiltz and Plotnick, 2013; Whipkey and Verity, 2015). These information filtering challenges align with different aspects of the information coordination for response teams, such as source (*who* shares information), topic (*what* is the information about), and location (*where* is the information shared from).

Prior research in crisis informatics on social media has indeed focused on mining topics and behavior in the content of shared information, studying credibility of information as well as estimating information origin (Imran et al., 2015). The focus of our study is an analysis of the source of information. For improving crisis response coordination, fine-grained understanding of information sources is critical to help improve systematic filtering and vetting of information for trustworthiness (Tapia et al., 2011; Hughes and Chauhan, 2015), such as through detecting on-ground informants (Starbird et al., 2012) or emergent informants (Purohit et al., 2014). Our goal is to focus on automatically detecting organization users, and organization-affiliated users such as traditionally recognized and virtual group volunteers (Reuter et al., 2013), who come forward to help response and relief coordination, however, may or may not be in coordination with each other. This problem is challenging given that most of the social media platforms, especially Twitter in this study, do not provide any field for such user type information in the user profile metadata. However, identifying such user types is essential, given that understanding the dynamics of engagement between emergent organizations and groups during crises (Majchrzak et al., 2007; Opdyke and Javernick-Will, 2014), both governmental and non-governmental stakeholders, is invaluable for improving response coordination, and requires both identification and interaction analysis of user types. The proposed method for automatic identification of user types in real-time can help improve understanding of diverse voices (individuals on behalf of organization and organizations themselves) to assist responding agencies better interact and explore the massive corpus of rapidly generated data on social media, and improve downstream analysis for filtered crowdsourced inputs to aid situational awareness and coordination (Blanchard, Carvin, Whitaker, Fitzgerald, Harman, Humphrey, 2012; Van de Walle, Brugghemans, and Comes, 2016).

We ask the following research questions in this study:

1. Can we classify information sourcing user types in social media communities during crises, i.e. specifically, *Organization, Organization-affiliated* (person identifying affiliation with an organization in his/her profile), *Non-affiliated* (person not identifying any affiliation), and others?
2. What are the patterns of participation of *Organization* user types during crisis responses of two recent events?
3. What are the patterns of content shared by the *Organization*, *Organization-affiliated* and *Non-affiliated* users?

We propose specifically a user classification method using supervised machine learning techniques for assisting rapid social media analytics on information streams of the Twitter microblogging platform, and present an analysis of two recent crises using this method. Our classifier achieved accuracy up to 75% and F1-score up to 71%, where the proposed method exploited user profile information for feature extraction, providing an advantage for real-time analytics to filter continuous information flow for *who*-what-where analysis during crisis responses. The following are examples of *Organization, Organization-affiliated* and *Non-affiliated* users on Twitter in our study, respectively: *a.) The official Twitter account for the American Red Cross, b.) PR Chick, Red Cross Disaster Volunteer, Traveler, Lover of Books, dismal dog trainer of Oscar Wild, and c.) Artist and illustrator, UK based. Digital painting and oil painting. #artist #illustrator #creative #painting #art #Hampshire.*

The proposed technique acts as a precursor for understanding and performing domain-driven analysis of content using domain taxonomies and ontologies of content categorization (Keßler et al., 2013). Responding organizations have increasingly followed keywords during crises and shared content, as well as followed other organizations and individuals on behalf of organizations, although communication of all these users may reflect different behavior as a part of the formal response community. This communication exchange, among responders, organizations and between these entities represent a unique subgroup of the larger corpus of "citizen voices". This subgroup can be inferred to represent a domain driven set of information sources and affiliations as a part of an established community of practice. Organizations also selectively follow specific organizational Twitter accounts with the aim that this trusted set of user accounts are a proxy information source for aligning common purpose-driven information. For instance, NetHope a consortium based NGO that collaborates with over 50 organizations, has a crisis informatics team that follows specific members' Twitter accounts during early phases of a crisis response to improve situational awareness of its members' activities and evolving response needs.[1] The proposed automated technique for source analysis can be used for finding the most informative or significant region-specific organizational user accounts for developing a repository for better future disaster preparedness.

RELATED WORK

Social media platforms have been extensively studied for crisis informatics lately (Imran et al., 2015). One premise described by Zavarella et al. (2014) is the need to transform social media information into a form that can populate existing crisis response knowledge bases, to allow harnessing of social media information into actionable knowledge for response coordination. For that, different kinds of analyses have been performed with a focus on information content and information source to provide some degree of structure to the unstructured data and develop a knowledge base. Primarily, the content-driven analysis of information flowing on social media has been explored extensively for topical and behavioral information extraction, both qualitatively and quantitatively. The dimension of information sources—users, still requires analysis from diverse perspectives.

Among the user analysis for crisis events, prior literature has broadly investigated problems of user influence analysis, patterns of trustworthiness, and onsite versus virtual users. Vieweg et al. (2010) characterized crisis events by different types of information sources who posted messages and contributed towards situational awareness to varied degrees, however, relying on a manual method for user type analysis. Similarly, Olteanu et al. (2015) presented an information source analysis for types of user accounts across several crisis events by

[1] Internal communications with NetHope Crisis Informatics: http://www.thepattersonfoundation.org/blog/the-anatomy-of-an-emergency-nethope-provides-information-to-emergency-responders.html

analyzing manual crowdsourced annotations of users. Among automated methods, Starbird et al. (2012) proposed an automated method to identify on-ground informative Twitter users, while Purohit et al. (2014) proposed a complementary automated method to identify emerging informative users using *who-talks-to-whom* interaction networks. Other approaches (Gupta et al., 2012; Kumar et al., 2013) have proposed methods for identifying community representatives in the network using centrality measures, and a set of *whom-to-follow* based on a user's topical affinity.

In these related approaches for crisis event analysis, the automated identification methods for *Organization* and *Organization-affiliated* user type analysis are lacking despite the recognition among disaster and humanitarian response communities that trusts between individuals and groups – how they share and exchange information – play a large role in coordination activities (Harvard Humanitarian Initiative, 2011; Vinck, 2013). Prior literature on social media analytics in general, non-humanitarian context provides guidance for detecting *Organization* type users on Twitter (De Choudhury et al., 2012; McCorriston et al., 2015; Oentaryo et al., 2015), although not for *Organization-affiliated* user types. We also suspect different communication patterns of *Organization* (or *group)* user types in the humanitarian context, as they are purpose-defined and communicate in a time-intensive environment to deliver response and relief. Foreman et al. (2013) provide a context for the role of emergent collective identity, where user types of *organization* and *organization-affiliated* can be investigated for voicing similar agendas through different channels. Operational use of organizational Twitter accounts (or affiliated individuals) can be inferred as a part of a trusted network of users with common operational interests during a crisis response that is critical to overcoming barriers for response agencies (Hiltz et al., 2014). The identification of such potential user types is essential.

CLASSIFYING USERS BY TYPES

Our goal is to study differences in the patterns of information sourcing and communication by the different types of users, by first automatically classifying them into three key groups of interest, followed by analyzing the content practices of such user type groups. Technically, our problem is a classification problem, where given a user on social media who has posted relevant content about a crisis event, we want to classify whether the user belongs to any of the following user types—*Organization*, *Organization-affiliated*, *Non-affiliated*, and others as *none*. We first describe data sets for our analysis, followed by manual user classification approach, which provided labels for designing an automatic classifier to categorize user types.

Table 1. Seed Keyword Sets for Event Data Collection

Event	Seeds
Matthew	daytona beach storm, daytona beach hurricane, #daytonabeach, #jacksonville, jacksonville storm, jacksonville hurricane, jacksonville rains, cape canaveral storm, cape canaveral hurricane, cape canaveral rains, brunswick storm, brunswick rains, brunswick hurricane, savannah storm, savannah hurricane, savannah rains, myrtle beach storm, georgetown storm, charleston storm, myrtle beach hurricane, georgetown hurricane, charleston hurricane, wilmington storm, wilmington hurricane, wilmington rains, myrtle beach rains, georgetown rains, charleston rains, matthew georgia, hurricane georgia, storm georgia, storm ga, hurricane ga, rains georgia, rains matthew south carolina, hurricane south carolina, storm south carolina, storm ga, hurricane sc, rains sc, carolina rains, carolina storm, carolina hurricane, matthew south carolina, hurricane south carolina, storm north carolina, storm nc, hurricane nc, rains nc
Louisiana	louisiana, baton rouge, louisianaflood, louisianafloods, louisianaflooding, prayforlouisiana

Datasets for Analysis

We collected data for two recent crisis events in 2016 with different scales of geographical impact. The first one is *Hurricane Matthew (Matthew)*—the deadliest hurricane of 2016 that affected over 15 countries including multiple states of United States and resulting in an international response for severely affected counties including Haiti. The second dataset is *Louisiana Floods (Louisiana)*—one of the largest recent natural disasters since Hurricane Sandy in the United States.

For collecting data, we employed a keyword-based crawling approach for English language tweets, which is the most common method for Twitter data studies in the prior literature for event analysis. For collecting relevant Twitter data for an event, we first prepared a seed set of keywords relevant to an event by observing tweets on the Twitter with searches for 'hurricane matthew' and 'louisiana flood' as well as related news articles, in addition to observing top 100 hashtags and terms in the collected data (seed sets provided in Table 1). We then used Twitter Streaming API[2] with 'filter/track' method to collect relevant tweets containing any of the seed keywords in tweet metadata fields[2], such as for a keyword w, it will provide any tweet containing w, #w or W. We stored all the relevant metadata such as tweet text, posting timestamp, tweet type such as retweets, as well as authoring user's self-reported author profile information such as full name, and location.

Manual User Classification

We discuss the crowdsourcing process here first. The annotation task was designed in a crowdsourcing platform—CrowdFlower[3]. Annotators were asked to visit user profiles on Twitter for the sampled set of users, in order to annotate the user type. At least three judgments were taken per sample for the annotation. The job instructions were refined initially with few test users (n=50) until the annotators fully understood the labels and annotated them per our needs (determined by the CrowdFlower platform using proportions of the number of missed judgments to the correct ones). The job instruction to identify the type of user account included a multiple choice single-select question to answer among the following options - a.) *Organization*: if the user profile identifies the Twitter screen-name/handle as an organization or group, such as through a website link to that organization or group, b.) *Organization-affiliated:* if the user looks like a person with an organizational affiliation, where the affiliation must be explicitly mentioned in the user profile (e.g., founder of..., manager at..., working for...), c.) *Non-affiliated*: if the user looks like a citizen, who does not show any organizational affiliations, and d.) *None:* if the user looks like a bot or cannot be determined.

Sampling for User Type Labeling

We select a sample of the data using stratified sampling approach (Nassiuma, 2001) to create a small sample of tweet authors for manual classification via the crowdsourcing task. A total of 1500 unique users were selected from each event dataset. We discarded resulting user annotations with confidence score[4] (platform-provided) less than 60%, to help ensure the quality of manually labeled data for automated classification. The resultant sample size of labeled users for Louisiana event is 1456 and Matthew event is 1472. Table 2 provides the descriptive statistics of our full and labeled dataset.

Table 2. Event Datasets and Labeled Data

Events (2016)	No. of Tweets	No. of Authors	Labeled Users Types			
			Organization	*Organization-affiliated*	*Non-affiliated*	*None*
Louisiana Floods (Aug 14 - Sep 30)	2,884,000	922,010 Labeled Users: 1456	182 12.5%	107 7.3%	1004 68.9%	163 11.1%
Matthew Hurricane (Oct 6 - Nov 30)	3,692,000	1,760,928 Labeled Users: 1472	242 16.4%	129 8.8%	997 67.7%	104 7.0%

Automatic User Classification

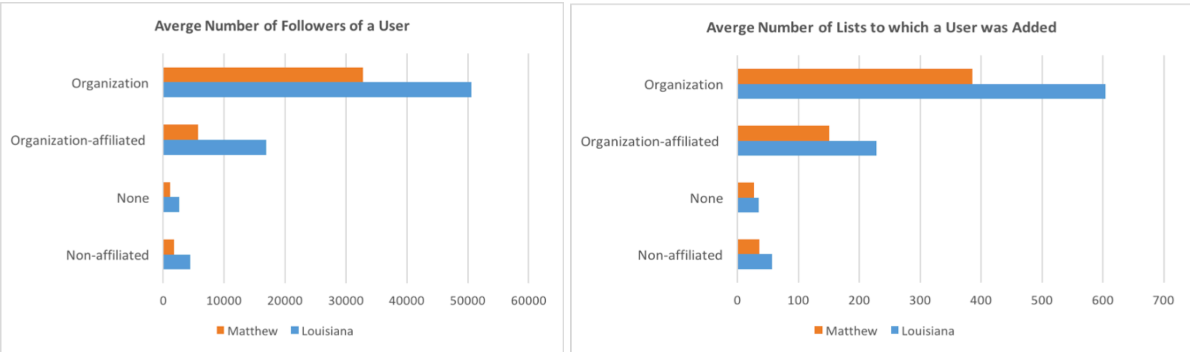
The user classification is done automatically using a classifier trained on the labeled dataset of the manual user classification. The required steps of the automated process consist of basic data preprocessing for acquiring and cleaning the specific metadata associated with users such as profile bio description. This is followed by extracting features from the metadata, such as word frequency in the bio description text. Finally, a supervised classifier is designed based on experimenting with different machine learning algorithms.

Candidate Feature Identification

We explored a variety of user profile metadata for identifying possible feature sets, using the labeled data corpus. Prior research on user modeling on Twitter has used users' social and activity features, such as the

[2] https://dev.twitter.com/streaming/overview/request-parameters#track
[3] https://www.crowdflower.com/
[4] Confidence score describes the level of agreement between multiple contributors (weighted by the contributors' trust scores), and indicates a "confidence" in the validity of the result: https://success.crowdflower.com/hc/en-us/articles/201855939-How-to-Calculate-a-Confidence-Score

number of friends, followers, and statuses. Figure 1a and 1b show the contrast between the distributions of an average number of followers and an average number of lists a user has been added to, for different user types, such as *Organization* versus *Non-affiliated* individual user types. We also exploited the user bio description to create text-based features, which are one of the critical sources of information about the user interest and background. A potentially informative feature for user type is also account status being 'Verified' on Twitter, which is often the case for *Organization* accounts, such as *@RedCross*. However, in our labeled user dataset, we observed that less than 2% of users actually had the 'verified' status, and thus, we did not include it in our potential feature set. It is likely due to the unique crisis context where a diverse range of users participates in the discussion on social media about the evolving situation. Interestingly, we noticed that the majority of organizational users in our labeled user dataset had external URLs in their profiles, linking to their organization's webpages. Thus, we involved this in our feature set as described in the subsequent section.



(1a) **(1b)**

Figure 1. A contrast between the characteristics of user types that informs the feature design of the classifier.

Feature Extraction

The Twitter API provides a diverse set of user metadata attributes, some of which can be leveraged to create features for capturing distinctive characteristics of user type classes. We specifically consider the following feature set for our experimental design:

1. *n-grams* (of user profile description) – unigram (single word), bigrams (a pair of consecutively written words) of the user description text, which provide key details about a user's type, such as *Organization*.
2. *Friends count* – The number of users a user is following, which shows user's interest towards other users, and we anticipate a lesser mean value for *Organization* users.
3. *Followers count* – The number of followers a user has, which shows a user's influence. *Organization* user types are likely to have more followers.
4. *Statuses count* – The number of tweets (including retweets) by a user, which show user activity in general.
5. *Favorites count* – The number of tweets a user has chosen as 'favorite' over time, which shows the user's consistent engagement activity.
6. *Listed count* – The number of public lists a user is a member of, which shows one way to gauge a user's influence degree if others have listed the user in their topical interest lists of followees.
7. *Profile_URL – A* binary feature for the presence or absence of an external URL in the profile metadata, which is often present for *Organization* user types.

For generating *n*-grams features, we first apply the standard text pre-processing steps – lowercasing, tokenization, and stop-words removal on the user description text field, followed by stemming, and transforming a preprocessed text string into *uni*- and *bi*-grams, using the *StringToWordVector* method in Weka[5] tool. The value of an *n*-gram feature is computed using the phrase frequency (*tf*-scoring) (Salton et al., 1975). We select the top 1000 features for the *n*-grams based on *tf*-scoring.

Classifier Algorithm and Results

Using Weka[5] data mining tool, we experimented for the user type classification task. We first explored Random Forest and SimpleCart algorithms that are popular for supervised classification. We further employed an adaptive boosting algorithm – AdaBoost – to improve the classification performance (Witten et al., 2016). These algorithmic approaches have been studied in prior literature for analyzing diverse types of data for classification

[5] http://www.cs.waikato.ac.nz/ml/weka/

problems, where they have performed well. The default parameters are used for the above algorithms in Weka tool. We perform a 10-fold Cross Validation (CV) for reporting robust performance indicators. We use the accuracy (proportion of correctly predicted training samples) and F1-score (harmonic mean of precision and recall, where precision is the ratio of predicted true positives to all predicted positives, and recall is the ratio of predicted true positives to all actual positives) as the performance measures. These are common measures to evaluate the performance for multiclass classification problems.

Table 3. Results for Automatic User Classification, using 10-fold CV (mean Accuracy and F1-score)

Experiment Algorithm	Louisiana		Matthew	
	Accuracy%	**F1-score%**	**Accuracy%**	**F1-score%**
SimpleCart (SC)	72.1	65.0	71.9	66.0
Random Forest (RF)	71.2	67.0	75.1	71.3
AdaBoost with SC	73.2	67.9	72.8	68.5
AdaBoost with RF	73.4	68.5	75.3	70.8

Results are provided in Table 3 that show a range of fair to good performance for accuracy and F1-score measures, with a value of area under the receiver operating characteristic curve up to 0.8 (good discrimination ability). We observed that the overall accuracy near 75% is likely due to the challenge of difficulty in estimating the latent inference of the user type by only user profile information. Although the use of content features from the user's past historical tweets could be useful to further boost performance, our context is particularly crisis situations where there is not enough time to collect historical data of users. We observed that the experiment of boosting algorithm with RF gives a better result than the experiment with SC algorithm for the multiclass case, it is likely because of RF being an ensemble classifier (Witten et al., 2016). We plan to explore the hierarchical classification approach in future studies, given its flexibility to develop an extensible framework for user type analyses, for example, classifying individuals further by demographics of gender.

Table 4. Classified Users in the Pruned Event Datasets across User Types

Types	Classified User Types in Events	
	Louisiana	**Matthew**
Organization	39,718 (6%)	78,809 (6.3%)
Organization-affiliated	11,318 (2%)	25,430 (2%)
Non-affiliated	613,301 (89%)	1,132,208 (90.3%)
None	24,505 (3%)	17,511 (1.4%)

ANALYSIS OF USER TYPES

To study the patterns of communication of the user type categories, we first applied the automatic classifier on a pruned dataset of the complete user set described in Table 2. The motivation for pruning was to only analyze those users and their content practices where the tweet content contained the seed words, unlike any metadata field of the tweet post. Table 4 presents the results for the classified users in the pruned dataset. The majority of the users are individuals with no affiliations reported in their profiles, which may likely be due to self reporting nature of the platform as well as anonymity and privacy concerns. We observe that nearly *6% Organization* user accounts are present in the two events., and only less than 3% (although still substantial numbers due to the scale of the datasets) users actually belong to *Organization-affiliated* user types (e.g., *11k* users for Louisiana event and *25k* users for Matthew event). It can be expected that organization accounts are fewer than individual accounts. Although the importance of such accounts can be generally observed with higher proportion of influence measures in general, for example, by number of followers. An organization account of a responding agency or its affiliated user's account is likely to be followed by many, if they engage on social media during crisis events. For instance, Twitter user account of *American Red Cross* has a number of followers as *3,743,915*.

Content Practices of *Organization*, *Organization-affiliated,* and *Non-affiliated* User Types

We anticipate diverse patterns for the content generation practices by the three types of users in our pruned datasets. In Table 5, we present a comparison between tweets posted by the three key user types, for different characteristics of tweeting practices: number of tweets being *Retweets (forwarding message/post)*, number of tweets being *Reply* or *Mention (referencing another user),* and number of tweets containing *External Links (implying external context linking).* We computed the proportion of each of these characteristics of tweets with respect to the total tweets posted by users of a type class.

Table 5. Comparison of Content Practices in Tweets Posted by the Classified User Types (in Table 4)

User Type	Retweet Proportion		Reply & Mention Proportion		External Links Proportion	
	Louisiana	Matthew	Louisiana	Matthew	Louisiana	Matthew
Organization	21%	22%	7%	8%	72%	62%
Organization-affiliated	46%	61%	11%	10%	67%	59%
Non-affiliated	71%	68%	8%	8%	57%	50%

We made a number of observations from Table 5 for analyzing crisis events effectively, by user types (information source types) in future. For instance, when analyzing the retweeting of a post by an *Organization* or *Organization-affiliated* user than *Non-affiliated* user*,* higher weight can be associated while vetting the information provided by the message post. Albeit, we are not proposing to completely discard the downstream analysis of the content of *non-affiliated* users independent of user types, which may be important from a perspective of another information source attributes in providing timely situational awareness information.

1. *Organization* users are less likely to *retweet* in contrast to *Non-affiliated* users with highest likelihood, reflecting their type of social media engagement during a crisis as information givers, instead of serving as receivers and propagators. Recent efforts (U.S. Department of Homeland Security, Science and Technology Directorate, Virtual Social Media Working Group, 2013) in the formal response community are starting to find ways for gradually increasing usage of social platforms via *Organization* accounts to source and receive information from citizens, beyond public relations (PR) type of engagement.
2. Both *Organization* and *Organization-affiliated* users are likely to participate in social media conversations with differing degrees. It shows an interesting direction for future analysis of crisis events, in understanding common or conflicting patterns of information sharing for a response *Organization* and its associated *Organization-affiliated* users.
3. We also note that *Organization* and *Organization-affiliated* users use external links in the content of their messages with higher degree than *Non-affiliated* users, which reflects the institutionalized practice of communication with evidence. It presents future study direction to explore the types of URLs shared by such user accounts, in contrast to *Non-affiliated* users. For instance, external URL pointing to information about response and relief versus multimedia content about the situation of affected region and people.

DISCUSSION AND FUTURE WORK

We discuss the lessons, limitations, and future work directions from the presented analysis in this section.

Lessons

We have analyzed the diverse user types participating in social media discussions surrounding real-world crisis events by first identifying such users and then studying patterns of their user-generated content. While proposing a baseline method for user type classification of *Organization*, *Organization-affiliated*, and *Non-affiliated* classes, we achieved a fair to good performance and noted a scope of improvement for both accuracy and F_1-score. Given the complexity of inferring a latent attribute of a user and that also in the context of informal user-generated content practices on social media, we anticipate further exploration to improve contextual features of learning, such as through historic data of users from diverse crisis events.

Limitations and Future Work

We note that our technical problem is a multiclass classification task, which is a more complex task than a binary classification task and has a higher complexity to achieve a better classification performance. However, to scope the study, we did not test different strategies for the efficient classification, such as binarization framework of one-vs-all. Our datasets are available for the research community and will facilitate such future studies. In addition, we explored the natural distribution of the user type classes for training the classifier, which showed an imbalance for user type labels, presenting a challenge for learning an efficient classifier. We did not employ any remedies for imbalance, which again provides a direction for future studies to build on the presented work. The presented analysis only included English language seed terms for collecting data from Twitter API, which provides a place for a multilingual study of events in the future. As a consequence, the percentage of classified users of *Organization* and *Organization-affiliated* types may be an underestimate, given that we were not able to identify users in non-English languages. Such users can be especially important for the events where many affected nations likely have non-English communications on Twitter. Our future work direction is to consider domain-driven content analysis after the precursor analysis of user types, for a better understanding of what information is communicated by which types of users, at a large-scale (given the automated user classifier method). Recent works such as Hodas et al. (2015), have explored the role of domain driven entities, (both experts and lexicon) on improving the automatic extraction of information during crises. In addition, further work is needed to understand what degree of a domain driven filtering process combined with the precursor analysis of user types can improve or provide added value to existing knowledge bases of humanitarian and disaster coordination efforts. For instance, during Hurricane Sandy, Federal Emergency Management Agency (FEMA) and the American Red Cross used Twitter to communicate situational updates, but also followed specific domain driven keywords to explore how it may improve their domain-specific knowledge base for response activities (U.S. Department of Homeland Security, Science and Technology Directorate, Virtual Social Media Working Group, 2013).

CONCLUSION

This study presented a new approach for studying users who engage on social media during crisis events. We specifically developed an automated classifier for classifying users by type - *Organization*, *Organization-affiliated*, and *Non-affiliated*. Our method achieved accuracy up to 75%. We applied this classifier to analyze communication patterns of user types for two recent crises and found diverse patterns of user engagement by the user types. We observed that *Organization* users mainly act as information disseminator than receivers or conversationalists on Twitter during crises, while they could benefit from interacting with and sourcing critical information through other users, including other *Organization* users. For an application, our proposed classification system can be employed for real-time content analysis during future crises, by relying on features of only user profile metadata of the continuous streaming posts.

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